



Diagnostic accuracy of wearable technologies for atrial fibrillation detection: a systematic review and meta-analysis

Alina Abbas,¹ Gauhar Hamid,² Beesham Kumar,³ Sajida Moiz Hussain Qamari,³ Hira Riaz⁴

¹King Edward Medical University, Lahore, Pakistan; ²Liaquat University of Medical and Health Sciences, Jamshoro, Pakistan; ³Jinnah Medical and Dental College (JMDC), Karachi, Pakistan; ⁴Kabul Medical College, Kabul, Afghanistan

Abstract

Atrial fibrillation (AF) is the most common sustained cardiac arrhythmia and a major cause of ischemic stroke. Because AF is frequently paroxysmal and asymptomatic, conventional short-term monitoring often fails to detect it. Wearable technologies have emerged as promising tools for AF screening, but their diagnostic performance requires comprehensive evaluation. We conducted a systematic review and diagnostic test accuracy meta-analysis following PRISMA-DTA guidelines. PubMed, Embase, and the Cochrane Library were searched from inception to 25 February 2026 for prospective and retrospective studies using electrocardiographic reference standards. Bivariate random-effects and Bayesian hierarchical models were used to pool diagnostic accuracy estimates. Fifty-one studies involving 33,374 participants from 15 countries were included. PPG-based smartwatches demonstrated the highest sensitivity (96.3%) with specificity of 93.6%. ECG-based smartwatches achieved sensitivity of 89.0% and specificity of 92.8% (DOR 103.9). Smartphone-based ECG devices showed the strongest overall diagnostic performance, with sensitivity of 94.5%, specificity of 95.8%, DOR of 396.4, LR+ of 22.6, and LR- of 0.057. Smartphone-based PPG applications achieved sensitivity of 92.0% and specificity of 91.9%. Apple Watch demonstrated sensitivity of 94.1% and specificity of 94.6%. Meta-regression revealed no statistically significant differences in diagnostic accuracy between device categories despite slightly higher point estimates for PPG-based smartwatches. No significant publication bias was detected (Deeks' test, $p=0.18$). Wearable devices demonstrate excellent diagnostic accuracy for AF detection, particularly smartphone-based ECG applications. These technologies support scalable AF screening and monitoring, although heterogeneity in study populations and diagnostic thresholds should be considered when applying these findings to routine clinical practice.

Key words: atrial fibrillation; wearable devices; photoplethysmography; electrocardiography; diagnostic accuracy..

Received: 17 April 2026; Accepted: 25 September 2025.

*Correspondence to: Hira Riaz, Kabul Medical College, G49M+JQX, Kabul University Rd, Kabul 100306, Afghanistan. E-mail: hirariaz385@gmail.com

Introduction

Atrial fibrillation (AF) is the most common sustained cardiac arrhythmia and represents a major contributor to cardiovascular morbidity and mortality worldwide. Recent epidemiological estimates suggest that more than 59 million individuals globally are affected by AF, and the prevalence is expected to rise substantially as populations age and cardiovascular risk factors increase.¹ AF is associated with a five-fold increased risk of ischemic stroke, as well as increased risks of heart failure and all-cause mortality, making early detection and treatment essential for preventing adverse outcomes.^{2,3}

Despite its clinical importance, AF often remains undiagnosed because many episodes are paroxysmal or asymptomatic, occurring intermittently and therefore escaping detection during routine clinical assessments. Conventional diagnostic strategies, such as standard 12-lead electrocardiography (ECG) or short-term Holter monitoring, provide only limited monitoring windows and may fail to capture transient arrhythmic episodes. Although prolonged monitoring with implantable or extended ECG devices can improve AF detection rates, these methods are costly, invasive, and impractical for large-scale population screening.⁴

Advances in mobile health technologies have led to the rapid

development of wearable devices capable of detecting AF in ambulatory settings, offering a potentially scalable approach for early arrhythmia identification. These technologies generally rely on two principal physiological sensing modalities: ECG and photoplethysmography (PPG). ECG-based devices measure the electrical activity of the heart directly and are commonly incorporated into handheld or smartphone-connected single-lead ECG systems. Devices such as the KardiaMobile platform have demonstrated promising diagnostic accuracy for AF detection in several validation studies, including those conducted by Himmelreich *et al.*⁵ and Bumgarner *et al.*,⁶ in which single-lead ECG recordings obtained through consumer devices were compared with standard clinical ECG references. Similarly, intermittent handheld ECG screening strategies have been evaluated for AF detection in community populations, with studies such as that by Svennberg *et al.*⁷ demonstrating the feasibility of repeated ECG recordings for identifying previously undiagnosed AF. In contrast, PPG-based technologies detect AF indirectly by analyzing pulse wave variability using optical sensors that measure changes in peripheral blood volume. These sensors are widely integrated into consumer wearables such as smartwatches and fitness trackers, allowing continuous or semi-continuous monitoring of heart rhythm. Several studies have demonstrated the ability of smartwatch-derived PPG signals to detect AF with high diagnostic accuracy. For example, Tison *et al.*⁸ showed that irregular pulse detection using smartwatch PPG data could identify AF with high sensitivity and specificity when validated against simultaneous ECG recordings. Additional studies using smartphone-based PPG applications, such as those by McManus *et al.*, Rozen *et al.*, and Proesmans *et al.*,^{9–11} have further demonstrated that pulse waveform analysis obtained through mobile devices can effectively differentiate AF from sinus rhythm. These findings highlight the growing potential of wearable technologies to facilitate AF detection outside traditional clinical settings.

The rapid expansion of consumer wearable devices has generated significant interest in their role in AF screening and long-term rhythm monitoring. Large-scale observational studies and validation trials have evaluated a wide range of wearable platforms, including smartphone-based ECG devices, smartwatch-integrated ECG systems, wrist-worn PPG sensors, and smartphone camera-based pulse detection technologies. However, existing studies vary substantially in device type, signal acquisition method, study design, and population characteristics, making direct comparisons difficult. Furthermore, many validation studies have been conducted in selected patient populations or controlled clinical environments, such as cardioversion cohorts, which may not reflect real-world screening scenarios. Although several individual validation studies and narrative reviews have explored wearable AF detection technologies, the overall diagnostic accuracy of these devices across different technological platforms remains uncertain. In particular, it is unclear how the diagnostic performance of wearable ECG-based devices compares with that of PPG-based monitoring systems and other emerging wearable technologies. A comprehensive synthesis of available evidence is therefore needed to better un-

derstand the reliability and clinical applicability of these tools. Accordingly, the aim of the present study is to perform a systematic review and diagnostic meta-analysis evaluating the accuracy of wearable devices for the detection of atrial fibrillation. By pooling evidence from studies evaluating smartphone-based ECG devices, smartwatch-derived PPG monitoring systems, and other wearable sensor technologies, this analysis seeks to provide robust estimates of diagnostic performance and to explore potential sources of heterogeneity across device categories. Such evidence may help clarify the role of wearable technologies in AF screening and inform future strategies for digital cardiovascular monitoring.

