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Smart Watches: Capturing Our Hearts

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Abstract

Smart watches are growing in popularity, with about one-in-five Americans reporting daily use of a smart watch or fitness tracker. Smart watches continue to gain functionality as technology improves, and have established their utility in several applications of physiological tracking including detection of atrial fibrillation, a common arrhythmia. Because they serve as a substitute for a typical wrist watch and have potentially lifesaving health and fitness features, smart watches present a unique opportunity to monitor and objectively track cardiac rhythm and sleep patterns. This current review seeks to explore the potential benefits and limits of smart watches in select cardiac applications, namely detecting arrhythmias and measuring heart rate variability (HRV). Because sleep quality and quantity often have an impact on cardiovascular systems, we also discuss smart watch sleep-cycle tracking functions.

Keywords

Smart watches, Arrhythmias, Heart rate variability, Sleep monitoring

Introduction

Commercially available wearable devices are a rapidly expanding market, forecast by Forbes to reach $27 billion by 2022 [1]. These devices are continuously evolving with increased functionalities to measure and monitor physiological parameters [2]. Wearable devices come in a variety of forms including chest-bands, wristbands, wristwatches, rings, wearable tattoos, and smart clothing, and are currently capable of collecting user data such as steps taken, distance traveled, elevation, exercise time, temperature, respiration, and heart rate [3,4]. More recent functionalities include capturing a single-lead ECG as well as measuring blood-oxygen saturation [5,6].

According to Pew Research, as of January 2020, roughly 21% of US adults wear a smart watch or activity tracker [7]. In a survey conducted in August 2021 of smart watch users in the United States, the market shares of Apple Watch and Fitbit were estimated at 43% and 40% respectively, making these the most popular smart watches in the US [8]. A separate survey revealed 82% of daily smart watch users were comfortable sharing data collected from the device with healthcare workers [9]. Thus, these devices already have extensive adoption, and are projected to increase in popularity, presenting an untapped opportunity to leverage smart watch data for health and wellness interventions.

As these devices increase in capability and popularity, so too do their potential healthcare applications. The use of Fitbit devices in interventions has been shown to promote physical activity, weight maintenance, and be useful to health professionals for patient monitoring and support [10]. Smart watches simplify and objectify the data collection process and, therefore, have the ability to prevent adverse medical outcomes and accelerate clinical research. As new applications arise, however, it is important to understand the current effectiveness and limitations of these devices. Thus, the goal of the current review is to explore the performance of the most popular commercially available smart phone compatible wristwatches (Fitbit and Apple Watch) in select cardiac applications, specifically their ability to detect arrhythmias, measure heart rate variability (HRV), and track user's sleep cycles.

Methods

A search of the literature was conducted in the English language on PubMed, MEDLINE, EMBASE, and Google Scholar databases using the key-words "smartwatch", "Apple watch",

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"Fitbit", "sleep tracking", "atrial fibrillation", "heart rate variability", "HRV" and "sleep apnea". Literature discussing the previously specified devices (Apple Watch and Fitbit) in the fields of arrhythmia, sleep cycle tracking, and HRV was reviewed. The bibliographies of the identified articles were also searched for other relevant literature.

Utility of Smart Watches

This review will discuss the utility of smart watches in the domains of 1) Detection of arrhythmia 2) Heart rate variability (HRV) measurement and 3) Sleep cycle tracking.

Detection of arrhythmia

The detection of atrial fibrillation (AF) is the most studied area involving smart watches. AF currently affects over 33 million individuals worldwide, and its prevalence is expected to more than double over the next 40 years [11]. AF is associated with heart failure, stroke and myocardial infarction, as well as premature death. Ischemic stroke resulting from AF is largely manageable with anticoagulation, but nearly one third of patients with AF are asymptomatic, making detection via passive data collection by a commercially available smart watch valuable [12].

