Real-time monitoring tool for heart rate and oxygen saturation in young adults

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ABSTRACT
Health monitoring is crucial to maintain optimal well-being, especially for young adults. Wearable sensors have become popular for collecting healthcare data, but there are concerns regarding their reliability and safety, particularly with wireless sensors that use radio-frequency (RF) based devices. Researchers have proposed real-time monitoring systems for measuring heart rate beats per minute (BPM) and blood oxygen saturation (SpO2) saturation levels, but more studies are needed to determine the accuracy and user acceptance of these tools among young adults. To address these concerns, this study proposes a real-time monitoring tool that incorporates MAX 30100 sensors to collect heart rate BPM and SpO2 data. The collected data is then connected to a visualization platform, i.e., InfluxDB and Grafana, to provide valuable insights of the body’s physiological state. By testing the feasibility and usability of the tool, we found motivating differences in resting heart rates and changes in heart rate after activity between male and female participants. By developing this real-time monitoring tool and investigating gender-specific differences in heart rate and activity-induced changes, our study contributes to the advancement of health monitoring technologies for young adults, ultimately promoting personalized healthcare and well-being.

Keyword(s): Embedded device, Heart rate, Internet of things, Oxygen saturation, Sensors

1. INTRODUCTION
Monitoring heart rate in beats per minute (BPM) and blood oxygen saturation (SpO2) is important for young adults to maintain optimal health and prevent serious health issues [1]-[3]. Regular monitoring of BPM and SpO2 levels can provide valuable insights into the body’s physiological state, and may help identify potential health problems before they become more serious. This is especially important in today’s world, where young adults may be at increased risk of developing respiratory illnesses, including COVID-19 [4]-[6]. In addition to respiratory illnesses, young adults who engage in certain activities such as endurance sports or weightlifting may also benefit from monitoring their BPM and SpO2 levels during exercise to ensure they are performing at a safe level [7], [8]. By utilizing reliable real-time monitoring systems, young adults can stay informed about their BPM and SpO2 levels and take necessary steps to maintain optimal health and well-being.

Wearable sensors are commonly used to collect healthcare data, which can be transmitted using wired or wireless technology [9]. While wired sensors can be reliable, they can also be cumbersome, expensive, and power-intensive. Wireless sensors that use radio-frequency (RF) based devices, such as Bluetooth, ZigBee, and 6LowPAN, are often preferred due to their convenience and ease of use [10]-[12]. However, long-term exposure to electromagnetic radiation (EMR) from RF devices can potentially have negative effects on human
health and may also impact the performance of medical instruments. Additionally, RF devices are not always secure and can be affected by inter-channel interferences, which can compromise their reliability [13], [14]. As a result, there is a growing need for alternative technologies that can complement or replace RF-based devices, while ensuring the safety and reliability of healthcare data collection.

Several researchers have proposed and implemented real-time monitoring systems to measure BPM and SpO2 levels in various settings. For instance, Ahmed et al. [15] utilized an Atmel Atmega 328P microcontroller unit (MCU) and a MAX30100 sensor to detect COVID-19, while Wan et al. [16] designed a SpO2 monitoring system with a smartphone app using a MAX30100 sensor and Contex-M3 MCU. Similarly, Abbasi et al. [17] implemented a real-time monitoring system for critical individuals using red and infrared light-emitting diode (LEDs) and Arduino IDE. Tanam et al. [18] proposed a system capable of measuring BPM, SpO2, and body temperature, utilizing sensors with the Arduino Due, MULTISIM® software, and BASCOM® SIMULATOR program. Soni [19] used Arduino Uno microcontroller, infrared (IR) transmitter, infrared detector, and MCP602 Opamp to enable continuous heart rate monitoring. Das et al. [20] proposed an internet of things (IoT) enabled health monitoring system based on a Raspberry Pi and a cloud-based platform, while Bakhri et al. [21] designed a low-cost oximetry system using the MAX30100 sensor with Arduino Uno and Raspberry Pi. Susana and Tjahjadi [22] created a portable oxygen saturation monitor based on the Raspberry Pi for use in home care, and Tham et al. [23] developed an elderly real-time monitoring system that measures BPM and SpO2 levels using a Node MCU (ESP8266) microcontroller and MAX30100 sensor. These studies have proposed and implemented real-time monitoring systems for measuring BPM and SpO2 levels, but the accuracy and reliability of these systems can vary depending on the technology usage. While real-time monitoring systems can be beneficial for young adults, but they also require individuals to wear sensors or carry devices with them at all times. Thus, in this work, a real-time monitoring tool is designed to investigate the user experience and acceptability of the tool among young adults to identify any barriers or challenges that may prevent widespread adoption. The rest of the paper is organized as follows. Section 2 presents the proposed system design. Section 3 includes the experimental testing and results of the study. Finally, the paper is concluded in section 4.

