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SYSTEMATIC REVIEW

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# Diagnostic accuracy of ECG smart chest patches versus PPG smartwatches for atrial fibrillation detection: a systematic review and meta-analysis

Olivier Sibomana[1*], Clyde Moono Hakayuwa[2], Abraham Obianke[3], Hubert Gahire[1], Jildas Munyantore[1] and Matimba Molly Chilala[2]

## Abstract

**Introduction** Atrial fibrillation (AF), the most common form of cardiac arrhythmia, is associated with significant morbidity, mortality, and financial burden. Traditional diagnostic methods, such as 12-lead electrocardiograms (ECG), have limitations in detecting intermittent AF episodes. Consequently, smart wearables have been introduced to enhance continuous AF monitoring. This systematic review and meta-analysis aimed to evaluate and compare the diagnostic accuracy of ECG smart chest patches and photoplethysmography (PPG)– based smartwatches in AF detection.

**Methods** From august 16–20, 2024, a comprehensive search was conducted across PubMed/MEDLINE, DOAJ, AJOL, and the Cochrane Library. Original studies assessing the performance of ECG smart chest patches and PPG smartwatches in detecting AF were included. Studies were screened based on predefined inclusion and exclusion criteria, and the most relevant were finally included. For ECG smart chest patches and PPG smartwatches groups, random-effects model was used to pool these performance metrics. Statistical analyses were performed using Jamovi 2.3.28, with a significance threshold of $p < 0.05$.

**Results** A total of 15 studies were included in the current systematic review and meta-analysis. ECG smart chest patches demonstrated a pooled sensitivity of 96.1% [(95% CI: 91.3–100.8), ($I^2 = 94.59\%$)], and a pooled specificity of 97.5% [(95% CI: 94.7–100.2), ($I^2 = 79.1\%$)]. PPG smartwatches showed a pooled sensitivity of 97.4% [(95% CI: 96.5–98.3), ($I^2 = 3.16\%$)], and a pooled specificity of 96.6% [(95% CI: 94.9–98.3), ($I^2 = 75.94\%$)]. Comparatively, both ECG smart chest patches and PPG smartwatches exhibited excellent performance in atrial fibrillation detection, with PPG smartwatches showing slightly higher sensitivity and ECG chest patches exhibiting marginally greater specificity.

**Conclusion** Both ECG smart chest patches and PPG smartwatches are highly effective for detecting atrial fibrillation. However, further advancements are needed to match their accuracy with that of standard diagnostic methods and achieve comprehensive digital cardiac monitoring.

*Correspondence:
Olivier Sibomana
oliviersibomana917@gmail.com

Full list of author information is available at the end of the article

**Keywords** Photoplethysmography (PPG), Electrocardiography (ECG), Wearable devices, Atrial fibrillation, Diagnostic accuracy

## Introduction

AF represents the most prevalent form of cardiac arrhythmia, primarily resulting from abnormal electrical activity within the atria, which leads to their chaotic and ineffective contractions, or fibrillation. Classified as a tachyarrhythmia, AF is typified by an excessively rapid heart rate that can compromise the heart's ability to effectively pump blood [1, 2]. This condition has become a significant public health concern worldwide, driven by both its increasing incidence and the substantial morbidity associated with its complications, such as heart failure and stroke [1].

The rising incidence of AF is primarily attributable to the increasing prevalence of chronic cardiovascular risk factors. The global burden of aging populations, alongside the growing incidence of diabetes, hypertension, obesity, and alcohol consumption, has contributed to both the development and progression of AF [3]. A 2017 systematic review estimated that AF now affects approximately 46.3 million people globally, with 3.8 million new diagnoses annually—a 32% increase over a decade from 2006 to 2016 [4]. Projections indicate that by 2050, AF prevalence will range between six and 12 million individuals in the U.S., and up to 17.9 million in Europe by 2060 [5].

Although AF was historically considered a disease predominantly affecting high-income countries, its prevalence has been increasing in low- and middle-income regions as well, particularly in Africa. In Sub-Saharan Africa, AF prevalence was estimated at 659.8 per 100,000 for men and 438.1 per 100,000 for women, with a 3.4% increase observed between 1990 and 2010 [6]. The rise in AF incidence in Africa parallels the growing burden of non-communicable diseases, and suggests that AF is becoming a global health issue, necessitating urgent action to address both prevention and management, particularly in resource-limited settings [6].

The clinical implications of AF are considerable, as it significantly impacts patients' functional status, hemodynamic stability, and overall quality of life. Moreover, AF substantially increases the risk of ischemic stroke, with annual stroke risk estimates for AF patients ranging from 1 to 20%, depending on the presence of additional risk factors such as hypertension and diabetes [7, 8, 9]. In the United States, AF is responsible for more than 70,000 ischemic strokes annually, accounting for 10–12% of all such strokes [7]. This underscores the necessity of timely diagnosis and effective therapeutic interventions to mitigate stroke risk and improve patient outcomes.

In 2019, AF was responsible for an estimated 219,437 deaths globally, highlighting its substantial public health burden [10]. Patients with AF face a 3.67-fold increased risk of all-cause death compared to the general population, with a crude mortality rate of 63.3 per 1,000 person-years [11]. However, recent trends show a decline in mortality rates due to advancements in medical care. The Framingham Heart Study reported a reduction in 5-year mortality from 55 to 39% in women and from 53 to 37% in men between 1958 and 2007, and similar trends were observed in data from Western Australia (1995–2010), which revealed a decline in 30-day, 1-year, and 3-year mortality rates associated with AF [12]. However, Dimri et al. reported a significant rise in AF-related mortality during the peak of the COVID-19 pandemic, even though it was followed by significant decrease during the decline phase of the pandemic [13]. While AF-associated mortality continues to decline, it remains a major cause of morbidity and mortality worldwide.

Alongside its clinical burden, AF imposes a substantial economic strain. A recent systematic review by Buja et al. [14] found a median annual direct medical cost of €9,409 per patient, equivalent to $13,333 USD in purchasing power parities. Moreover, a study by Jiang et al. [15] compared healthcare utilization between patients with and without AF, revealing that AF patients had 9.04 more outpatient visits, 0.82 more emergency department visits, 0.33 more inpatient admissions, and an overall $15,095 higher total healthcare costs [15]. These underscore the significant economic burden of AF, emphasizing the need for effective management strategies to reduce both clinical and financial impacts.

Accurate diagnosis of AF is essential for optimal management. Failure to detect AF in a timely manner can result in severe consequences, while overdiagnosis can lead to unnecessary interventions, including inappropriate anticoagulation therapy, which carries a heightened risk of major bleeding [16]. ECG is the primary diagnostic tool for AF; However, single-time-point ECGs often fall short in detecting paroxysmal AF, a common form of arrhythmia characterized by intermittent episodes of irregular heart rhythm, due to its episodic nature [17]. Consequently, there is increasing interest in wearable devices that leverage ECG or PPG technology, which enable continuous monitoring, offering significant potential to enhance AF detection, particularly in non-clinical settings [18]. While ECG technology records the electrical activity of the heart, PPG employs a light source and a photodetector placed on the skin's surface to track changes in blood volume during circulation, enabling heart rhythm monitoring [19].

