Diagnostic performance of a smart device-based algorithm for atrial fibrillation detection: A pilot study of AF screening (Pre-mAFA II registry)

Yong-Yan Fan1,2, PhD; Yan-Guang Li2, PhD; Jian Li2, PhD; Hao Wang3, PhD; Xiang-Ming Shi2, MD, PhD; Wen-Kun Cheng2, MS; Zhao-Liang Shan2, MD, PhD; Yu-Tang Wang1,3, MD, PhD; Yu-Tao Guo2, MD, PhD

1College of Medicine, Nankai University, Tianjin, China
Departments of 2Cardiology and 3Geriatric Cardiology, Chinese PLA General Hospital, Beijing, China

Corresponding Authors:
Yu-Tao Guo, MD, PhD
Department of Cardiology
Chinese PLA General Hospital
28 Fuxing Rd.
Beijing, 100853
China

Yu-Tang Wang, MD, PhD
College of Medicine
Nankai University
94 Weijin Rd.
Tianjin, 300071
China
Department of Geriatric Cardiology
Chinese PLA General Hospital
28 Fuxing Rd.
Beijing, 100853
China
Abstract

Background: Atrial fibrillation (AF) is the most common sustained cardiac arrhythmia. The asymptomatic nature and paroxysmal frequency of AF lead to suboptimal early detection. A novel technology, photoplethysmography (PPG), has been developed for AF screening. However, there has been limited validation of smartphone and smart band applications with PPG compared to 12-lead electrocardiograms (ECG).

Objective: We investigated the feasibility and accuracy of a smartphone- and smart band-based algorithm (PRO AF PPG) for AF detection using pulse data measured by PPG.

Methods: One hundred twelve consecutive inpatients were recruited from the Chinese PLA General Hospital from 15 March to 1 April 2018. Participants were simultaneously tested with smartphones (HUAWEI Mate 9, HUAWEI Honor 7X), smart bands (HUAWEI Band 2), and 12-lead ECG for 3 minutes.

Results: One hundred eight patients (56 with normal sinus rhythm, 52 with persistent AF) were enrolled in the final analysis after excluding 4 patients with unclear cardiac rhythms. The corresponding sensitivity and specificity of the smart band PPG were 95.36% (95% confidential interval, CI 92.00-97.40%) and 99.70% (95% CI 98.08-99.98%), respectively. The positive predictive value of the smart band PPG was 99.63% (95% CI 97.61-99.98%), the negative predictive value was 96.24% (95% CI 93.50-97.90%), and the accuracy was 97.72% (95% CI 96.11-98.70%). Moreover, the diagnostic sensitivity, specificity, positive predictive value, negative predictive value, and accuracy of smartphones with PPG for AF detection were over 94%. There was no significant difference after further statistical analysis of the results from the different smart devices compared with the gold-standard ECG (P=.999).

Conclusions: The algorithm based on smartphones and smart bands with PPG demonstrated good performance in detecting AF and may represent a convenient tool for AF detection in at-risk individuals, allowing widespread screening of AF in the population.

Trial Registration: The present study was registered in the Chinese Clinical Trial Registry, International Clinical Trials Registry Platform of the World Health Organization (ChiCTR-OOC-17014138).

Keywords: atrial fibrillation; photoplethysmography; detection; accuracy;
smartphone; smart band; algorithm
Introduction

Atrial fibrillation (AF) is the most common sustained cardiac arrhythmia encountered in clinical practice and is associated with increased risk of stroke, systemic embolism, heart failure, hospitalization, and death [1-3]. At least one-third of patients with AF are asymptomatic [4]. Due to the asymptomatic nature and paroxysmal frequency of this arrhythmia, early detection is challenging and often unsuccessful [5]. Strikingly, acute stroke or heart failure is often the first sign of AF [6, 7]. Asymptomatic AF is also related with worse outcomes compared with symptomatic AF [8]. However, around 70% of AF-related strokes could be avoided with early detection and early management, such as initiation of oral anticoagulants [9]. The European Society of Cardiology now recommends screening of AF in the primary care of high-risk patients including those aged ≥65 years, which is important for the prevention of stroke [10].