Methodology

Study design and reporting

This study was conducted as a systematic review and diagnostic test accuracy (DTA) meta-analysis to evaluate the accuracy of wearable devices for the detection of cardiac arrhythmias. The review followed a predefined protocol and was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses of Diagnostic Test Accuracy Studies (PRISMA-DTA) guidelines.¹² The protocol for this systematic review and meta-analysis was prospectively registered on the Open Science Framework (OSF) platform. The registration is publicly accessible at <https://osf.io/4kvdp/overview>.

Database search

A comprehensive and systematic literature search was performed to identify diagnostic accuracy studies evaluating wearable devices for atrial fibrillation detection. Electronic databases, including PubMed/MEDLINE, Embase, and the Cochrane Library, were searched from the inception of the databases to the most recent search date prior to analysis.

The search strategy combined controlled vocabulary terms and free-text keywords related to wearable technologies and cardiac arrhythmias. Core search terms included variations of wearable devices (*e.g.*, smartwatch, fitness tracker, handheld ECG, ECG patch, photoplethysmography, PPG devices, portable ECG, smartphone-based devices) and arrhythmia-related terms (*e.g.*, atrial fibrillation, cardiac arrhythmia, rhythm disorder, arrhythmia detection). The full search strategy is provided in the Supplementary Material. Reference lists of included studies and relevant reviews were manually screened to identify additional eligible studies.

Eligibility criteria

Studies were eligible for inclusion if they were prospective or retrospective diagnostic accuracy studies evaluating wearable or smartphone-based devices for the detection of atrial fibrillation in adults (≥ 18 years).¹³ Studies were required to use a clinically accepted electrocardiographic reference standard, such

as 12-lead ECG, Holter monitoring, or physician-adjudicated ECG interpretation.

Studies reporting sufficient data to construct 2×2 contingency tables (true positives, false positives, false negatives, true negatives) or directly reporting sensitivity and specificity were included. Publication bias was assessed using Deeks' funnel plot asymmetry test, with $p < 0.10$ indicating potential bias. Randomized controlled trials, cohort studies, and cross-sectional diagnostic studies were all considered eligible if they met diagnostic accuracy criteria.

Studies were excluded if they were reviews, editorials, case reports, conference abstracts without full data, or if they relied solely on automated reference standards without clinical confirmation.

Index tests and device classification

Devices were categorized into four groups based on sensing modality and platform: ECG-based smartwatch devices, PPG-based smartwatch devices, smartphone-based ECG devices, and smartphone-based PPG applications. This classification was applied consistently across all analyses to enable comparison of diagnostic performance across device types.

Reference standard

The reference standard for arrhythmia diagnosis across included studies was conventional electrocardiographic assessment, including 12-lead ECG, Holter monitoring, or rhythm adjudication by qualified healthcare professionals. Studies in which arrhythmia diagnosis was based solely on automated interpretation without clinician confirmation were excluded.

Because AF is frequently paroxysmal, the timing of the reference standard relative to the index test was also recorded during data extraction and considered when interpreting pooled estimates. Studies were classified according to whether the reference standard was obtained simultaneously with the index test (*e.g.*, concurrent Holter or continuous ECG telemetry worn alongside the wearable device) or sequentially/intermittently (*e.g.*, a separate short-duration ECG obtained before or after index testing, or spot-check comparisons). Simultaneous recording allows direct beat-to-beat or episode-level comparison between the index test and reference standard, whereas sequential or intermittent designs are more susceptible to underestimating diagnostic accuracy because a transient AF episode captured by one method may not be present during the recording window of the other. This distinction is noted narratively where reported by study authors (Section 3.2 and Supplementary Table S2) and is discussed further as a source of heterogeneity (Section 4.4) and as a limitation (Section 4.6), since it was not consistently or explicitly reported across studies and could therefore not be incorporated as a formal subgroup or meta-regression variable.

Handling of non-interpretable tracings and signal artifacts was also extracted where reported. Approaches varied across studies: some explicitly excluded uninterpretable or artifact-corrupted recordings from the denominator prior to calculating

sensitivity and specificity, while others retained them and adjudicated them as false negatives (if the device returned an inconclusive or “unclassified” reading for a true AF episode) or, less commonly, as false positives. Because this handling was inconsistently reported and not uniformly applied across the included studies, we did not re-derive contingency tables to harmonize this classification; pooled estimates therefore reflect each study's original treatment of non-interpretable data. This represents an important source of variability in real-world device performance and is addressed further in Sections 4.4 and 4.6.

Data extraction

Two reviewers independently extracted data using a standardized data extraction form. Extracted variables included study characteristics, participant characteristics, device type, reference standard, and diagnostic accuracy outcomes. Sensitivity and specificity were extracted directly when reported or calculated from available data where necessary. Discrepancies were resolved through discussion or consultation with a third reviewer.

Quality assessment

The methodological quality and risk of bias of included studies were independently assessed using the Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool.¹⁴ Risk of bias was evaluated across four domains: patient selection, index test, reference standard, and flow and timing. Applicability concerns were assessed for patient selection, index test, and reference standard.

Statistical analysis

Between-study heterogeneity was assessed through visual inspection of forest plots and hierarchical summary receiver operating characteristic (HSROC) curves, as well as estimation of between-study variance parameters. Although I^2 is not routinely recommended for diagnostic meta-analyses, variability was interpreted using prediction regions and random-effects parameters.

Meta-regression analyses were conducted to evaluate the effect of device type on diagnostic performance. Statistical significance was assessed using likelihood ratio tests. For analyses involving smartphone-based PPG applications, a Bayesian hierarchical model was employed to account for sparse data and variability. Non-informative priors were used, and model convergence was assessed using standard diagnostic criteria.

Results

Study selection

A total of 274 records were identified through database searches. After removing 36 records prior to screening—which

included duplicate records ($n=23$), records marked as ineligible by automation tools ($n=4$), and records removed for other reasons ($n=9$)—238 records remained for initial screening. Following the screening of titles and abstracts, 124 records were excluded. Of the 114 reports sought for retrieval, 109 were successfully retrieved and assessed for eligibility. Five reports could not be retrieved. Upon full-text assessment, 58 reports were excluded for the following reasons: different population ($n=42$), required intervention not present ($n=12$), and wrong study type ($n=4$). Ultimately, 51 new studies met the inclusion criteria and were included in the review. The search strategy is summarized in Supplementary Table S1. Study selection is shown in Figure 1 in the PRISMA flow diagram.