Traditional ECGs rely on Silver/Silver Chloride (Ag/AgCl) electrodes and multiple leads to provide detailed cardiac monitoring [20]. In contrast, modern PPG-based devices, such as smartwatches, wristbands, and rings, utilize a single optical sensor, offering a more comfortable and reusable design [21]. While PPG-based devices have demonstrated promise in improving access to long-term health monitoring, sensitivity challenges remain. A post hoc analysis of the TRENDS study revealed that daily ECG recordings detected AF in only 50% of patients, while 24-hour ECGs demonstrated a sensitivity of just 35% for arrhythmia detection [22]. However, advancements in artificial intelligence (AI) have significantly improved AF detection rates. Devices like the Apple Watch have shown a 98% sensitivity for AF detection compared to traditional ECG [23].

Given the expanding market for wearable health devices, which is expected to reach USD 70 billion by 2025 [24], these tools are poised to play a crucial role in the future of cardiovascular diagnostics. Despite this, there remains a scarcity of studies directly comparing the diagnostic accuracy of PPG-based devices with single-lead ECG smart chest patches. This systematic review and meta-analysis seek to compare the diagnostic performance of single-lead ECG smart chest patches with PPG-based smartwatches in the detection of AF. This comparative meta-analysis will provide critical insights into the diagnostic performance of emerging wearable technologies, informing clinical practice and guiding future research in AF management.

## Methodology

### Registration

The protocol of this systematic review and meta-analysis was registered in Open Science Framework (OSF) registries with registration ID: https://doi.org/10.17605/OSF.IO/3R85P.

**Table 1** Boolean operators based search parameters in PubMed

| Search | Search string | Number of results |
|---|---|---|
| #1 | (((ECG chest patch) OR (electrocardiogram patch)) OR (smart chest patches)) OR (wearable ECG) Filters: from 2014–2024 | 2,542 |
| #2 | (((smartwatch) OR (scan watch)) OR (apple watch)) OR (wrist wearables) Filters: from 2014–2024 | 3,532 |
| #3 | (atrial fibrillation) OR (cardiac arrytmia) Filters: from 2014–2024 | 109,035 |
| #4 | #1 OR #2 | 5,798 |
| #5 | #3 AND #4 | 1,015 |

### Reporting

The current systematic review and meta-analysis were performed in alignment with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [25].

### Databases search

From august 16–20, 2024, a thorough and systematic search was executed across PubMed/MEDLINE, DOAJ, AJOL, and the Cochrane Library, to identify original studies assessing the accuracy of ECG smart chest patches or PPG smartwatches in detecting atrial fibrillation. In addition to database searches, manual searches via Google and Google Scholar were conducted to capture relevant grey literature such as preprints, conference proceedings, technical reports, theses and dissertations, and white papers. Key search terms included "ECG chest patch," "electrocardiogram patch," "smart chest patch," "single-read ECG," "wearable ECG," "cardiac monitoring," "smartwatch," "scan watch," "Apple watch," "wrist-wearables," "artificial intelligence," "machine learning," "deep learning," "atrial fibrillation," and "cardiac arrhythmia." Boolean operators were applied, as detailed in Table 1, particularly for the PubMed search. The scope of the search was confined to literature published from 2014 onwards to ensure fetching of updated literature in 10 years. The complete search strategy for each database is provided in the supplementary material. The collected references, including those from grey literature, were imported into Rayyan software for the deduplication process and were subsequently screened according to predefined inclusion and exclusion criteria.

### Inclusion and exclusion criteria

Following deduplication in Rayyan, the literature was meticulously screened based on predefined inclusion and exclusion criteria to ensure the selection of relevant studies (Table 2).

### Data extraction

Two authors independently extracted pertinent data from the selected studies using a standardized Microsoft Excel template. The data extracted included author identification, study design, the country of study, total number of subjects enrolled, actual number of participants involved, mean age, male percentage, sensor type (ECG smart chest patch or PPG smartwatch), the reference gold standard ECG measurement, and key performance metrics such as accuracy, sensitivity, specificity, Positive Predictive Value (PPV), and Negative Predictive Value (NPV). Any discrepancies encountered during data extraction were addressed through discussion, with further resolution achieved by consulting a third reviewer.

**Table 2** Inclusion and exclusion criteria

| Criterion | Included | Excluded |
|---|---|---|
| Study design | Diagnostic validation studies, clinical trials, cross-sectional, case–control, and prospective cohort studies | Commentaries, perspectives, case reports, conference proceedings, reports, reviews, opinions, and letter to the editors |
| Year of publication | Studies published from 2014 to 2024 | Studies published before 2014 |
| Outcome of interest | Reporting performance (sensitivity and specificity with or without other parameters like accuracy, PPV and NPV) of either ECG smart chest patches or PPG smartwatches in detection of AF | • Not reporting both sensitivity and specificity<br>• Smart chest devices other than patches (ex: ECG sensors, textile ECG)<br>• Chest patches plus others (ex: using chest patch and smartwatch simultaneously)<br>• ECG Smartwatches<br>• Wrist-worn devices other than smartwatches<br>• ECG chest patches or PPG smart watches for other cardiac monitoring purposes, not AF detection (ex: Heart rate or blood pleasure monitoring) |
| Accessibility | Abstract and full text assessable | • Abstract and full text inaccessible<br>• Abstract accessible, full text inaccessible |
| Language | Studies reported in English language | Studies reported in all other remaining languages besides English |
| Quality | Medium and high-quality studies | Low quality studies |

NPV: Negative Predictive Value

PPV: Positive Predictive Value

ECG: Electrocardiogram

PPG: Photoplethysmography

AF: Atrial Fibrillation

### Quality assessment

The quality of the included studies was assessed using the Joanna Briggs Institute (JBI) critical appraisal tool for diagnostic test accuracy studies [26]. Studies were classified into three quality levels: high quality (JBI score > 70%), medium quality (JBI score between 50% and 70%), and low quality (JBI score < 50%). For this systematic review and meta-analysis, only studies rated as medium or high quality were considered.

### Statistical analysis

To manage the expected heterogeneity, the meta-analysis applied a Restricted Maximum Likelihood (REML) random-effects model to separately estimate the pooled sensitivity and specificity of ECG smart chest patches and PPG smartwatches for atrial fibrillation detection. Heterogeneity was assessed with the $I^2$ statistical test. Analyses were conducted using Jamovi 2.3.28 and Python 3.12. Specifically, Jamovi 2.3.28 was used for generating forest plots to estimate pooled sensitivity and specificity and funnel plots to check for publication bias. Python 3.12 facilitated the creation Bland-Altman plots to visualize the level of agreement between sensitivity and specificity across studies in each group. A significance level of $p < 0.05$ was used for all statistical tests.

