Abnormal heart rate detection through real-time heart monitoring application

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Article Info

Article history:

Received Oct 4, 2022
Revised Dec 27, 2022
Accepted Jan 26, 2023

Keywords:

Heart monitoring
Mobile health
Patient-oriented
Real-time
Wearable technology

ABSTRACT

Health monitoring that requires doctors and patients at the healthcare center may not be practical during the coronavirus disease 2019 (COVID-19) pandemic. Alternatively, mobile health (mHealth) should be embraced to minimize contact between patients and healthcare personnel. This research aims to enhance the detection of abnormal heart rate (HR) detection by developing a real-time heart rate monitoring (RTHM) application. Sixteen healthy adults participated in a physical real-time HR monitoring testbed. Participants HR was measured for three minutes resting and three minutes performing moderate-intensity physical activity. The results were compared with the polar beat app. Additionally, the energy consumption, the time taken to receive an alarm message, and an acceptance test were analyzed. The app is acceptably accurate, the mean absolute percentage error less than 2%. The response time to receive the alarm message is 30 seconds on average, which is under an acceptable range of medical standards. Moreover, the app is power efficient, 477 mW on average. Participants show a positive attitude towards using RTHM. RTHM is expected to provide a more plausible tool for monitoring the heart towards enhancing abnormal HR detection by promoting patient-oriented healthcare and minimizing sudden deaths due to heart failure.

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1. INTRODUCTION

Doctors play a major role in the traditional approach of health monitoring. It requires doctors and patients together present at the healthcare center for diagnosing and treatment. In some cases, patients have to be admitted to a ward and wired to bedside biomedical devices for a lengthy period. However, the approach may not practical during the coronavirus disease 2019 (COVID-19) pandemic that is affected globally. Coronavirus is an extremely infectious virus related to substantial morbidity and mortality. Minimizing contact between healthcare personnel and patients who have COVID-19 is a vital step in controlling its spread. Moreover, social distancing should be practiced. Instead of the face-to-face visits, many electrophysiology consultations may possibly have done by reviewing the chart and monitoring data. Alternatively, telehealth, remote monitoring, or virtual visits through secure internet, phone, or video should be embraced to reduce unnecessary COVID-19 exposure to patients and healthcare personnel [1]. As opposed to the traditional approach, the modern approach is patient-oriented whereby patients play a more active role in disease diagnosis and prevention [2]. Therefore, a reliable and readily available patient monitoring system is crucial in the patient-oriented approach.

The development of healthcare monitoring applications has been progressing toward larger patient mobility and physiological sensor independence. Over 94% of the world population, accounted for 6.8 billion people, are subscribers of mobile phone, and about 2.7 billion subscribers are using the internet [3]. More than 60% of mobile phone users utilize their phones to access health information and acquire education about illnesses and health conditions [4]. Moreover, the number of connected wearable devices worldwide is projected to increase from 526 million in 2017 to over 1.1 billion in 2022 [5]. Unobtrusive and wearable heart rate (HR) sensors allow data to be collected and reported automatically, thus reducing the cost and inconvenience of regular visits to the clinic. Bluetooth electrocardiogram (ECG) sensor that used to monitor the heart may transmit medical data to a mobile phone that provided a low cost and lightweight alternative to existing ECG event monitors [6].