Although studies have shown that more frequent monitoring can improve AF detection [11-13], population-based screening remains suboptimal because of the inconvenience and high-expense of current screening approaches, such as Holter monitoring with different time durations (24 h and 7 days) [14, 15]. In addition, the diagnostic value of the standard 12-lead electrocardiogram (ECG) is limited by the need for patients to obtain ECG diagnostic equipment, as well as the requirement that AF be present at the time of the ECG recording. As such, we need a more convenient heart rhythm screening or detection approach to identify AF and initiate early treatment.

Technical options to detect AF have significantly improved within the past decade. Different technologies such as blood pressure monitors [16], single lead cardiac event monitors (Kardia Mobile case or card) [17], and smartphone applications using photoplethysmographic signals have emerged for this purpose [18, 19]. Taggar et al [20] analyzed 21 studies that investigated 39 interventions for detecting AF prior to 16 March 2015. Their meta-analysis found that the most accurate methods for detecting AF were blood pressure monitors, which had a sensitivity of 98% and a specificity of 92%, and non-12-lead ECG, which had a sensitivity of 91% and a specificity of 95%. Although blood pressure monitors and non-12-lead ECG both had relatively high diagnostic accuracies, the need for a blood pressure monitor and a clinical specialist to analyze the non-12-lead ECG pose a challenge for wide-scale implementation of AF
The novel technology photoplethysmography (PPG) has been developed for AF screening. PPG is an optical method measuring changes in tissue blood volume through the skin capillary bed, which can be performed by using a smartphone without any additional peripherals [21, 22]. The PPG waveform is generally acquired by the built-in camera of a smartphone to measure pulsatile changes in light absorption reflected from a fingertip illuminated by the light-emitting diode (LED) flash [19]. Most smart bands currently on the market use PPG technology, and heart rate sensors on most smart bands work via PPG [23]. Detecting AF using easily accessible devices, such as smartphones and smart bands, may represent a novel opportunity to passively and automatically detect asymptomatic AF that does not require additional hardware and is simple to operate. However, there has been limited validation of smartphone and smart band PPG compared to 12-lead ECG.

In this study, we tested the hypothesis that pulse waveform signals recorded using smart-devices, including smartphones and smart bands, can be analyzed by a realizable algorithm and can distinguish AF from normal sinus rhythm (SR). The present study also provides data on AF screening technology for the Chinese population.

**Methods**

**Study Population**

One hundred twelve consecutive inpatients were recruited from the Chinese PLA General Hospital from 15 March to 1 April 2018. Information regarding demographic characteristics, medical history, blood test results, and medications was recorded.

Patients aged ≥18 years were included in the study. Exclusion criteria included: patients unable to use smartphones and smart bands, with mental or memory problems, or with a pacemaker or implantable cardioverter defibrillator. Written informed consent was obtained and signed by each individual willing to take part in the present study.

Ours is a single-center pilot study of AF screening (Pre-mAFA II registry). The mAFA
The Medical Ethics Committee of the Chinese PLA General Hospital and the China Food and Drug Administration approved the present study protocol (Approval Number: S2017-105-02). The present study is registered in the Chinese Clinical Trial Registry, International Clinical Trials Registry Platform of the World Health Organization (ChiCTR-OOC-17014138).

**Signal Acquisition and Processing**

Smartphones (HUAWEI Mate 9, HUAWEI Honor 7X) (Huawei Technologies Co., Ltd., Shenzhen, China) and smart bands (HUAWEI Band 2) were used for collecting pulse waveform signals. Pulse waveform recordings were performed by the participants under the supervision of trained study personnel. A dedicated data collection application, Heartbeats (Preventicus GmbH, Jena, Germany), was responsible for the pulse waveform signal acquisition and was installed in the HUAWEI smartphones.