Study characteristics

A total of 51 studies comprising 33,374 participants were included in the analysis. Study designs included prospective diagnostic studies, retrospective analyses, and validation cohorts, encompassing both wearable and smartphone-based devices for the detection of AF. The studies were conducted across multiple countries, including the USA, France, Switzerland, the Netherlands, Norway, Taiwan, Hong Kong, Japan, Saudi Arabia, Turkey, Finland, China, Australia, Belgium, and the UK. Sample sizes ranged widely, from small pilot studies with 20 participants (*e.g.*, Bonomi *et al.*)¹⁵ to large population-based cohorts exceeding 10,000 participants (Chan *et al.*).¹⁶ The mean age of partici-

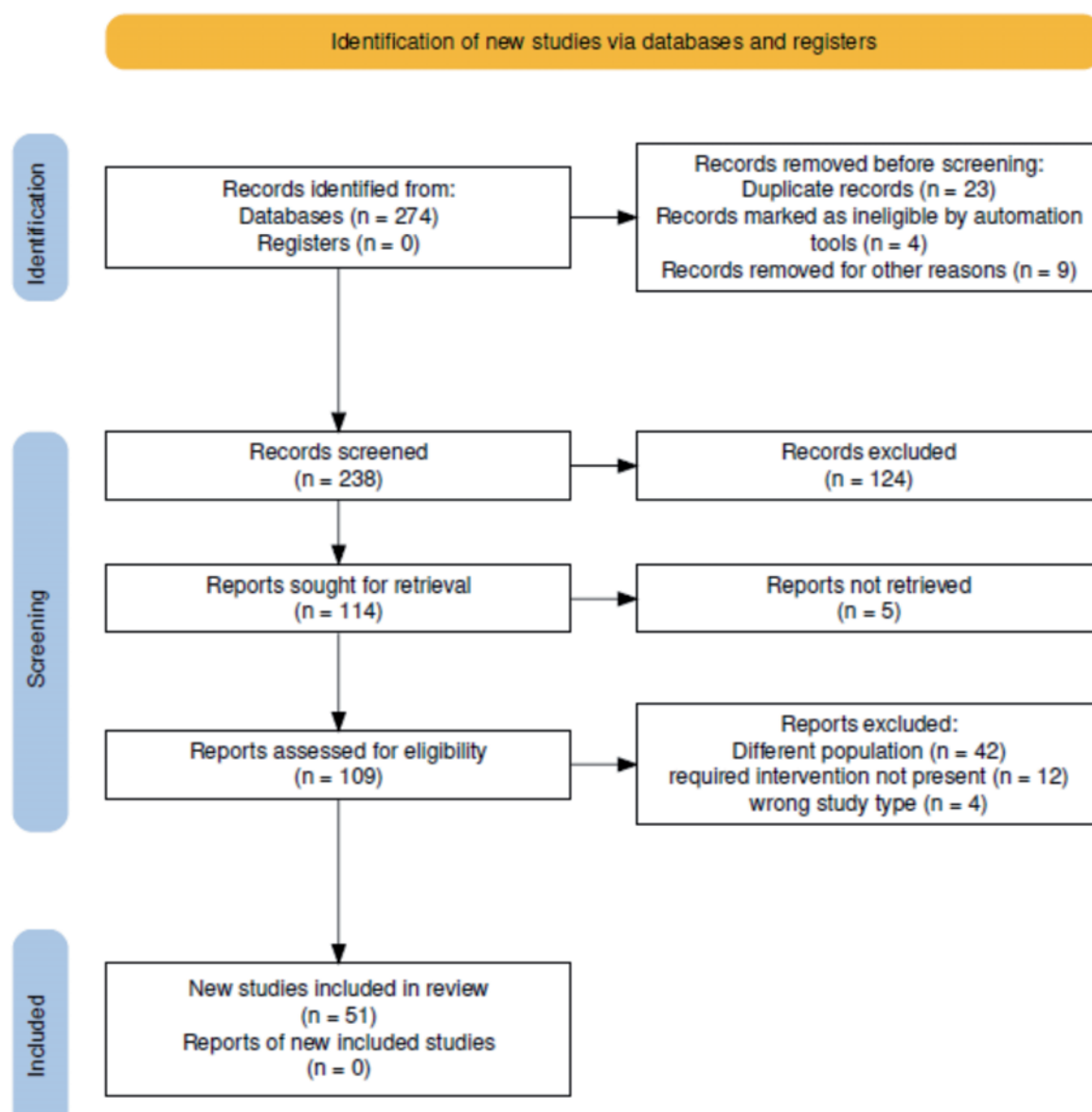


Figure 1. Prisma flow diagram.

pants varied from 36 years (Haberman *et al.*)¹⁷ to 78.6 years (Chan *et al.*)¹⁶ with a majority of studies including predominantly male populations, although the proportion of male participants ranged from 17% to 83%.

The included studies evaluated a variety of wearable and smartphone-based sensors, including photoplethysmography (PPG) smartwatches, ECG smartwatches (Apple Watch, Samsung, Withings, Fitbit, KardiaBand), and smartphone-based ECG or PPG applications. Some studies used multiple device types within the same cohort. PPG-based wearables were frequently used in prospective studies, with ECG-based smartwatches predominantly assessed in clinical diagnostic validation studies. Smartphone-based devices utilized either PPG (facial or fingertip) or single-lead ECG modalities.

Gold-standard comparators varied across studies, with the majority using 12-lead ECG interpreted by cardiologists, followed by 24-hour or 7-day Holter ECG, telemetry, or implantable cardiac monitors (*e.g.*, Reveal LINQ). AF detection protocols ranged from short-duration recordings (30–60 seconds) to continuous monitoring over several days, reflecting heterogeneity in diagnostic approaches. Overall, the included studies provide a comprehensive evaluation of the accuracy and feasibility of wearable and smartphone-based technologies for AF detection across diverse populations, age groups, and clinical settings. Results are summarized in Supplementary Table S2.

Quality assessment (QUADAS-2)

The methodological quality of the included studies was assessed using the QUADAS-2 tool across four domains: patient selection, index test, reference standard, and flow and timing, along with three domains evaluating applicability concerns.

Overall, the included studies demonstrated low risk of bias across most domains, indicating generally high methodological quality. The patient selection domain was judged to be at low risk of bias in all included studies, reflecting appropriate sampling strategies and avoidance of inappropriate exclusions. Similarly, the index test domain showed predominantly low risk of bias, with only a small number of studies rated as having unclear risk due to insufficient reporting of blinding or pre-specified thresholds. Results are summarized in Supplementary Table S3.

For the reference standard domain, most studies were considered low risk; however, a minority were rated as having unclear risk of bias, primarily due to limited detail regarding blinding of outcome assessors or the exact criteria used for atrial fibrillation diagnosis. The flow and timing domain was also largely assessed as low risk, although a few studies were categorized as unclear due to incomplete reporting of the interval between index testing and reference standard assessment or potential patient exclusions from the final analysis.

Regarding applicability concerns, most studies were judged to have low concern across all domains. However, a small proportion of studies demonstrated unclear applicability in the index test and reference standard domains, largely due to variations in device algorithms, implementation settings, or lack of clarity regarding clinical applicability to general population screening.

Overall, most studies demonstrated low to moderate risk of bias across QUADAS-2 domains. However, several concerns were identified. Patient selection bias was present in studies enrolling highly selected populations, such as patients undergoing cardioversion or clinical arrhythmia evaluation, which may limit generalizability. Additionally, variability in index test thresholds and incomplete reporting of blinding procedures contributed to unclear risk in some studies. These factors suggest the possibility of spectrum bias and should be considered when interpreting pooled estimates.

