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REVIEW

Home detection of atrial fibrillation using cardiac activity analysis: technologies available to the patient

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ABSTRACT

Introduction: Atrial fibrillation (AF) is the most common cardiac arrhythmia, whose incidence and prevalence have increased over the last 20 years and will continue to increase over the next 30 years. It is characterized by irregular atrial activation, leading to complications as stroke and heart failure. Due to its intermittent and asymptomatic nature, diagnosing and monitoring AF is challenging but crucial for effective treatment and prevention of serious complications.

Areas covered: This study reviews noninvasive medical devices available for home detection of AF by analyzing cardiac activity through ECG or photoplethysmography (PPG). The review covers the technologies underlying single-lead ECG acquisition and PPG sensors, and describes how these are used, also in combination, in home-use medical devices (including smartwatches and wristbands).

Expert Opinion: Single-lead ECG and PPG technologies in consumer electronics have revolutionized AF detection, making it more accessible and convenient for patients. Despite some limitations in signal quality and diagnostic scope, these devices offer significant benefits for early AF detection and management. The use of wearable devices, including smartwatches and wristbands, for heart activity monitoring represents a promising advancement in patient-lead healthcare, potentially leading to better outcomes through timely medical intervention and improved patient engagement in managing their condition.

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KEYWORDS
Atrial fibrillation; Single-lead ECG; PPG; wearable devices; arrhythmias

1. Introduction

Cardiac arrhythmias are deviations from the normal heart rhythm that can occur in both mild and severe forms and often require special examinations and ongoing treatment. Atrial fibrillation (AF) is the most frequent cardiac arrhythmia, with more than 30 million people affected worldwide [1].

AF is a cardiac arrhythmia characterized by the irregular activation of the atria. It is not fatal but can lead to serious complications such as stroke, heart failure, and cardiomyopathy. During an AF episode, the electrocardiogram (ECG) is characterized by the absence of the P wave, which is replaced by rapid oscillations called fibrillation waves. The diagnosis of AF can be particularly difficult, as this condition can occur in intermittent episodes and disappear spontaneously, without any recognizable symptoms. This intermittent and often asymptomatic nature makes it difficult to diagnose and monitor AF.

Timely diagnosis is extremely important to treat cardiac arrhythmias effectively and avoid complications. This allows the most appropriate therapy to be applied at an early stage, preventing strokes and cardiac complications.

The primary monitoring strategies for patients with paroxysmal AF include ambulatory ECG monitoring or Holter monitors for prolonged 24-hour or 7-day recordings. However, these strategies are based on occasional intermittent recordings or on long-term continuous monitoring and do not always allow the diagnosis of arrhythmia. Due to the intermittent nature of both arrhythmic events and these monitoring methods, the ability of the different types of monitoring to diagnose AF depends on the coincidence between the monitoring period and the occurrence of AF. For this reason, the European Society of Cardiology guidelines [2] emphasize the importance of novel tools and wearable technologies for screening and detection of AF, which offer new home-use diagnostic possibilities to patients at risk.

Several medical devices for home use that can automatically detect an AF episode are currently available on the market, either Food and Drug Administration (FDA) approved, or CE marked (Conformité Européenne). These devices allow patients to monitor any AF episodes on a daily basis, even outside the hospital. Most devices are based on the recording and processing of a single-lead ECG trace. Others use photoplethysmography (PPG) sensors for heart rhythm analysis. It is possible to obtain an immediate analysis of the heart rhythm made by the device or to send the recording to a smartphone/tablet application that implements the AF episode detection algorithm. The recording can usually then be sent to a doctor or clinical center for further diagnosis.

Other devices that can be used for the diagnosis of AF include blood pressure monitors, implantable loop recorders and devices for the recording and possible transmission of one

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Article highlights

- Review of the available technologies for the self-management of AF.
- Discussion of the main technologies adopted by these devices.
- The role of the destination of use for wearable devices: medical devices vs not medical devices.
- Comparison of the devices' performances in terms of specificity and sensitivity reported by the manufacturer and literature data.
- The role of the AI support in wearable devices for AF detection

or more ECG tracings. These devices can also be used to diagnose and manage other pathologies, and their intended use is not always focused solely on the detection of AF episodes.

This study examines the medical devices currently available on the market for the automatic detection of AF episodes through specific algorithms implemented into wearable and/or home-use technologies based on the analysis of cardiac activity using ECG or PPG signal.

The strength of this paper lies in its ability to provide a comprehensive and in-depth examination of products designed for AF detection. Unlike previous studies that focus on individual devices or adopt a narrower perspective, this research distinguishes itself through a broad and systematic evaluation of wide range of available solutions. It rigorously assesses their effectiveness, reliability, and technological advancements, providing a complete overview of the field. Furthermore, its value extends beyond technical assessment by situating its findings within the current clinical landscape. By offering practical insights for medical applications and identifying emerging trends, this study not only enhances the understanding of existing technologies but also paves the way for future innovations in AF detection.

2. Atrial fibrillation

AF is a cardiac arrhythmia characterized by irregular and disorganized atrial contractions [2]. It represents the most common sustained cardiac arrhythmia globally, with an increasing prevalence attributable to an aging population and improvements in diagnostic techniques. It is estimated that it affects approximately 2–4% of the adult population, with a particularly high prevalence among the elderly. In the over 75 age group, the prevalence reaches 10–15%, while among those over eighty it can reach up to 20% [3].

There are approximately 3 million new cases worldwide each year, and the numbers are expected to triple by 2060 in Western countries [1].

The main factors that contribute to the spread of AF include advanced age, cardiovascular diseases such as high blood pressure, heart failure and ischemic heart disease, as well as conditions such as diabetes, obesity, sleep apnea and chronic lung diseases. Unhealthy lifestyles, such as excessive alcohol consumption and smoking, also play a significant role [1,4].

Under normal conditions, the electrical impulse propagates from the sinus atrial node through the atria and stimulates the coordinated contraction of the upper chambers of the heart [5]. During AF, numerous waves of disorganized electrical impulses originate from various points in the atria and cause an uncoordinated and disorganized contraction of the atrial chambers. On electrocardiographic examination, this disorder is characterized by the complete absence of P waves, which are replaced by rapid, chaotic, and disordered oscillations called fibrillation waves. These oscillations vary continuously in amplitude, shape and frequency and are accompanied by an irregular ventricular response [4,6].

Diagnosing AF using an occasional ECG can be particularly challenging due to its intermittent and, in many cases, asymptomatic nature. This condition often presents paroxystically, with episodes that can last from a few minutes to several hours or days, and then resolve spontaneously. During periods of normal sinus rhythm, the ECG shows no signs of arrhythmia, making it difficult to identify the disorder if the episode is not recorded [6]. So, AF can remain undiagnosed for a long time.

However, its timely diagnosis is a fundamental goal for the correct therapy. Additionally, an early diagnosis allows you to address and treat underlying conditions, which often contribute to the onset of AF.

The therapies adopted depend on various factors, such as the duration of the arrhythmia, the presence of symptoms, the patient's clinical condition and the risk of thromboembolic events. Therapeutic approaches mainly focus on three main objectives: prevention of complications, rhythm control and heart rate control [2,7,8].

Regarding the prevention of complications, one of the most important aspects in the management of AF is the prevention of ischemic stroke. If untreated AF increases the risk of stroke fivefold since during an episode of AF, blood clots can form in the fibrillating atria as a result of local stasis. These clots can then dislodge causing embolization to the cerebral circulation (particularly upon the return of atrial contraction with sinus rhythm restoration) [4]. Intervening early with proper therapies can prevent such events. To reduce this risk, anticoagulant therapy is used, which is based on the assessment of the patient's thromboembolic risk.

In this context, diagnostic tools play a crucial role in the timely identification of atrial fibrillation. Although the ECG is the gold standard for confirming the diagnosis, its effectiveness is limited to episodes detectable at the time of recording. For this reason, in patients at risk or with intermittent symptoms, prolonged monitoring techniques are used, also through wearable devices such as smartwatches with integrated ECG sensors which are revolutionizing the diagnostic approach, offering the possibility of detecting cardiac rhythm anomalies even at outside the clinical environment. This possibility offers a significant advantage, especially considering that AF can often be asymptomatic or paroxysmal, making early diagnosis difficult using traditional tools such as the ECG performed in the office. Interestingly, it is hypothesized that daily use of a short-term ECG (>30 seconds) over a few weeks will allow the detection of a greater number of AF episodes than a single 24-hour Holter ECG performed over the same period [9–12]. Recent literature has confirmed the superiority of daily short-duration ECG use over a single 24- or

48-hour Holter recording in detecting patients with AF episodes. In the AGNES-ESC study, daily ECG use also appeared better than the 6-day Holter recording [13].

3. Technologies for the detection of atrial fibrillation episodes

Over the past few years, technological advances in the fields of electronics and computer science have made medical devices accessible for home use that were previously reserved only for hospital settings due to their cost and complexity. Thus, medical devices previously intended for use exclusively by specialized medical personnel became accessible for use by the public in home environments. Cardiac activity recorders are a significant example of this change. Technologies that can be used at home to acquire information on cardiac activity can broadly be divided into those that provide an ECG and those with non-ECG approaches [2]. In this study we will refer to single-lead ECGs and implantable cardiac monitor belonging to the first group, and to PPG sensors and oscillometry these being the home-usable technologies on which the currently market available medical devices are based.