With advancing technology in the smart watch space, the Apple Watch developed an algorithm to detect AF based on beat-to-beat variability [13]. The validity of smart watch devices to detect AF was first studied in the Apple Watch device in the prospective Apple Heart Study, which showed an 84% concordance between irregular pulse notifications and AF detected on a portable Holter-monitor, resulting in FDA approval for this use in 2019 [14]. Similar manufacturer-funded studies have been conducted including the Huawei Heart Study, completed in 2019, and the Fitbit Heart Study whose enrollment is currently complete, and final outcomes pending [15].

The utility of smart watches in the detection of arrhythmia is not limited to AF [13]. Case reports detail instances of the use of the electrocardiogram (ECG) feature of the Apple Watch to detect other arrhythmias including atrioventricular nodal reentrant tachycardia (AVNRT), paroxysmal supraventricular tachycardia (PSVT), and ventricular tachycardia (VT) [16-18]. In addition, detection of ECG abnormalities associated with sudden cardiac death (pre-excitation, Brugada patterns, long QT, and signs suggestive of HCM and ARVC/D) is possible with a smartwatch ECG [19,20]. In symptomatic patients, the advent of a reliable, single-lead ECG tracing presents an exciting opportunity for patients experiencing unpredictable, rare episodes of symptoms, allowing capture of an ECG tracing that would otherwise be difficult to record without longer duration, continuous Holter-monitors or implantable loop-recorders [21].

While these devices can detect arrhythmias, it is important to also consider their limitations. For the Apple Watch, detection of AF requires either 1) Activation of the "irregular heart rate notification" feature on the smartphone and/or 2) Capture of an ECG tracing during an AF episode. Thus, there is a certain level of patient participation required. Notably, the accuracy of the algorithm used by the Apple Watch to detect AF breaks down at both high (> 150 bpm) and low (< 50 bpm) heart rates, making its utility in detection of AF with rapid ventricular response or an underlying bradycardia rather limited [14].

In the controlled setting of the WATCH-AF trial, sensitivity and specificity at detection of AF were estimated as high as 93.7% and 98.2% respectively [22]; however, the accuracy of these devices is sensitive to movement artifact, and data collected from 22% of participants in the WATCH-AF trial were excluded due to poor data collection quality [23]. Additionally, the highest rates of smart watch adoption were among younger, healthier individuals, who also tend to have lower baseline rates of AF and arrhythmia in the first place. As such, the low baseline prevalence of AF among smart watch users consequently decreases the positive predictive value and increases the number needed to screen, raising concern for increased false positives [23]. Thus, the risk-benefit consideration in the utility of smart watches must weigh the psychological and medical-resource utilization associated with false positives against the potential prevention of stroke or other adverse outcomes due to management of AF that would have otherwise gone undetected. Given the potentially devastating consequences of AF, this presents a ripe area for further evaluation.

There are also ethical considerations regarding the use of smart watches in AF detection, including inequality, data protection, and misunderstanding of the accuracy and limitations of the devices [24]. There are concerns regarding the equality of access to smart watch devices given their high cost, with the greatest rates of usage in individuals of high socioeconomic status, level of education, and technological literacy [9]. Additionally, there are questions regarding demographic representation among the validation studies. For example, the Apple Heart Study population mainly consisted of young (average age 41 years), white (68%) participants [14].

Heart rate variability (HRV) measurement

Heart rate variability (HRV) describes the instantaneous variations of heart rate and R-R interval at a given moment of time and has come to be a widely accepted non-invasive surrogate for vagal activity [25]. HRV has been utilized in a variety of applications ranging from monitoring athletic training responses to serving as a marker of fatigue, stress, and overall state of health [26]. High HRV is associated with positive general health and wellness, whereas low HRV is associated with disease states, fatigue, and stress [27]. Measurement of HRV usually requires an ECG and specialized software, typically limiting its use to the laboratory setting. A newer alternative measurement of HRV has been developed using photoplethysmography (PPG) [28]. This technique involves illumination of the subcutaneous tissue with a light source (typically a light-emitting diode) and subsequent detection with a photo detector. Comparison of the characteristics of the light received by the photo detector with the known emitted light from the LED as well as mathematical processing allows inference of a variety of tissue characteristics such as oxygen saturation and, in the interest of HRV measurement, determination of blood perfusion to estimate pulse rate [29].