Participants were simultaneously tested with smartphones (HUAWEI Mate 9, HUAWEI Honor 7X), smart bands (HUAWEI Band 2), and 12-lead ECG for 3 min. Participants were advised to lie down in a supine position with spontaneous breathing. A HUAWEI mate 9 (smartphone 1) was positioned on the left-hand finger (either the index or middle finger) with the camera lens and LED light placed on the fingertip of the participant. Similarly, a HUAWEI honor 7X (smartphone 2) was positioned on the finger of the right hand. PPG measurements were performed by using the Heartbeats smartphone application. The participant was asked to wear two smart bands, one each on the left and right hand. A 3-min pulse waveform recording was obtained from each participant using the smart devices and a formal 12-lead ECG simultaneously. Then all 3-min pulse waveform recordings using the smart devices were uploaded to the online cloud center and analyzed by a realizable algorithm (PRO AF PPG) provided by Preventicus (Preventicus GmbH, Jena, Germany). Figure 1 shows a prototype for AF detection using HUAWEI smartphones and smart bands.

**Rhythm Diagnosis**

ECG results remain the gold-standard for the measurement of heart rhythms, and they
were confirmed by two independent cardiologists who were blinded to the baseline information of participants, and the results of the algorithm were independently reviewed for each 12-lead ECG. For participants whose ECG were initially affected by artifacts, they were instructed by trained study personnel to repeat the recordings to provide optimal tracing for subsequent reading by the cardiologists. The Heartbeats application added a pulse waveform quality assessment step to reject recordings that were corrupted or too noisy and to prompt the user to retake a measurement.

After data collection, the novel heart beat detection algorithm (PRO AF PPG) based on a combination of morphology and frequency analysis of the pulse waveform was applied to perform beat-to-beat rhythm analysis and determine whether or not the participant suffered from AF. The diagnostic performance of the algorithm in detecting AF was then evaluated using the 12-lead ECG interpretation as the standard. Figure 2 shows a flowchart of the study.

**Statistical Analysis**
Continuous variables were tested for normality by the Kolmogorov-Smirnov test. Data with a normal distribution are presented as means ± standard deviation and were analyzed using the t test for two independent samples. Data with a non-normal distribution are presented as medians (interquartile range, IQR) and were analyzed using the Mann-Whitney U test. Data with discrete variables are presented as percentages and were analyzed using the Pearson Chi-square test or Fisher’s exact test.

Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and accuracy with 95% confidence interval (CI) were used to measure the performance of our AF-screening algorithm in the smart devices. The diagnostic performance of the algorithm in different devices was evaluated against reference ECG recordings, from which was calculated the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Sensitivity, specificity, positive predictive value, negative predictive value, and accuracy for AF diagnosis were calculated as simple proportions for the PRO AF PPG algorithm. The sensitivity was calculated as TP/(TP+FN) (true positives divided by all positives) and specificity as 1-FP/(TN+FP) (true negatives divided by all negatives). The corresponding
positive predictive value was defined as TP/(TP+FP), and the negative predictive value as TN/(FN+TN). The corresponding accuracy was calculated as (TP+TN)/(TP+TN+FP+FN). Statistical evaluation was performed with SPSS 19.0 (Statistical Packages for Social Sciences; SPSS Inc., Chicago, IL, USA). A value of \( P < .05 \) was considered statistically significant.

**Results**

Among the 112 participants who fulfilled the inclusion criteria of the present study, 4 participants were excluded because the ECG recordings showed unclear cardiac rhythms. As a result, 108 patients (56 with normal SR, 52 with persistent AF) were enrolled into the final analysis. Table 1 summarizes the clinical characteristics of the study population. Participants with persistent AF were significantly older (\( P = .002 \)), had a higher body mass index (\( P = .024 \)), and had more prevalent heart failure (\( P = .006 \)). Thromboembolic risk and bleeding risk were higher in participants with persistent AF compared to those with normal SR based on CHA\(_2\)DS\(_2\)-VASC score (median [IQR] 3 [2–5] vs 2 [1.3–3.75], \( P = .003 \)) and HAS-BLED score (median [IQR] 2 [1–2] vs 1 [0–2], \( P = .005 \)), respectively. The use of oral anticoagulants for preventing stroke was 76.92% in participants with persistent AF and 17.86% in participants with normal SR (\( P < .001 \)). The use of diuretics and digoxin were significantly higher in participants with persistent AF compared to those with normal SR (\( P = .025; P = .015 \), respectively), as well as the use of class III antiarrhythmic drugs (\( P < .001 \)).

