Review

Current State of Smartphone Applications for Monitoring of Heart-rate, Heart-rate Variability and Atrial Fibrillation: A Narrative Review

Authors
Ka Hou Christien Li 1,2,3, Francesca Anne White 3, Timothy Tipoe 1,2, Tong Liu MD PhD 4, Martin CS Wong MD FFPH FESC FACC 5, Aaron Jesuthasan BSc 3, Adrian Baranchuk MD FACC FRCPC FCCS 6, Gary Tse PhD FESC FACC FHRS FRCP 1,2,*, Bryan P Yan MBBS FRACP FESC FACC FRCP 1*

Institutions
1 Department of Medicine and Therapeutics, Faculty of Medicine, The Chinese University of Hong Kong, Hong Kong, HKSAR, China
2 Li Ka Shing Institute of Health Sciences, Faculty of Medicine, The Chinese University of Hong Kong, Hong Kong, HKSAR, China
3 Faculty of Medicine, Newcastle University, United Kingdom
4 Tianjin Key Laboratory of Ionic-Molecular Function of Cardiovascular Disease, Department of Cardiology, Tianjin Institute of Cardiology, Second Hospital of Tianjin Medical University, Tianjin 300211, People’s Republic of China
5 JC School of Public Health and Primary Care, Faculty of Medicine, The Chinese University of Hong Kong, Hong Kong, HKSAR, China
6 Division of Cardiology, Kingston General Hospital, Queen's University, Kingston, Ontario, Canada

Corresponding Authors
Prof. Bryan P Yan
Associate Professor
Division of Cardiology,
Department of Medicine and Therapeutics,
The Chinese University of Hong Kong,
Hong Kong, HKSAR, China
Telephone: +852 35051750
Fax: +852 35054755
Email: bryan.yan@cuhk.edu.hk
Abstract
Smartphone applications capable of monitoring arrhythmias and heart rate are becoming widely available. These applications involve the use of photoplethysmography and recording through a hand-held external electrocardiographic recording device attached to the smartphone or wristband. This enables recordings to be obtained for analysis, which could be useful for screening, diagnosis and monitoring of heart rate and rhythm disorders. We conducted a narrative review into the use of smartphone devices by searching PubMed and Embase from their inception to April 2018. Potentially relevant papers were then compared against a checklist for relevance and reviewed independently for inclusion, with the focus on four allocated topics of i) smartphone monitoring, ii) atrial fibrillation, iii) heart rate and iv) heart rate variability.

Keywords
Smartphone applications; atrial fibrillation; heart rate; arrhythmia; photoplethysmography; hand-held electrocardiographic device; digital health
Introduction
Over the past years, there has been a significant increase in the number of smartphone applications (apps) focused on cardiovascular diseases (CVD). These apps are designed to monitor cardiovascular risk factors such as obesity, smoking, sedentary lifestyle, diabetes, hypertension, etc. as well as to prevent and manage chronic conditions such as atrial fibrillation (AF) [1-5]. There are currently more than 100,000 available mobile health apps on iTunes and Google Play, as well as more than 400 wearable activity monitors [6]. Approximately 64% of adults possess a smartphone in the USA and 62% of smartphone owners use their phones to access health information and obtain education about diseases and health conditions [6]. Previous research has reported that the benefits of using mobile health in modifying behavior to improve cardiovascular health, through dietary management, physical activity promotion, smoking cessation, weight control, blood pressure control, cholesterol management and blood sugar measurement [7-12]. However, there remains some ambiguity when it comes to the use of such applications in heart rate (HR), heart rate variability (HRV) and AF for clinical purposes.

Currently, Smartphone-based photoplethysmography (PPG) and hand held electrocardiograph (ECG) recorders are the two main concepts utilized in monitoring HR, HRV and AF [13, 14]. PPG is an optical technique that detects heartbeats by analyzing changes in skin color and light absorption. The PPG sensor detects variations in light intensity via transmission through or reflection from the tissue (the reflectance and transmittance model). The variations in the light intensity are related to changes in the blood perfusion of the tissue, and based on these changes heart-related information can be retrieved [13, 15].