With advances in semiconductor technology, the use of PPG has increasingly been adopted among smart watches [30]. Importantly, PPG can be performed using light of different colors (wavelengths), each of which has unique properties. Green-light, commonly used in smart watches, has a shorter wavelength and has a more ideal signal-noise ratio, but has limited depth of penetration, especially in darker skin tones. In contrast, red-light, commonly used in pulse-oximeters, has the benefit of deeper penetration, allowing for measurement of additional biophysical markers, but comes with the tradeoff of increased susceptibility to motion artifact and increased noise-signal ratio [31]. Study conditions also have an effect: PPG has good performance when compared to ECG at resting-state, but performance tends to break down while in motion and during exercise and thus readings are subject to error [32].

Commercially available smart watches with PPG capabilities utilize proprietary algorithms to calculate HRV. Of the studied devices, only the Apple Watch has undergone third-party validation, against which it was compared to the Polar H7 chest-band (validated against ECG) and found to be accurate at rest with a reliability and agreement greater than 0.9 [33]. Of note, during this validation study, there were several lapses in data collection. Roughly 10% of RR-intervals were not recorded by the Apple Watch, both while in motion and at rest, which raises questions about the watch's external generalisability to real-world conditions [33]. These missing beats were typically consecutive, and may have significant impacts on the calculated HRV. Given that the Apple Watch HRV calculation is a proprietary algorithm, it is unknown whether this is corrected for.

Sleep cycle tracking

Sleep is a vital component to wellness, contributing to overall levels of alertness, performance, cardiovascular health and ultimately quality of life. It is estimated that between 50-70 million Americans suffer from disorders of sleep and wakefulness [5]. Chronically, these conditions are associated with several cardiovascular sequelae including hypertension, myocardial infarction, and stroke [34]. Thus, objective sleep tracking is critical to diagnosis and management of sleep disorders.

The gold standard of sleep tracking is polysomnography (PSG) [34]. This involves tracking eye movement, brain activity, heart rate, muscle tone, and physical movement; it is a cumbersome process requiring a great deal of equipment, and specialized laboratories [35]. The desire for a less invasive and more readily available sleep tracking technology has led to the addition of sleep tracking features to several commercially available wearables, including Fitbit and Apple Watch. These devices rely upon a technique known as actigraphy which is an accelerometry-based activity measurement with which inferences are made of sleep versus wake-state. The Fitbit family of devices has been validated in a variety of small, real-world trials with sensitivity 97-98% and specificity 35-36% when compared to the gold standard of PSG and the ActiWatch 2 [35]. While the Apple Watch has not been validated for the accuracy of the Apple Sleep application, a study demonstrated a reliable sleep cycle tracking algorithm utilizing the raw data collected from the Apple Watch [36]. Notably, this study was also validated against the ActiWatch 2.

Obstructive sleep apnea (OSA) is a disorder associated with significant morbidity and mortality [37]. The gold standard of OSA diagnosis is through PSG, but a recent study has developed an algorithm to detect sleep apnea via smart watch utilizing motion data from the accelerometer with a precision of 0.97 and F1-score (accuracy) of 0.96 when compared to PSG [38]. As a defining feature of OSA is apneic periods, the addition of blood-oxygen measurement in the newest generation of Apple Watch presents a new, potentially useful parameter that may increase its accuracy in the detection of sleep apnea [39].

The processing of the raw data collected by the accelerometers on smart watch devices relies upon proprietary algorithms that are trade secrets and not subject to FDA regulation at this time [40]. Additionally, the existing validation studies of smart watch devices to accurately measure sleep-cycle tracking are limited to small sample-size studies, and involve comparisons against other devices that are inherently not perfect either [41]. Therefore, it is important to consider the quality of data collected by these devices if they are to be used for medical decision making. To this end, the American Association of Sleep Medicine released a position statement calling for increased validation of devices that currently feature sleep cycle tracking [42].