We split the 3-min pulse waveform recordings of each participant obtained from smartphones and smart bands into 3 1-min segments for further analysis with results from the 12-lead ECG. After splitting, there were 614 valid 1-min segments of pulse waveform recordings in total obtained from smart bands, divided into 280 for AF and 334 for normal SR based on ECG. Thirty-four 1-min segments of signal recordings were deemed "poor quality" and were disregarded. The diagnostic performance of the PRO AF PPG AF screening algorithm in smart bands was evaluated against reference ECG recordings and demonstrated a sensitivity of 95.36% (95% CI 92.00-97.40%) and a specificity of 99.70% (95% CI 98.08-99.98%) for the detection of AF. The corresponding positive predictive value of the PRO AF PPG algorithm for AF screening was 99.63% (95% CI 97.61-99.98%), the negative predictive value was
96.24% (95% CI 93.50-97.90%), and the accuracy was 97.72% (95% CI 96.11-98.70%).

As for smartphones, we obtained 611 valid 1-min segments of pulse waveform recordings in total, of which 310 were obtained from smartphone 1 and 301 from smartphone 2, divided into 278 for AF and 333 for normal SR based on standard ECG recordings. Thirty-seven 1-min segments of signal recordings were omitted because of poor quality, of which 14 were recorded by smartphone 1 and 23 by smartphone 2. The diagnostic sensitivity and specificity of the PRO AF PPG algorithm for AF detection using smartphone 1 and smartphone 2 were 94.96% (95% CI 91.51-97.11%) and 99.70% (95% CI 98.07-99.98%), respectively. The positive predictive value was 99.62% (95%CI 97.59-99.98%), the negative predictive value was 95.95% (95%CI 93.15-97.68%), and the accuracy of the algorithm for AF detection was 97.55% (95%CI 95.89-98.57%). Moreover, the diagnostic sensitivity, specificity, positive predictive value, negative predictive value and accuracy of smartphone 1 alone or smartphone 2 alone with PPG for AF detection were over 94%. Detailed diagnostic performance of the PRO AF PPG algorithm for AF screening in different smart devices is summarized in Table 2. There was no significant difference in further statistical analysis of the results from different smart devices compared with ECG (P=.999).

Table 3 lists data from the literature on AF detection with different technologies. Compared with recent studies on AF detection, the PRO AF PPG algorithm showed good diagnostic performance from each smart device.

Discussion

Principal Findings

In this study, we demonstrated good diagnostic performance of the smart devices based on the PRO AF PPG algorithm for AF detection using pulse waveform data measured by PPG. To the best of our knowledge, this is the first study on AF screening technology in a Chinese population. The main findings were, first, the PRO AF PPG algorithm demonstrated promising potential for accurate detection and discrimination of AF from normal SR in a trial setting, and may be applied to any smartphone or smart band for AF screening. Second, there was no significant
difference in the results from different smart devices compared with ECG, and the model of smartphone had little impact on the diagnostic performance of the algorithm