According to the European Society of Cardiology guidelines [2], an AF episode can be recognized by the absence of distinct repeating P-waves on an ECG trace and irregularly irregular RR intervals.

According to this approach, devices for AF diagnosing typically rely on two main approaches, often used in combination: rhythm analysis and P-wave evaluation. Both methods aim to detect the arrhythmia, but they differ in complexity and diagnostic precision. Clearly, recognition of the absence of P waves is only possible using at least one ECG trace, while heartbeat irregularity can also be assessed using other sensors [10,11].

For this reason, the latest guidelines on the management of AF suggest the use of non-ECG-based devices only for screening purposes and not for clinical diagnosis [2].

Devices that focus solely on rhythm analysis identify AF by examining irregularities in the intervals between heartbeats (RR intervals). This approach detects the hallmark of AF: the absence of a predictable pattern in these intervals. Algorithms, often supported by artificial intelligence, assess the variability and irregularity of the RR intervals to flag potential AF episodes. Such devices are commonly used for continuous monitoring in portable or wearable devices like smartwatches and handheld monitors, utilizing single-lead ECG and/or PPG sensors. However, rhythm-based analysis alone may not reliably differentiate AF from other conditions, such as atrial or ventricular ectopic beats, which also cause irregular rhythms.

In recent years, AI has significantly advanced the detection, prediction, and management of AF. Various machine learning (ML) and deep learning (DL) techniques have been explored, ranging from traditional feature-based models to neural networks capable of end-to-end learning from raw ECG or PPG signals [14–16].

Convolutional neural networks (CNNs) have demonstrated high performance in AF detection, particularly when applied to 12-lead ECGs. Studies have shown that CNN-based models can achieve high sensitivity and specificity by analyzing raw ECG waveforms and identifying AF-specific morphological patterns [17,18]. Moreover, CNNs have been successfully adapted for single-lead ECG signals, making them suitable for wearable devices and mobile health (mHealth) applications [19].

Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been employed to capture the temporal dependencies in ECG data collected through a single-lead ECG device, allowing for more robust AF classification in long-term recordings. These models are particularly effective in distinguish AF from other arrhythmias by analyzing the irregularity of RR intervals and other features [20].

With the increasing adoption of smartwatches and mobile applications for AF screening, AI-based PPG analysis has gained attention. Deep learning models applied to PPG signals can detect pulse irregularities associated with AF, offering a noninvasive and continuous monitoring solution [21,22]. However, while PPG-based AF detection is promising, it generally shows lower specificity compared to ECG-based approaches [21,23].

The integration of AI into AF detection has shown considerable promise, with CNNs, RNNs, and hybrid models playing a central role in improving diagnostic accuracy. While AI-powered ECG and PPG analysis have the potential to enhance early AF detection, further clinical validation and standardization are necessary to ensure their reliability and integration into routine healthcare practice [24].

3.1. Medical device regulations: CE and FDA

In this study, only devices that have obtained the CE certification or FDA approval as medical devices were considered. This distinction is fundamental, as the market also includes devices intended for medical use that lack proper certification. These uncertified devices are not subjected to the rigorous regulatory controls imposed by European (CE mark) or U.S. (FDA) authorities, meaning they do not offer the same guarantees in terms of safety, performance, and reliability.

The CE mark and FDA approval represent key regulatory that ensure a medical device meets strict requirements regarding quality, efficacy, and risk management. These regulations are particularly stringent for devices that provide critical health data, as they must demonstrate not only technical accuracy but also clinical validity.

With regard to the use of medical devices for the detection of AF episodes, CE certification or FDA approval/clearance guarantees that the risks related to their use for the diagnosis of complex conditions such as AF have been considered.

Specifically, with regard to performance and safety, these devices are tested following the reference standards to guarantee diagnostic accuracy in the clinical setting. This minimizes the risk of false positives (diagnosis of AF when the heart beats normally) or false negatives (failure to detect AF when it is present), which could lead the patient to undertake unnecessary treatments or, conversely, not to seek medical assistance when AF is actually present, with serious risks such as stroke or heart failure.

With regard to safety, certification/approval-clearance guarantees that the risks related to electrical and mechanical

safety, biocompatibility of materials and ease of use of the user interface have been considered and minimized, aspects guaranteed by compliance with international standards included in the regulatory framework provided in Europe with the CE mark (but also in the United States and in many other countries around the world).

In the context of home-based AF detection, relying on certified medical devices is essential to ensure accurate and clinically reliable results. The use of non-certified devices poses potential risks, such as incorrect diagnoses or misleading data, which could negatively impact patient management and medical decision-making. As wearable health technologies continue to evolve, regulatory oversight remains a crucial factor in safeguarding patient safety and maintaining the integrity of digital health innovations.

3.2. Single lead ECG

Single lead ECG devices use two electrodes to record an ECG trace. These devices allow for continuous or intermittent ECG monitoring and can be wearable or used on demand. The placement of the electrodes is crucial for determining the type of information that can be obtained from the system [9]. In some cases, electrodes are metal plates that must be placed in contact with the skin of different parts of the body (i.e. wrist, fingers or chest). In other cases, adhesive electrodes are used which can be of various types. There are devices that use disposable electrodes either of the type commonly used in clinical contexts or of a proprietary type in terms of shape, material or type of connection to the device. In other devices, reusable electrodes are used.

The single-lead ECG stands out for its simplicity, portability and practicality, making it ideal for continuous cardiac monitoring and in non-clinical contexts. Lighter and more compact than multi-lead systems, it can be easily integrated into wearable devices, allowing discreet and prolonged surveillance of cardiac health. The ease of use reduces preparation time and the risk of errors, while the low cost makes it accessible to a wider audience, especially in resource-limited contexts. Although it does not offer the complete view of cardiac activity that the 12-lead ECG provides, it is sufficient to detect arrhythmias and common abnormalities [12]. Thus, the single-lead ECG represents a versatile and complementary solution, promoting the diffusion of life-saving tools for preventive and continuous monitoring of cardiac health.

Some single-lead ECG devices use the dual approach by analyzing both the absence of a P wave and the irregularity of the heart rhythm. Others, however, base the detection of an AF episode only on the irregularity of the rhythm.

The detection of a P-wave from a single-lead ECG may be affected by two major factors: depending on the electrode placement, P-waves may not be included in the measured potential, or it may be buried in noise. With regards to the electrode placement, no existing algorithms, even those implementing AI solutions, can reliably reconstruct the P-wave or accurately detect AF when the wave is not captured. On the other hand, photoplethysmography-based methods account for inter-beat interval, offering an alternative approach. However, the use of RR interval analysis may poorly perform in distinguishing AF from NSR when applied in particular class of patients, as those treated with antiarrhythmic drugs (e.g. β-blockers or calcium-channel blockers) [25]. Additionally, studies applying AI to RR interval analysis have been conducted on small cohorts (51 and 72 subjects [23,26] respectively), including only patients with either NSR or AF, without considering other cardiovascular diseases, that could influence the detection.

While AI alone cannot compensate for the complete absence of P-wave information, it can significantly enhance ECG signal quality through denoising techniques, thereby facilitating P-wave detection when it is present but obscured by noise.

AI has shown promise in improving ECG signal quality through noise reduction techniques. For instance, the use of convolutional denoising autoencoders has led to a significant enhancement in the signal-to-noise ratio (SNR) [27].

An innovative approach for improving ECG signal quality is the use of DL algorithms [28]. The use of CNNs enhances noise reduction by capturing correlations between successive cycles, leading to a significant improvement in the SNR and root-mean-square error (RMSE) when compared to traditional filtering techniques.

Finally, while AI cannot compensate for the absence of P-wave information due to the inherent limitations of single-lead ECG, it plays a crucial role in enhancing signal quality through advanced denoising techniques, ultimately improving the detection and accurate analysis of P-waves when present.

3.3. Photoplethysmography sensors

Photoplethysmography (PPG) measures cardiac activity by detecting changes in blood volume in the skin through light absorption. This noninvasive method brings a light emitter and receiver (LED and photodiode) in contact with the skin. The LED emits a beam of light with a specific wavelength and intensity. When the light penetrates the skin, it is partially absorbed by tissue and blood. The photodiode then measures the amount of light that is either absorbed or reflected by the blood, generating a signal (PPG signal) which is synchronous to the blood pumping regulated by the heart activity [29,30]. This technology is simple, inexpensive, and can be integrated into smartphones and smartwatches by attaching the sensor to the wrist or fingertip.

Given the waveform of the PPG signal, PPG-based devices can only estimate the irregularity of the heartbeat to detect AF episodes without analyzing the P-waves. The algorithms for detecting AF with PPG focus on identifying the heart rate and its irregularity, which makes them relatively simple. Although this method offers good accuracy, it is generally less specific than methods that also consider the absence of distinct repeating P waves [31].

This technology offers a practical and accessible approach to heart monitoring by detecting changes in blood volume in the skin through light absorption. Its integration into consumer electronics enables broad application and supports early detection of cardiac arrhythmia episodes, particularly AF, through relatively simple algorithms that focus on the timing and irregularity of heartbeats.

