New approaches to detection of atrial fibrillation

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Atrial fibrillation (AF) is a global epidemic associated with significant cardiovascular comorbidity and mortality, with resultant burden on healthcare systems worldwide. However, silent or undetected AF is common, especially in the older population. Early detection and diagnosis of AF is therefore paramount to provide comprehensive management, to manage symptoms, slow progression of the disease, prevent severe complications like stroke and heart failure, reduce AF-related hospitalisations and possibly improve survival.

Arrhythmia documentation via 12-lead ECG recording is considered the gold standard to confirm an AF diagnosis. While this is of significant yield in those with persistent forms of the arrhythmia, those with paroxysmal or asymptomatic AF pose a greater challenge. In such scenarios, other forms of screening or monitoring may thus be warranted. In this context the European Society of Cardiology (ESC) guidelines for the management of AF recommend opportunistic screening for AF in all patients >65 years by pulse palpation or ECG recording.[1] However, the proportion of incident AF yielded by opportunistic screening is relatively low, and paroxysmal AF is often missed. Besides invasive devices to monitor the heart rhythm, other methods have been developed to detect arrhythmias, such as smartphone applications, smart watches and wearable fitness trackers, which make use of photoplethysmography (PPG)—digital pulse waveforms—to detect irregularities in the heart rhythm.

In their *Heart* paper, Poh *et al*[2] report on their findings using a deep neural learning system for automated detection of AF in PPG pulse waveforms. Deep neural systems use machine learning algorithms, generating information based on statistical data modelling. This has demonstrated high accuracy in performing pattern recognition, and forms the 'knowledge' behind artificial intelligence systems. Previously it has been applied in the detection of retinopathy in diabetes mellitus.[3] A deep convolutional neural network (DCNN), using a data set of 149 048 PPG waveforms is developed. PPG segments with concurrent ECGs were analysed and assigned to four rhythm classes: sinus rhythm, noise, ectopic rhythm and AF. DCNN was then clinically validated through a smartphone (iPhone 4S; Apple) using an independent test data set with 3039 PPG waveforms from 1013 participants. A single-lead I ECG was performed through a handheld device, to confirm the cardiac rhythm and to compare against the results of -deep convolutional neural network (DCNN) . This resulted in an AF diagnosis in 28 participants (2.8%), confirmed by a standard 12-lead ECG, and in 5 of these patients (17.9%) new AF was detected. With an overall accuracy of 96%, a sensitivity of almost 98% and a specificity of 96.5%, the algorithm performed well for detection of AF.

Similarly, researchers from the University of California in San Francisco recently reported on their proof-of-concept study using PPG through a smartwatch application with deep neural networking. In this study data were derived from Apple watches (Apple), which were input into a deep neural network.[4] The authors first collected heart rate and step count data by means of the Apple watch, which were sequences of sensor-measured pulse rates and step counts projected to approximate a range of R-R intervals across time spans. Validation of the deep neural network was performed against a reference 12-lead ECG in a separate cohort of 51 patients with persistent AF presenting for cardioversion. The results of the deep neural network in this cohort demonstrated good discrimination (C-statistic 0.97) with a sensitivity of 98% and specificity of 90.2% to detect AF. However, testing the network in an ambulatory subcohort of 1617 participants, 64 (4%) of whom reported having persistent AF, was less hopeful. The discrimination to detect persistent AF through the network was much lower with a C-statistic of 0.72, with a sensitivity of 67.7% and a specificity of 67.6%, and illustrates the difficulty of accurately diagnosing AF in ambulatory individuals.

These studies provide important insights in the application of deep neural systems through devices using PPT. Smartphones and watches are easily accessible and a feature of modern society, used in all age categories and across the population spectrum. Alternative monitoring systems, such as implantable loop recorders, have the ability to monitor the electrical activity in the heart and to detect irregularities over longer periods of time. However, they are invasive and often expensive, and with the growing prevalence of AF in an ageing population this is an important financial consideration for healthcare systems. Nevertheless, implantable devices such as pacemakers or defibrillators allow for continuous monitoring and are able to identify atrial high rate episodes (AHRE), which are associated with an increased risk of overt AF, as well as ischaemic stroke or systemic embolism. A recent systematic review and meta-analysis investigating the subclinical device-detected AF and the associated stroke risk demonstrated that subclinical AF is highly prevalent in cardiac implantable electronic devices, and is associated with a 2.4-fold increase in stroke risk.[5] However, in subclinical AF the risk of stroke is lower compared with clinical AF and therefore the net clinical benefit of anticoagulation in these patients is unknown. Stroke prevention in AHRE, with the use of oral anticoagulant therapy, is currently under investigation with the ARTESiA Trial (Apixaban for the Reduction of Thrombo-Embolism in patients with device-detected subclinical AF)[6] and in the NOAH – AFNET 6 Trial (Non-vitamin K antagonist Oral anticoagulants in patients with AHRE).[7]