## Results

### Study selection

Initially, 2,415 studies were identified, 2,387 from the electronic database search and 28 from grey literature. After excluding 589 duplicates, 1,826 studies were left for screening. Of these, 1,685 were excluded based on titles and abstracts due to irrelevance, resulting in 141 studies for full-text evaluation. Out of these, 126 studies were excluded—118 for not addressing the outcome of interest and 8 for being inaccessible in full text. Consequently, 15 unique studies fulfilled all criteria and were included in the systematic review and meta-analysis (Fig. 1).

### Characteristics of included studies

Among the 15 studies analyzed, the distribution of research locations was varied, with 5 studies (33.3%) conducted in the USA [27, 28, 29, 30, 31], 3 studies (20%) in China [32, 33, 34], and 2 studies (13.3%) each in Taiwan [35, 36] and the Netherlands [37, 38]. Japan [39] and Finland [40] each contributed 1 study (6.7%). Additionally, a multinational study (6.7%) was conducted in Germany and Switzerland [41]. The majority of the studies focused on diagnostic validation, while the remaining were clinical trials. Excluding one study that did not report the total number of participants, the remaining 14 studies involved a total of 12,802 participants, with 11,208 actively participating. The mean age of the participants was 65.89 years, and the gender distribution was 61.85% male and 38.15% female. The studies evaluated two types of sensors: single-lead ECG chest patches and PPG smartwatches. To measure the accuracy of these sensors, the most commonly used gold standards were 12-lead ECG, Holter ECG, and telemetry ECG. Table 3 shows detailed characteristics of the included studies.

### Performance of ECG chest patches and PPG smartwatches in atrial fibrillation detection

The Bland-Altman plot compared the difference between sensitivity and specificity against their average for ECG smart chest patches (Fig. 2) and PPG smartwatches

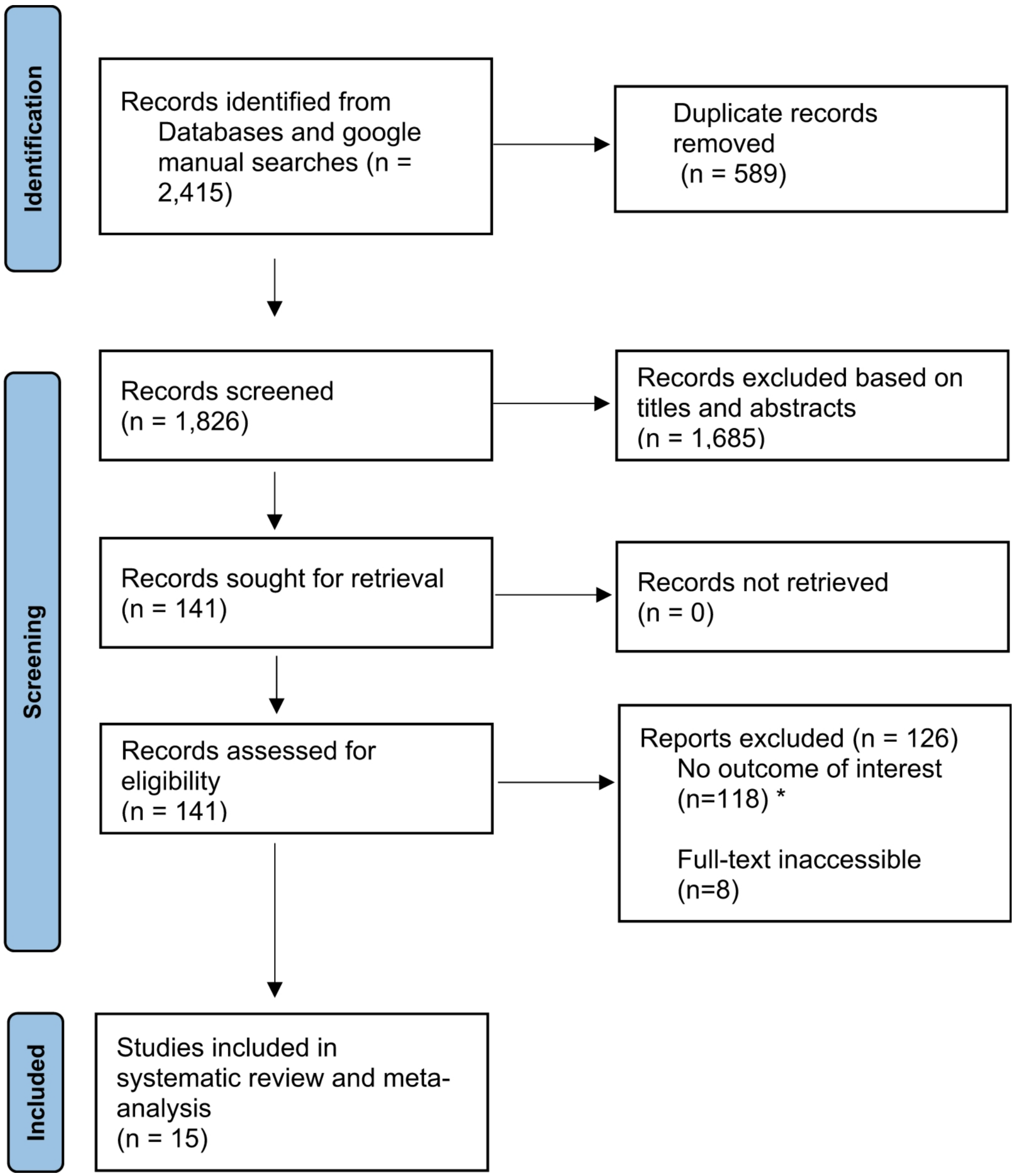


**Fig. 1** PIRSMA Flowchart diagram of the study selection. *No outcome of interest (118): • Not reporting both sensitivity and specificity ($n=7$). • Smart chest devices other than patches (ex: 13). • Chest patches coupled with other wearables ($n=3$). • ECG Smartwatches ($n=42$). • Wrist-worn devices other than smartwatches (12). • ECG chest patches or PPG smart watches for other cardiac monitoring purposes, not AF detection ($n=41$)

