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Application of Artificial Intelligence in the Detection and Prediction of Atrial Fibrillation in ECG Recordings – A Narrative Review

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Abstract

Introduction and purpose. Atrial fibrillation (AF) is the most common sustained cardiac arrhythmia and a leading cause of ischaemic stroke, yet it frequently remains undiagnosed because of its paroxysmal and often asymptomatic nature. Artificial intelligence (AI), and in particular deep learning applied to the electrocardiogram (ECG), has emerged as a transformative approach both for detecting AF when the arrhythmia is present and for predicting future AF from an ECG recorded during sinus rhythm. The purpose of this narrative review is to summarise the current state of knowledge on AI-enabled ECG analysis for the detection and prediction of AF and to critically appraise its clinical readiness.

Description of the state of knowledge. Convolutional neural networks can classify AF on single-lead and twelve-lead ECG with cardiologist-level accuracy (area under the curve, AUC, above 0.97 for rhythm classification) and can identify an "electrocardiographic signature" of AF on a normal sinus-rhythm tracing (AUC approximately 0.87). Consumer wearables using photoplethysmography and single-lead ECG achieve pooled sensitivity and specificity around 95%. Predictive models for incident AF reach AUC values of 0.78–0.85 and have been validated prospectively, enriching the diagnostic yield of screening. Nevertheless, false positives, unclassifiable tracings, limited external validity, and the absence of trials demonstrating a reduction in stroke temper enthusiasm.

Summary. AI-ECG is a mature and accurate tool for AF detection and a promising instrument for AF prediction, but its translation into improved patient-relevant outcomes remains unproven. Rigorous external validation, outcome-driven randomised trials, and clear regulatory and implementation frameworks are required before routine clinical adoption.

Keywords: Atrial Fibrillation; Artificial Intelligence; Deep Learning; Electrocardiography; Mass Screening; Stroke

Introduction

Atrial fibrillation (AF) is the most prevalent sustained cardiac arrhythmia worldwide and a major, independent risk factor for ischaemic stroke, heart failure, cognitive decline, and death. A central clinical problem is that AF is frequently paroxysmal and asymptomatic, so that the first clinical manifestation may be a disabling stroke. Because effective oral anticoagulation can substantially reduce the risk of AF-related stroke, the early identification of individuals with—or at high risk of developing—AF has become a public-health priority [1,2].

The electrocardiogram (ECG) remains the diagnostic reference standard for AF, but conventional, rule-based computerised ECG interpretation is imperfect; a United States hospital study found that roughly one-third of ECGs with a computerised AF interpretation were misread, with inappropriate downstream treatment or testing initiated in a meaningful minority of patients [3]. Over the past decade, artificial intelligence (AI)—especially deep learning with convolutional neural networks (CNNs)—has changed the way the ECG can be used [4-8]. Two conceptually distinct tasks have emerged: first, the **detection** of AF when the arrhythmia is actually present on the recording; and second, the **prediction** of AF from an ECG recorded during normal sinus rhythm, exploiting subtle features invisible to the human eye and thought to reflect atrial structural and electrical remodelling [9,10].

The purpose of this narrative review is to provide clinicians and biomedical researchers with an integrated, critical overview of how AI is applied to the ECG for the detection and prediction of AF. The review describes the landmark algorithms and their diagnostic performance, the role of consumer wearables, the evidence for AF prediction from sinus-rhythm tracings, and the prospective and comparative data available to date. It then addresses the principal barriers to clinical adoption—dataset bias, limited generalisability, overdiagnosis, the unresolved anticoagulation dilemma for device-detected AF, and the regulatory landscape—before summarising current guideline positions and future directions.

Description of the state of knowledge

Methodological approach

This is a narrative (non-systematic) review. The English-language medical literature was examined for original studies, systematic reviews and meta-analyses, clinical practice guidelines, and scientific statements addressing AI-enabled ECG analysis for AF detection and prediction, with emphasis on landmark and recent high-impact publications (2019–2026). Priority was given to prospective studies, external validation cohorts, randomised trials, and consensus documents from major cardiology societies.