As for the handheld ECG recorder, three main components are required for it to work: a mobile device, ECG sensors, and an electrocardiographic mobile application that must be used simultaneously and in conjunction with each other. This will then allow for a standard lead I ECG to be recorded [14]. Validation studies have been conducted using smartphone applications, such as AliveCor, to detect arrhythmias such as AF, atrial flutter, atrial and ventricular premature beats, bundle branch blocks and ST-segment abnormalities [16-19]. As the use of smartphone applications in cardiovascular care is a rapidly evolving field, this literature review seeks to act as a checkpoint, encapsulating the current state of smartphone based PPG and ECG recorders in monitoring HR, HRV and AF and its relevant challenges.

Methods
A PubMed and Embase search that primarily concerned the utilization of smartphone applications for monitoring HR, HRV and AF was conducted. The following search string was employed: (‘mobile applications’ OR ‘smartphone’ OR ‘digital health’) AND (‘atrial fibrillation’ OR ‘heart rate’). The search period was determined as beginning from the earliest available publications in the databases through to 10th April 2018. No language restrictions were included.

The search results were subsequently transferred to Microsoft Excel (Microsoft Corp., Redmond WA) and all potentially relevant reports, were retrieved as complete manuscripts and abstracts and assessed for compliance with relevance to the four core principles of this narrative review: (1) smartphone applications; (2) heart rate; (3) heart rate variability; (4) atrial fibrillation. Three authors (CL, FW and TT) independently reviewed each publication and report, findings were agreed upon by consensus with input from two senior researchers.
A total of 923 articles were found, and after screening, 101 articles were utilized for this narrative review.

**Atrial fibrillation and other arrhythmias**

**Atrial fibrillation – KardiaMobile app**

The KardiaMobile app, developed by AliveCor [20], is a commonly used device in studies investigating the monitoring of AF. The equipment comprises a fingerpad sensor for the left and right hand, which is attached to the smartphone, and an app that receives the transmitted information. A 2017 study gives a detailed account of the technology used by the device [21]. When fingers are placed on the sensors, recording begins. Using a 19,000Hz centre frequency and a modulation index of 200Hz/mV (FMECG), electrical activity is transmitted to the smartphone via ultrasound signal frequency modulation to obtain the ECG trace. The FMECG signal that is transmitted to the microphone of the smartphone is digitized at 44.1kHz, 24-bit resolution. The application is then able to produce an ECG trace from the received signal (300 samples/s, 16-bit resolution), which can either be viewed as it is produced or be stored as a PDF file for later viewing. Based on the absence of P-waves and irregularity of the RR interval, the associated algorithm within the application produces a potential AF diagnosis [21].

The Lau et al study [22] took a group of 109 patients, 39 of which were in AF, and used the AliveCor algorithm to analyse the rhythms, obtaining a sensitivity of 87% and specificity of 97% when compared to interpretation by a cardiologist. The algorithm was then altered by increasing the weighting of absent P waves in the diagnostic process, and recordings were carried out on this same set of patients. The optimized algorithm was found to have a sensitivity of 100% and specificity of 96%. A second set of 204 patients, with 48 having known AF, were then analysed by the optimized algorithm, which obtained a sensitivity of 98% and specificity of 97% in this second data set. Other studies have largely found the sensitivity of the AliveCor device to be in the region of 90-98%, with specificity values ranging from 29.2% to 99% in various studies [23-28]. However, a study into the use of AliveCor in inpatients on cardiology and geriatric wards only found a sensitivity of 54.5% and 78.9% respectively for these groups [25], whereas another study published in 2017 used the AliveCor algorithm as a control, found a sensitivity of 71.4% for AliveCor [29]. A study of 13,222 patients identified 101 participants to have previously undiagnosed AF, with 65.3% of these patients reporting no symptoms prior to this diagnosis [23]. The device is generally well tolerated and report patients finding it easy to use [26]. Implementation of the AliveCor in community healthcare settings has also been investigated. Patients generally responded positively to the suggestion of an ECG being carried out by a pharmacist while they were attending the pharmacy for other purposes [30]. However, some patients were unwilling to have this carried out for fear of discovering something was wrong. In a primary care setting, the use of AliveCor was well-received by patients but staff had some reservations about being involved due to a self-perceived lack of knowledge [31]. Patients also report that they felt more confident in managing their AF through using the application [26, 32]. The AliveCor device [17, 33-35], has also been incorporated with patient education to increase the knowledge of the patients about AF [36]. Mobile applications have been extended to monitor paroxysmal AF for intermittent anti-coagulation [37].