**Table 3** Characteristics of included studies

| Author ID | Study design | Country | Number of subjects | Total number screened | Mean age | Male (%) | Type of sensor | Gold standard | Accuracy | Sensitivity | Specificity | PPV | NPV | JBI Quality Score | Reference |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dörr et al.,2019 | Prospective case control trial | Germany and Switzerland | 672 | 508 | 76.4 | 55.7 | PPG Smartwatch | 12 - Lead ECG | 96.1 | 93.7 | 98.2 | 97.8 | 94.7 | Moderate | [41] |
| Chang et al. 2022 | Prospective Diagnostic accuracy study | Taiwan | 200 | 112 | 66.1 | 63.5 | PPG Smartwatch | 24-h Holter ECG | 93.5 | 97.3 | 88.6 | 91.6 | 96.3 | High | [36] |
| Selder et al.,2023 | Prospective Diagnostic accuracy study | Netherlands | 78 | 78 | 66 | 53.5 | PPG Smartwatch | 12 - Lead ECG | 97 | 98 | 96 | 96 | 99 | Moderate | [38] |
| Nonoguchi et al.,2022 | Prospective single-centre study | Japan | 1500 | 166 | 66.5 | 68 | PPG Smartwatch | Single-lead Telemetry ECG | | 98 | 90.6 | 69.4 | 99.5 | High | [39] |
| Bashar et al.,2019 | Prospective single-centre study | USA | 46 | 46 | - | - | PPG Smartwatch | 7-lead Holter ECG | 97.54 | 98.18 | 97.43 | - | - | High | [31] |
| Bashar et al.,2019 | Prospective Diagnostic accuracy study | USA | 20 | 20 | - | - | PPG Smartwatch | 7-lead Holter ECG | 97.11 | 96.15 | 97.37 | - | - | High | [30] |
| Bonomi et al.,2018 | Prospective cohort clinical trial | Netherlands | 20 | 18 | 59.6 | 55.5 | PPG Smartwatch | Single-lead ECG apparatus (Actiwave Cardio) | 98 | 96 | 100 | 100 | 98 | Moderate | [37] |
| | | | 40 | 34 | 67.4 | 61.1 | PPG Smartwatch | 24-h Holter ECG | 97 | 93 | 100 | 100 | 95 | | |
| Liao et al.,2022 | Prospective single-centre study | Taiwan | 116 | 116 | 59.6 | 67 | PPG Smartwatch | 24-h Holter ECG | 95.8 | 97 | 94 | 96 | 95.4 | Moderate | [35] |
| Han et al.,2020 | Prospective Diagnostic accuracy study | USA | 37 | 37 | 70.49 | 78.3 | PPG Smartwatch | 7-Lead Holter ECG | 97.95 | 98.18 | 97.9 | 91.53 | 99.57 | High | [27] |
| Tison et al.,2018 | Prospective Diagnostic accuracy study | USA | 9750 | 9750 | 42 | 63 | PPG Smartwatch | 12 - Lead ECG | 97 | 98 | 90.2 | 90.9 | 97.8 | High | [23] |
| Ding et al.,2019 | Prospective Diagnostic accuracy study | USA | 40 | 40 | 71 | 80 | PPG Smartwatch | 7-Lead Holter ECG | 98.1 | 98.2 | 98.1 | 91.5 | 99.6 | High | [29] |

**Table 3** (continued)

| Author ID | Study design | Country | Number of subjects | Total number screened | Mean age | Male (%) | Type of sensor | Gold standard | Accuracy | Sensitivity | Specificity | PPV | NPV | JBI Quality Score | Reference |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Santala et al.,2022 | Feasibility and Diagnostic Accuracy Study | Finland | 178 | 178 | 72.5 | 46.5 | Single-lead ECG patch | 3-lead Holter ECG | 97.2 | 100 | 94.9 | 94 | 100 | High | [40] |
| Lai et al.,2020 | Diagnostic Accuracy study | China | 50 | 50 | 70 | 52 | Single-lead ECG patch | 12-lead ECG Holter | 91.65 | 89.21 | 98.98 | - | - | High | [33] |
| Lai et al.,2020 | Diagnostic Accuracy study | China | 55 | 55 | 69 | 60 | Single-lead ECG patch | 12-lead ECG Holter | 93.1 | 93.1 | 93.4 | - | - | Moderate | [32] |
| Shao et al.,2020 | Diagnostic Accuracy study | China | - | - | - | - | Single-lead ECG patch | Public Database and cardiologist | 99.62 | 99.61 | 99.64 | - | - | High | [34] |

(Fig. 3) in detecting AF. In both groups, the mean differences (bias) were close to zero, indicating no significant systematic discrepancy between sensitivity and specificity. The limits of agreement (LOA), set at ± 1.9 standard deviations (SD) in both groups, established an interval within which most data points were contained. Notably, a few points were located near the upper and lower LOA, suggesting some degree of variability. Overall, the plot demonstrated an acceptable agreement between sensitivity and specificity, although some variability was observed across certain study outcomes.

The meta-analysis assessed the performance of ECG smart chest patches and PPG smartwatches in detecting atrial fibrillation, revealing high pooled sensitivity and specificity for both modalities (Table 4). For ECG smart chest patches, the pooled sensitivity was 96.1% (95% CI: 91.3-100.8), with considerable heterogeneity ($I^2$ = 94.5%) (Fig. 4), while the pooled specificity was 97.5% (95% CI: 94.7-100.2), with moderate heterogeneity ($I^2$ = 79.1%) (Fig. 5). In contrast, PPG smartwatches demonstrated a pooled sensitivity of 97.4% (95% CI: 96.5–98.3) with minimal heterogeneity ($I^2$ = 3.1%) (Fig. 6) and a pooled specificity of 96.6% (95% CI: 94.9–98.3) with moderate heterogeneity ($I^2$ = 75.9%) (Fig. 7). According to results, both ECG smart chest patches and PPG smartwatches exhibited excellent performance in atrial fibrillation detection.

### Comparing performance of ECG chest patches and PPG smartwatches in atrial fibrillation detection

The comparison of sensitivity and specificity between the two technologies revealed that while there is no significant difference in their overall diagnostic accuracy, PPG smartwatches exhibited a slightly higher sensitivity (97.4%) compared to ECG smart chest patches (96.1%). Conversely, ECG smart chest patches demonstrated marginally higher specificity (97.5%) than PPG smartwatches (96.6%). Despite these little differences, both modalities were found to be highly effective in detecting atrial fibrillation.