Prior to the development of the PRO AF PPG algorithm, several algorithms were validated for the detection of AF based on smartphones and wearable devices (Table 3). Root mean square of successive difference of RR intervals (RMSSD), Shannon entropy (ShE), Poincaré plot analysis (PPA), and the AliveCor automated algorithm have been used to discriminate between AF and SR by analyzing pulse waveform signals recorded using smart devices in several recent studies [19, 21, 24, 25]. McManus et al [24] described an application using a camera and LED light of an iPhone 4S to record pulse waves obtained from the fingertips of patients. The signal recorded was processed through an algorithm combining RMSSD and ShE. They evaluated the algorithm in 76 patients before and after cardioversion, effectively using each patient as their own control, and reported a sensitivity of 96.2%, specificity of 97.5%, and accuracy of 96.8%. Krivoshei et al [19] applied the same published algorithm as McManus et al to detect AF with 80 consecutive patients. They demonstrated that the algorithm reliably discriminated between normal SR and AF based on pulse wave signals from an iPhone 4S camera only, and achieved a sensitivity and specificity of 80% and 95%, respectively. Rozen et al [26] conducted a study to assess the Cardiio Rhythm smartphone application as a diagnostic tool in 97 patients before and after electrical cardioversion, and achieved a sensitivity of 93.1%, a specificity of 90.9%, a positive predictive value of 92.2%, and a negative predictive value of 92.0% for AF detection. Bumgarner et al [25] reported that the Kardia Band algorithm from AliveCor paired with an Apple smartwatch accurately differentiated AF from SR in 100 patients before and after cardioversion, and demonstrated 93% sensitivity and 84% specificity. Tison et al [27] demonstrated that smartwatch PPG coupled with a deep neural network can passively detect AF compared to standard 12-lead ECG among 51 sedentary participants undergoing cardioversion with a sensitivity of 98.0% and specificity of 90.2%, but with some loss of sensitivity (67.7%) and specificity (67.6%) in 1617 ambulatory participants.

Compared with other algorithms reported in previous studies, the PRO AF PPG algorithm performed better for AF screening in different smart devices with generally higher sensitivity, specificity, positive predictive value, negative predictive value, and
accuracy. The majority of false positives originated from pulse waveforms that were corrupted by finger movement artifacts that may have affected the detection algorithm. Although the diagnostic sensitivity of the PRO AF PPG algorithm was numerically lower compared with that from McManus et al [24] (95.56% vs. 96.20%), this may be due to our different study design. In the present study, we analyzed heart rhythm data from 108 consecutive inpatients, whereas McManus et al performed repeated measurements in the same individual patients before and after cardioversion. We consider our study design more reasonable and closer to the intended use of AF detection in a large-scale, high risk population.

Although short-term pulse waveform recordings with smartphones for AF screening are superior to a single spot-checks in the clinic, they are vulnerable to misdiagnosis in many patients with paroxysmal AF. We attempted to partially address this limitation by using smart bands, which can be worn on the wrist for 24-48 h or even longer to obtain long-term pulsatile PPG signals. Therefore, mobile devices, either smartphones or smart bands, may provide at-risk patients with important tools for screening AF in a single shoot or over a long duration, which may help facilitate the early detection and early management of asymptomatic AF before a devastating outcome such as ischemic stroke occurs.

**Strengths and Limitations**

This is the first study on AF screening technology in China, and it demonstrates an easy AF screening approach using an algorithm based on smart devices with PPG and shows optimal diagnostic accuracy for heart rhythm readings. The advantage of AF screening with smartphones is that it does not require additional hardware, as optical video monitoring of the fingertip with a camera provides an accurate pulsatile time series related to variability in heart rate signals, making it more accessible and appealing to patients.

Some limitations of this study need to be addressed. First, we only focused on discriminating between AF and SR in the present study. However, the effect of other arrhythmias such as premature atrial beats, premature ventricular beats, and atrial flutter on the performance of the algorithm should be evaluated, as these are common in the general population and might be similar in appearance to AF. Second, the
algorithm is unable to detect atrial flutter with a fixed atrioventricular conduction proportion that may also confer some risk of stroke and that frequently accompanies AF. Third, although we reported the feasibility of using pulsatile PPG signals acquired from smartphones and smart bands to detect AF in a group of participants preselected for their heart rhythm status, the ability to diagnose or screen AF with ambulatory outpatients has not been adequately investigated. Finally, although this was a pilot study, the sample size was relatively small, and more extensive clinical studies will need to be performed in the future.

**Conclusions**

AF can be detected and heart rhythms analyzed using the broadly accessible smart device-based PRO AF PPG algorithm. It provides an accurate and easy method of discriminating AF from SR, and may be used to detect asymptomatic patients with AF. Further studies are needed to assess the efficacy of this approach in detecting, screening, and diagnosing AF early, which we are currently performing.