QardioCore (Qardio®, San Francisco, CA, USA) is designed for day-to-day continuous ECG monitoring by using a chest strap ECG sensor [7]. The CardioCore is used together with cardio app to visualize live ECG records in charts, and graphs to analyze the patterns of the heart records. The user can share 30 seconds of their ECG records with physicians by email. On the other hand, AliveCor KardiaMobile ECG device (AliveCor®, Mountain View, CA, USA) is a single-lead ECG device [8]. The device records ECG data from a user's fingers placed on the KardiaMobile's electrodes. The ECG recordings can be viewed and saved by Kardia app. The app is capable to detect atrial fibrillation and abnormal HR with at least 30 seconds of ECG recording [9], [10]. Once the ECG is completed, the app notifies users their heart status. Similarly, Zenicor-ECG (Zenicor EKG® thumb, Stockholm, Sweden) records 10 to 30 seconds ECG data from a user's thumbs placed on two electrodes of the Zenicor-ECG [11]. Zenicor-ECG doctor system is a web-based system that enables physicians to save, process, and view their patients ECG recordings. The system has ECG analysis for a faster and safer diagnosis. Moreover, both ECG app on apple watch series 4 or later (Apple Inc., Cupertino, CA) [12] and samsung galaxy watch app (Samsung, Seoul, South Korea) [13] records 30 seconds ECG reading. The ECG record is similar to a single lead ECG. The app is designed to detect atrial fibrillation. Once the 30 seconds ECG reading is successfully, the app shows classification of the result known as sinus rhythm (normal HR), atrial fibrillation (irregular rhythm), and inconclusive (cannot be classified). In addition, ECG app on apple watch has low HR, or high HR classification. The user can share the ECG recording results with physicians exporting the results in a PDF file format. The drawback of the existing heart monitoring apps is the apps do not send an alert notification and patient's location to care givers, physicians, or medical when abnormal HR occurred. The alert notification is very vital especially for cardiac patients, hence an instant action or treatment can be taken to safe life.

Although smartphones along with wearable technology and cloud computing can offer a new potential of the real-time and patient-oriented heart monitoring system, concerns are there that may possibly affect the performance of the heart monitoring system. The concerns include accuracy of the heart reading, reliable data transmission, response time to alert concerned entities when abnormal HR occurred, battery issues, and user-friendliness of the system [14]–[16]. The current study addresses the concerns raised by proposing a real-time heart monitoring (RTHM) application by integrating a wearable HR sensor and a smartphone. Subsequently, RTHM application is validated in terms of accuracy, response time, energy consumption, and users' acceptance. The RTHM is an android-based HR monitoring app intended to real-time monitor and to early detect abnormal HR. A wearable HR sensor is used to generate HR data which is then transmitted to a smartphone wirelessly through bluetooth low energy (BLE) technology. Further, the collected data and the HR monitoring results are transferred to a cloud database. The proposed system generates an alert notification when an abnormal HR is detected.

The remainder of this paper proceeds as follows. Section 2 discuss system architecture and implementation. Research methods in the course of participants, experimental design, and data analysis are explained in section 3. Next, section 4 presents the results obtained from this study and follow with discussion. Finally, section 5 concludes the study with some indication for future work.

2. THE PROPOSED SYSTEM ARCHITECTURE AND IMPLEMENTATION

2.1. System architecture

RTHM uses three-tier architecture, as illustrated in Figure 1. Wearable HR sensor is the first tier. The sensor provides heart data as the input to RTHM. It transmits wirelessly the heart data by using a Bluetooth connection to the smartphone that installed the RTHM app. The smartphone is the second tier, responsible for heart data extraction, HR variability features calculation, analysis, and display of the results of the HR monitoring. A cloud server is in the third tier. The cloud server is the storage system and data access layer. Users profiles and the results of HR monitoring are stored in the cloud server. Wireless communication such as Wi-Fi and 5G connection could transmit the results of HR monitoring to the cloud server.