3.4. Oscillometric signal

Oscillometry is the blood pressure measurement methodology used in most automated blood pressure measuring devices (ABPMDs). These devices were developed in the 1970s to replace mercury sphygmomanometers based on manual auscultatory measurement of blood pressure (BP). ABPMDs follow the same procedures as manual auscultation regarding cuff placement and arm position. These devices control the inflation and deflation of the cuff electronically and use proprietary algorithms to estimate blood pressure by analyzing the pressure waves transmitted by the cuff, namely the oscillometric signal. Since the waveform recorded by the cuff is synchronous with the heart rhythm, some ABPMDs incorporate algorithms that evaluate the pulse irregularity from the oscillometric signal during BP measurement, giving information about the presence of an episode of AF or irregular heart rhythm [32–34].

3.5. Cardiac electrogram

A cardiac electrogram is the tracing of the electrical potentials of the heart recorded by electrodes placed under the skin in the left shoulder region overlying the heart. Cardiac electrograms can be continuously acquired by the so-called Implantable Loop Recorders (ILRs) or Insertable Cardiac Monitors (ICMs) which are small subcutaneous devices placed under the skin and composed of electrodes, a battery, and a circuitry for signal acquisition. These devices allow continuously monitoring of the heart's electrical activity over extended periods (years). They are useful for the diagnosis of intermittent cardiac arrhythmias, such as atrial fibrillation, which cannot be detected by an ECG or Holter test. The indications for an ICM have expanded over the years and currently include syncope, post-myocardial infarction, suspected unproven epilepsy, unexplained falls and palpitations, and cryptogenic stroke or embolic stroke of unknown origin [35]. ILRs/ICMs are placed under the skin of the chest during a surgical procedure which has become easier and more tolerable for patients [35,36].

Technological advancements have significantly enhanced the capabilities of ILRs/ICMs. Modern ILRs/ICMs are equipped with sophisticated algorithms that improve their ability to accurately detect and record abnormal heart rhythms. These algorithms can automatically detect and store episodes of arrhythmias, which healthcare providers can then review. The AF detection algorithms differ per manufacturer but are primarily based on R-R interval irregularity.

Moreover, the physical design of ILRs/ICMs has improved. Advances in miniaturization have resulted in devices that are smaller, lighter, and more comfortable for patients. Despite their reduced size, these modern ILRs can store extensive data and have longer battery lives, often lasting several years before needing replacement.

4. Home use medical devices for the automatic detection of AF episodes based on single-lead ECG or PPG technology

Currently, on the market, there are different types of medical devices for home use whose intended use includes the identification of AF episodes. These devices use different technologies and sensors as described in the previous paragraph.

Table 1 shows the currently available home-use medical devices for automatic detection of AF episodes, based on single-lead ECG or PPG technology. A total of 16 devices have been identified: 7 smartwatches, wristbands, and smartbands that use both ECG and PPG sensors, 6 dedicated medical devices that record an ECG trace, and 3 mobile Apps that analyze the PPG signal. The table lists the device name (Product), the manufacturer (Company), the country where the manufacturer is based (Country), the device's usage mode (SA: stand-alone – APP: via smartphone app), the market where it is sold (Market), the duration of the recording (Duration), the sensor used to collect the data (Sensor) and values for sensitivity, representing the ability of the device to correctly identify positive cases, and specificity, the device's ability to correctly identify negative cases (Sensitivity/Specificity). Regarding sensitivity and specificity, both the values provided the manufacturers and those obtained from a literature analysis of various studies are reported.

All the medical devices reported in Table 1 (except one) implement algorithms for the detection of AF episodes, and after each measurement, the patient receives a report that can be sent to their healthcare provider. The algorithms used in the devices operate entirely on-device or within their respective applications, meaning they do not require an internet connection or cloud-based processing for AF detection. This ensures that all analysis is performed locally, without transmitting patient data to external servers, thereby enhancing privacy and reducing potential latency. The only exception is Coala Heart Monitor, which differs from the others by relying on a cloud system for automatic AF diagnosis. In this case, the device transmits data to a secure API server, where the analysis is performed before the validated results are stored in an encrypted database.

Table 1 specifically indicates whether the medical device can operate independently (SA) or requires a smartphone application (APP). Most of the devices function exclusively through an app, while four support SA use. This distinction is important since many users, particularly elderly individuals, may struggle with smartphone applications due to limited technological familiarity, visual impairments, or cognitive difficulties. If a device relies solely on an APP for operation, data interpretation, or storage, it may become inaccessible to users who are uncomfortable with digital tools, increasing the risk of use or abandonment of the device. Another key concern is the dependency on an internet connection. If a device requires continuous network access to function, users in areas with poor connectivity or those who experience temporary internet outages may be unable to use it when needed, potentially compromising timely AF detection and monitoring.

4.1. Smartwatches

Smartwatches are digital watches offering numerous additional functionalities compared to traditional ones. Some of them can record the heart's electrical activity, generating an

Table 1. Characteristics of home medical devices for automatic AF diagnosis.

Product	Company	Country	SA/ APP	Market	Duration	Sensor	Sensitivity/ Specificity
Smartwatch							
Apple Watch	Apple Inc.	California, USA	APP	Shop/ Online	30s	ECG, PPG	M: 97%/99% [37]
Mannhart et al. [38]							85%/75%
Ford et al. [39]							50%/100%
Scholten et al. [40]							94.4%/98.2%
Abu-Alrub et al. [41]							90%/95%
Withings ScanWatch	Withings	France	APP	Shop/ Online	30s	ECG	M: 96.3%/100% [42]
Mannhart et al. [38]							58%/75%
Scholten et al. [40]							97.5%/94.9%
Abu-Alrub et al. [41]							78%/80%
Galaxy Watch	Samsung Technology Ltd	Seoul, South Korea	APP	Shop/ Online	30s	ECG, PPG	M: 98.1%/100% [43]
Mannhart et al. [38]							85%/75%
Abu-Alrub et al. [41]							88%/81%
CardiacSense Watch	CardiacSense	Israel	SA, APP	Online	30s	ECG, PPG	M: 99%/99% [44]
Hochstadt et al. [45]							100%/93.1%
Huawei Watch	Huawei	Shenzen, China	APP	Shop/ Online	30s	ECG, PPG	M: 96.05%/94.76% [46]
Wristband and smartband							
KardiaBand	Alive Cor Inc.	California, USA	APP	Online	30s	ECG	M: 93%/84% [47]
Ford et al. [39]							93%/97%
Bumgarner et al. [48]							96%/93%
Fitbit	Fitbit Inc.	California, USA	APP	Shop/ Online	30s	PPG	M: 98.7%/100% [49]
Mannhart et al. [38]							67.6%/98.4%
Lubitz et al. [50]							66%/79%
Dedicated Medical Devices							
Coala Heart Monitor	Coala Life AB	Sweden	APP	Online	30s	ECG, PCG*	M: 95.1%/97.6% [51]
Nordin et al. [52]							98.9%%/100%
Cardionica	MIR	Rome, Italy	SA, APP	Online	60s	ECG	Not reported
MyDiagnostick	MyDiagnostick Medical BV	Netherlands	SA	Online	60s	ECG	M: 90%/95% (min) [53]
Kamga et al. [54]							60.5%/93.3%
Desteghe et al. [55]							100%/95.9%
KardiaMobile 1 L	AliveCor Inc.	California, USA	APP	Online	30s	ECG	M: 94.6%/92.9% [56]
Mannhart et al. [38]							92%/95%
Selder et al. [57]							98%/97%
Lau et al. [58]							94%/99%
Haberman et al. [59]							79%/69%
Himmelreich et al. [60]							87%/97.9%
Carrington et al. [61]							97%/94%
Bansal & Joshi [62]							98%/97%
Pak-Hei Chan et al. [63]							71.4%/99.4%
Lowres et al. [64]							98.5%/91.4%
KardiaMobile 6 L	AliveCor Inc.	California, USA	APP	Online	30s	ECG	M: 99%/97% [65]
Scholten et al. [40]							99.4%/91.4%
Krzowski et al. [66]							86.4%/97.4%
HomeECG+	Lohman Technologies	Milwaukee, USA	SA	Online	45s	ECG	Not reported
Awario	Heart2Save	Kuopio, Finland	APP	Online	30s	ECG	M: 98%/99% [67]
Santala et al. [68]							96%/100%
Santala et al. [69]							100%/100%
App							
FibriCheck	IMEC	Leuven, Belgium	APP	Online	60s	PPG	M: 98%/99% [70]
Proesman et al. [71]							95.6%/96.6%
Preventicus Heartbeats	Preventicus GmbH	Jena, Germany	APP	Online	60s	PPG	M: 92%/99% [72]
Brasier et al. [73]							89.9%/99.1%
CardioSignal	Precordior	Finland	APP	Online	60s	GCG**	M: 95.3%/96% [74]

*PCG: Phonocardiogram.
**GCG: Gyrocardiography.

ECG trace, using electrodes placed behind the watch and on the watch crown, others use PPG sensors to analyze heart activity, and some use both techniques [54].

As reported in Table 1, 5 smartwatches are currently available in the market and certified as medical devices for automatic detection of AF episodes: the Apple Watch (Apple Inc.) [38–41,75,76], Withing ScanWatch (Withings) [76], Galaxy Watch (Samsung Technology Ltd) [39], CardiacSense Watch (CardiacSense) [45], and Huawei Watch (Huawei) [46,77]. Notably, not all the smartwatches which claim to record heart activity are medical devices. As already clarified, in this study we only refer to medical devices. Among the 5 identified smartwatches declared as medical devices for the detection of AF episodes or heart rhythm irregularity, in some cases the CE mark or FDA approval concerns the entire device, in other cases it concerns only the software in the form of a mobile

App. In particular, the entire device is considered a medical device in the case of the Withing and the CardiacSense Watch. In other cases, only the app is considered a medical device (Apple ECG App, Samsung ECG Monitor App, Huawei ECG App).