2. SYSTEM DESIGN

In this work, an indoor scenario is considered, wherein an individual health is continuously monitored. We used the MAX30100 sensor to collect and monitor the individual BPM and SpO2 in real-time. The sensor is connected with a Raspberry Pi, and is composed of an LED light, modulated using the sensing data. Simultaneously, the data is transmitted to InfluxDB platform and Grafana was used to visualize the data. Figure 1 shows the block diagram of the proposed system.

![Figure 1. Block diagram](image)

2.1. Breadboard diagram and prototype

The breadboard diagram of the prototype is shown in Figure 2(a). The system uses Raspberry Pi 4 as a small single board computer, MAX30100 as a blood oxygen and heart rate sensor, and LED to alert when the result is abnormal. Besides, the prototype design is shown in Figure 2(b).

2.2. InfluxDB configuration

InfluxDB is a distributed time series database designed for high write and query loads, commonly used for storing and processing performance metrics, sensor data, and events. It is horizontally scalable, has a structured query language (SQL) query language, and can be integrated with various tools and platforms.
InfluxDB is popular in IoT, DevOps, and real-time analytics applications [24]. The installation and setup were made using a MAC OS through secure shell (SSH) to Raspberry Pi. Figure 3 shows the service that has been launched successfully.

2.3. Grafana configuration

Grafana is an open-source data visualization and monitoring platform that allows users to create and display data dashboards from various sources, such as InfluxDB, Prometheus, and Elasticsearch. It has a flexible web interface and a large plugin ecosystem for data visualization options. Grafana is widely used for visualizing time series data for internet infrastructure and application analytics, and in other domains such as industrial sensors, home automation, weather, and process control [25]. Like InfluxDB, Grafana was accessed on a Mac OS using SSH for this study. Figure 4 shows the service that has been launched successfully.
3. EXPERIMENTAL TESTING AND RESULTS

During the testing phase, a total of 18 participants were engaged to evaluate the performance of the system. The testing was carried out on 21st December 2022 at the Multipurpose Lab, Faculty of Information Science and Technology, Multimedia University. The participants were selected from diverse backgrounds, including individuals of different genders, to ensure a representative sample. The aim of the testing was to determine how well the system performs under practical conditions and to identify any issues or areas for improvement. The participants were instructed to carry out a series of tasks using the system, while their interactions with the system were monitored and recorded. The tasks were designed to assess the system’s functionality, and overall performance. The results of the testing are presented in this section, including a detailed analysis of the performance of the system. To begin the study, a survey was administered to the participants to gather initial data. The survey included participants of both genders, with representation of male and female respondents as shown in Figure 5.

According to the results obtained from the survey administered to the participants, it was found that most of them (55.6%) reported engaging in regular physical activity, either by playing badminton or basketball. On the other hand, the remaining 44.4% of the participants reported not engaging in any regular physical activity, as illustrated in Figure 6. These findings suggest that a significant proportion of the participants lead an active lifestyle, while a sizeable minority do not prioritize physical activity in their daily routines.

Figure 5. Participants gender data  Figure 6. Participants exercise/sports data

Besides, the survey responses obtained from the participants revealed that most of them (66.7%) engage in physical activity once a week, while a smaller percentage (11.1%) reported exercising or playing sports twice a week. Only a few participants (5.6%) claimed to engage in physical activity three times a week but not on consecutive days. Additionally, a significant number of participants (16.7%) reported not engaging in any form of physical activity at all, as depicted in Figure 7. These findings suggest that while many of the participants do engage in some form of physical activity, they may not be meeting the recommended course of action for regular exercise, which is at least 150 minutes of moderate-intensity aerobic activity or 75 minutes of vigorous-intensity aerobic activity per week, spread out over at least three days per week.