**Atrial fibrillation – CardioRhythm app**

The detection of AF by analysis of finger and facial PPG signals using the CardioRhythm smartphone application has been tested in two recent studies. In the study by Chan et al [29], finger PPG waveforms of 20 seconds duration were captured 3 times using an iPhone 4S
equipped with the CardiioRhythm application and compared to the AliveCor single-lead ECG as referenced. Finger PPG waveforms were captured using the LED flash of the iPhone and the camera, which detected reflected light to measure the arterial pulsation. These waveforms were recorded at 30Hz, with the duration of each recording being 17.1 seconds, and were filtered with a bandpass filter using a range of 0.7-4.0Hz. AF was diagnosed from this if two of the three PPG recordings were irregular. This was defined as a lack of repeating pattern, using a Support Vector Machine to classify the waveforms as similar or non-similar to other waveforms. Analysis of the diagnoses put forward by the CardiioRhythm app in this study showed a sensitivity of 92.9% and specificity of 97.7% in detecting AF, compared to a sensitivity of 71.4% for the AliveCor device that was obtained by this study. This study found the specificities for the two devices to be comparable.

In another study by Yan et al, the CardiioRhythm application was used to analyze facial PPG signals in 217 patients recorded using the front camera of an iPhone 6S without physical contact (Figure 1) [38]. Three successive 20-second recordings were acquired per patient. Pulse irregularity in ≥1 PPG readings or 3 uninterpretable PPG readings were considered a positive AF screening result. The CardiioRhythm facial PPG application demonstrated a sensitivity of 94.7% and specificity of 95.8%. The positive and negative predictive values were 92.2% and 97.1%, respectively.

Figure 1. (A) Patient set-up (B) CardiioRhythm application facial PPG analysis interface (C) Complete facial PPG signals report.

Atrial fibrillation – FibriCheck app
A recent study conducted by Mortelmans et al. [39] used the PPG application FibriCheck. The patient places the left index finger over the flashlight and camera, holding their finger horizontally and keeping the finger in place for one minute. To ensure an accurate reading, the screen becomes red when appropriate contact has been made and the practitioner manually commences the measurement. The amount of light that is reflected onto the camera is then captured; and used to calculate the variation in local arteriole blood volume pulse variation. The rhythm of the pulse is then identified based on the R-R interval. The application in the smartphone then judges the quality of the signal based on the detection of the pulse. If the
detection was masked with noise, or beats were absent, these recordings were not included in the application’s analysis. When measurements were detected as a good signal, this data was interpreted by the AF algorithm. Concurrently with the PPG measurement, a single-lead ECG was taken and analysed by the FibriCheck application. Selection of the data took place based on quality, and good quality measurements were analysed by the AF algorithm, using variability between R-R intervals to detect irregularities. The FibriCheck app was used on an iPhone 5s. With 242 participants, this study found a sensitivity of 98%, specificity of 88% and accuracy of 93% for the FibriCheck algorithm when the data was obtained via PPG. Interpretation by the application of single-lead ECG performed better, yielding a sensitivity of 98%, specificity of 90% and accuracy of 94% when compared to standard ECG. When comparing the two methods by false positive results, when analysed by FibriCheck, 8 false positives were produced from a trace obtained by PPG measurement and 11 false positives were produced from a trace obtained by a single-lead ECG.

Atrial fibrillation – other methods of detection

Some studies have looked at the use of the Inertial Measurement Unit (IMU), using modern microelectromechanical (MEMS) sensors already present in smartphones, to detect AF [40]. The patient is advised to lie supine and place the smartphone on their chest. The accelerometer of the smartphone, which detects the orientation of the phone, can detect cardiogenic movements of the chest. The movements detected are those caused by the opening of the aortic valve, and so the interval between each successive valve opening is recorded and considered in order to determine the presence of AF. This yielded a sensitivity of 93.8% and specificity of 100% in the detection of AF. A similar study used the MEMS sensors of smartphones in order to obtain measurements, which when analysed by machine learning methods found a sensitivity of 98.5% and specificity of 95.2% in its best performing method [41].