These 5 smartwatches which are declared to have medical purpose for the detection of AF episodes are very similar to each other in terms of external design and way of use. They may differ in the implemented algorithms, notification strategy to the patient, in the number and type of detectable arrhythmias (atrial fibrillation only, or bradycardia and tachycardia) and in the possibility of performing continuous heart activity monitoring (using PPG signal) [39,46,75].

Among the 5 smartwatches identified for the detection of AF episodes or heart rhythm irregularity, some manufactures explicitly claim the use of AI-based algorithms for arrhythmia detection. For example, the Apple ECG App [37] and Samsung ECG Monitor App [43] utilize proprietary AI models for signal analysis and rhythm classification. However, while these AI algorithms enhances detection capabilities, they primarily serve to automate feature extraction and classification rather than predictive analysis or decision-making support.

When evaluating the performance of the five smartwatches, the data presented in Table 1 reveal notable variation in their diagnostic accuracy. Indeed, the sensitivity and specificity of each device, as reported by various studies, demonstrate different levels of reliability in detecting AF episodes. For the CardiacSense Watch the performance reported by the manufacturer is similar to those reported by clinical studies (sensitivity and specificity values reaching up to 99% vs 100% and 93.1%, respectively) [44,45]. This suggests it performs particularly well in terms of low number of false negatives. The Apple Watch, which combines both ECG and PPG sensors, reports high manufacturer-stated accuracy (97% sensitivity, 99% specificity) [37], with clinical studies showing a broader range of values (50%-94.4% for sensitivity and 75%-100% for specificity) [38–41]. Such variability may indicate that, while the Apple Watch performs well in many cases, its accuracy can be influences by certain factors, such as the method of data acquisition or the context in which the device is used. Similarly, the Galaxy Watch also presents higher values of sensitivity (98.1%) and specificity (100%) [43] declared by the manufacturer, indicating reliable performance, but clinical studies report different results [38,41]. On the other hand, the Withings ScanWatch shows significant manufactured-reported performances 96.3% for sensitivity and 100% for specificity [42]. However, clinical studies present mixed results [38,40,41] which could imply that, while it is highly accurate in some contexts, it may struggle with detection in others. For the Huawei Watch, while the manufacturer's data report a sensitivity of 96.05% and specificity of 94.76% [46], these values have not been independently validated through peer-reviewed studies. As such, while these values may be indicative of the device's potential, they should be interpreted with caution until further external validation is available.

4.2. Wristbands or smartbands

These are compact versions of smartwatches, shaped like bracelets with smaller displays and fewer features [54]. Some of these devices use photoplethysmography (PPG) to monitor heart activity, while others use ECG.

Among the huge number of available wristbands or smartbands that claim to record heart activity, only 2 are medical devices. One is the Kardiaband (AliveCor Inc.) [22,48,78], a wristband with an ECG sensor that replaced the band of the Apple Watch (Apple Inc.). The devices from AliveCor use their applications for data analysis, featuring algorithms that classify the acquired signal. The other is represented by the Fitbit family, some models of which feature the Fitbit Irregular Rhythm Notifications application, which is certified as a medical device for the detection of AF episode. For example, the Fitbit Sense and Fitbit Charge 5 incorporate advanced PPG technology to continuously monitor heart rate and detect irregularities. The Fitbit Irregular Rhythm Notifications app works by analyzing heart rhythm data and alerting users if signs of AF are detected. This feature has been validated through clinical studies and is approved by the FDA, ensuring it meets all the standards required for medical devices [50].

About the algorithms, Kardiaband uses AI-driven algorithms to enhance ECG or PPG signal analysis. KardiaAI, the software behind AliveCor's devices, claims to use machine learning for AF classification [79].

Regarding the performances of the two wristbands, the data presented in Table 1 highlight distinct differences in their sensitivity and specificity. The KardiaBand shows relatively high accuracy in detecting AF episodes. The manufacturer's data report a sensitivity 93% and specificity of 84% [47]. The subsequent values from clinical studies [39,48] demonstrate greater consistency in both sensitivity and specificity, suggesting that the device performs reliably when tested outside of the manufacturer's data. The integration of AI-driven algorithms (KardiaAI) enhances its detection capabilities, and although this technology supports the device's AF classification. In contrast, Fitbit shows a broader range of performance: the manufacturer's sensitivity and specificity values (98.7% and 100%) [49] are higher than those arising from clinical studies (sensitivity as low as 66% [38] and specificity ranging from 79% to 98.4% [50]).

4.3. Dedicated medical devices

These devices are designed for acquiring and recording ECG traces using electrodes, which can be metallic and touched with fingers or hands, or adhesive and applied to the chest. Many available devices feature wireless connectivity, allowing them to connect to a smartphone or tablet for activation and data download. The ECG trace analysis for AF diagnosis can be performed on the device, via app or cloud.

The medical devices with adhesive electrodes currently on the market include the Coala Heart Monitor (Coala Life AB) [51,52] and the Cardionica (MIR – Medical International Research SpA) [80]. Both use an ECG sensor placed directly on the chest, but the Coala Heart Monitor also includes a phonocardiogram (PCG) for recording heart sounds. These two devices transmit data to a smartphone via downloadable applications. However, Cardionica (MIR) has an additional

stand-alone mode by featuring colored icons feedback to the patient.

Another subgroup of dedicated medical devices includes finger sensors such as MyDiagnostick (MyDiagnostick Medical BV) [38,55], KardiaMobile (AliveCor Inc.) [57–64,81], and HomeECG+ (Lohman Technologies) [82]. MyDiagnostick and HomeECG+ are stand-alone devices that use a LED system to provide feedback to the patient. HomeECG+ has a screen that displays the ECG trace along with the results. KardiaMobile has two models available for AF detection: KardiaMobile 1 L, with two electrodes for finger placement, and KardiaMobile 6 L, with a third electrode placed under the device to be positioned on the left leg or ankle to record a 6-lead ECG [62–64]. Kardia 12 L is also available, but it is intended for professional use only and has not been included in this study, as it falls outside the scope of our analysis. Like the previously described KardiaBand, KardiaMobile is connected to a smartphone and uses its app Kardia for data analysis.

Notably, the MyDiagnostick device is for home use but under the direction of a doctor, who can obtain the device and provide it to patients for a certain period.

Another medical device used as a finger sensor is called Awario (Heart2Save), which uses the Movesense (Movesense Ltd) sensor that is certified as medical device. As the KardiaMobile, also Awario has a proper application downloadable on the smartphone that can make the detection of AF episode [68,69].

KardiaMobile's KardiaAI and Awario's Movesense technology claim to leverage AI for automated classification of ECG signals [70]. However, these systems primarily act as detection tools, and their role in predictive analytics remains unverified. In Table 1 the performances of these devices are reported, which reveals varying levels of sensitivity and specificity across different models.

The Coala Heart Monitor is declared by the manufacturer to have sensitivity and specificity of 95.1% and 97.6%, respectively [51]. Notably, an independent clinical study reported a higher accuracy of 98.9% and 100% [52]. The MyDiagnostick device presents different results. While manufacturer data suggest a sensitivity and specificity of 90% and 95% as minimum [53], respectively, clinical studies report a much wider range, with as low as 60.5% in one study [55] but reaching 100% [54] in another. The KardiaMobile series, particularly the KardiaMobile 1 L, has undergone extensive validation, with sensitivity and specificity values varying across different studies. While manufacturer data indicate 94.6%/92.9% [56], clinical studies report a broad range [38,57–64]. The KardiaMobile 6 L presents manufacturer-reported accuracy (99%/97%, sensitivity and specificity) [65] and clinical validation supporting high specificity but with sensitivity values fluctuating [40,66]. These findings suggest that while the device is highly specific in detecting AF, sensitivity may depend on signal acquisition conditions. The Awario device shows strong manufacturer-reported sensitivity and specificity (98%/99%) [67], with clinical studies corroborating high performance [68,69].

For both Cardionica and HomeECG+, no reported accuracy data are available, making them difficult to directly compare their performance with other devices.

4.4. APP

These software devices use a smartphone's LED as a PPG sensor to capture heart activity signals. By placing a finger on the phone's camera, a PPG signal is obtained and analyzed in terms of heart rate using the app's algorithms. Not all apps are classified as medical devices by their manufacturers.

The currently available apps certified as medical devices to detect AF episodes in the App Store and Play Store are three: FibriCheck whose values of sensitivity and specificity in detecting AF have been recently published [71]; Preventicus Heartbeats which has been validated in clinical studies and has received CE certification, ensuring it meets European regulatory standards for medical devices [73]; CardioSignal uses a different approach by using gyrocardiography (GCG), which leverages motion sensors integrated into smartphones, such as the gyroscope and accelerometer. This app requires users to place the smartphone on their chest while lying down. The app's algorithms analyze micro-vibrations caused by heartbeats to detect AF [74].