Discussion

Smart watch devices have evolved over time to collect increasing amounts of data on biophysical variables. Their cutting-edge functionality and widespread adoption positions them as a potential tool to objectively gather patient data, supplement the delivery of high-value healthcare and revolutionize large-scale trials [43,44]. For example, the Heartline™ Study is a partnership between Apple and Johnson and Johnson, enrolling up to 180,000 smart watch naive participants over the age of 65 to evaluate the performance of the Apple Watch in detecting AF in a real-world setting [45]. The study has been referred to as a "giga-trial" referring to the collection of large quantities of data on a large number of participants, and doing so at a fraction of the cost that would be required for a traditional laboratory-based study of the same size [46]. Wearable device data is increasingly used in large studies across several fields of medicine. Another example is the tracking of HRV, resting heart rate, and respiratory rate as a measurement of tolerance in patients after receiving the Pfizer-BioNTech COVID-19 vaccine [47].

As the capabilities of wearable devices expand, new applications are limited only by the creativity of the developers and healthcare professionals. However, it is important to also consider the potential pitfalls and limitations of these devices. Of tantamount importance is that smart watches undergo proper vetting and validation, including real-world performance studies, and maintain proper regulation and oversight, especially if they are used in medical decision making and future clinical trials. Currently, adoption of these

devices favors younger Caucasians of higher socioeconomic/education status and higher technological literacy [24]. This issue of representation among device-users presents a unique opportunity to either maintain the status quo and exacerbate the disparity in representation of these "giga-studies" or, alternatively, increase representation through partnership with industry by making these devices available to underserved and diverse populations. For example, the Heartline™ Study is recruiting subjects who are not already using the Apple Watch, and loaning participants the device for the duration of the study and/or providing a discounted price for them to purchase one of their own [45]. This approach, paired with intentional recruitment of a diverse, representative population, is a major strength of the study that helps it simulate a more meaningful real-world experience.

Manufacturers continue to invest in new functionality of these devices, and their population adoption is growing as prices decrease. The consumer wearable device industry is growing exponentially, and as consumers have increasing biophysical data at their disposal, healthcare providers can choose to encourage proper vetting of these devices and embrace the data as ancillary support to medical decision making [48].

By requiring standards of third-party validation of these devices in real-world settings, we can continue to allow data collected by smart watches to play an increasing role in our medical decision making, specifically related to the detection and monitoring of conditions, and trial designs [47,49]. Consumer-available devices present an ever-changing and exciting field of possibilities, especially in the cardiac patient [50]. With proper validation and patient education, these devices could prove revolutionary in the way that we interact with our patients and how they become engaged in their own healthcare [22,45].

Conclusion

Smart watches and other wearables are not only being used to monitor heart rhythm and blood pressure, but also expanding into other areas. Such devices are now being used within the domains of cardiology, pulmonology, neurology, psychiatry, sleep, and exercise to provide more objective data on patient medical status. This is especially important as healthcare providers in the United States see patients on average about twice a year. Thus, smart watches and other wearables can help monitor some important user health and fitness parameters for the other 363 days of the year!

We already know that smart watches and wearables, in conjunction with smart phone/computer apps, can monitor and improve exercise, diet, weight, stress, and sleep. Importantly, we need to remember their limitations, and need a standardized approach to measure safety and efficacy, and to certify these devices so we are providing accurate and evidence-based information to providers and patients that will assist them in improving their health and wellness. We believe that such devices will not replace healthcare providers, but rather may integrate and improve access to/for them. In addition, such devices may serve as a handy tool to evaluate and motivate users, especially those with limited access to healthcare.

Smart watches and other wearables have great potential uses in clinical management, preventive care, public health, clinical trials, and rehabilitation. Down the line, monitoring of respiration, blood pressure, temperature, and blood sugar levels may lead to exciting clinical applications including their role in screening, disease management, treatment monitoring, and trial data collection. With future developments, smart watches may indeed provide a window to our health and truly 'capture our hearts'.

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Conflict of Interest Statement

There is no apparent conflict of interest for any of the authors. The authors have no financial or other interest in the products or distributor of the products in the manuscript. In addition, the authors have no other kinds of associations, such as consultancies, stock ownership, or other equity interests or patent-licensing arrangements, with any of the products in the manuscript.

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