The feasibility of producing a wearable sensor that records heart rate and transmit information to a smartphone application was examined [42]. The way this application identifies AF is similar to the FibriCheck App. As an example, a 42 year old male admitted with new-onset AF of undetermined duration, was deemed appropriate for electrocardioversion due to his FitBit Charge HR device recording the time at which increased heart rate was observed, allowing the onset of AF to be identified [43]. In a study by Yan et al. the diagnostic accuracy of the CardiioDeepRhythm application, a deep convolutional neural network for detecting AF from PPG signal acquired using an off-the-shelf wrist-worn device (Empatica E4, Milan, Italy) was tested on 51 in-hospital patients, reporting a sensitivity and specificity of 93% and 94%, respectively [44]. These findings demonstrate the promising value of PPG sensors for ambulatory AF monitoring. Krivoshei et al [45] conducted a study investigating the use of PPG in AF with a view to implementing the technology in a smartwatch; the protocol for this trial was published in abstract [46]. Table 1 summarizes the sensitivities and specificities of the applications in AF detection. Further research is required to fully understand the potential role of smartwatches in this area.

Table 1. Sensitivities and specificities for five applications in AF detection.
Heart rate and heart rate variability

Heart rate
There has been considerable innovation in the use of smartphone applications for the purpose of heart rate monitoring in adults. In particular, numerous studies have investigated the potential of two specific methods – seismocardiograms (SCG) and PPG – in producing accurate heart rate measurements. Landreani et al., for instance, described the application of SCG and ballistocardiogram (BCG) signals for heart rate monitoring applications in smartphone-embedded accelerometers [47]. This is achieved by determining the R-R interval of sufficient amplitude, and subsequently detecting the fiducial peak from the SCG and BCG signals. In PPG, the accuracy of this method was also demonstrated in a study by Alaleef et al, who found a 99.7% accuracy and maximum absolute error of 0.4 beats/min [48]. The accuracy and feasibility of PPG signals from smart phone applications also varied between different types of PPG applications. In Parpinel et al., higher feasibilities and accuracies were found for contact PPG-based applications compared to the non-contact PPG-based ones [49]. Koenig et al [50] found that their algorithm using PPG to assess heart rate had a consistent accuracy when compared to ECG (R>0.99).

Gold standards and validation of smartphone HR apps
While there is currently no consensus on the gold standard for the validation of heart rate apps, Vanderberk et al. suggested the comparison of the heart rate on smartphone applications with an ECG system via R-R intervals. With regards to the actual accuracy of these smartphone application, there was no significant difference (p = 0.92) found between the interval measurements of the heart rate application and the ECG system, suggesting that the heart rate applications have a comparable accuracy with ECGs [51].

Heart rate applications in different fields
The use of heart rate applications has been tested in different clinical settings. In a specific app reviewed by Chaudhry et al. named “Unique Heart Rate Monitor”, PPG was used for the measurement and categorization of workout intensity, it also allows subjects to check their heart rate in response to medical therapy [52]. The clinical use of HR apps during exercise was also assessed by numerous studies. In particular, some studies noted that the measurement accuracy tended to differ at different exercise intensities. In one study, the application had higher measurement errors at increased exercise intensities when compared with Holter echocardiography monitors; however, it had similar accuracy to the Holter monitor at resting and recovery stages [53]. Yan et al. presented similar findings, although the correlations between the facial PPG estimated heart rate and ECG heart rate had smaller variations (r= 0.997 upon resting compared to 0.982 with post-moderate intensity exercise) [54]. Furthermore, it was also found that both iOS and Android operating systems, with the same heart rate application, had concurrent validity with an FT7 Polar heart rate monitor at rest and at post-exercise time points [55]. While many studies reported the use of smartphones as the media for measuring and interpreting heart rates, some studies used smartphone applications as a feedback system rather than the actual heart rate sensor. Through the use of Bluetooth communication, subjects had their heart rate measured by a specially-devised heart rate sensor at different exercise intensities, and this information was transferred via Bluetooth back to the smartphone for analysis based on existing information during the pre-exercise period [56]. In addition, some cardiac heart rate monitors have a built-in alert system with real time bradycardia and tachycardia arrhythmia detection. In the study by Golzar et al., users
reported almost zero delays with data transmission and a 91.62% performance accuracy in comparison with regular ECG monitoring [57].