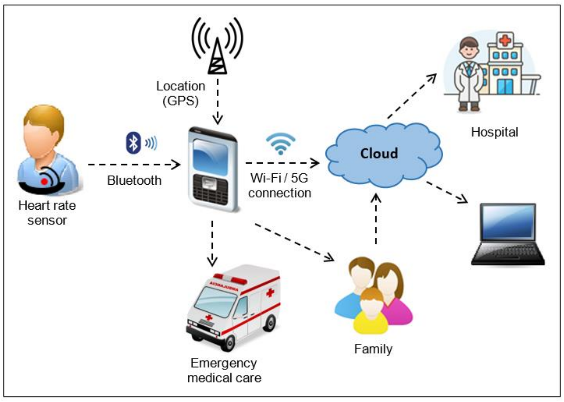


Figure 1. RTHM architecture

2.2. Data acquisition

Polar H10 (polar electro oy, Kempele, Finland) has been chosen as the wearable HR sensor to collect heart data and then transferred it to a smartphone. Polar H10 is a chest-strap HR sensor. It measures HR based on the electrical activity of the heart. It comes with the pro strap that has seven distinct areas that are engineered to guard against electrical noise and to conduct a proper ECG measurement [17]. Polar H10 uses BLE to transmit data to other devices including smartphones. The sensor is selected because its reading is highly accurate despite intense activities with strong body movements and provides continuous measurement [17], [18]. Prior to data acquisition, a user is required to wear Polar H10 below his chest muscles. The smartphone that installed RTHM app is connected to polar H10 for round-Robin (RR) intervals data transmission via Bluetooth link. When polar H10 detects skin contact, BLE starts to advertise to be connectable with the smartphone that installed RTHM app. The app sends a connection request by clicking on the “search sensor” icon as illustrated in Figure 2.

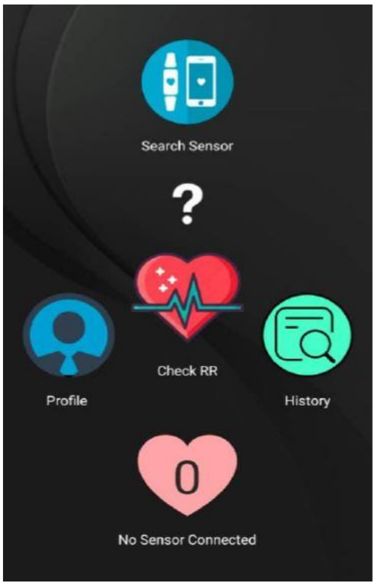


Figure 2. Main menu

Once the connection has been established between polar H10 and the smartphone, data acquisition from polar H10 to the smartphone can be started by clicking on the “check RR” icon as shown in Figure 2. The sensor transmits RR interval values with a resolution of ms (unit of 1/1024 seconds) to the phone at 1-second intervals. The default duration for the RR data acquisition is three minutes. If the polar H10 sensor does not detect skin contact for 20 to 30 seconds, the sensor will terminate the Bluetooth connection and switch to a standby mode to save power. Figure 3 illustrates the flowchart of data acquisition from a wearable HR sensor to a smartphone.

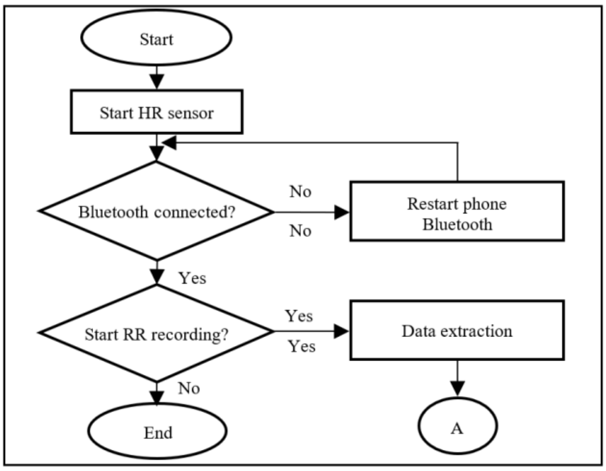


Figure 3. Flow chart of data acquisition

2.3. Detection of abnormal heart rate

HR is the number of heart beats per minute (bpm) measured. It indicates the pumping efficiency of the heart. Table 1 presents the threshold for HR classification. The HR is considered normal when the ranges between 60 and 100 bpm for adults. The abnormal HR can either be too slow (bradycardia) or too fast (tachycardia). HR less than 60 bpm is classified as bradycardia, whereas tachycardia for HR more than 100 bpm [19]. Figure 4 shows the flowchart of abnormal HR detection. The HR measurement of three minutes (default measurement duration) is displayed on the app screen. Abnormal HR is detected when the HR less is than 60 bpm (bradycardia) or greater than 100 bpm (tachycardia). A pop-up message will be displayed to get confirmation from the user for sending an alert notification to the family or emergency medical care (EMC). The alert notification will be sent to the family or EMC via WhatsApp if the user clicks on the "ok" button or does not respond (click neither "ok" nor "cancel" button) after 30 seconds (default response waiting time) as illustrated in Figure 5(a). The alert notification contains the user's name, HR reading, and his current location as shown in Figure 5(b). The results are then sent to the firebase cloud server via Wi-Fi or broadband cellular network of the smartphone.