However, long-term application and safety of clinical decision making based on detection of AF through wearable devices is not available yet and, as the authors state, further studies would be required to both validate this approach and determine its suitability for clinical decision making with an appropriate treatment pathway in ambulatory settings. A potential management algorithm is presented in figure 1, and indicates the important role of integrated AF services in this perspective.[8] Indeed, the complexity of AF diagnosis through such technology was highlighted with the recently presented, but as yet unpublished, results of the mSTOPS Study (mHealth Screening to Prevent Strokes), in which a wearable ECG patch resulted

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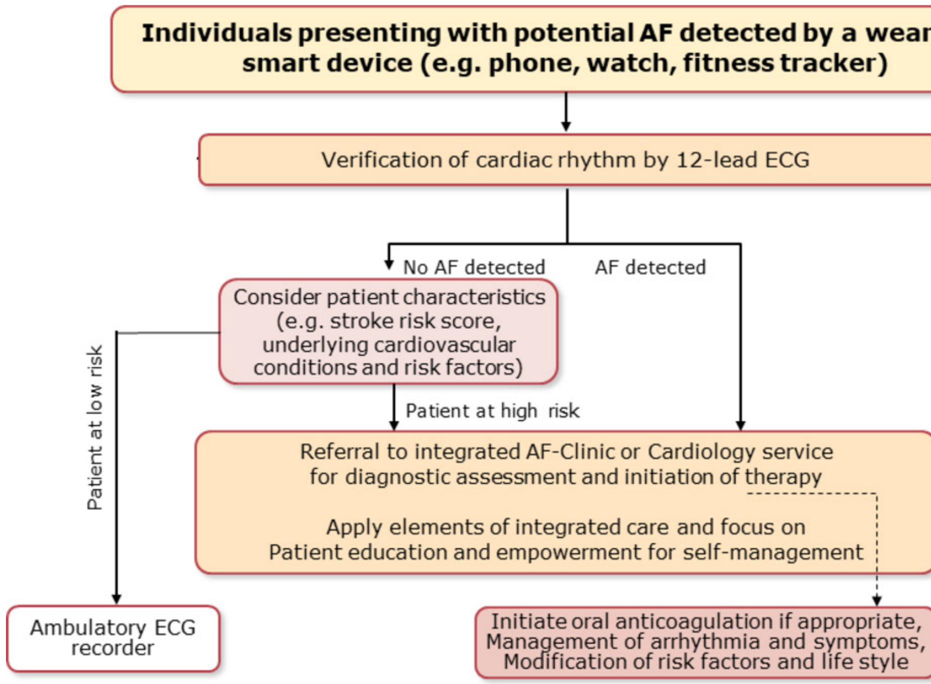

Figure 1 Potential management algorithm of atrial fibrillation (AF) detected by a wearable smart device.

in a threefold increase in the diagnosis of AF in a population at risk for AF, but no difference in clinical outcomes including rates of stroke, myocardial infarction, systemic embolism, emergency department visits or inpatient hospital stays at 1 year. There were, however, fewer strokes in the subset of individuals with an AF diagnosis who were monitored compared with controls. The monitored group in this study had a significantly greater number of visits to their primary care practitioner and cardiologist, which illustrates the potential significant impact on workload and healthcare utilisation that wearable technology may impose. Other practical issues include the appropriate method of alerting individuals to a potential AF diagnosis, and the possible legal ramifications to the clinician who is presented with such an individual, without the guidance of a clearly defined clinical pathway for treatment. Also, how much can we expect from our patients in self-detecting AF and appropriate self-management responses to this? Besides a number of important challenges in the use of smartphone devices (eg, noise correction, limitation of single lead recordings, transmitting security and data storage) the European Heart Rhythm Association consensus document on screening for AF states the importance of systematic ECG screening according to ESC guidelines, and ECG confirmation of AF before consideration of anticoagulation therapy.[9] Indeed, the increased healthcare resource utilisation such an algorithm could potentially create needs careful consideration, and the cost-effectiveness of this approach would need to be demonstrated. While early diagnosis of AF may seem an attractive option, many questions about the validity and application of this approach need answering before it could be widely used.

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