Apart from using heart rate apps for exercise heart rate monitoring, other studies also investigated the potential use of heart rate monitoring to reduce the exercise-induced risk of hypoglycemia. Studies used heart rate as part of a feedback system in closed-loop control artificial pancreas studies and found that heart rate monitoring reduced the blood glucose decline during exercise (p = 0.022), was an indication of lower blood glucose index (p=0.3) and resulted in fewer hypoglycemic events during exercise (p= 0.16 for none versus two events) [58].

The use of camera-based PPG has also been suggested for use in other age-groups, including infants and the newborn. Although the method has reported inaccuracies due to subject movements throughout the day, Kevat et al. found that this method of heart rate measurement had increased clarity and precision in neonates receiving phototherapy [59]. Although this specific application of PPG may have potential use in paediatric patients, the inaccuracies of this method in remains. Thus, when PPG is compared to normal ECG monitoring, different phone apps had lower accuracies for heart rate measurements using the finger/toe, but higher at the ear-lobes. Heart rate measurements were inaccurate above 120 bpm [60]. These results suggest that the technique is still evolving and requires considerable research before implementing it as a standard alternative to regular ECG heart rate monitoring for pediatric populations.

Apart from heart rate measurements in neonates and children, android-based heart rate apps have also been developed to track and increase adherence to certain activities such as breathing awareness meditation (BAM). In the study by Gregoski et al., a tension tamer (TT) heart rate app utilized PPG via phone camera lens to transmit time-stamped heart rates back to the hospital server for real-time adherence collection [61]. However, the very small sample size prevents definite conclusions to be drawn. The inaccuracies of these smart phone applications were also found in the context of foetal heart rate monitoring by Soffer et al., who reviewed 30 unique apps and found that over 33% of the applications did not put disclaimers and/or provided false medical information [62].

While PPG has been widely investigated, the use of smartphones to generate phonocardiograms has been reviewed by many investigators such as Chen et al. who used the iPhone 4s to record heart sounds from subjects at rest or post-exercise, and used these sounds for heart rate calculation in phonocardiograms via the peak-based-detection method [63]. Although the use of this online PCG-template extraction and matching was found to be accurate, however more statistical analysis needs to be done to validate this finding.

**Heart rate variability**

Apart from heart rate, heart rate variability (HRV) measurements in smartphone applications have also been extensively researched. With the use of PPG, Bolkovsky et al. used both Android and iphone smartphones to obtain R-R intervals and subsequently deduce HRV via complex HRV algorithms. Although the results were statistically the same as the ECG gold standard, the main issue was the insufficient sampling rate in both phones (20 Hz in Android and 30 Hz in iphone) which was below the suggested rate of 250 Hz [64]. Smartphone PPG has also been advocated by Plews et al., who reported almost perfect correlations of PPG with the ECGs (R = 0.99), with acceptable technical error of estimates (TEE) and trivial
differences in standardized differences [65]. The accuracy and reliability of smartphone PPGs have also been validated in other studies; in some cases, smartphone PPGs were found to have comparable accuracies to commonly used HRV computer software programs (R = 0.92) [66]. Other methods of HRV measurement have also been studied, such as seismocardiography. While sampling frequency from smartphone devices accounted for a significant source of error, R-R series measurements differed by less than 10 ms in some studies, suggesting the comparable accuracy of this measuring technique [67].

While many studies support smartphone PPG, common errors in using this low-cost technology include frequent noise and artifacts in measurement. To reduce the impact of noise, however, Huang et al. proposed the use of a continuous wavelet transform (CWT) denoising technique to extract the pulse signal, and subsequently deduce the R-R intervals in the denoised signal. The experiments showed low mean absolute errors of only 3.53 ms, highlighting the efficacy of this proposed method in reducing smartphone PPG errors. The use of this technique for error reduction should thus be investigated further [68].