Photoplethysmography-based smartwatches

Diagnostic accuracy estimates for PPG-based smartwatch devices are summarized in Supplementary Table S4. The pooled sensitivity was 96.3%, while the pooled specificity was 93.6%, indicating high diagnostic accuracy for detecting atrial fibrillation (AF). The corresponding negative likelihood ratio was 0.039, suggesting a low probability of AF in cases with a negative test result. Visual inspection of the hierarchical summary receiver operating characteristic (HSROC) plot demonstrated notable heterogeneity, with individual study estimates dispersed around the pooled summary point (Supplementary Figure S1). The 95% confidence region surrounding the summary estimate was relatively narrow, indicating precision in the pooled estimate. However, the 95% prediction region was broader, reflecting substantial between-study variability in diagnostic performance (Supplementary Figure S2).

Electrocardiography-based smartwatches

Diagnostic accuracy estimates for ECG-based smartwatch devices are summarized in Supplementary Table S4. The pooled sensitivity was 89.0% (95% CI: 84.7–92.2%), while the pooled specificity was 92.8% (95% CI: 89.2–95.3%), indicating good diagnostic performance for detecting atrial fibrillation (AF) (Supplementary Figures S3 and S4). The false positive rate was 7.2% (95% CI: 4.7–10.8%). The pooled diagnostic odds ratio was 103.93 (95% CI: 53.12–203.34), demonstrating strong overall discriminatory ability of the devices, although lower than previously observed estimates.

The positive likelihood ratio was 12.35 (95% CI: 8.05–18.92), indicating a moderate to strong increase in the probability of AF following a positive test result. Conversely, the negative likelihood ratio was 0.119 (95% CI: 0.084–0.168), suggesting that a negative test result substantially reduces, but does not eliminate, the probability of AF.

Visual inspection of the HSROC plot demonstrated notable heterogeneity, with individual study estimates dispersed around the pooled summary point (Supplementary Figure S5). The 95% confidence region surrounding the summary estimate was relatively narrow, indicating reasonable precision in the pooled estimates. However, the 95% prediction region was broader, reflecting considerable between-study variability in diagnostic performance. The estimated correlation between random effects was 0.388, suggesting the presence of a moderate threshold effect across studies.

Smartphone-based electrocardiography devices

Diagnostic accuracy estimates for smartphone-based ECG devices are summarized in Supplementary Table S4. The pooled sensitivity was 94.5% (95% CI: 89.6–97.2%), while the pooled specificity was 95.8% (95% CI: 93.3–97.4%), indicating high diagnostic accuracy for detecting atrial fibrillation (AF) (Supplementary Figure S6). The false positive rate was 4.2% (95% CI: 2.6–6.7%). The pooled diagnostic odds ratio was 396.39 (95% CI: 180.14–872.27), reflecting strong overall discriminatory performance.

The positive likelihood ratio was 22.63 (95% CI: 14.12–36.26), indicating a substantial increase in the probability of AF following a positive test result. Conversely, the negative likelihood ratio was 0.057 (95% CI: 0.030–0.110), suggesting a low probability of AF in cases with a negative test result.

Visual inspection of the HSROC plot demonstrated notable heterogeneity, with individual study estimates dispersed around the pooled summary point (Supplementary Figure S7). The 95% confidence region surrounding the summary estimate was relatively narrow, indicating good precision in the pooled estimates. However, the 95% prediction region was broader, reflecting considerable between-study variability in diagnostic performance. The estimated correlation between random effects was -0.215 , suggesting a mild inverse relationship and limited evidence of a threshold effect across studies.

Smartphone-based photoplethysmography applications

Diagnostic accuracy estimates derived from the Bayesian hierarchical model are summarized in Table S4. The pooled sensitivity was 92.0% (95% posterior interval: 85.3–95.5%), while the pooled specificity was 91.9% (95% posterior interval: 83.5–95.9%), indicating good overall diagnostic performance for detecting AF (Supplementary Figures S8 and S9). The corresponding false positive rate was 8.1% (95% posterior interval: 4.1–16.5%). The pooled diagnostic odds ratio was 128.14 (95% posterior interval: 35.84–397.36), reflecting moderate to strong discriminatory ability. HSROC plot is shown in Supplementary Figure S10.

The positive likelihood ratio was 11.34 (95% posterior interval: 5.34–22.53), indicating a meaningful increase in the probability of AF following a positive test result. Conversely, the negative likelihood ratio was 0.087 (95% posterior interval: 0.048–0.169), suggesting that a negative test result substantially reduces the probability of AF, although not to negligible levels.

On the logit scale, the posterior median for sensitivity (μ_1) was 2.438 (95% posterior interval: 1.759–3.052), and for specificity (μ_0) was 2.429 (95% posterior interval: 1.623–3.143). Substantial between-study heterogeneity was observed, with between-study standard deviations of 0.826 for logit sensitivity and 0.899 for logit specificity. The estimated between-study correlation was 0.679 (95% posterior interval: 0.029–0.961), indicating a strong positive association and suggesting the presence of a threshold effect across studies.

The estimated accuracy parameter (Λ) was 4.936 (95% posterior interval: 3.700–6.110), while the cutpoint parameter (Θ) was 0.103 (95% posterior interval: -0.842 to 1.039). The shape parameter (β) was 0.087 (95% posterior interval: -0.610 to 0.796), indicating no strong asymmetry in the summary receiver operating characteristic curve. The variability in cutpoint and accuracy parameters was reflected by standard deviations of 0.116 and 0.464, respectively, further supporting the presence of between-study heterogeneity.

Device-specific analysis: Apple watch

Diagnostic accuracy estimates for Apple Watch devices are summarized in Table S4. The pooled sensitivity was 94.1% (95% CI: 90.0–96.6%), while the pooled specificity was 94.6% (95% CI: 89.1–97.4%), indicating high diagnostic accuracy for detecting atrial fibrillation (AF). The false positive rate was 5.4% (95% CI: 2.6–10.9%). The pooled diagnostic odds ratio was 282.36 (95% CI: 103.68–769.00), demonstrating strong overall discriminatory performance (Supplementary Figure S11).

The positive likelihood ratio was 17.49 (95% CI: 8.42–36.32), indicating a substantial increase in the probability of AF following a positive test result. Conversely, the negative likelihood ratio was 0.062 (95% CI: 0.036–0.108), suggesting a low probability of AF in cases with a negative test result.

Visual inspection of the HSROC plot demonstrated notable heterogeneity, with individual study estimates dispersed around the pooled summary point (Supplementary Figure S12). The 95% confidence region surrounding the summary estimate was relatively narrow, indicating good precision in the pooled estimates. However, the 95% prediction region was broader, reflecting considerable between-study variability in diagnostic performance. The estimated correlation between random effects was 0.111, suggesting a minimal threshold effect across studies.