## Discussion

This meta-analysis evaluated 15 studies to compare the diagnostic accuracy of ECG smart chest patches and PPG smartwatches in detecting atrial fibrillation. ECG smart chest patches had a pooled sensitivity of 96.1% (95% CI: 91.3-100.8) and a pooled specificity of 97.5% (95% CI: 94.7-100.2). In comparison, PPG smartwatches demonstrated a pooled sensitivity of 97.4% (95% CI: 96.5–98.3) and a pooled specificity of 96.6% (95% CI: 94.9–98.3). Both devices showed high diagnostic performance, indicating that ECG chest patches and PPG smartwatches are equally effective tools for detecting atrial fibrillation. Meanwhile, significant heterogeneity was observed

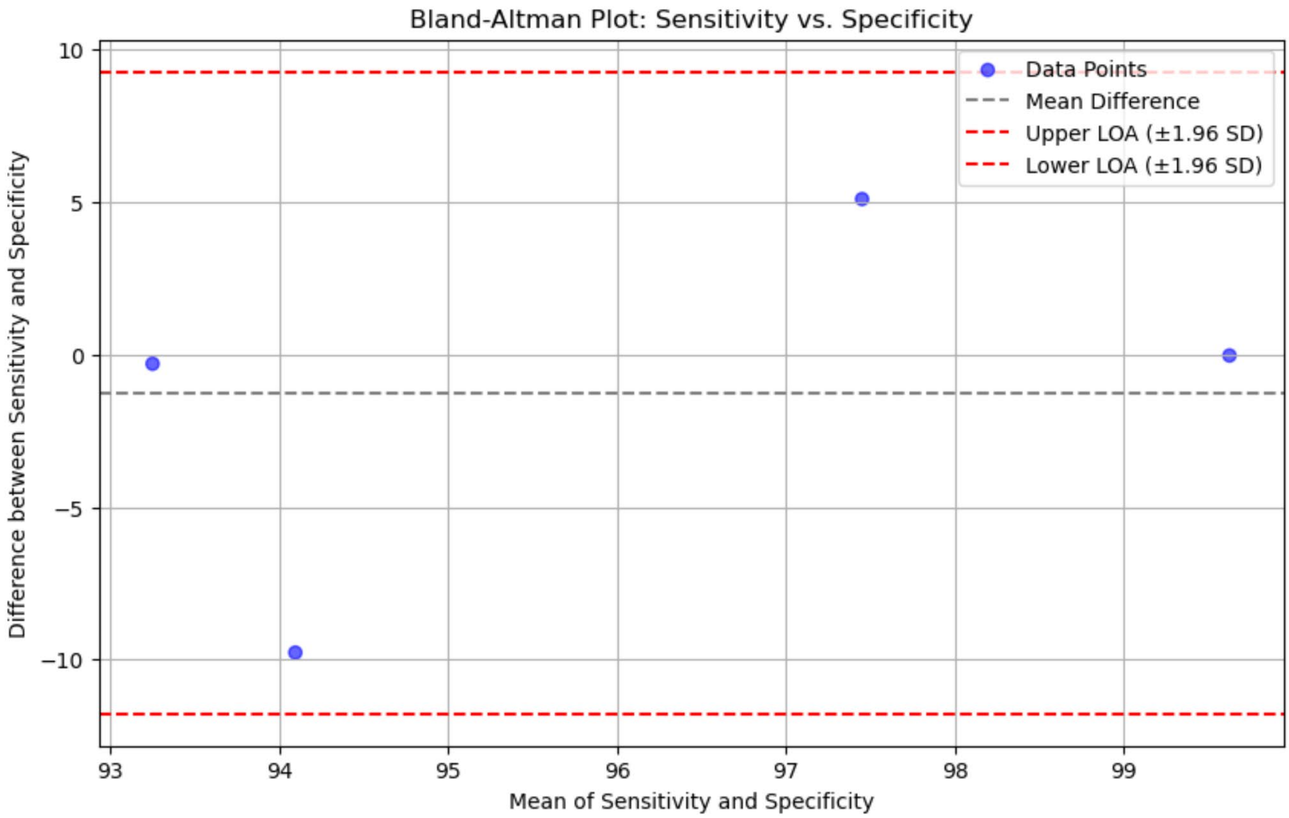


**Fig. 2** Bland-Altman plot for ECG smart chest patches in AF detection

among the studies, potentially attributable to variations in patient demographics, reference standards for comparison, and methodologies employed for atrial fibrillation detection. These factors must be carefully accounted for when interpreting the results.

Several systematic reviews and meta-analyses have explored the diagnostic accuracy of wearable devices in detecting AF, with results largely consistent with the current study. While no previous meta-analysis has specifically evaluated the diagnostic performance of ECG smart chest patches or compared them with other smart wearables, previous meta-analyses have assessed the accuracy of general smart devices or other specific smart wearables. Prasitlumkum et al. investigated the diagnostic accuracy of various smart gadgets, reporting a sensitivity of 94% and specificity of 96% for smartphones, while smartwatches demonstrated similar accuracy with a specificity of 94% and sensitivity of 93% [42]. Similarly, Nazarian et al.'s meta-analysis found that smartwatches had an overall sensitivity of 100% (95% CI: 0.99–1.00), specificity of 95% (95% CI: 0.93–0.97), and accuracy of 97% (95% CI: 0.96–0.99) [43]. In a separate meta-analysis, Vetta et al. reported a sensitivity of 94% (95% CI: 90–96%) and specificity of 97% (95% CI: 95–98%) for smartwatches in detecting cardiac arrhythmias [44]. These findings reinforce the high diagnostic performance of smart wearables, aligning with the current study's results on AF detection.

Given the comparable diagnostic accuracy between ECG smart chest patches and PPG smartwatches, it is crucial to consider additional factors such as cost and practical settings when selecting the most appropriate wearable device. Diagnostic performance alone should not dictate the choice. For instance, the cost comparison between these devices reveals notable differences in both technology and production. ECG chest patches generally incur higher manufacturing costs due to the inclusion of advanced sensors, sophisticated signal processing systems, and the design of flexible, durable patches [45]. In contrast, PPG technology, which primarily uses light sensors to monitor blood flow, is less expensive to produce. The integration of PPG sensors into smartwatches offers broader market accessibility, making these devices more affordable and appealing to a wider consumer base [46]. Therefore, cost-effectiveness and market considerations may favor PPG smartwatches in certain settings.

Considering settings, ECG smart chest patches, by directly measuring the electrical activity of the heart, are more suited for clinical use, particularly in patients at higher risk of atrial AF or those with pre-existing cardiovascular conditions. These devices provide detailed ECG waveforms that healthcare professionals can review,