Deep learning for AF detection from the ECG

The proof that deep learning could match expert human performance in arrhythmia classification was provided by Hannun and colleagues, who trained a 34-layer deep neural network on 91,232 single-lead ambulatory ECG recordings from 53,549 patients to classify twelve rhythm classes, including AF. The network achieved an average AUC above 0.97 and an average F1 score of 0.837, exceeding the average cardiologist score of 0.780; at the average cardiologist specificity, the model's sensitivity surpassed that of cardiologists for every rhythm class [11]. Subsequent device-agnostic models trained on resting twelve-lead ECGs generalised to ambulatory patch and benchmark databases, achieving 94% sensitivity and 98% positive

predictive value for AF episode detection on the MIT-BIH database despite differences in leads and sampling frequency [12].

Meta-analytic data confirm high accuracy for AF detection across modalities. A systematic review and meta-analysis of 31 studies reported pooled sensitivity and specificity of 95.1% and 96.2% for photoplethysmography (PPG)-based AI and 92.3% and 96.2% for single-lead ECG AI, respectively—though between 0% and 43% of PPG tracings and up to 38% of single-lead ECG tracings were unclassifiable, an important real-world caveat [13].

Consumer wearables and point-of-care devices

AI-enabled consumer and point-of-care technologies have moved AF detection out of the clinic [14]. The Apple Heart Study enrolled 419,297 participants using PPG-based irregular-pulse detection; only 0.52% received a notification, but among those undergoing subsequent ECG-patch monitoring the positive predictive value of an irregular-pulse notification was 0.84 [15]. A meta-analysis of smartwatch studies (26 studies, 17,349 patients) found pooled sensitivity of 95%, specificity of 97%, and an AUC of 0.97, with PPG-based and ECG-based approaches performing comparably [16]. A dedicated Apple Watch ECG meta-analysis reported pooled sensitivity and specificity of approximately 95% each [17]. The Fitbit Heart Study (455,699 participants) reported a positive predictive value of 98.2% for concurrent AF among those wearing confirmatory ECG patches [18], and the Huawei Heart Study, using PPG in more than 2.8 million users, confirmed AF in 93.8% of those flagged [19].

The FDA-cleared single-lead KardiaMobile device illustrates both the promise and the limitations of these tools: community and primary-care validation studies reported automated-algorithm sensitivity ranging from 55% to 98% and specificity from 60% to 98%, but expert interpretation of the same tracings approached 100% sensitivity and specificity, underscoring that the automated algorithm, not the signal, is often the limiting factor [20,21]. The REHEARSE-AF study showed a nearly four-fold increase in AF detection using KardiaMobile in older patients at elevated stroke risk [19]. The real-world importance of **inconclusive tracings** was quantified by the head-to-head BASEL Wearable Study of five direct-to-consumer devices: when inconclusive recordings were excluded, all devices exceeded 90% sensitivity and specificity, but in an intention-to-diagnose analysis sensitivity fell to 58–85% with 17–26% of tracings inconclusive [22]. AI re-interpretation of the same wearable signals can mitigate this problem—one neural-network algorithm achieved pragmatic sensitivity and specificity of 98.4% and 96.1%, versus 78.1% and 81.0% for a native smartwatch algorithm, while reducing inconclusive outputs by 92% [23].

Prediction of atrial fibrillation from the sinus-rhythm ECG

The conceptual leap from detection to prediction was made by Attia and colleagues at the Mayo Clinic, who trained a CNN on hundreds of thousands of sinus-rhythm twelve-lead ECGs to identify patients with AF who happened to be in sinus rhythm at the time of recording. A single ten-second ECG yielded an AUC of 0.87 (sensitivity 79.0%, specificity 79.5%), rising to 0.90 when multiple ECGs from the first month were used [10]. The model was independently reproduced at a European centre with an identical AUC of 0.87, and saliency analyses in both settings implicated the P-wave as the most influential segment—consistent with the hypothesis that the network detects atrial substrate abnormalities such as fibrosis and remodelling [24].

Building on this, several groups developed models to predict **incident** AF over defined horizons. A deep neural network predicted one-year incident AF with an AUC of 0.85 and a number-needed-to-screen of nine [25]. Khurshid and colleagues trained an ECG-AI model for five-year incident AF that performed comparably to the eleven-variable CHARGE-AF clinical score (AUROC 0.823 at the development institution), with a combined ECG-plus-clinical model (CH-AI) consistently superior (AUROC up to 0.838); again, saliency mapping highlighted the P-wave [26]. A model developed on more than 900,000 veteran ECGs predicted AF within 31 days with high discrimination that was robust across women and Black patients and across multiple sites [27]. Models from the Montreal Heart Institute (AUC 0.78 internally; 0.77 on external MIMIC-IV validation) outperformed both CHARGE-AF and a polygenic risk score [28]; other groups have likewise demonstrated end-to-end prediction of incident AF directly from the raw twelve-lead ECG using deep neural networks [29]. A multinational community study across the Framingham Heart Study, UK Biobank, and ELSA-Brasil reported an AUC of 0.82, improving to 0.85 when combined with CHARGE-AF, while also predicting heart failure, myocardial infarction, stroke, and mortality [30]. Table 1 summarises representative studies.