Regression analysis

Meta-regression analysis by device type

A meta-regression analysis was conducted to evaluate whether diagnostic performance differed according to device type (ECG smartwatch, PPG smartwatch, smartphone ECG, and smartphone PPG). The summary receiver operating characteristic (SROC) curves demonstrated high overall diagnostic accuracy across all device categories, with curves clustered toward the upper-left corner of the ROC space (Supplementary Figure S13). The accuracy plot is given in Figure S14. Tables S5, S6, and S7 summarize the regression outcomes.

Among the evaluated modalities, PPG smartwatches showed the highest clustering near the top-left region, indicating consistently high sensitivity and specificity with minimal variability. ECG smartwatches demonstrated similarly high diagnostic performance but with slightly greater dispersion, particularly in specificity. Smartphone ECG devices exhibited good sensitivity but comparatively wider variability in specificity, as reflected by

broader confidence regions. Smartphone PPG showed the widest spread of confidence and prediction regions, indicating greater heterogeneity and comparatively lower and less consistent diagnostic performance.

The overlap of confidence and prediction regions across all device types suggests that differences in diagnostic accuracy between modalities were not statistically significant, although trends favored wearable smartwatch-based technologies—particularly PPG-based systems.

Publication bias

Deeks' funnel plot asymmetry test did not show statistically significant evidence of publication bias ($p=0.18$). The funnel plot appeared approximately symmetrical on visual inspection, suggesting a low likelihood of small-study effects (Supplementary Figure S15). However, these findings should be interpreted cautiously due to between-study heterogeneity.

Discussion

Principal findings

In this systematic review and diagnostic meta-analysis, wearable technologies demonstrated high overall accuracy for detecting AF across multiple device types, including smartwatch- and smartphone-based ECG and PPG systems. Pooled sensitivity ranged from 89.0% to 96.3%, while specificity ranged from 91.9% to 95.8%, indicating a strong ability to both detect AF and exclude non-AF rhythms.

PPG-based smartwatches showed the highest sensitivity, supporting their role in initial AF detection, whereas ECG-based smartphone devices demonstrated the highest specificity and diagnostic odds ratios, highlighting their utility in confirming AF. ECG smartwatches showed comparatively lower performance, particularly for ruling out AF, while PPG smartphone applications exhibited greater variability across studies.

The Apple Watch-specific analysis demonstrated consistently high diagnostic accuracy, comparable to other leading device categories. Across all groups, heterogeneity and variable threshold effects were observed, reflecting differences in study populations, device algorithms, and implementation as noted in several contemporary meta-analyses.^{18–20}

Comparison with existing studies

The findings of the present meta-analysis are consistent with a growing body of literature demonstrating the high diagnostic accuracy of wearable technologies for atrial fibrillation detection. Early investigations by Himmelreich *et al.* and Haberman *et al.* reported that smartphone-operated single-lead ECG devices reliably detect rhythm abnormalities in primary care settings.^{15,17} These findings were further validated by studies demonstrating that patient-operated recordings could achieve high-quality tracings equivalent to clinical Lead I standards.²¹

Similarly, Bumgarner *et al.*⁶ reported high diagnostic accuracy of smartwatch-based algorithms capable of automatically detecting AF using single-lead ECG recordings obtained from consumer wearable devices.

PPG-based approaches have also been widely validated. Initial work demonstrated the feasibility of identifying irregular pulse rhythms suggestive of AF using smartphone cameras.⁹ Subsequent research confirmed that smartphone applications could accurately differentiate AF from sinus rhythm in both clinical and community populations.^{10,11,22,23} Recent innovations have expanded this to contactless sensing; researchers have demonstrated the feasibility of using facial and fingertip PPG with high diagnostic precision.^{24–26} In the smartwatch domain, Tison *et al.*⁸ and Wasserlauf *et al.*²⁷ showed that passive monitoring achieves high accuracy compared to continuous ECG reference standards. A systematic review and meta-analysis evaluating smartphone-based PPG detection further reported pooled sensitivity and specificity exceeding 90%, supporting the diagnostic reliability of these technologies when validated against ECG reference standards.²⁸ These findings are consistent with the high sensitivity observed for smartphone PPG applications in the present study.

Recent meta-analyses evaluating wearable AF detection technologies have reported similar diagnostic performance across device platforms. A systematic review including multiple smart devices found pooled sensitivities of approximately 94% and specificities around 96% for smartphone and smartwatch-based AF detection systems, indicating comparable accuracy between PPG-based and ECG-based technologies.¹⁸ Similarly, a more recent meta-analysis comparing ECG-based and PPG-based smartwatches reported a pooled sensitivity of approximately 97% and a specificity of 96%, further supporting the strong diagnostic capabilities of modern wearable devices.¹⁹

Smartwatch-based monitoring systems have demonstrated high diagnostic accuracy in both observational and validation studies. Passive AF detection using smartwatch-derived PPG signals achieves high sensitivity when validated against simultaneous ECG monitoring.^{8,15,27} Recent investigations using machine-learning algorithms applied to wrist-worn sensors have reported similarly strong performance.^{29–31} Continuous monitoring via these platforms allows for the capture of paroxysmal events that might otherwise be missed.³²

Large-scale screening studies have also provided evidence for the potential population-level impact of wearable AF detection technologies. The STROKESTOP trial⁷ demonstrated that intermittent handheld ECG screening in older adults significantly increased the detection of previously undiagnosed AF, enabling earlier initiation of anticoagulation therapy for stroke prevention. Likewise, the mStoPS trial showed that home-based monitoring using wearable ECG patches significantly increased AF detection compared with routine clinical care.³³ These studies highlight the potential role of wearable technologies not only for arrhythmia monitoring but also for large-scale AF screening initiatives. Additional evidence confirms the high diagnostic yield of smartwatches in real-world outpatient settings.^{34–36} Finally, Chang *et al.*³⁷ highlighted that AI-enabled ECG interpreta-

tion significantly enhances diagnostic stability across varying patient conditions.

More recently, smartwatch platforms incorporating integrated ECG functionality have been evaluated in dedicated validation studies. Investigations evaluating Apple Watch-based rhythm detection algorithms have demonstrated high diagnostic accuracy when compared with physician-adjudicated ECG recordings.³⁸⁻⁴⁰ Contemporary meta-analyses similarly report pooled sensitivities of approximately 95% and specificities of approximately 97% across smartwatch platforms,²⁰ further supporting their potential utility for AF detection in ambulatory populations.

Collectively, the findings of the present study align with previous validation studies and meta-analyses demonstrating that wearable ECG and PPG technologies provide reliable detection of atrial fibrillation. However, differences in study populations, monitoring strategies, and algorithmic approaches continue to contribute to heterogeneity across studies.