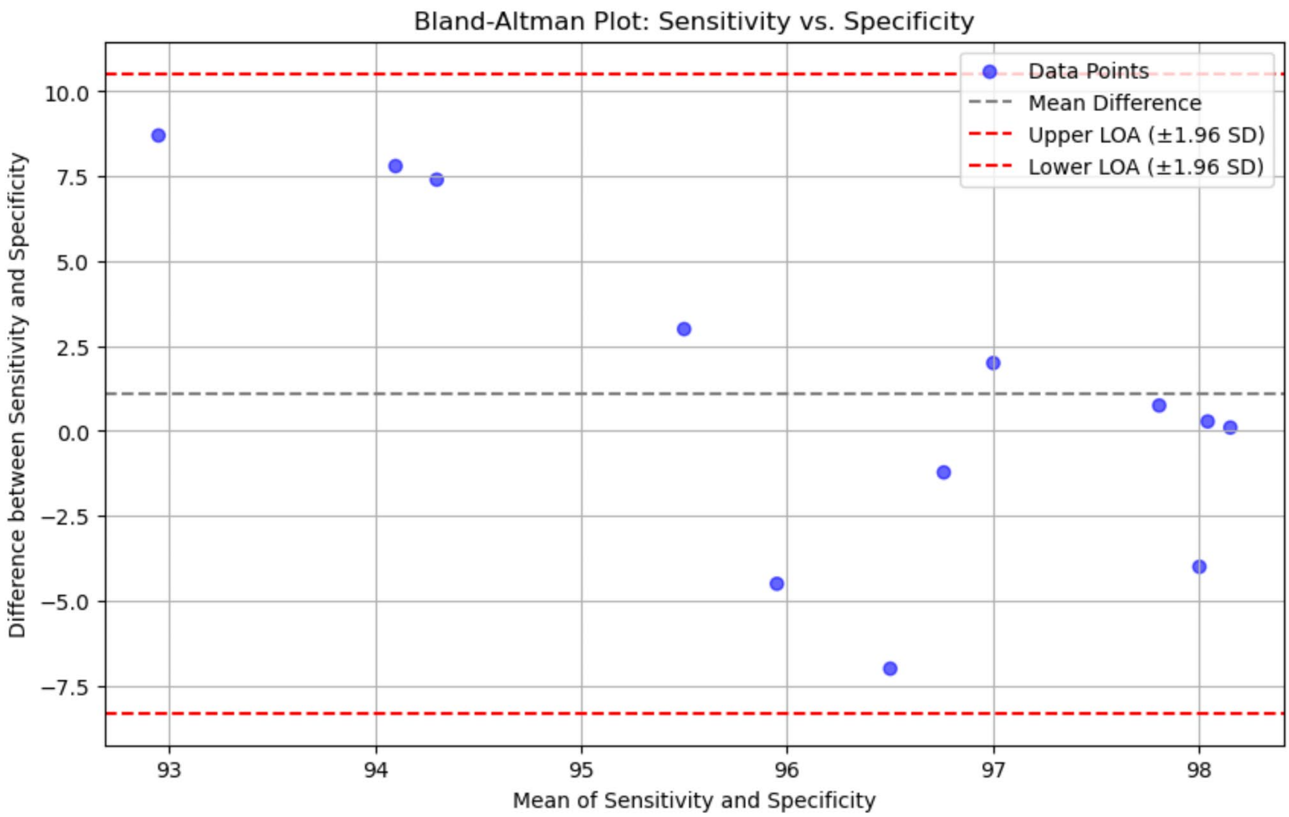


**Fig. 3** Bland-Altman plot for PPG smartwatches in AF detection

**Table 4** Summary of pooled performance of ECG smart chest patches and PPG smartwatches in detecting AF

| Type of wearable | Pooled sensitivity | | | Pooled specificity | | |
|---|---|---|---|---|---|---|
| | **Sensitivity** | **95% CI** | **($I^2$)** | **specificity** | **95% CI** | **($I^2$)** |
| ECG smart chest patches | 96.1% | 91.3-100.8 | 94.5% | 97.5% | 94.7-100.2 | 79.1% |
| PPG smartwatches | 97.4% | 96.5–98.3 | 3.1% | 96.6% | 94.9–98.3 | 75.9% |

offering greater diagnostic value, especially in high-risk populations requiring comprehensive heart rhythm monitoring. Conversely, PPG-based smartwatches are more appropriate for lower-risk individuals seeking to monitor their health in non-clinical settings. The convenience and ease of use of smartwatches make them ideal for personal health tracking, enabling consumers to engage in self-monitoring without the need for continuous medical supervision, thus broadening their utility in everyday health management [47, 48, 49].

Smart wearables are garnering significant attention in the era of AI and the Internet of Things (IoT), offering advancements beyond traditional clinical cardiac monitoring. These devices enable users to monitor their health and detect early warning signs of cardiac irregularities. Studies suggest that individuals using smart wearables are more likely to identify irregular heart rhythms, prompting earlier medical consultations and facilitating timely interventions [50]. Due to their continuous monitoring capabilities and user-friendly design, wearables have gained popularity for personal health tracking. Research indicates that over 80% of global consumers, particularly among younger demographics, express a willingness to utilize these devices for health monitoring [51, 52]. However, challenges such as data privacy concerns and demographic disparities in usage remain, highlighting the need for further research and strategies to improve accessibility and inclusivity.

While smart wearables are increasingly utilized for health tracking in healthcare, they are often associated with a certain degree of false positives and other inaccuracies, which may lead to unnecessary clinical interventions and anxiety for users. To address these limitations, further research and development are required to enhance AI algorithms embedded in these devices. Optimizing the sensitivity and specificity of those AI models is crucial for achieving accurate health monitoring. In cardiology, advancing these models to achieve diagnostic accuracy comparable to that of a standard 12-lead electrocardiogram (ECG) would significantly enhance the