Although methods have been proposed to reduce the impact of noise and artifacts in HRV measurement, other studies have investigated the effect of smartphone models on the beat-to-beat error measurement (SDE) of HRV indices. In one study, two different smartphone models (Samsung S5 and Motorola) showed significant device influence in the supine posture measurement, with the Motorola model having a higher SDE than the Samsung S5 [69].

**Application of Heart Rate Variability**

In one case report, Lai et al. reported the potential use of heart rate variability measurement analysis in monitoring concussed athletes, as well as assessing their capacity to “return-to-play” [70]. Via an “AliveCor smartphone ECG” application, HRV parameters were statistically significant in symptomatic and recovered concussed athletes. However, the study noted that this difference was affected by the severity of traumatic brain injury, while other similar studies reported no difference in HRV parameters [71, 72]. Other studies also proposed the potential use of smartphone derived HRV in athletic training programmes; for instance, collection of daily HRV data on smartphones using ultrashort HRV measures provides trainers with numerical indicators on athlete coping and adaptation [73]. Similar studies by Flatt et al. also found that measuring the log-transformed root mean square of successive R-R intervals multiplied by 20 (lnRMSSDx20) obtained by smartphone applications were sensitive markers to the changes in training load in soccer team’s training programme [74].

HRV by smartphone apps have also been utilized as an accurate predictor of acute mountain sickness (AMS) at high altitudes. In one study, Mellor et al. reported lower HRV scores in mild and severe AMS compared to those without AMS (p = 0.007), and found that a fall in HRV >5 had an 83% sensitivity and 60% specificity of identifying severe AMS. Since this is the first study of its kind, further studies should be conducted to confirm these findings [75].

HRV measurement by smartphone apps was also investigated with regards to the autonomic nervous system and mental health. For instance, Heathers et al. found that pulse rate variability (PRV) could be measured by smartphone substitutes with accuracies ranging from 2 to 5% for low and high frequency spectral power respectively [76]. Smartphone apps thus may play a future role in psychophysiological research. In addition, smartphones have also been used in stress classification via the use of night-time HRV data, and as a monitoring tool
for mental stress in different psychological settings [77, 78]. The drawbacks of these studies, however, are the fairly low accuracies (59%) and that the HRV measurements were confined to ultra-short time periods. The potential for long-term measurement should thus be investigated [78].

Limitations

Photoplethysmography
Despite being effective in accessing HR and HRV, the applications of PPG monitoring are limited by multiple confounders such as finger pressure, skin tone, light intensities and user movement leading to artefactual measurements [79, 80]. As such, this will have an impact on the feasibility and reliability of smartphone-based PPG within clinical practice. A minimum sampling rate is necessary for clinically accurate measurements – 30Hz for HR and 200Hz for HRV measurements [81, 82]. However, the frame-rate of smartphones usually operates around 30Hz, which is a major limitation identified by Bolkhovsky et al. [64]. It was proposed that using cubic interpolation, the second derivative and the zero crossing algorithm instead of minima detection would overcome this limitation and allow for better HR detection [83-86]. A filter is required to remove artefacts without compromising the original signal when conducting time domain analysis to evaluate small variations occurring in N-N intervals [87]. Examples of filters are independent component analysis using accelerometer data to remove artefacts [88] or employing a 4th order bandpass filter [83, 85]. A heating problem was also noticed by Garcia-Agundez et al. when testing their algorithm, which resulted in complaints about the discomfort of holding the smartphone [86]. Furthermore, while the SCG accelerometers could be used without supporting ECG signals, heart rate detection was only possible if patients were motionless and supine, leading to considerable variability in data collection due to different measurement positions. There were also difficulties encountered in setting appropriate R-peak thresholds, and in comparing the data with simultaneous ECG signals (the gold standard technique) [89, 90].