Clinical implications

These findings have important implications for the evolving role of digital health in cardiovascular care. Early detection of AF is critical for preventing thromboembolic complications, particularly ischemic stroke, and wearables help bridge the diagnostic gap for paroxysmal episodes. However, conventional diagnostic approaches often fail to detect paroxysmal or asymptomatic AF episodes due to limited monitoring durations. Wearable technologies capable of continuous or intermittent rhythm monitoring may help bridge this diagnostic gap by enabling prolonged surveillance outside traditional healthcare settings. Smartphone-based and smartwatch-integrated technologies offer several practical advantages for AF detection, including widespread availability, noninvasive monitoring, and the ability to collect longitudinal rhythm data in real-world environments. These features may facilitate large-scale screening programs, particularly in populations at increased risk of AF, such as older adults or individuals with cardiovascular comorbidities.⁴¹⁻⁴⁴ Furthermore, integration of wearable monitoring data with telemedicine platforms and electronic health records may enable more efficient clinical workflows and earlier diagnostic evaluation of suspected arrhythmias.

Importantly, the high specificity observed in passive monitoring devices suggests that wearable technologies may effectively minimize unnecessary clinical evaluations resulting from false-positive alerts. Positive test results from wearable monitoring systems are highly informative and warrant confirmatory clinical evaluation. This is particularly relevant for continuous monitoring systems, where even modest false-positive rates could lead to large numbers of unnecessary diagnostic investigations.

Sources of heterogeneity

Despite high accuracy, heterogeneity was present across several analyses. Variability likely reflects differences in study populations, such as highly controlled cardioversion cohorts *versus*

general population settings. Motion artifacts and signal noise during daily activities can significantly impact PPG accuracy compared to resting conditions. Additionally, biological factors such as skin pigmentation and peripheral perfusion, along with the presence of premature contractions, can influence diagnostic performance.

An additional source of heterogeneity relates to differences in study setting. Several included studies were conducted in highly controlled clinical environments, such as cardioversion units or specialized arrhythmia clinics, whereas others evaluated wearable devices in ambulatory or community-based screening populations. Patients enrolled in clinical validation cohorts generally have a higher pre-test probability of atrial fibrillation, more sustained arrhythmia episodes, and controlled recording conditions, all of which may enhance diagnostic performance. In contrast, community screening studies evaluate individuals with lower disease prevalence, greater motion-related signal artifacts, and a higher likelihood of intermittent or asymptomatic atrial fibrillation, potentially resulting in lower sensitivity and specificity. Although diagnostic performance remained high across both settings, modest differences in pooled estimates suggest that study setting contributes to between-study heterogeneity and should be considered when interpreting the applicability of wearable technologies in routine clinical practice.

Differences in reference standard implementation may have also contributed to heterogeneity. Although all included studies confirmed atrial fibrillation using electrocardiographic reference standards on the same day as wearable device assessment, the reference recordings were obtained sequentially rather than simultaneously. Given the paroxysmal nature of atrial fibrillation, spontaneous rhythm conversion between index testing and reference standard acquisition may have resulted in apparent diagnostic disagreement despite appropriate device performance. Consequently, some discordant results may reflect temporal variation in cardiac rhythm rather than true device inaccuracy. Future diagnostic validation studies should preferentially employ simultaneous wearable and reference electrocardiographic recordings to minimize this potential source of bias.

Impact of device type on diagnostic performance

In this meta-analysis, meta-regression based on device type did not demonstrate statistically significant differences in diagnostic accuracy between modalities. However, important trends were observed.

Wearable smartwatch-based technologies, particularly PPG smartwatches, demonstrated more consistent and reliable performance, likely due to continuous monitoring capabilities, improved sensor quality, and better signal acquisition under real-world conditions. In contrast, smartphone-based approaches, especially PPG-based applications, exhibited greater variability, which may be attributed to user dependency, inconsistent measurement conditions, and susceptibility to motion artifacts.

ECG-based modalities, both in smartwatches and smartphones, showed high specificity, reflecting their ability to directly capture cardiac electrical activity. However, their performance may be limited by intermittent use and user adherence.

Although these findings suggest a potential advantage of smartwatch-based systems, the lack of statistically significant differences indicates that all device types provide clinically useful diagnostic accuracy for atrial fibrillation detection. The observed heterogeneity highlights the importance of considering device characteristics, patient population, and real-world usability when selecting screening tools. Future studies with standardized protocols and head-to-head comparisons are needed to better delineate the relative performance of these technologies.

Strengths and limitations

This study has several strengths. First, we performed a comprehensive systematic review and diagnostic meta-analysis synthesizing evidence across multiple wearable technology platforms. Second, the use of a bivariate random-effects model allowed simultaneous estimation of pooled sensitivity and specificity while accounting for between-study heterogeneity. Third, the inclusion of hierarchical summary receiver operating characteristic analyses enabled robust evaluation of overall diagnostic performance across device categories.

Several limitations should also be considered. Many included studies were conducted in selected populations, including patients undergoing cardioversion or clinical arrhythmia evaluation, which may limit generalizability to population-based screening settings. Additionally, heterogeneity in device algorithms, monitoring protocols, and reference standards across studies may influence pooled diagnostic estimates. A related limitation is that included studies did not consistently report whether the reference standard was obtained simultaneously with, or sequentially/intermittently from, the index test; given the paroxysmal nature of AF, sequential designs are likely to underestimate diagnostic accuracy for reasons unrelated to true device performance, and this could not be reliably disentangled across the pooled dataset. Similarly, studies varied in how non-interpretable tracings or signal artifacts were handled, with some excluding them from analysis and others classifying them as false negatives or false positives; this inconsistency was not uniformly reported and may materially affect estimates of real-world diagnostic performance. Publication bias is also possible, as studies demonstrating favorable diagnostic performance may be more likely to be published. Finally, rapid technological evolution in wearable devices means that diagnostic algorithms may continue to improve beyond those evaluated in currently published studies.

Several limitations should be considered when interpreting our findings. Although wearable technologies demonstrated consistently high diagnostic accuracy, many included studies

enrolled selected populations, including patients undergoing cardioversion or evaluation in specialized arrhythmia clinics, potentially limiting generalizability to community-based screening populations. In addition, although all included studies used electrocardiographic confirmation on the same day as index testing, reference standard recordings were obtained sequentially rather than simultaneously. Because atrial fibrillation is frequently paroxysmal, transient changes in rhythm between recordings may have influenced estimates of diagnostic accuracy. Finally, most primary studies excluded non-interpretable recordings or signal artifacts from diagnostic analyses rather than classifying them as test failures. Consequently, the pooled sensitivity and specificity reported in this review may represent device performance under interpretable recording conditions and may therefore modestly overestimate performance in routine real-world practice. Publication bias remains possible despite a non-significant Deeks' funnel plot asymmetry test, and ongoing technological advances mean that the diagnostic performance of contemporary wearable devices may continue to evolve beyond the studies included in this review.

Device-specific detection algorithms and diagnostic thresholds varied substantially across studies. Because manufacturers use proprietary signal-processing methods and many studies did not fully report algorithm characteristics or threshold definitions, these variables could not be evaluated quantitatively in meta-regression. Nevertheless, this variability likely contributed to the observed between-study heterogeneity and may partly explain differences in diagnostic performance across wearable platforms.