FibriCheck uses AI-enhances algorithms to analyze heart activity [70]. It applies machine learning techniques to detect AF episodes from PPG data. This application demonstrates the potential of AI in digital health, its scope remains limited to detection rather than prediction.

The performance analysis of these apps, as summarized in Table 1, highlights a generally high level of accuracy in detecting AF episodes.

FibriCheck reports a manufacturer-stated sensitivity and specificity of 98% and 99% [70], respectively, aligning closely with values from clinical studies [71]. Given that FibriCheck employs AI-enhanced algorithms for PPG signal analysis, its ability to automate feature extraction contributes to its consistency across different studies. Preventicus Heartbeats also exhibits high accuracy, with manufacturer-reported sensitivity of 92% and specificity of 99% [72]. Independent clinical validation [73] confirms a similar performance. The specificity ensures that misclassification of normal rhythms as AF remains low, making it a promising tool for screening purposes. CardioSignal, which uses gyrocardiography rather than PPG, present manufacturer-reported accuracy values of 95.3% sensitivity and 96% specificity [74]. This suggests that while the app effectively reduces false positive detections, it may not be as sensitive as PPG-based solutions in capturing all AF episodes.

5. Other medical devices

5.1. Blood pressure monitors

The technology based on the oscillometric signal and implemented in ABPMDs was the first technology available for the detection of AF episodes for home use. It is therefore a much more consolidated technology than that based on single-lead ECG or the PPG signal, and the data in the literature are numerous, both in terms of sensitivity and specificity, and in terms of effectiveness in the management of AF [83].

Currently the ABPMDs that incorporate automatic detection of AF episode or of rhythm irregularity are made by at

least the following manufacturers: Omron, Beurer, Microlife, A&D, Rossmax. One model by Omron incorporates Kardia (Omron Complete). This latest model combines the functionality of a blood pressure monitor with those of a device for recording a single-lead ECG, using Alive Cor's Kardia technology to detect AF episodes, previously described in paragraphs 4.2 and 4.3 [63,84,85].

This technique represents a noninvasive and practical AF screening method, especially in clinical and home settings. Notably, the definitive diagnosis of AF requires confirmation by ECG, since the oscillometric signal can also be influenced by other factors, such as different arrhythmias, extrasystoles, or patient movements, which could generate false positives.

A recent review of the scientific literature relating to these devices reported high sensitivity (96.2%) and specificity (94%) in the detection of AF [86]. However, the results highlight that it is not advisable to rely exclusively on a single positive AF result obtained through repeated blood pressure measurements. Furthermore, as suggested by international guidelines, the use of these devices as a screening tool should be limited to high-risk populations (e.g. people older than 65 years). In fact, despite the high sensitivity and specificity, the positive predictive values are strongly influenced by the prevalence of atrial fibrillation. The use of these devices in low-risk populations could thus lead to a high number of false positives, with both negative economic and clinical consequences.

5.2. Implantable loop Recorders/cardiac monitor

The implantable loop recorders market is highly consolidated, and a few companies are currently dominating the market. The most important ones include Abbott, Boston Scientific Corporation, Medtronic, BIOTRONIK, Vectorious, Angel Medical System Inc. The devices produced by these companies differ in the type of connectivity, the way in which alerts are configured, and the proprietary algorithms implemented. A review of these devices, which analyzed data from the literature on their performance in detecting AF episodes, revealed that the overall positive predictive value for AF episode detection was at least 73%. Moreover, this value improved as the duration of the detected episodes increased [35].

Key developments of these devices include implementation of artificial intelligence algorithms to improve arrhythmia detection and reduce false alerts and improvements in battery life. These devices can be considered as devices to be used at home, but under the supervision of the doctor, who must also decide the appropriateness of the implant and the methods and frequency of data follow up. Therefore, even though they carry out the automatic diagnosis of AF, they cannot be considered as devices that the patient can use independently to monitor the heart health [36,87].

5.3. Medical devices for ECG acquisition

n addition to dedicated devices that carry out the automatic detection of AF episodes starting from an ECG trace, there are also medical devices available on the market that can be used at home which allow the recording and possible transmission of ECG traces, but which do not have on-board algorithm for the automatic diagnosis of cardiac arrhythmias.

Basically, they rely solely on a retrospective analysis conducted when the device is returned to the healthcare provider, or the ECG is sent to a medical center or a physician.

A non-exhaustive list of these kind of devices includes the ZioPatch (iRhythm Technologies Inc.) [88], the BodyGuardian Mini (Preventice) [89,90], the BardyDx Carnation Ambulatory – CAM (Baxter) [9], the Mobile Cardiac Outpatient Telemetry – MCOT (BioTel Heart) [9,50], and the CardioStat (Icentia Inc.) [88,89]. These are medical devices with an adhesive electrode placed on the chest, capable of monitoring the heart activity for periods ranging from 14 and 30 days. These devices, which use single-lead ECG configurations (except for the MCOT that uses a 3-lead ECG), continuously record ECG data, providing a comprehensive overview of the patient's heart activity over an extended period.

Some devices like ZioPatch, BodyGuardian Mini, and CardioStat are used only for monitoring, and, once the acquisition period is over, they are brought back to the healthcare provider for signal analysis. BardyDx CAM and MCOT are capable of transmitting data wirelessly, allowing for more immediate review and intervention if necessary.

Another medical device that is based on a finger sensor is Zenicor ECG (Zenicor Medical Systems AB). This device is completely different from those previously described because it does not rely on continuous monitoring of heart activity. Instead, measurements are taken when the patient places their fingers on the metallic sensors, with each acquisition lasting 30 seconds. This method allows for easy and convenient spot-checks of the heart's rhythm, which can be particularly useful for patients who experience symptoms intermittently. The Zenicor ECG is designed to transmit data remotely to healthcare providers [91].

Overall, while these devices do not automatically detect AF, they play a crucial role in recording and providing ECG data for subsequent analysis by healthcare professionals.

6. Conclusion

This study has demonstrated the importance of a comprehensive and systematic evaluation of AF detection technologies, highlighting their strength and potential for clinical integration. Unlike previous works focusing on individual devices, our analysis provides a broad perspective, examining multiple solutions in terms of effectiveness, reliability, and technological advancements. By contextualizing these findings within the current clinical landscape, this research offers valuable insights for both healthcare professionals and individuals seeking to use these technologies for AF monitoring and detection.

AF is one of the most common cardiac arrhythmias, capable of causing severe complications such as stroke and heart failure. Early and accurate detection of this arrhythmia is crucial for effective patient management and preventing complications. Diagnosis relies on analyzing cardiac activity, which becomes irregular and mechanically ineffective during AF. The

gold standard for diagnosis involves analyzing an ECG trace, but indications of irregular cardiac activity can also be provided through heart rate analysis.

Due to intermittent and asymptomatic nature of AF, home monitoring represents a valuable diagnostic opportunity, which has seen significant industrial research advancements in recent years.

From a public health perspective, it is crucial for individuals intending to use these technologies for AF monitoring to understand technical aspects such as signal quality and algorithm performance, to make informed choices.

The study involves a literature review and market analysis. Sixteen home-use medical devices implementing automatic detection of AF episodes based on single-lead ECG and/or PPG signal were identified, including dedicated medical devices, smartwatches, and smartphone app-based software. Marketed as medical devices, they must comply with safety and efficacy requirements set by international regulatory frameworks, which vary slightly across Europe, the U.S.A., and other regions but share common technical standards recognized globally. The accuracy values of the devices have not been mentioned because manufacturers can always update their information based on new scientific publications and clinical studies.

In addition to these devices, ABPMDs, invasive ILRs/ICMs and other devices for ECG recording and transmission are also described. The ABPMDs devices allow to obtain an automatic diagnosis of AF or irregular heartbeat, and the algorithms have been improved in recent years to reduce the number of false positives. ILRs/ICMs are devices with high accuracy for the diagnosis of AF, they are invasive and expensive, and their use in the context of cardiac arrhythmias must be appropriately evaluated considering the cases in which the diagnosis was not possible using other cheaper and noninvasive methods. Devices that allow the recording and transmission of ECGs can be considered an evolution of Holter systems, they are used under the supervision of a doctor and do not always make the patient independent in managing the arrhythmia.

In the context of AI-based AF detection, recent advancements highlight the significant progress made by wearable devices such as those from Apple, Samsung, Fibricheck, Awario, and Kardia, all of which feature claims of reliable detection. Recent literature offers a comprehensive comparison of various AI models, including CNNs, RNNs, and hybrid models, showcasing their potential for integration into wearable devices [17–23]. These models, when effectively incorporated into such technologies, could enhance the precision and reliability of AF detection, paving the way for more accurate, real-time monitoring and everyday settings. In this clinical context, explainability is crucial because knowing how the model arrives at the diagnosis of AF is essential to ensure that decisions are reliable, understandable and safe for patients. It is important to be able to understand how the model made its prediction, especially in the case of incorrect diagnoses, so that informed decisions can be made about the patient's treatment.

In conclusion, home-based devices for AF detection through cardiac activity analysis, currently available on the market, represent a promising technology for automatic detection of AF episodes. However, ongoing development and evaluation are necessary to optimize their effectiveness and integrate them effectively into clinical practices. Further research is therefore needed to address current challenges and maximize their potential in AF diagnosis and monitoring.