Table 1. Threshold for HR classification

Type	Heart rate (bpm)
Bradycardia	HR<60
Normal	60≤HR≤100
Tachycardia	HR>100

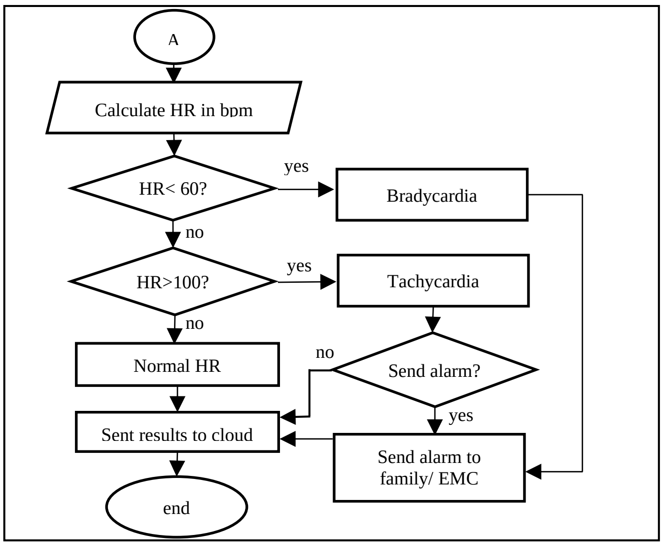
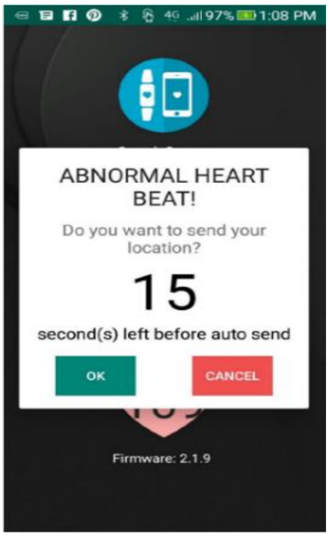
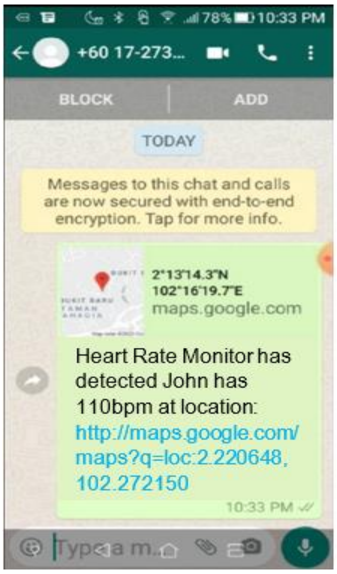


Figure 4. Flow chart of abnormal HR detection



(a)



(b)

Figure 5. Graphical user interface for (a) request permission to send an alarm message and (b) alert notification

3. METHOD

3.1. Participants

The primary author identified potential participants and contacted them via telephone. Sixteen (nine females and seven males) adults whose age between 18 and 52 years old (age 28.6±10.3 years old, body height 165.5±7.3 cm, body weight 65.2±13.7 kg, body mass index 23.8±4.6 kg/m^2) agreed to participate in this study. All participants are healthy and free from cardiovascular diseases. None of them were taking any medicines affecting the HR. The participants completed a written informed consent form and physical activity readiness questionnaires prior to taking part in the study.

3.2. Procedures

A physical real-time HR monitoring testbed was set up to evaluate: i) the accuracy of RTHM under resting condition and moderate-intensity physical activity, ii) the response time to receive an alert notification when abnormal HR is detected, iii) the energy consumption, and iv) users acceptance of RTHM app. The polar beat app was used to compare the accuracy of RTHM under resting conditions and three minutes of moderate-intensity physical activity including jogging on a treadmill at 11 km/h (gait activity), jumping jack, and jog in place. Polar beat is a fitness, running, and workout app by polar. The app features include live HR, tracking, and analyzing users workouts. The data collection was scheduled during the daytime (8.00 am–5.00 pm; temperature 31.2±1.4 °C). A room equipped with a treadmill, body weight and body height scale, polar H10, and mobile phones was prepared for the data collection. All participants were told not to refrain from any kind of diet or activity. The physical readiness questionnaire and informed consent form were completed by all participants before data collection began. All participants' body weight and body height were measured. Prior to the HR monitoring, a polar H10 elastic electrode strap was placed below the participant's chest muscles as illustrated in Figure 6. The strap length was fitted to the participant's chest circumference as described by the manufacturer manual.