The influence of proprietary detection algorithms and device-specific diagnostic thresholds could not be formally explored because these characteristics were inconsistently reported across primary studies. We acknowledge that study setting represents a potentially important source of heterogeneity. However, evaluation of study setting was not a prespecified subgroup analysis in our review protocol, and therefore a *post hoc* subgroup analysis was not performed. Future studies should specifically investigate whether diagnostic performance differs between clinical validation cohorts and community-based screening populations.

Future directions

Future research should focus on evaluating wearable AF detection technologies in large, prospective population-based cohorts to better define their role in routine clinical screening. Studies integrating wearable monitoring with clinical management pathways are also needed to determine whether earlier AF detection using these technologies translates into improved clinical outcomes, including reductions in stroke incidence and cardiovascular mortality. Additionally, further research is warranted to refine signal processing algorithms, reduce motion-related artifacts, and improve diagnostic performance in real-world ambulatory environments.

Conclusions

Wearable technologies demonstrate high diagnostic accuracy for detecting atrial fibrillation across multiple device platforms, including ECG- and PPG-based systems. While these findings support their potential role in screening and long-term monitoring, most evidence is derived from controlled or selected populations. Further large-scale prospective studies in real-world settings are needed to determine their clinical impact, cost-effectiveness, and role in routine cardiovascular care. In interpretation of these findings should consider differences in study setting, sequential reference standard assessment, and the exclusion of non-interpretable recordings in many primary studies, all of which may influence real-world diagnostic performance.

Authors' contributions

All the authors read and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

Conflict of interest

The authors declare that they have no known financial or personal relationships that could have influenced the work reported in this paper.

Funding

No funding or grants were received for this study.

Ethics approval and consent to participate

Ethical approval and informed consent were not required. No Institutional Review Board (IRB) approval was required for this manuscript as no new human subjects were involved.

Data availability

All studies included in this research are publicly available through PubMed Central. Data supporting the findings of this study are provided within the article and Supplementary Material files. Additional information can be obtained from the corresponding author upon request.

References

- Lippi G, Sanchis-Gomar F, Cervellin G. Global epidemiology of atrial fibrillation: an increasing epidemic and public health challenge. *Int J Stroke* 2021;16:217-21.
- Wolf PA, Abbott RD, Kannel WB. Atrial fibrillation as an independent risk factor for stroke: the Framingham Study. *Stroke* 1991;22:983-8.
- Hindricks G, Potpara T, Dagres N, et al. 2020 ESC guidelines for the diagnosis and management of atrial fibrillation developed in collaboration with the European Association for Cardio-Thoracic Surgery (EACTS). *Eur Heart J* 2021;42:373-498.
- Sanna T, Diener HC, Passman RS, et al. Cryptogenic stroke and underlying atrial fibrillation. *N Engl J Med* 2014;370:2478-86.
- Himmelreich JCL, Karregat EPM, Lucassen WAM, et al. Diagnostic accuracy of a smartphone-operated, single-lead electrocardiography device for detection of rhythm and conduction abnormalities in primary care. *Ann Fam Med* 2019;17:403-11.
- Bumgarner JM, Lambert CT, Hussein AA, et al. Smartwatch algorithm for automated detection of atrial fibrillation. *J Am Coll Cardiol* 2018;71:2381-8.
- Svennberg E, Engdahl J, Al-Khalili F, et al. Mass screening for untreated atrial fibrillation: the STROKESTOP study. *Circulation* 2015;131:2176-84.
- Tison GH, Sanchez JM, Ballinger B, et al. Passive detection of atrial fibrillation using a commercially available smartwatch. *JAMA Cardiol* 2018;3:409-16.
- McManus DD, Lee J, Maitas O, et al. A novel application for the detection of an irregular pulse using an iPhone 4S in patients with atrial fibrillation. *Heart Rhythm* 2013;10:315-9.
- Rozen G, Vaid J, Hosseini SM, et al. Diagnostic accuracy of a novel mobile phone application for the detection and monitoring of atrial fibrillation. *Am J Cardiol* 2018;121:1187-91.
- Proesmans T, Mortelmans C, Van Haelst R, et al. Mobile phone-based use of the photoplethysmography technique to detect atrial fibrillation in primary care: diagnostic accuracy study of the FibrCheck app. *JMIR Mhealth Uhealth* 2019;7:e12284.
- McInnes MDF, Moher D, Thoms BD, et al. Preferred reporting items for a systematic review and meta-analysis of diagnostic test accuracy studies: the PRISMA-DTA statement. *JAMA* 2018;319:388-96.
- Deeks JJ, Macaskill P, Irwig L. The performance of tests of publication bias and other sample size effects in systematic reviews of diagnostic test accuracy was assessed. *J Clin Epidemiol* 2005;58:882-93.
- Whiting PF, Rutjes AWS, Westwood ME, et al. QUADAS-2: a revised tool for the quality assessment of diagnostic accuracy studies. *Ann Intern Med* 2011;155:529-36.
- Bonomi AG, Schipper F, Eerikainen LM, et al. Atrial fibrillation detection using a novel cardiac ambulatory monitor based on photoplethysmography at the wrist. *J Am Heart Assoc* 2018;7:e009351.
- Chan NY, Choy CC, Chan CK, et al. Effectiveness of a nongovernmental organization-led large-scale community atrial fibrillation screening program using the smartphone electrocardiogram: an observational cohort study. *Heart Rhythm* 2018;15:1306-11.
- Haberman ZC, Jahn RT, Bose R, et al. Wireless smartphone ECG enables large-scale screening in diverse populations. *J Cardiovasc Electrophysiol* 2015;26:520-6.
- Prasitlumkum N, Cheungpasitporn W, Chokesuwattanaskul A, et al. Diagnostic accuracy of smart gadgets/wearable devices in detecting atrial fibrillation: a systematic review and meta-analysis. *Arch Cardiovasc Dis* 2021;114:4-16.
- Luo DY, Zhang ZW, Sibomana O, et al. Comparison of diagnostic accuracy of ECG-based versus photoplethysmography-based smartwatches for atrial fibrillation detection: a systematic review and meta-analysis. *Ann Med Surg (Lond)* 2025.
- [Authors to be added]. Accuracy of smartwatches in the detection of atrial fibrillation: a systematic review and diagnostic meta-analysis. *JACC Adv* 2025. doi:10.1016/j.jacadv.2025.102133.
- Tarakji KG, Wazni OM, Callahan T, et al. Using a smartphone-based self-recording ECG system for detecting atrial fibrillation. *J Am Coll Cardiol* 2015;65:1486-7.
- Guo Y, Wang H, Zhang H, et al. Mobile photoplethysmographic technology to detect atrial fibrillation. *J Am Coll Cardiol* 2019;74:2365-75.
- Selder JL, Postema PG, Breur L, et al. A mobile health strategy for atrial fibrillation screening in the general population. *Neth Heart J* 2019;27:541-7.
- Yan BP, Lai WH, Chan CK, et al. High-throughput, contactless and highly accurate detection of atrial fibrillation using a smartphone camera. *Clin Cardiol* 2018;41:1510-4.