Handheld ECG recorders
For handheld single lead ECG recorders, which corresponds to the standard lead I, it does not cater to potential positional variability. For example, in cases where the heart is positioned more vertically, the amplitude of the QRS complexes may be reduced and comparable to the amplitude of artefacts [14]. Furthermore, a single recorded lead I ECG also does not allow for differentiation between types of narrow and wide complex QRS tachycardia [14]. Though small studies have been conducted to show that it is plausible to use a one-lead ECG to diagnose ST-segment elevation acute coronary syndrome [91], it is not sufficient to warrant routine clinical use. In some situations, new materials and sensors (e.g. biopatches) have allowed for these ECGs to be recorded from atypical places (e.g. mastoid area) [92] and under different environmental conditions like after immersion in water or in areas with magnetic fields between 1.5 and 3T (during magnetic resonance imaging) [93-96]. Novel biopatches have also allowed for other parameters such as respiratory rate, body position, temperature, and quality of sleep or physical activity to be monitored, which aids in excluding ST-depression caused by increased physical activity or changes in body position [19, 97, 98]. However, when this is coupled with fewer leads, not only will there be suboptimal signal-to-noise ratio, signals generated might be different from those produced by standard ECG leads [14]. Furthermore, the utility of biopatches comes with a drawback of having a short inter-sensor distance, which could potentially compromise the quality of the P wave recorded [14].
**Healthcare infrastructural implementation**

Despite being a promising concept, there are currently clear limitations to the use of smartphone applications for HR, HRV and AF monitoring. Looking beyond the technological drawbacks, there is little evidence as to how smartphone monitoring will be matched with healthcare infrastructural changes to allow for such data to sync with the electronic medical record [99, 100]. Furthermore, not all patients will have the same device or smartphone, which may result in different recorded results. Special clinical attention also has to be given to incidental findings of ECG abnormalities such as ventricular and supraventricular tachycardia in asymptomatic low risk patients [14]. The impact of application use on healthcare services is also not to be underestimated; the necessity for a healthcare professional to confirm arrhythmias detected by these applications will result in a significant burden on services. Given the transient nature of some arrhythmias, an application with a high specificity is likely to be more beneficial to avoid over-investigation and treatment of patients, reducing the impact on existing services.

**Conclusions**

In this study, we conducted a systematic review of the literature surrounding the usage of smartphone applications in the monitoring of heart rate and rhythm. The findings of this narrative review suggest that there is a role for smartphone application in the diagnosis, monitoring and screening for arrhythmias and heart rate. The usage of applications in specific situations, such as during and following exercise or to measure corrected QT interval following the administration of medications, has also shown a role for the applications in more specific scenarios. While the majority of literature reviewed focused on adult patients, the use of PPG applications in paediatric and neonatal patient populations require further studies.

Some problems identified with the use of these devices have included patient movement resulting in artefact, and in positional variability in patient usage affecting results. This has been demonstrated in studies investigating both adult and paediatric patients [101]. There is also an issue regarding consistency and availability of smartphones, with variation in the devices used. Given the impressive degree of sensitivity (>90%) and specificity (>90%) in most cases/applications, neither sensitivity nor specificity is more important than the other. Instead, it is important for both sensitivity and specificity to be maintained at a high level or be on par with the standard ECG, especially in patients with pacemakers or ICDs [102]. Therefore, further studies are required to address these issues before they can be routinely implemented.

**Acknowledgements**

GT would like to thank the Croucher Foundation of Hong Kong for their support. The International Research Mentorship Programme organized by the Newcastle University Cardiovascular Society supported FW and TT.

**Author Contributions**

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.
Conflict of Interest
The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations
AF: atrial fibrillation
AMS: acute mountain sickness
Apps: applications
BAM: breathing awareness meditation
BCG: ballistocardiogram
CVD: cardiovascular diseases
CWT: continuous wavelet transform
ECG: electrocardiograph
FMECG: frequency and modulation index
HR: heart rate
HRV: heart rate variability
ICD: implantable cardioverter defibrillator
IMU: inertial measurement unit
LED: light-emitting diode
MEMS: microelectromechanical sensors
PPG: photoplethysmography
PRV: pulse range variability
SCG: seismocardiogram
SDE: beat to beat error measurement
TT: tension tamer
References