Bluetooth connection between RTHM app and polar H10 sensor as well as the Bluetooth connection between polar beat app and polar H10 sensor was confirmed. Each app was installed on two different phones. All participants were rested for five minutes before the heart monitoring begun. Subsequently, three minutes HR recording was done simultaneously using RTHM app and polar beat app. The participants were seated on a chair in resting condition during the recording. Next, participants rested for one minute before beginning the second HR recording. In the second recording, three minutes HR recording was done simultaneously using RTHM app and polar beat app during participants performing a moderate-intensity physical activity. If abnormal HR is detected by the RTHM app, the time taken to receive the alert notification via WhatsApp was recorded. 4G communication protocol was used to send the alert notification. Both phones were placed 10 m from the participant in both recordings. Both apps were handled by research assistance during the recordings. Moreover, the energy consumption in processing the HR monitoring starting from data acquisition until the end of the HR monitoring was measured by using an android app known as PowerTutor.

Next, participants rested for five minutes. Following, all the participants were asked to use RTHM app for five to ten minutes to test the users' acceptance. The intention and satisfaction level of the potential users to use RTHM app will be ascertained from the acceptance test. Consequently, all the participants completed the user's acceptance questionnaire. The instrument was a six-part questionnaire that consists of participant's demographic, and five constructs of compatibility, perceived usefulness, perceived ease of use, trust, perceived financial cost, and behavioral intention to use. All items in the questionnaire were measured by using 5 points likert scale.

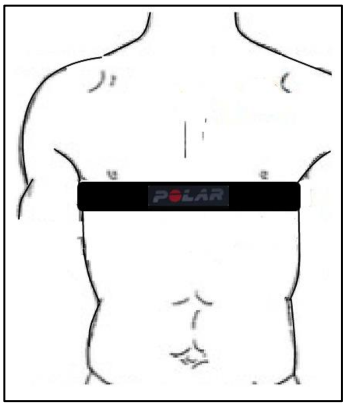


Figure 6. Schematic of polar H10 chest strap placement

3.3. Data analysis

Means and standard deviations (SDs) were calculated for the HR recorded by RTHM app and polar beat app. Pearson product-moment correlation was conducted to examine overall HR associations. The mean absolute percentage error (MAPE) was calculated to examine the measurement error of the RTHM app.

4. RESULTS AND DISCUSSION

There were sixteen participants in total. Table 2 displays a summary of participants demographics. Within the sample population, 9 (56.25%) were females and 7 (43.75%) were males. More than half of the participants (56.35%) were young adults whose ages between 21 and 30 years old. The majority of the participants (62.5%) had normal BMI. Their levels of education ranged from high school to doctoral degrees.

Means ± SD of the HR recorded from RTHM and polar beat app during resting conditions was 83.69±7.77 and 82.75±7.77 respectively, while 111.43±7.87 and 111.38±77.89 respectively during moderate physical activities. On average, the MAPE value of the RTHM was 1.79% during resting and 0.99% during moderate physical activities, which were off by 2%. The MAPE was lower during moderate physical activities than resting. Table 3 summarizes the comparison between RTHM and polar beat app during resting and moderate physical activities. The results were similar to the previous studies that reported a decrease in MAPE with increased physical activity intensity. They observed that the MAPE of running is slower than walking [20], [21].