Table 1. Representative AI-ECG studies for atrial fibrillation detection and prediction.

Study (year)	Task	Input	Key performance metric
Hannun et al. (2019) [11]	Classify 12 rhythms incl. AF	Single-lead ambulatory ECG	Average AUC 0.97; F1 0.837 (> cardiologists 0.780)
Attia et al. (2019) [10]	Detect AF signature during sinus rhythm	12-lead ECG	AUC 0.87 (single); 0.90 (multiple ECGs)
Raghunath/Yazdi (2021/2025) [25]	Predict 1-year incident AF	12-lead ECG	AUC 0.85; number-needed-to-screen 9
Khurshid et al. (2022) [26]	Predict 5-year incident AF	12-lead ECG + clinical	AUROC 0.823 (ECG-AI); 0.838 (combined)
Yuan et al. (2023) [27]	Predict AF within 31 days	12-lead ECG	High, calibrated, multi-site; robust by sex/race
Jabbour et al. (2024) [28]	Predict 5-year incident AF	12-lead ECG	AUC 0.78 internal; 0.77 external
Brant et al. (2025) [30]	Predict incident AF (community)	12-lead ECG	AUC 0.82; 0.85 with CHARGE-AF

Noseworthy et al. (2022) [31]	Prospective AI-guided screening	12-lead ECG	AF detection 10.6% vs 3.6% (hazard ratio 2.85)
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Prospective and comparative evidence

The first prospective validation of AI-guided screening was the Mayo Clinic non-randomised interventional trial, in which patients with a high AI-ECG risk score underwent up to 30 days of continuous monitoring. Among high-risk patients, the AI-based programme increased the AF diagnosis rate to 10.6% versus 3.6% with usual care (hazard ratio 2.85, 95% confidence interval 1.83–4.42), and anticoagulation was initiated in roughly three-quarters of newly diagnosed patients [31]. The same programme illustrated the trade-off inherent in prediction: 63% of patients tested "positive," and specificity for detecting at least 30 seconds of AF during monitoring was only 38%, so the great majority of high-risk patients did not have detectable AF during the monitoring window [31].

Head-to-head comparisons with the CHARGE-AF clinical score generally show that AI-ECG provides complementary rather than wholly independent information: the two are moderately correlated, and combined models consistently discriminate best [26,32]. In a post-hoc analysis of the cluster-randomised VITAL-AF primary-care screening trial [33], ECG-AI (AUROC 0.784) and a combined CH-AI model (AUROC 0.788) outperformed CHARGE-AF (AUROC 0.711), and a screening benefit was observed specifically in the highest decile of AI-defined risk, suggesting that AI can concentrate the yield of screening on those most likely to benefit [34]. AI analysis of handheld single-lead ECGs from the same trial achieved discrimination comparable to the full clinical score [35]. Prediction from single-lead tracings is nonetheless more difficult: performance in an age-homogeneous screening population fell to an AUC of 0.62 compared with 0.80 across a wide age range, reflecting the contribution of age to the prediction [36]. Pragmatic randomised trials of smartphone-based screening pathways have also been undertaken to identify undiagnosed AF at scale in the community [37].

Limitations: bias, generalisability, overdiagnosis, and the anticoagulation dilemma

Despite impressive metrics, several limitations constrain clinical translation. **Dataset bias and data dependency** are foremost: many landmark models were developed at single tertiary centres, and models achieving 98–99% accuracy internally have dropped to 53–92% on external datasets owing to class imbalance, differing preprocessing, and hardware heterogeneity [38]. External validation of the five-year CH-AI model showed AUROC declining from 0.823 at the development institution to 0.705 in the UK Biobank, with over-estimation of risk that required recalibration [26]. A multicentre validation of a commercial one-year prediction model met a prespecified specificity threshold (92%) but achieved a sensitivity of only 31% [39], and performance of AF-detection models varies by geography, sex, and age [40].