7. Expert opinion

The increasing prevalence of AF and its associated complications needs advancements in early detection and management strategies. Early diagnosis is crucial, as timely intervention can prevent the progression of AF and its severe complications, such as stroke and heart failure. Given the intermittent and often asymptomatic nature of AF, its diagnosis is challenging, because the patient must be monitored when an episode is occurring. Recent advances in technologies for the home detection of AF, particularly single-lead ECG and PPG devices present a potential for clinical and economic outcomes. These devices can bridge the diagnostic gap by enabling continuous monitoring outside clinical settings. Allowing patients to monitor their cardiac activity outside clinical environments, these devices can facilitate timely medical attention, reducing the risk of severe complications. The facilitation of early diagnosis is a key part of modern healthcare's focus on prevention, improving the efficacy of treatment strategies like anticoagulation therapy and rhythm control. Furthermore, empowering patients to actively participate in their own care through remote monitoring can lead to increased patient engagement and adherence to treatment plans, improving overall quality of life.

One of the most important aspects of these technologies lies in their regulatory status. Devices certified as medical devices under CE and/or FDA standards guarantee safety, reliability, and diagnostic accuracy while devices not considered medical devices cannot be accounted for as part of the healthcare path. It is therefore important to spread this awareness to all stakeholders (from manufacturers to doctors to users/patients). This consideration also concerns the software (embedded algorithm) which in some cases is considered the medical device, following the associated regulatory path.

Despite these advances, integrating these tools into routine clinical practice remains challenging. To maximize their potential, further improvements are essential. Enhancing signal quality to minimize noise and motion artifacts is critical, particularly for devices designed for continuous use. For this purpose, artificial intelligence (AI) algorithms can be used, which can also improve diagnostic accuracy and differentiate AF from other arrhythmias. Recent advancements in AI-based AF detection have been demonstrated in several wearable devices, including those developed by Apple, Samsung, AliveCor, IMEC and Heart2Save, which all claim reliable AF detection capabilities. In addition to these developments, recent studies emphasize the importance of incorporating advanced AI models to improve the accuracy of detection. Particularly, AI is also being leveraged to enhance the quality of ECG signals through noise reduction techniques, a crucial aspect for ensuring more precise and reliable AF detection. These innovations, when integrated into wearable devices, have the potential to significantly improve real-time monitoring, thereby contributing to more effective and accessible

clinical applications. Notably, the implementation of AI needs rigorous validation in terms of population and diseases used for training data, as well as of utilized algorithms. Another key issue for improvement in terms of simplification of patient care refer to the interoperability of data collected by these devices with electronic health records, at national or country level (e.g. Europe, U.S.A.). The integration of these emerging technologies into healthcare systems also demands a focus on patient engagement and education. Ensuring that patients understand how to use these devices correctly and interpret their results is vital for maximizing their benefits.

Future research would be helpful if focused on studies assessing the impact of these technologies on long-term health outcomes. Additionally, refining machine-learning algorithms to distinguish AF from other arrhythmias and extending device functionality to detect border cardiovascular anomalies could expand their utility. Also, clear communication from healthcare providers and user-friendly device interfaces are essential.

The future of AF monitoring likely lies in a synergistic approach, combining wearables, AI, and remote patient monitoring systems integrated with telemedicine platforms of healthcare systems. However, promising areas like the investigation of further cardiac arrhythmias through wearable devices should be explored. In the next five to ten years, clinical workflows may increasingly rely on home monitoring, transitioning from reactive to proactive care. While this evolution could enhance personalization and efficiency, it risks overreliance on technology and potential data overload, which must be carefully managed.

Looking five years ahead, the field of AF detection will likely witness significant advancements in device accuracy and integration into standard care protocols. Wearable devices, enhanced by AI-driven diagnostics, will likely become more prevalent and trusted by clinicians, bridging the gap between consumer electronics and medical-grade tools. The incorporation of additional monitoring capabilities, such as detecting other arrhythmias or physiological parameters like oxygen saturation and stress levels, will make these devices multifunctional health companions. Furthermore, integrating device data with telehealth platforms in real-time could transform patient care by enabling continuous and personalized management. Technological developments and the miniaturization of devices will further improve usability, promoting wider adoption. However, success in implementation will depend on addressing current obstacles, including regulatory alignment, ensuring accessibility of devices, and the development of guidelines integrating these technologies into existing health frameworks. Additionally, the explainability of AI algorithms will be a key factor in fostering trust among healthcare providers and patients, ensuring that diagnostic decisions are interpretable and clinically justifiable. By 2030, we may see a shift toward hybrid monitoring models, combining wearable and implantable devices for comprehensive and continuous cardiac surveillance, particularly in high-risk populations. While such progress will likely reduce the prevalence of undiagnosed AF and its complications, balancing technology-driven care with human oversight will remain crucial.

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References

1. Lippi G, Sanchis-Gomar F, Cervellin G. Global epidemiology of atrial fibrillation: an increasing epidemic and public health challenge. Int J Stroke. 2021;16(2):217–221. doi: 10.1177/1747493019897870
2. Van Gelder IC, Rienstra M, Bunting KV, et al. ESC scientific document group, 2024 ESC guidelines for the management of atrial fibrillation developed in collaboration with the European Association for cardio-thoracic surgery (EACTS): developed by the task force for the management of atrial fibrillation of the European society of cardiology (ESC), with the special contribution of the European heart rhythm association (EHRA) of the ESC. Endorsed by the European stroke organisation (ESO). Eur Heart J. 2024 Sep 21;45 (36):3314–3414. doi: 10.1093/eurheartj/ehae176
3. Go AS, Hylek EM, Phillips KA, et al. Prevalence of diagnosed atrial fibrillation in adults: national implications for rhythm management and stroke prevention: the AnTicoagulation and risk factors in atrial fibrillation (ATRIA) study. JAMA. 2001;285(18):2370. doi: 10.1001/jama.285.18.2370
4. Wolf PA, Abbott RD, Kannel WB. Atrial fibrillation as an Independent RiskFactor for stroke: the Framingham study. Stroke. 1991;22(8):983–988. doi: 10.1161/01.STR.22.8.983
5. Gulizia MM, Casolo G, Zuin G, et al. Documento di consenso ANMCO/AIIC/SIT: Definizione, precisione e appropriatezza del segnale elettrocardiografico di elettrocardiografi, sistemi per ergometria, sistemi Holter ECG, telemetrie e monitor posto-letto. [ANMCO/AIIC/SIT Consensus Doc: Definition, Accuracy, And Appropriateness Of The Electrocardiographic Signal From Electrocardiographs, Ergometry Syst, Holter ECG Syst, Telem, And Bedside Monitors]. G Ital Cardiol. 2016;17(6):393–415.
6. Lévy S, Maarek M, Coumel P, et al. Characterization of different subsets of atrial fibrillation in general practice in France: the ALFA study. The college of French cardiologists. Circulation. 1999;99 (23):3028–3035. doi: 10.1161/01.cir.99.23.3028
7. Kerr C, Boone J, Connolly S, et al. Follow-up of atrial fibrillation: the initial experience of the Canadian registry of atrial fibrillation. Eur Heart J. 1996;17(suppl C):48–51. doi: 10.1093/eurheartj/17.suppl_c.48
8. Kerber RE. Transthoracic cardioversion of atrial fibrillation and flutter: standard techniques and new advances. Am J Cardiol. 1996;78 (8A):22–26. doi: 10.1016/s0002-9149(96)00562-0
9. Bouzid Z, Al-Zaiti SS, Bond R, et al. Remote and wearable ECG devices with diagnostic abilities in adults: a state-of-the-science scoping review. Heart Rhythm. 2022;19(7):1192–1201. doi: 10.1016/j.hrthm.2022.02.030
10. Xintarakou A, Sousonis V, Asvestas D, et al. Remote cardiac rhythm monitoring in the era of smart wearables: present assets and future perspectives. Front Cardiovasc Med. 2022;9:853614. doi: 10.3389/fcvm.2022.853614