Table 2. Summary of participants' profiles

Demographic variables	Categories	Frequency	Percentage (%)
Gender	Female	9	56.25
	Male	7	43.75
Age	11-20	3	18.75
	21-30	9	56.25
	31-40	0	0
	41-50	3	18.75
	51-60	1	6.25
BMI (kg/m^2)	<18.5	1	6.25
	18.5-25	10	62.5
	25-30	4	25
	>30	1	6.25
Education level	High school	6	37.5
	Diploma	3	18.75
	Bachelor	4	25
	Master	2	12.5
	PhD	1	6.25

Table 3. Comparison between RTHM and polar beat app in different activities

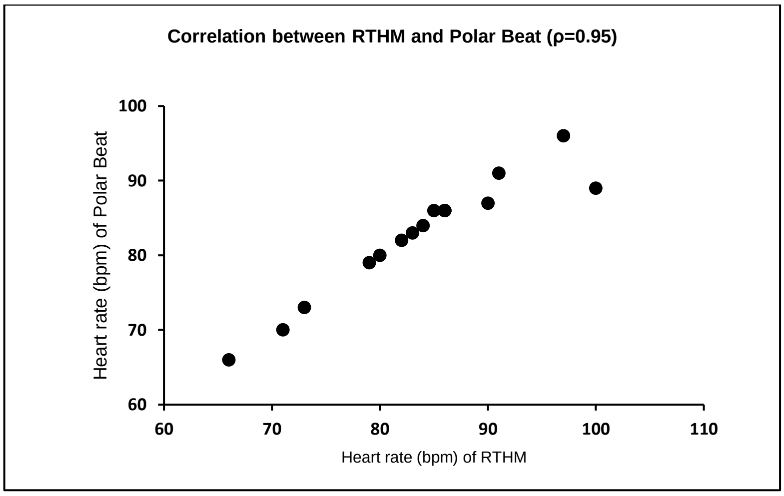
Activity	RTHM Mean±SD	Polar beat Mean±SD	Correlation coefficient (ρ)	MAPE (%)
Resting	83.69±7.77	82.75±7.77	0.95	1.79
Moderate physical activities	111.43±7.87	111.38±77.89	0.99	0.99

Moreover, Figures 7(a) and (b) show the correlation between RTHM and polar beat app during resting and moderate physical activities respectively. RTHM had a significant correlation with polar beat at the 0.01 level (2-tailed). The correlation coefficient value was 0.95 during resting and 0.99 during moderate physical activities. Overall, strong correlations were observed between RTHM and polar beat app during resting (ρ=0.95) and moderate physical activities (ρ=0.99). This suggests that RTHM would provide comparable accuracy to the more established HR monitoring app.

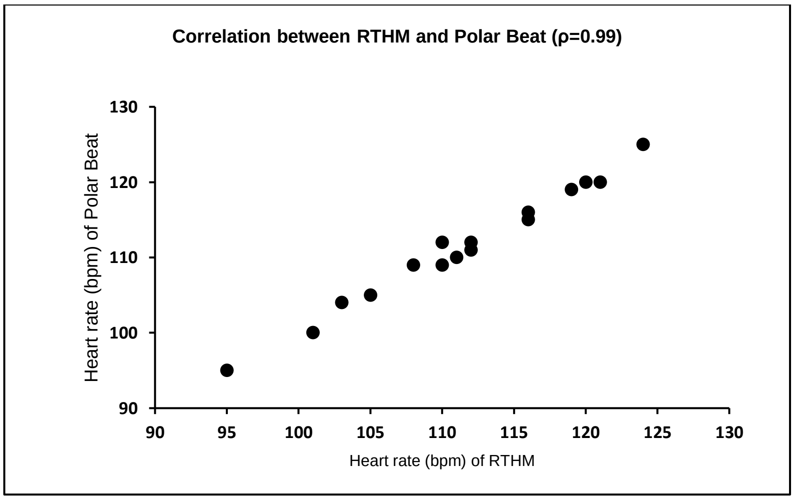
The design of an application impacts the smartphone battery life. It is highly recommended to design a low power consumption app to maximize its operational runtime over smartphones. In this study, power consumption was measured as the power consumed when a user used RTHM during three minutes of HR monitoring. The power consumed by RTHM was 477 mW on average. RTHM consumed about 15% less power as compared to the polar beat app. RTHM is an energy-efficient app that provides optimal performance with less energy consumption over a smartphone. Moreover, the app utilizes BLE for data transmission between the heart sensor and smartphone. The use of BLE ensures reduced power consumption without compromising the communication range [22]. Additionally, polar H10 stops BLE connection and switches to power saver mode when no skin contact is detected for 20 to 30 seconds.