25. Yan BP, Lai WHS, Chan CKY, et al. Contactless screening of atrial fibrillation by a smartphone-based facial video-based photoplethysmography: a pilot study. *J Am Coll Cardiol* 2018;71:A455.
26. Poh MZ, McDuff DJ, Picard RW. Non-contact, automated cardiac pulse measurements using video imaging and blind source separation. *Opt Express* 2010;18:10762-74.
27. Wasserlauf J, You C, Patel R, et al. Smartwatch performance for the detection and quantification of atrial fibrillation. *Circ Arrhythm Electrophysiol* 2019;12:e006834.
28. Gill S, et al. Smartphone detection of atrial fibrillation using photoplethysmography: a systematic review and meta-analysis. *Heart* 2022.
29. Bashar SK, Han D, Hajeb-Moghadam H, et al. Atrial fibrillation detection from wrist photoplethysmography signals using smartwatches. *Sci Rep* 2019;9:15054.
30. Han D, Bashar SK, Lázaro J, et al. A combined pulse rate variability and deep learning method for atrial fibrillation detection using a smartwatch. *IEEE J Biomed Health Inform* 2020;25:1567-75.
31. Ding EY, Bashar SK, Han D, et al. Accuracy of a smartwatch-based atrial fibrillation detection algorithm in a large hospital-based cohort. *mHealth* 2019;5:27.
32. Fiorina L, Labbé P, Sideris G, et al. Atrial fibrillation detection after cryptogenic stroke: long-term monitoring using a smartwatch. *J Clin Med* 2024;13:1125.
33. Steinhubl SR, Waalen J, Edwards AM, et al. Effect of a home-based wearable continuous ECG monitoring patch on detection of undiagnosed atrial fibrillation: the mSToPS randomized clinical trial. *JAMA* 2018;320:146-55.
34. Dörr M, Nothgriff V, Brasier N, et al. The WATCH AF trial: Smart-WATCHes for detection of atrial fibrillation. *JACC Clin Electrophysiol* 2019;5:199-208.
35. Nonoguchi M, Katano S, Hashimoto A, et al. Feasibility of a smartwatch for detecting atrial fibrillation in patients with suspected arrhythmia. *CJC Open* 2022;4:854-61.
36. Alnasser AW, Alghonaim M, Alonazi A, et al. Effectiveness of wearable devices for atrial fibrillation detection in the general population: a prospective observational study. *J Pers Med* 2023;13:782.
37. Chang HY, Yang PH, Wu YH, et al. Artificial intelligence-enabled electrocardiogram for the detection of atrial fibrillation: a systematic review and meta-analysis. *J Clin Med* 2022;11:5113.
38. Caillol T, Strik M, Ramirez FD, et al. Accuracy of Apple Watch for detection of atrial fibrillation. *Circ Arrhythm Electrophysiol* 2021;14:e008697.
39. Seshadri DR, Bittel B, Browsky D, et al. Accuracy of Apple Watch for detection of atrial fibrillation in patients with cardiovascular disease. *npj Digit Med* 2020;3:125.
40. Müller P, Heise S, Clauss S. Validation of a new smartwatch for the detection of atrial fibrillation in clinical practice. *Sci Rep* 2024;14:1023.
41. Ploux S, Strik M, Caillol T, et al. Performance of a smartwatch algorithm for the detection of atrial fibrillation in patients with sinus rhythm and premature contractions. *Arch Cardiovasc Dis* 2022;115:589-97.
42. Campo G, et al. Smartphone-based ECG for atrial fibrillation screening in high-risk patients. *J Am Coll Cardiol* 2022.
43. Abu-Alrub S, et al. Accuracy of Apple Watch for detection of atrial fibrillation in a clinical cohort. *Circ Arrhythm Electrophysiol* 2022.
44. Rajakariar K, Seshadri DR, Drumm S, et al. The role of smartphone ECG for the screening of atrial fibrillation in an underserved community. *Med J Aust* 2020;212:467-8.

Online supplementary material:

Supplementary Table S1. Search strategy.

Supplementary Table S2. Study characteristics

Supplementary Table S3. Quality assessment of included studies.

Supplementary Table S4. Summary of pooled diagnostic accuracy of wearable and smartphone-based devices for atrial fibrillation detection.

Supplementary Table S5. Results of meta-regression evaluating the effect of device type (ECG smartwatch, PPG smartwatch, smartphone ECG, and smartphone PPG) on pooled sensitivity estimates. Coefficients represent the change in logit sensitivity relative to the reference category.

Supplementary Table S6. Results of meta-regression assessing the impact of device type on pooled specificity estimates. Coefficients are presented on the logit scale with corresponding confidence intervals and p-values.

Supplementary Table S7. Results of the bivariate meta-regression model evaluating the association between device type and overall diagnostic accuracy, incorporating both sensitivity and specificity while accounting for their correlation and between-study heterogeneity.

Supplementary Figure S1. Forest plots of diagnostic accuracy showing the sensitivity and specificity estimates with 95% confidence intervals for Smartwatch-Based PPG.

Supplementary Figure S2. SROC curve for Smartwatch-Based PPG and handheld devices, demonstrating the hierarchical SROC (HSROC) curve with the pooled sensitivity and specificity estimate, along with the 95% confidence region and 95% prediction region for the included studies.

Supplementary Figure S3. Forest plots of diagnostic accuracy showing the sensitivity estimates with 95% confidence intervals for Smartwatch-Based ECG.

Supplementary Figure S4. Forest plots of diagnostic accuracy showing the specificity estimates with 95% confidence intervals for Smartwatch-Based ECG.

Supplementary Figure S5. SROC curve for Smartwatch-Based ECG, demonstrating the hierarchical SROC (HSROC) curve with the pooled sensitivity and specificity estimate, along with the 95% confidence region and 95% prediction region for the included studies.

Supplementary Figure S6. Forest plots of diagnostic accuracy showing the sensitivity and specificity estimates with 95% confidence intervals for Smartphone ECG.

Supplementary Figure S7. SROC curve for Smartphone ECG, demonstrating the hierarchical SROC (HSROC) curve with the pooled sensitivity and specificity estimate, along with the 95% confidence region and 95% prediction region for the included studies.

Supplementary Figure S8. Forest plots of diagnostic accuracy showing the sensitivity estimates with 95% confidence intervals for Smartphone PPG.

Supplementary Figure S9. Forest plots of diagnostic accuracy showing the specificity estimates with 95% confidence intervals for Smartphone PPG.

Supplementary Figure S10. SROC curve for Smartphone PPG, demonstrating the hierarchical SROC (HSROC) curve with the pooled sensitivity and specificity estimate, along with the 95% confidence region and 95% prediction region for the included studies.

Supplementary Figure S11. Forest plots of diagnostic accuracy showing the sensitivity and specificity estimates with 95% confidence intervals for Apple Watch Dedicated Subset.

Supplementary Figure S12. SROC curve for Apple Watch Dedicated Subset, demonstrating the hierarchical SROC (HSROC) curve with the pooled sensitivity and specificity estimate, along with the 95% confidence region and 95% prediction region for the included studies.

Supplementary Figure S13. Regression analysis.