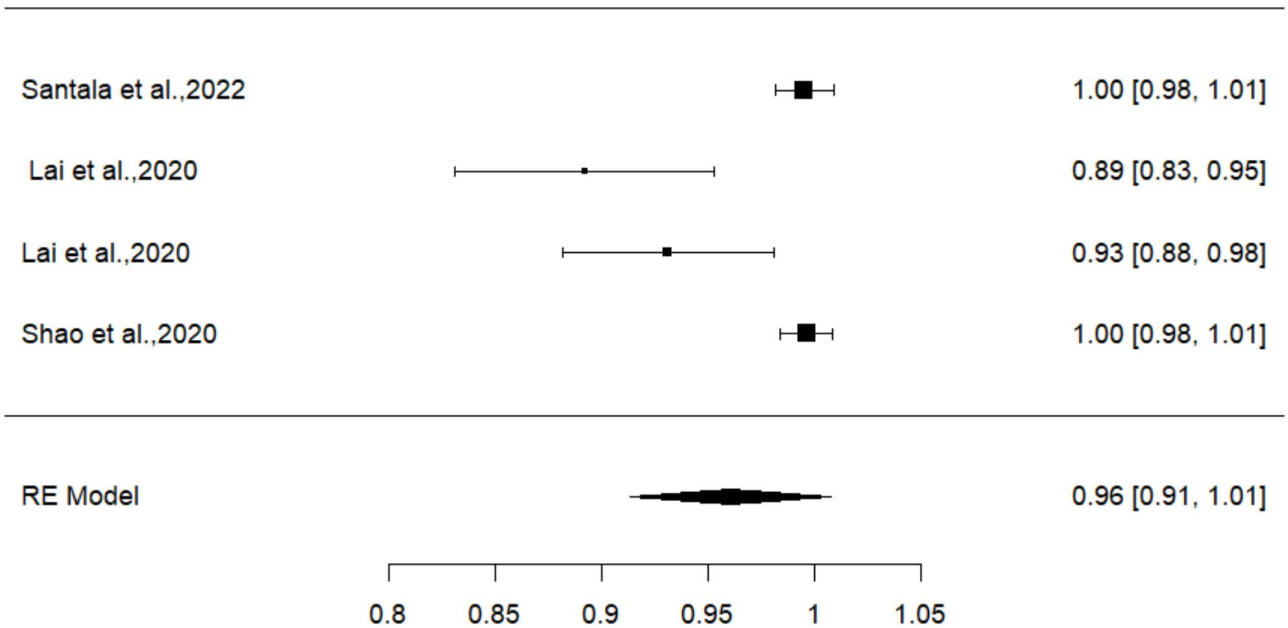


**Fig. 4** Pooled sensitivity of ECG smart chest patches in atrial fibrillation detection

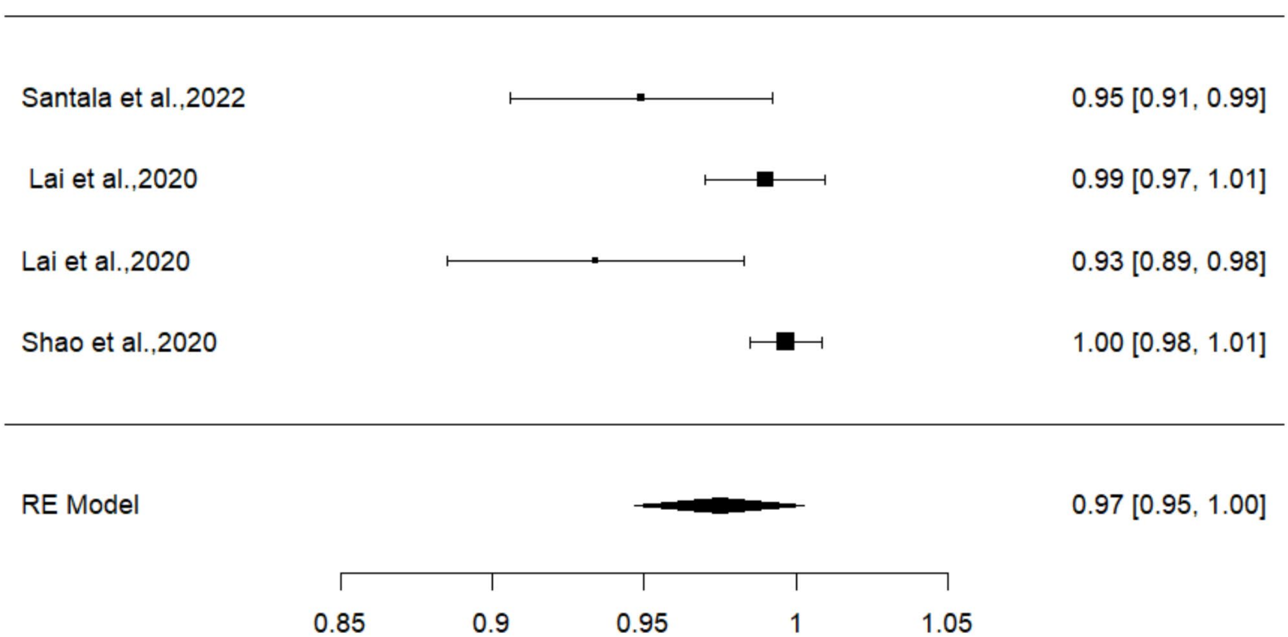


**Fig. 5** Pooled specificity of ECG smart chest patches in atrial fibrillation detection

digitalization of cardiac monitoring. Such advancement would be useful to improve patient outcomes by facilitating more accurate detection and management of cardiac conditions.

### Strengths and limitations

This systematic review and meta-analysis incorporated high-quality studies conducted on diverse patient populations from multiple countries to evaluate the diagnostic accuracy of ECG chest patches and PPG smartwatches in detecting atrial AF. The findings from these studies provide a critical resource for clinical decision-making, offering insights into how these wearables can be employed in various healthcare settings. In particular, the results guide clinicians and consumers in choosing suitable devices based on the clinical context, patient risk profiles, and intended use. However, like all studies, this review has limitations that should be acknowledged, particularly when applying its conclusions in practice. These limitations highlight the importance of continuous research in