11. Bayoumy K, Gaber M, Elshafeey A, et al. Smart wearable devices in cardiovascular care: where we are and how to move forward. Nat Rev Cardiol. 2021;18(8):581–599. doi: 10.1038/s41569-021-00522-7
12. Hermans ANL, Gawalko M, Dohmen L, et al. Mobile health solutions for atrial fibrillation detection and management: a systematic review. Clin Res Cardiol. 2022;111(5):479–491. doi: 10.1007/s00392-021-01941-9
13. Sikorska A, Baran J, Piotrowski R, et al. Daily ECG transmission versus serial 6-day holter ECG for the assessment of efficacy of ablation for atrial fibrillation - the AGNES-ECG study. J Interv Card Electrophysiol. 2022;65(2):373–380. doi: 10.1007/s10840-022-01166-4
14. Hannun AY, Rajpurkar P, Haghpanahi M, et al. Cardiologist level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nat Med. 2019;25(1):65–69. doi: 10.1038/s41591-018-0268-3
15. Nagendran M, Chen Y, Lovejoy CA, et al. Artificial intelligence versus clinicians: systematic review of design, reporting standards, and claims of deep learning studies. BMJ. 2020;368:m689. doi: 10.1136/bmj.m689
16. Hicks SA, Isaksen JL, Thambawita V, et al. Explaining deep neural networks for knowledge discovery in electrocardiogramanalysis. Sci Rep. 2021;11(1):10949. doi: 10.1038/s41598-021-90285-5
17. Cai W, Chen Y, Guo J, et al. Accurate detection of atrial fibrillation from 12-lead ECG using deep neural network. Comput BiolMed. 2020;116:1033778. doi: 10.1016/j.compbiomed.2019.103378
18. Jo YY, Cho Y, Lee SY, et al. Explainable artificial intelligence to detect atrial fibrillation using electrocardiogram. Int J Cardiol. 2021;328:104–110. doi: 10.1016/j.ijcard.2020.11.053
19. Baalman SWE, Schroevers FE, Oakley AJ, et al. A morphology based deep learning model for atrial fibrillation detection using single cycle electrocardiographic samples. Int J Cardiol. 2020;316:130–136. doi: 10.1016/j.ijcard.2020.04.046
20. Kim J, Lee SJ, Ko B, et al. Identification of atrial fibrillation with single-lead Mobile ECG during normal sinus rhythm using deep learning. J Korean Med Sci. 2024;39(5):e56. doi: 10.3346/jkms.2024.39.e56
21. Chen E, Jiang J, Su R, et al. A new smart wristband equipped with an artificial intelligence algorithm to detect atrial fibrillation. Heart Rhythm. 2020;17(5):847–853. doi: 10.1016/j.hrthm.2020.01.034
22. Tison GH, Sanchez JM, Ballinger B, et al. Passive detection of atrial fibrillation using a commercially available smartwatch. JAMA Cardiol. 2018;3(5):409–416. doi: 10.1001/jamacardio.2018.0136
23. Aschbacher K, Yilmaz D, Kerem Y, et al. Atrial fibrillation detection from raw photoplethysmography waveforms: a deep learning application. Heart Rhythm O2. 2020;1:3–9. doi: 10.1016/j.hroo.2020.02.002
    - **Description of the role of AI in the analysis of PPG data for the detection of AF episode.**
24. Pluymaekers NAHA, Hermans ANL, van der Velden Rmj, et al. Implementation of an on-demand app-based heart rate and rhythm monitoring infrastructure for the management of atrial fibrillation through teleconsultation: TeleCheck-AF. Europace. 2021;23(3):345–352. doi: 10.1093/europace/euaa201
25. Corino VD, Ulimoen SR, Enger S, et al. Rate-control drugs affect variability and irregularity measures of RR intervals in patients with permanent atrial fibrillation. J Cardiovasc Electrophysiol. 2015;26(2):137–141. doi: 10.1111/jce.12580
26. Blok S, Gielen W, Piek MA, et al. Performance of a medical smartband with photoplethysmography technology and artificial intelligence algorithm to detect atrial fibrillation. Mhealth. 2025;11:5. doi: 10.21037/mhealth-24-10
27. Martínez-Sellés M, Marina-Breysse M. Current and future use of artificial intelligence in Electrocardiography. J Cardiovasc Dev Dis. 2023;10(4):175. doi: 10.3390/jcdd10040175
28. Rasti-Meymandi A, Ghaffari A. A deep learning-based framework for ECG signal denoising based on stacked cardiac cycle tensor. Biomed Signal Process Control. 2022;71:103275. doi: 10.1016/j.bspc.2021.103275
29. Iqbal SMA, Leavitt MA, Mahgoub I, et al. Advances in cardiovascular wearable devices. Biosensors (Basel). 2024;14(11):525. doi: 10.3390/bios14110525
30. Using PPG for designing optical heart rate sensors | ansys [Internet]. [cited 2024 Feb 26]. Available from: https://www.ansys.com/it-it/blog/modeling-human-skin-and-optical-heart-rate-sensors
31. Guo Y, Wang H, Zhang H, et al. Mobile photoplethysmographic technology to detect atrial fibrillation. J Am Coll Cardiol. 2019;74(19):2365–2375. doi: 10.1016/j.jacc.2019.08.019
32. Stergiou GS, Karpettas N, Protogerou A, et al. Diagnostic accuracy of a home blood pressure monitor to detect atrial fibrillation. J Hum Hypertens. 2009;23(10):654–658. doi: 10.1038/jhh.2009.5
33. Balanis T, Sanner B. Detection of atrial fibrillation using a home blood pressure monitor. Vasc Health Risk Manag. 2021;17:407–414. doi: 10.2147/VHRM.S317859
34. Park SH, June KJ, Choi YK. Predictive validity of automated oscillometric blood pressure monitors for screening atrial fibrillation: a systematic review and meta-analysis. Expert Rev Med Devices. 2019;16(6):503–514. doi: 10.1080/17434440.2019.1620102
35. Sakhi R, Theuns DAMJ, Szili-Torok T, et al. Insertable cardiac monitors: current indications and devices. Expert Rev Med Devices. 2019;16(1):45–55. doi: 10.1080/17434440.2018.1557046
36. Nadkarni A, Devgun J, Jamal SM, et al. Subcutaneous cardiac rhythm monitors: state of the art review. Expert Rev Med Devices. 2021;18(7):587–596. doi: 10.1080/17434440.2021.1935873
37. U.S. Food and Drug Administration (FDA) [Internet]. Premarket notification (510(k)) - K213971. FDA. [cited 2025 Mar 21]. Available from: https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfPMN/pmn.cfm?ID=K213971
38. Mannhart D, Lischer M, Knecht S, et al. Clinical validation of 5 direct-to-consumer wearable smart devices to detect atrial fibrillation: BASEL wearable study. JACC Clin Electrophysiol. 2023;9(2):232–242. doi: 10.1016/j.jacep.2022.09.011
    - **Comparison between the devices that today are the most used, from independent data.**
39. Ford C, Xie CX, Low A, et al. Comparison of 2 smart watch algorithms for detection of atrial fibrillation and the benefit of clinician interpretation: SMART WARS study. JACC Clin Electrophysiol. 2022;8(6):782–791. doi: 10.1016/j.jacep.2022.02.013
40. Scholten J, Jansen WPJ, Horsthuis T, et al. Six-lead device superior to single-lead smartwatch ECG in atrial fibrillation detection. Am Heart J. 2022;253:53–58. doi: 10.1016/j.ahj.2022.06.010
41. Abu-Alrub S, Strik M, Ramirez FD, et al. Smartwatch electrocardiograms for automated and manual diagnosis of atrial fibrillation: a comparative analysis of three models. Front Cardiovasc Med. 2022;9:836375. doi: 10.3389/fcvm.2022.836375
42. U.S. Food and Drug Administration (FDA) [Internet]. Premarket notification (510(k)) - K201456. FDA. [cited 2025 Mar 21]. Available from: https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfpmn/pmn.cfm?ID=K201456
43. U.S. Food and Drug Administration (FDA) [Internet]. Premarket notification (510(k)) - K230292. FDA. [cited 2025 Mar 21]. Available from: https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfpmn/pmn.cfm?ID=K230292
44. CardiacSense [Internet]. CardiacSense – heart health at your fingertips. CardiacSense. [cited 2025 Mar 21]. Available from: https://www.cardiacsense.com/en/
45. Hochstadt A, Chorin E, Viskin S, et al. Continuous heart rate monitoring for automatic detection of atrial fibrillation with novel bio-sensing technology. J Electrocardiol. 2019;52:23–27. doi: 10.1016/j.jelectrocard.2018.10.096
46. Harrison SL, Buckley BJR, Zheng Y, et al. Liverpool-huawei stroke study investigators. Evaluation of huawei smart wearables for detection of atrial fibrillation in patients following ischemic stroke: the Liverpool-huawei stroke study. Am Heart J. 2023;257:103–110. doi: 10.1016/j.ahj.2022.12.004
47. AliveCor [Internet]. Cleveland Clinic study affirms accurate detection of atrial fibrillation by KardiaBand for apple watch. AliveCor. [cited 2025 Mar 21]. Available from: https://alivecor.com/press/