**Acknowledgments**

This research project was funded by the Chinese PLA Healthcare Foundation (17BJ208) and National Natural Science Foundation of China (H2501). HUAWEI (Huawei Technologies Co., Ltd., Shenzhen, China) provided the smartphones (Mate 9, Honor 7X) and smart bands (Band 2) for study purposes. Preventicus (Preventicus GmbH, Jena, Germany) provided the Heartbeats smartphone application and the PRO AF PPG algorithm.

**Authors' Contributions**

Yong-Yan Fan conducted data collection and analysis, and wrote the initial draft of the manuscript. Yu-Tao Guo and Yu-Tang Wang are supervisors of this project as well as joint senior authors. Yan-Guang Li, Jian Li, Hao Wang, Xiang-Ming Shi, Wen-Kun Cheng, and Zhao-Liang Shan provided guidance concerning statistical analysis. All coauthors contributed revisions to the manuscript and approved the final manuscript.

**Conflicts of Interest**

None declared.
**Abbreviations**

AF: atrial fibrillation  
CI: confidence interval  
ECG: electrocardiogram  
FP: false positives  
FN: false negatives  
IQR: interquartile range  
NPV: negative predictive value  
PPA: Poincaré plot analysis  
PPG: photoplethysmography  
PPV: positive predictive value  
RMSSD: root mean square of successive difference of RR intervals  
ShE: Shannon entropy  
SR: sinus rhythm  
TP: true positives  
TN: true negatives

**References**


Table 1 Baseline characteristics of participants

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Sinus rhythm (n=56)</th>
<th>Persistent AF (n=52)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age, mean ± SD</td>
<td>58 ± 14.78</td>
<td>66.56 ± 13.17</td>
<td>.002a</td>
</tr>
<tr>
<td>Female, n (%)</td>
<td>26 (46.43)</td>
<td>19 (36.54)</td>
<td>.298</td>
</tr>
<tr>
<td>Body Mass Index, kg/m², mean ± SD</td>
<td>24.44 ± 2.875</td>
<td>25.98 ± 3.974</td>
<td>.024a</td>
</tr>
<tr>
<td><strong>Medical history</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heart failure, n (%)</td>
<td>2 (3.57)</td>
<td>12 (23.08)</td>
<td>.006a</td>
</tr>
<tr>
<td>Hypertension, n (%)</td>
<td>29 (51.79)</td>
<td>35 (67.31)</td>
<td>.101</td>
</tr>
<tr>
<td>DM, n (%)</td>
<td>15 (26.79)</td>
<td>17 (32.69)</td>
<td>.502</td>
</tr>
<tr>