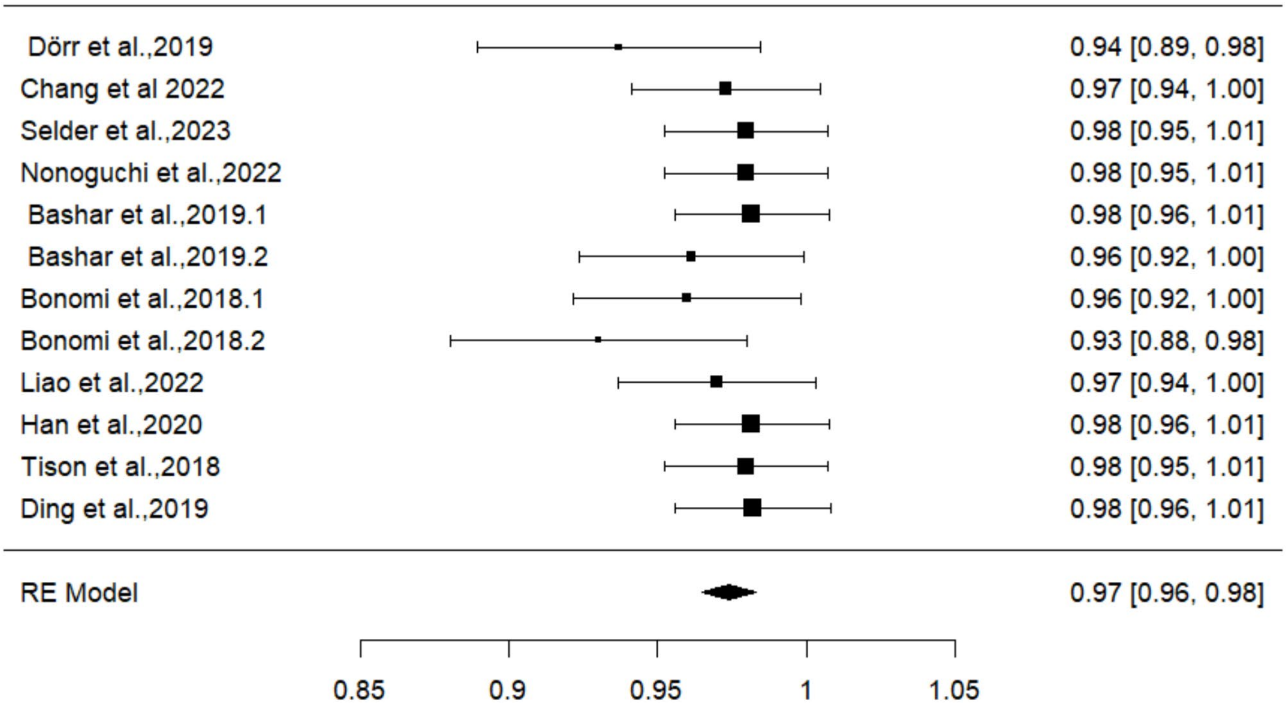


**Fig. 6** Pooled sensitivity of PPG smartwatches in atrial fibrillation detection

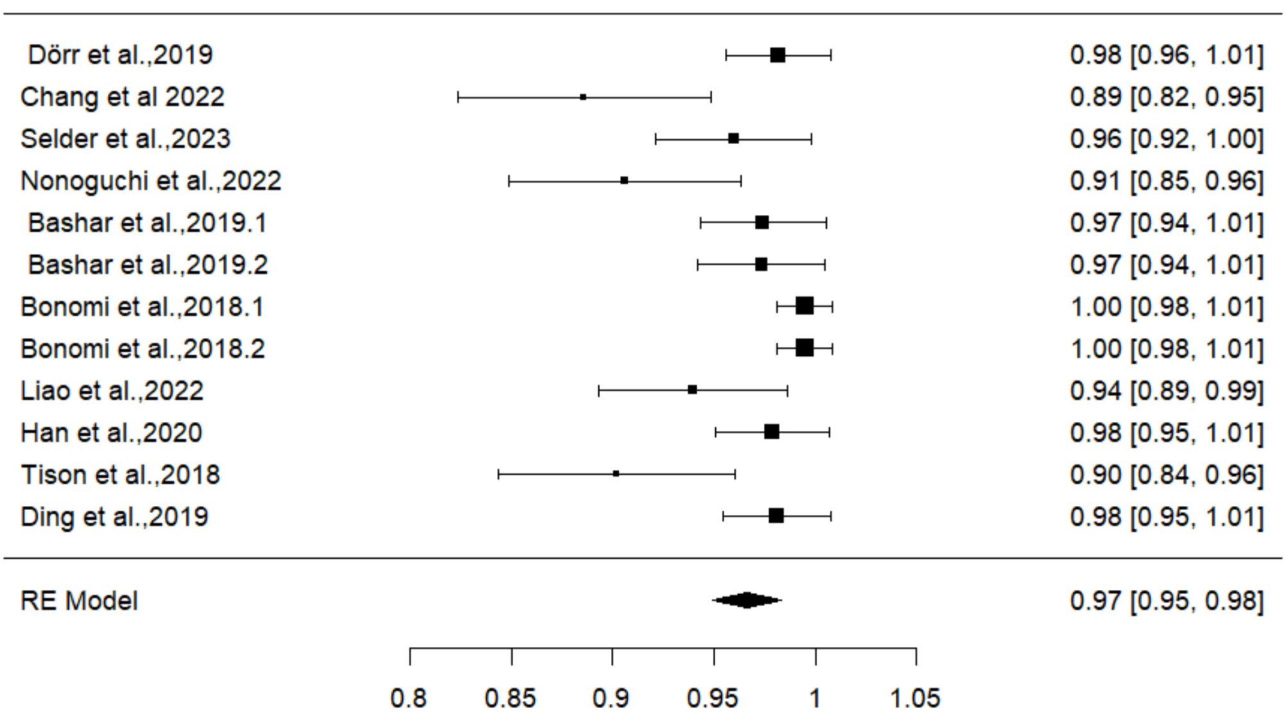


**Fig. 7** Pooled specificity of PPG smartwatches in atrial fibrillation detection

this rapidly evolving field of wearable technology for cardiac monitoring and management.

One major limitation of this study lies in the restricted scope of the literature search. The search strategy was confined to widely-used databases such as PubMed/MEDLINE, Google Scholar, DOAJ, AJOL, and the Cochrane Library, which excluded potentially relevant studies available in other scientific repositories. This restricted access may have resulted in the omission of key studies that could have provided further insights into the diagnostic accuracy of ECG chest patches and PPG smartwatches. As a consequence, the comprehensiveness of the meta-analysis may have been impacted, and the results might not fully capture the global evidence landscape on wearable AF detection technologies.

Additionally, the included studies were conducted across different populations, clinical settings, and geographical regions, with each employing varying gold standards for AF detection, such as 12-lead ECG, Holter monitors, and telemetry ECG. These variations could introduce substantial heterogeneity into the diagnostic accuracy estimates. This variability makes it challenging to directly compare and synthesize the findings across studies, thereby limiting the precision of pooled estimates. The observed heterogeneity among the studies may reflect differences in healthcare infrastructure, patient demographics, gold standards used for comparison, or the methodology used in AF detection, all of which contribute to the complexity of interpreting these results. Despite these limitations, the generalizability of the study remains strong, as the included evidence encompasses a wide range of clinical and non-clinical settings. The insights derived from this review are applicable to both high-risk and low-risk populations, offering guidance on the use of wearables in the diagnosis and management of cardiac arrythmia.

## Conclusion

Both ECG smart chest patches and PPG smartwatches demonstrate high sensitivity and specificity for detecting atrial fibrillation, with PPG smartwatches showing slightly higher sensitivity and ECG chest patches exhibiting marginally greater specificity. This study is the first to directly compare these two technologies within a meta-analysis framework, highlighting its novelty and significance in advancing the understanding of wearable diagnostics for atrial fibrillation. Given the minimal difference in diagnostic accuracy, the choice between these wearables should consider clinical settings, cost, and practical barriers such as affordability, accessibility, and integration into healthcare systems. Despite their high performance, further research is needed to improve device accuracy, reduce false positives, and address concerns such as data privacy and interoperability, as these findings could inform advancements in device design, guide manufacturers to enhance diagnostic precision and user-friendliness, and influence regulatory approvals for wearable technologies. By advancing these capabilities, wearable devices could play a pivotal role in fully digitizing atrial fibrillation detection and improving overall patient outcomes in cardiac care.

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12872-025-04582-2.

Supplementary Material 1

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None.

### Author contributions

O.S. led the conceptualization, methodology, and project administration. C.M.H., A.O., H.G., J.M., and M.M.C. contributed resources. O.S., Cs.H., A.O., H.G., J.M., and M.M.C. participated in writing the first draft, review, and editing. H.G. contributed to methodology, and J.M. conducted the investigation. All authors reviewed and approved the final manuscript.

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### Data availability

Data that support the findings of this study are available from the corresponding author upon reasonable request.

## Declarations

### Ethics approval and consent to participate

No ethical approval was needed as the study did not directly involve human or animal subjects.

### Consent for publication

No consent was needed as the study did not directly involve human or animal subjects.

### Competing interests

The authors declare no competing interests.

### Author details

[1]Department of General Medicine and Surgery, College of Medicine and Health Sciences, University of Rwanda, Kigali, Rwanda
[2]Department of Public Health, Copperbelt University, Ndola, Zambia
[3]Department of General Medicine and Surgery, Ambrose Alli University, Edo, Nigeria

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