The response time is measured as the time taken to receive an alert notification via WhatsApp when an abnormal HR is detected. Response time is critical among cardiac patients to minimize the risk of sudden death due to heart attack. The response time was 30 seconds on average. Kakria *et al.* [23] reported that the response time of their proposed health monitoring to send an alert notification from patient to doctor was 30 seconds with Wi-Fi networks and 56 seconds with a 3G network. AHA recommended the golden period of saving a cardiac patient between sudden fall or rise in cardiac vital signs and sending an alert notification to a cardiologist is in between four to six minutes [23]. Therefore, RTHM response time is less than the recommended ideal time. Response time is critical among cardiac patients to minimize the risk of sudden death due to a heart attack.

Table 4 presents a descriptive analysis of the constructs obtained from the acceptance test. All mean values were above 4.0 except for perceived financial cost, indicating that participants generally had positive evaluations on RTHM app. 93.75% of the participants believed RTHM is suitable for their lifestyles. Majority of the participants (95%) rated scale 4 (agree) and 5 (strongly agree) for all items under perceived usefulness, ease of use, and behavioral intention to use constructs. The perceived usefulness and ease of use of the newly designed HR monitoring app upturns participants' willingness to adopt the innovative technology. The results are consistent with previous studies [24]–[26]. Hence, the easier the new app to use; the more willing users will be to use and recommend it to their contacts. Moreover, all participants agree and strongly agree that RTHM app can help them with continuous HR monitoring. The results of the acceptance test showed that perceived trust is an important construct that can influence participants intention to use RTHM. More than 80% of the participants would use and recommend RTHM app to their friends.



(a)



(b)

Figure 7. Correlation between RTHM and polar beat app during (a) resting and (b) moderate physical activities

Table 4. Descriptive analysis of the user acceptance constructs

Construct	Mean±SD
Compatibility	4.25±0.58
Perceived usefulness	4.38±0.67
Perceived ease of use	4.38±0.57
Trust	4.56±0.51
Perceived financial cost	3.56±1.26
Behavioral intention to use	4.28±0.63

Conversely, technology cost is one of the barriers to technology adoption in healthcare [27]. In this study, about half of the participants perceived that a smartphone required to deploy the RTHM app is expansive. Further analysis indicated that most of the participants who perceived high cost ranged from 19 to 25 years old. Most of them had diploma degrees and still studying at the institute of higher education at the time the study was conducted. The financial cost is particularly pertinent to them considering that many of them are students and do not have financial income. Overall, the acceptance results indicated that participants show a positive attitude towards using RTHM for real-time HR monitoring.

5. CONCLUSION

This study proposed and validated the RTHM app for real-time heart monitoring and abnormal HR detection using a wearable HR sensor. The RTHM app is able to collect and process heart data collected from a wearable HR sensor and save the results to a cloud database. The accuracy of the app is found to be comparable to the more established HR monitoring app. Moreover, in comparison with the existing heart monitoring apps, RTHM is specifically designed to send an alert notification to a family member or EMC via Wi-Fi or broadband cellular networks when an abnormal HR is detected. The response time to send the alert notification is under an acceptable range of medical standards. In terms of power consumption, the app is power efficient due to its minimal design and utilizes BLE for data transmission. Realizing the usefulness and ease of use of the RTHM app in addition to trust, participants show a positive attitude towards using RTHM for real-time HR monitoring. RTHM is expected to provide a more plausible tool for monitoring HR towards enhancing abnormal HR detection by promoting patient-oriented healthcare and minimizing the number of sudden deaths due to heart failure. In addition, the app is suitable for healthy persons or athletes to continually monitor their HR for a healthy lifestyle.

ACKNOWLEDGEMENTS

This study was supported by the Universiti Teknikal Malaysia Melaka under Grant PJP/2019/FTMK(7B)/S01681 and JURNAL/2020/FTMK/Q00055.

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