<td>Previous stroke/SE/TIA, n (%)</td>
<td>4 (7.14)</td>
<td>9 (17.31)</td>
<td>.185</td>
</tr>
<tr>
<td>CAD, n (%)</td>
<td>25 (44.64)</td>
<td>19 (36.54)</td>
<td>.392</td>
</tr>
<tr>
<td>Vascular disease, n (%)</td>
<td>31 (55.36)</td>
<td>37 (71.15)</td>
<td>.089</td>
</tr>
<tr>
<td>COPD, n (%)</td>
<td>1 (1.79)</td>
<td>3 (5.77)</td>
<td>.558</td>
</tr>
<tr>
<td>Renal dysfunction, n (%)</td>
<td>2 (3.57)</td>
<td>8 (15.38)</td>
<td>.074</td>
</tr>
<tr>
<td>Hepatic dysfunction, n (%)</td>
<td>0</td>
<td>2 (3.85)</td>
<td>.229</td>
</tr>
<tr>
<td>Sleep apnea, n (%)</td>
<td>2 (3.57)</td>
<td>6 (11.54)</td>
<td>.226</td>
</tr>
<tr>
<td>Hyperthyroidism, n (%)</td>
<td>1 (1.79)</td>
<td>4 (7.69)</td>
<td>.317</td>
</tr>
<tr>
<td>Current smoking, n (%)</td>
<td>16 (28.57)</td>
<td>17 (32.69)</td>
<td>.642</td>
</tr>
<tr>
<td>Current drinking, n (%)</td>
<td>13 (21.15)</td>
<td>11 (23.21)</td>
<td>.797</td>
</tr>
<tr>
<td>CHA²DS²-VASc score, median [IQR]</td>
<td>2[1-3.75]</td>
<td>3[2-5]</td>
<td>.003a</td>
</tr>
<tr>
<td>HAS-BLED score, median [IQR]</td>
<td>1[0-2]</td>
<td>2[1-2]</td>
<td>.005a</td>
</tr>
<tr>
<td><strong>Medications, n (%)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OAC</td>
<td>10 (17.86)</td>
<td>40 (76.92)</td>
<td>&lt;.001a</td>
</tr>
<tr>
<td>Anti-platelet drug</td>
<td>15 (26.79)</td>
<td>23 (44.23)</td>
<td>.058</td>
</tr>
<tr>
<td>CCB</td>
<td>17 (30.36)</td>
<td>13 (25.00)</td>
<td>.535</td>
</tr>
<tr>
<td>ACEI/ARB</td>
<td>21 (37.5)</td>
<td>16 (30.77)</td>
<td>.461</td>
</tr>
<tr>
<td>Diuretic</td>
<td>5 (8.93)</td>
<td>13 (25.00)</td>
<td>.025a</td>
</tr>
<tr>
<td>Digoxin</td>
<td>3 (5.36)</td>
<td>11 (21.15)</td>
<td>.015a</td>
</tr>
<tr>
<td>Anti-arrhythmic drug</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Class I</td>
<td>6 (10.71)</td>
<td>2 (3.85)</td>
<td>.320</td>
</tr>
<tr>
<td>Beta-blocker</td>
<td>27 (48.21)</td>
<td>34 (65.38)</td>
<td>.072</td>
</tr>
<tr>
<td>Class</td>
<td>Count</td>
<td>Percentage</td>
<td>p-value</td>
</tr>
<tr>
<td>--------</td>
<td>-------</td>
<td>------------</td>
<td>---------</td>
</tr>
<tr>
<td>III</td>
<td>3</td>
<td>(5.36)</td>
<td>&lt;.001*</td>
</tr>
<tr>
<td>IV</td>
<td>3</td>
<td>(5.36)</td>
<td>1.00</td>
</tr>
</tbody>
</table>