Overdiagnosis and false positives scale with the screened population. Even at 95% specificity, screening one million people with a 2% AF prevalence would generate tens of thousands of false positives; if a proportion are anticoagulated, a predictable number will experience avoidable bleeding [41]. This connects to the central unresolved clinical question: how to manage **device-detected subclinical AF**, which carries roughly half the stroke risk of clinical

AF. The ARTESiA trial showed that apixaban reduced stroke or systemic embolism (0.78% versus 1.24% per year) but increased major bleeding, whereas NOAH-AFNET 6 was stopped early for a doubling of major bleeding without a clear efficacy benefit; a pooled analysis showed a 32% relative reduction in ischaemic stroke offset by increased major bleeding, with net benefit likely confined to patients at the highest clinical risk [42-44]. Critically, large screening trials—including LOOP and GUARD-AF—have increased AF detection and anticoagulation without demonstrating a significant reduction in stroke, and the AMALFI patch-screening trial likewise showed no clear stroke benefit [45,46].

Regulatory and implementation considerations

Most cardiovascular AI tools, including AF-detection software, have reached the market through the FDA 510(k) pathway, with only a small minority supported by high-quality clinical trials and an identified risk of "predicate creep" [47]. Adaptive algorithms, model drift, black-box interpretability, liability, workflow integration, and alert fatigue are recognised barriers; the 2026 HRS scientific statement frames successful deployment around the "five rights" of clinical decision support and warns that many AI-ECG algorithms currently run post hoc, generating alerts that may be overlooked [48]. Continuous post-market monitoring with multisite validation has been proposed as the foundation of responsible clinical oversight [49].

Current guideline positions

The 2024 European Society of Cardiology (ESC) AF guidelines recommend opportunistic screening in patients aged 65 years or older and list AI algorithms among screening tools, while cautioning that their clinical performance and broad applicability "are not yet known" and requiring physician confirmation of any screen-positive result with a 30-second rhythm strip or twelve-lead ECG [1]. The 2023 ACC/AHA/ACCP/HRS guideline describes device algorithms as generally reliable but mandates professional over-read, states that PPG alone is insufficient to diagnose AF, and notes that it is "not yet established" that screening high-risk individuals improves stroke or survival outcomes [50]. The US Preventive Services Task Force continues to judge the evidence insufficient for routine population screening [3]. The 2025 EHRA/HRS/ESC scientific statement affirms that multiple independent teams have shown CNNs can detect an AF signature during sinus rhythm, while documenting substantial gaps in the reporting quality of AI-ECG studies [51].

Summary

Artificial intelligence applied to the ECG has become a powerful and well-validated tool for the **detection** of atrial fibrillation, matching or exceeding expert human performance for rhythm classification and underpinning a generation of accurate consumer wearables and point-of-care devices. Its most innovative contribution is the **prediction** of AF from a sinus-rhythm tracing, where deep-learning models achieve area-under-the-curve values of roughly 0.78–0.90, complement established clinical risk scores, and have been shown prospectively to enrich the diagnostic yield of targeted screening. These advances offer a realistic path toward identifying occult and future AF earlier than ever before.

However, the field has not yet demonstrated what matters most to patients. No completed randomised trial has shown that AI-guided AF screening reduces stroke, systemic embolism, or mortality, and the parallel uncertainty surrounding anticoagulation for device-detected

subclinical AF means that a positive AI result does not automatically translate into a beneficial intervention. False positives at population scale, unclassifiable tracings, limited external validity across populations and devices, and an immature regulatory and implementation framework remain substantial obstacles. The responsible way forward requires rigorous multisite external validation, transparent reporting, continuous post-market surveillance, and—above all—outcome-driven randomised trials linking AI-ECG screening to hard clinical endpoints. Until that evidence matures, AI-ECG is best regarded as a highly promising adjunct that augments, rather than replaces, clinical judgement and physician-confirmed diagnosis.

Disclosure

Author Contribution

Conceptualization, [S.P.] and [P.M.]; methodology, [W.N.]; software, [D.M.]; validation, [M.S.], [Z.S.] and [P.U.]; formal analysis, [S.P.]; investigation, [P.M.]; resources, [W.N.]; data curation, [D.M.]; writing—original draft preparation, [M.S.]; writing—review and editing, [Z.S.] and [P.U.]; visualization, [S.P.]; supervision, [P.M.]; project administration, [W.N.]; funding acquisition, [D.M.]. All authors have read and agreed to the published version of the manuscript.

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