press_release/cleveland-clinic-study-affirms-accurate-detection-of-atrial-fibrillation-by-kardiaband-for-apple-watch
48. Bumgarner JM, Lambert CT, Hussein AA, et al. Smartwatch algorithm for automated detection of atrial fibrillation. J Am Coll Cardiol. 2018;71(21):2381–2388. doi: 10.1016/j.jacc.2018.03.003
49. U.S. Food and Drug Administration (FDA) [Internet]. Premarket notification (510(k)) - K200948. FDA. [cited 2025 Mar 21]. Available from: https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfpmn/pmn.cfm?ID=K200948
50. Lubitz SA, Faranesh AZ, Selvaggi C, et al. Detection of atrial fibrillation in a large population using wearable devices: the fitbit heart study. Circulation. 2022;146(19):1415–1424. doi: 10.1161/CIRCULATIONAHA.122.060291
51. Insulander P, Carnlöf C, Schenck-Gustafsson K, et al. Device profile of the coala heart monitor for remote monitoring of the heart rhythm: overview of its efficacy. Expert Rev Med Devices. 2020;17(3):159–165. doi: 10.1080/17434440.2020.1732814
52. Paul Nordin A, Carnlöf C, Insulander P, et al. Validation of diagnostic accuracy of a handheld, smartphone-based rhythm recording device. Expert Rev Med Devices. 2023;20(1):55–61. doi: 10.1080/17434440.2023.2171290
53. MyDiagnostick. MyDiagnostick [Internet]. [cited 2025 Mar 21]. Available from: https://www.mydiagnostick.com/
54. Kamga P, Mostafa R, Zafar S. The use of wearable ECG devices in the clinical setting: a review. Curr Emerg Hosp Med Rep. 2022;10(3):67–72. doi: 10.1007/s40138-022-00248-x
•• **Comprehensive review of the technology available for AF detection.**
55. Desteghe L, Raymaekers Z, Lutin M, et al. Performance of handheld electrocardiogram devices to detect atrial fibrillation in a cardiology and geriatric ward setting. Europace. 2017;19(1):29–39. doi: 10.1093/europace/euw025
56. AliveCor [Internet]. KardiaMobile for the ambulatory detection of atrial fibrillation. AliveCor. [cited 2025 Mar 21]. Available from: https://www.alivecor.co.uk/resource-hub/kardiamobile-for-the-ambulatory-detection-of-atrial-fibrillation-pdf-2285965569121477.pdf
57. Selder JL, Breukel L, Blok S, et al. A mobile one-lead ECG device incorporated in a symptom-driven remote arrhythmia monitoring program. The first 5,982 hartwacht ECGs. Neth Heart J. 2019;27(1):38–45. doi: 10.1007/s12471-018-1203-4
58. Lau JK, Lowres N, Neubeck L, et al. iPhone ECG application for community screening to detect silent atrial fibrillation: a novel technology to prevent stroke. Int J Cardiol. 2013;165(1):193–194. doi: 10.1016/j.ijcard.2013.01.220
59. Haberman ZC, Jahn RT, Bose R, et al. Wireless smartphone ECG enables large-scale screening in diverse populations. J Cardiovasc Electrophysiol. 2015;26(5):520–526. doi: 10.1111/jce.12634
60. 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(5):403–411. doi: 10.1370/afm.2438
61. Carrington M, Providência R, Chahal CAA, et al. Monitoring and diagnosis of intermittent arrhythmias: evidence-based guidance and role of novel monitoring strategies. Eur Heart J Open. 2022;2(6):oeac072. doi: 10.1093/ehjopen/oeac072
62. Bansal A, Joshi R. Portable out-of-hospital electrocardiography: a review of current technologies. J Arrhythm. 2018;34(2):129–138. doi: 10.1002/joa3.12035
63. Chan PH, Wong CK, Pun L, et al. Head-to-head comparison of the AliveCor heart monitor and microlife WatchBP office AFIB for atrial fibrillation screening in a primary care setting. Circulation. 2017;135(1):110–112. doi: 10.1161/CIRCULATIONAHA.116.024439
64. Lowres N, Neubeck L, Salkeld G, et al. Feasibility and cost-effectiveness of stroke prevention through community screening for atrial fibrillation using iPhone ECG in pharmacies. The SEARCH-AF study. Thromb Haemost. 2014;111(6):1167–1176. doi: 10.1160/TH14-03-0231
65. AliveCor [Internet]. KardiaMobile 6L is superior to one-lead personal devices. AliveCor. [cited 2025 Mar 21]. Available from: https://alivecor.com/press/press_release/kardiamobile-6l-is-superior-to-one-lead-personal-devices
66. Krzowski B, Skoczylas K, Osak G, et al. Kardia Mobile and ISTEL HR applicability in clinical practice: a comparison of Kardia Mobile, ISTEL HR, and standard 12-lead electrocardiogram records in 98 consecutive patients of a tertiary cardiovascular care centre. Eur Heart J Digit Health. 2021;2(3):467–476. doi: 10.1093/ehjdh/ztab040
67. Awario [Internet]. Awario is an AI-powered, clinically validated real-time ECG report. Awario; [cited 2025 Mar 21]. Available from: Santala OE, Lipponen JA, Jäntti H, et al. Necklace-embedded electrocardiogram for the detection and diagnosis of atrial fibrillation. Clin Cardiol. 2021;44(5):620–626. doi: 10.1002/clc.23580
68. Santala OE, Lipponen JA, Jäntti H, et al. Necklace-embedded electrocardiogram for the detection and diagnosis of atrial fibrillation. Clin Cardiol. 2021;44(5):620–626. doi: 10.1002/clc.23580
69. Santala OE, Halonen J, Martikainen S, et al. Automatic Mobile health arrhythmia monitoring for the detection of atrial fibrillation: prospective feasibility, accuracy, and user experience study. JMIR Mhealth Uhealth. 2021;9(10):e29933. doi: 10.2196/29933
70. U.S. Food and Drug Administration (FDA) [Internet]. Premarket notification (510(k)) - K173872. FDA. [cited 2025 Mar 21]. Available from: https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfPMN/pmn.cfm?ID=K173872
71. 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 FibriCheck app. JMIR Mhealth Uhealth. 2019;7(3):e12284. doi: 10.2196/12284
•• **The AF strategies in consumer devices.**
72. Preventicus [Internet]. Kurz erklärt – Preventicus. Preventicus. [cited 2025 Mar 21]. Available from: https://www.preventicus.com/fuer-anwender/kurzerklaert/
73. Brasier N, Raichle CJ, Dörr M, et al. Detection of atrial fibrillation with a smartphone camera: first prospective, international, two-centre, clinical validation study (DETECT AF PRO). EP Europace. 2019 Jan 1;21(1):41–47. doi: 10.1093/europace/euy176
74. CardioSignal [Internet]. IT CardioSignal. [cited 2024 Mar 26]. Available from: https://it.cardiosignal.com
75. Prieto-Avalos G, Cruz-Ramos NA, Alor-Hernández G, et al. Wearable devices for physical monitoring of heart: a review. Biosensors (Basel). 2022;12(5):292. doi: 10.3390/bios12050292
76. Campo D, Elie V, de Gallard T, et al. Atrial fibrillation detection with an analog smartwatch: prospective clinical study and algorithm validation. JMIR Form Res. 2022;6(11):e37280. doi: 10.2196/37280
77. Niu Y, Wang H, Wang H, et al. Diagnostic validation of smart wearable device embedded with single-lead electrocardiogram for arrhythmia detection. Digit Health. 2023;9:20552076231198682. doi: 10.1177/20552076231198682
78. Rajakariar K, Koshy AN, Jk S, et al. Accuracy of a smartwatch based single-lead electrocardiogram device in detection of atrial fibrillation. Heart. 2020;106(9):665–670. doi: 10.1136/heartjnl-2019-316004
79. U.S. Food and Drug Administration (FDA) [Internet]. Premarket notification (510(k)) - K181823. FDA. [cited 2025 Mar 21]. Available from: https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfPMN/pmn.cfm?ID=K181823
80. Mattei E, Lino S, Censi F, et al. Personalized antiarrhythmic therapy using a self-managed daily-ECG device. Diagnostics (Basel). 2023;13(18):2864. doi: 10.3390/diagnostics13182864
81. Lown M, Yue AM, Shah BN, et al. Screening for atrial fibrillation using economical and accurate technology (from the SAFETY study). Am J Cardiol. 2018;122(8):1339–1344. doi: 10.1016/j.amjcard.2018.07.003
82. Tech L. Solution [Internet]. HomECG. 2024 [cited 2024 Mar 26]. Available from: https://www.homecg.com/how-it-works
83. Verberk WJ, de Leeuw PW. Accuracy of oscillometric blood pressure monitors for the detection of atrial fibrillation: a systematic review. Expert Rev Med Devices. 2012;9(6):635–640. doi: 10.1586/erd.12.46
84. Wiesel J, Arbesfeld B, Schechter D. Comparison of the microlife blood pressure monitor with the omron blood pressure monitor for

detecting atrial fibrillation. Am J Cardiol. 2014;114(7):1046–1048. doi: 10.1016/j.amjcard.2014.07.016
85. Wiesel J, Fitzig L, Herschman Y, et al. Detection of atrial fibrillation using a modified microlife blood pressure monitor. Am J Hypertens. 2009;22(8):848–852. doi: 10.1038/ajh.2009.98
86. Tang EWL, Yip BHK, Yu C-P, et al. Sensitivity and specificity of automated blood pressure devices to detect atrial fibrillation: a systematic review and meta-analysis of diagnostic accuracy. Front Cardiovasc Med. 2022;9:956542. doi: 10.3389/fcvm.2022.956542
87. Assaf A, Theuns DA, Michels M, et al. Usefulness of insertable cardiac monitors for risk stratification: current indications and clinical evidence. Expert Rev Med Devices. 2023;20(2):85–97. doi: 10.1080/17434440.2023.2171862
88. Côté JM, Chetaille P, Abadir S, et al. Diagnostic efficacy of a single-lead ambulatory 14-day ECG monitor in symptomatic children. CJC Open. 2021;3(11):1341–1346. doi: 10.1016/j.cjco.2021.06.011
89. Nault I, André P, Plourde B, et al. Validation of a novel single lead ambulatory ECG monitor - Cardiostat™ - compared to a standard ECG holter monitoring. J Electrocardiol. 2019;53:57–63. doi: 10.1016/j.jelectrocard.2018.12.011
90. Doliwa PS, Frykman V, Rosenqvist M. Short-term ECG for out of hospital detection of silent atrial fibrillation episodes. Scand Cardiovasc J. 2009;43(3):163–168. doi: 10.1080/14017430802593435
91. Malmqvist J, Engdahl J, Sjölund G, et al. Sensitivity and specificity of handheld one lead ECG detecting atrial fibrillation in an outpatient clinic setting. J Electrocardiol. 2024;83:106–110. doi: 10.1016/j.jelectrocard.2024.02.001