A *p* value less than .05 is considered as statistically significant.

AF=atrial fibrillation; SD=standard deviation; DM=diabetes mellitus; SE=systemic arterial embolism; TIA=transient ischemic attack; CAD=coronary artery disease; COPD=chronic obstructive pulmonary disease; CHA\(_2\)DS\(_2\)-VASc=congestive heart failure, hypertension, age≥75years, stroke (doubled), vascular disease, age 65-74, female sex; HAS-BLED=hypertension, abnormal renal function, abnormal liver function, stroke, bleeding, labile INR, age≥65years, drugs or alcohol; OAC=oral anticoagulant; CCB=calcium channel blockers; ACEI/ARB=angiotensin-converting-enzyme inhibitor, angiotensin receptor blockers.
Table 2 Detailed diagnostic performance of the PRO AF PPG algorithm for AF screening in different smart devices

<table>
<thead>
<tr>
<th>Index</th>
<th>Smart bands</th>
<th>Smartphones</th>
<th>Smartphone 1</th>
<th>Smartphone 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity, % (95% CI)</td>
<td>95.36 (92.00-97.40)</td>
<td>94.96 (91.51-97.11)</td>
<td>94.41 (88.91-97.38)</td>
<td>95.56 (90.16-98.18)</td>
</tr>
<tr>
<td>Specificity, % (95% CI)</td>
<td>99.70 (98.08-99.98)</td>
<td>99.70 (98.07-99.98)</td>
<td>100 (97.20-100)</td>
<td>99.40 (96.18-99.97)</td>
</tr>
<tr>
<td>PPV, % (95% CI)</td>
<td>99.63 (97.61-99.98)</td>
<td>99.62 (97.59-99.98)</td>
<td>100 (96.55-100)</td>
<td>99.23 (95.16-99.96)</td>
</tr>
<tr>
<td>NPV, % (95% CI)</td>
<td>96.24 (93.50-97.90)</td>
<td>95.95 (93.15-97.68)</td>
<td>95.43 (90.88-97.86)</td>
<td>96.49 (92.17-98.57)</td>
</tr>
<tr>
<td>Accuracy, % (95% CI)</td>
<td>97.72 (96.11-98.70)</td>
<td>97.55 (95.89-98.57)</td>
<td>97.42 (94.78-98.80)</td>
<td>97.67 (95.05-98.97)</td>
</tr>
<tr>
<td>Study and year</td>
<td>Population studied</td>
<td>AF detection protocol</td>
<td>Sensitivity (%)</td>
<td>Specificity (%)</td>
</tr>
<tr>
<td>----------------</td>
<td>---------------------</td>
<td>-----------------------</td>
<td>-----------------</td>
<td>---------------</td>
</tr>
<tr>
<td>McManus et al, 2013</td>
<td>76 patients before and after cardioversion</td>
<td>An iPhone 4S, an algorithm combining RMSSD and ShE</td>
<td>96.2</td>
<td>97.5</td>
</tr>
<tr>
<td>Chan et al, 2016</td>
<td>1013 patients</td>
<td>Cardiio Rhythm smartphone application</td>
<td>92.9</td>
<td>97.7</td>
</tr>
<tr>
<td>Krivoshei et al, 2017</td>
<td>80 consecutive patients</td>
<td>AliveCor automated algorithm</td>
<td>71.4</td>
<td>99.4</td>
</tr>
<tr>
<td>Krivoshei et al, 2017</td>
<td>80 consecutive patients</td>
<td>An iPhone 4S, an algorithm combining RMSSD and ShE</td>
<td>80</td>
<td>95</td>
</tr>
<tr>
<td>Krivoshei et al, 2017</td>
<td>80 consecutive patients</td>
<td>An iPhone 4S, an algorithm combining RMSSD and PPA</td>
<td>95</td>
<td>95</td>
</tr>
<tr>
<td>Rozen et al, 2018</td>
<td>97 patients before and after electrical cardioversion</td>
<td>An iPhone, Cardiio Rhythm Mobile Application</td>
<td>93.1</td>
<td>90.9</td>
</tr>
<tr>
<td>Study</td>
<td>Participants</td>
<td>Methodology</td>
<td>Sensitivity</td>
<td>Specificity</td>
</tr>
<tr>
<td>--------------------------</td>
<td>--------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>-------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Bumgarner et al, 2018</td>
<td>100 patients before and after cardioversion</td>
<td>Kardia Band from AliveCor paired with an apple smartwatch, AliveCor automated algorithm</td>
<td>93</td>
<td>84</td>
</tr>
<tr>
<td>Tison et al, 2018</td>
<td>51 sedentary participants undergoing cardioversion</td>
<td>smartwatch PPG coupled with a deep neural network</td>
<td>98</td>
<td>90.2</td>
</tr>
<tr>
<td></td>
<td>1617 ambulatory participants</td>
<td>smartwatch PPG coupled with a deep neural network</td>
<td>67.7</td>
<td>67.6</td>
</tr>
</tbody>
</table>

AF=atrial fibrillation; PPV=positive predictive value; NPV=negative predictive value; RMSSD=root mean square of successive difference of RR intervals; ShE=Shannon entropy; PPA=Poincaré plot analysis; PPG=photoplethysmography.
Figure 1 A prototype for atrial fibrillation detection using HUAWEI smartphones and smart bands.

A: A patient is simultaneously checked with HUAWEI smartphones (Mate 9, Honor 7X), HUAWEI smart bands (Band 2), and 12-lead ECG.
B: A fingertip is placed in contact with the built-in camera lens of a HUAWEI mate 9 smartphone and is illuminated by the adjacent LED flash.
C: A screenshot of the pulse waveform data collection application (Heartbeats) running on a HUAWEI mate 9 smartphone.
D: Representative pulse waveform recording from a patient with normal sinus rhythm.
E: Representative pulse waveform recording from a patient with persistent atrial fibrillation.
Figure 2 A flowchart of the study.
AF=atrial fibrillation; SR=sinus rhythm.