Figure 7. Participants frequency of exercise/sports data

The experiment was conducted using a setup comprising of two monitors and a laptop. The Raspberry Pi 4 was connected to one monitor, while the Nintendo Switch was connected to the other monitor, as depicted in Figure 8. The Nintendo Switch is a hybrid video game console which was utilized in the experiment to provide a range of activities for the participants. The use of multiple monitors also facilitated a more immersive and engaging experience for the participants, contributing to the overall effectiveness of the experiment.
The initial step in the testing procedure involves measuring the participant’s resting blood oxygen level and heart rate. This can be achieved by asking the participant to hold the designed prototype in a particular manner for three minutes as shown in Figure 9.

Following the initial measurements, participants will be required to engage in activities involving using Nintendo Switch, with a duration of approximately three minutes. To perform these activities, participants will play a game called "Ringfit Adventure" that involves jogging based on the game map. These activities are intended to simulate exercise for the participants as shown in Figure 10.

After completing the activities, participants will be instructed to sit in a straight and relaxed position for three minutes while their blood oxygen level and heart rate are measured once again as shown in Figure 11. It is essential that individuals maintain an upright and motionless posture while measuring their pulse or oxygen blood level. Participants are advised to refrain from any physical movements or talking during this period to ensure precise and reliable readings.
The data from sensors were analyzed based on the participant’s gender and lifestyle. These data were retrieved from the InfluxDB and shown in BPM for heart rate and SpO2 for blood oxygen level. The blue line in the graphs represents BPM, while the purple line represents SpO2. The data are represented for heart rate monitoring as x-axis labeled with time scale (seconds) and the y-axis labeled with the heart rate values BPM as shown in Figure 12. Additionally, the Grafana refresh time for our data updates occurred every 3 minutes. The results of the analysis showed that some male participants had a higher resting heart rate, with their heart rate before activity ranging between 100 to 120 bpm, as seen in Figure 12(a). However, their heart rate increased after doing some activities, as shown in Figure 12(b). After resting for three minutes, the participant’s heart rate started to drop, indicating that the participant had rest from the previous activity. On the other hand, a few female participants had a lower resting heart rate compared to male participants, with their average resting heart rate ranging between 65 to 90 bpm. An example of a female participant’s heart rate before activity is shown in Figure 12(c), while their heart rate after activity is shown in Figure 12(d). Table 1 compares the results from male and female participants. The average heart rate before and after the activities did not differ much among male participants, with an average heart rate of 110 bpm. The average blood oxygen level remained constant among male and female participants, as there were no uncertainties observed. However, the average heart rate slightly increased for female participants after the activities, with an average resting heart rate of 77.5 BPM before activities and 82.5 BPM after activities.

Figure 11. Testing process (part 3)

Figure 12. Male and female heart rate of before and after activities: (a) male resting heart rate BPM before activities, (b) male heart rate BPM after activities, (c) female resting heart rate BPM before activities, and (d) female heart rate BPM after activities
Subsequently, participants were categorized as either sporty or non-sporty based on their regular exercise or sports activity habits. The results of the study indicated that some sporty participants displayed a more stable heart rate BPM during physical activity as shown in Figure 13. Specifically, Figure 13(a) shows that sporty individuals exhibited a heart rate between 90 and 93 BPM before engaging in physical activity, and Figure 13(b) illustrates that their heart rate did not significantly increase after activity. In contrast, non-sporty participants displayed lower baseline heart rates (between 80 and 100 BPM) compared to sporty participants before physical activity as shown in Figure 13(c). After engaging in activity, non-sporty participants demonstrated a significantly higher heart rate, as depicted in Figure 13(d). On average, sporty individuals had a heart rate of 91.5 BPM, while non-sporty individuals had an average heart rate of 110 BPM, as reported in Table 2. Notably, the average heart rate of sporty participants before and after activity was nearly identical, whereas non-sporty participants exhibited a substantial increase in heart rate following an activity. Both sporty and non-sporty participants had an average blood oxygen level of 100%, as they did not have any known health conditions.

### Table 1. Male and female heart rate of before and after activities

<table>
<thead>
<tr>
<th>Gender</th>
<th>Average heart rate BPM Before</th>
<th>Average heart rate BPM After</th>
<th>Average SpO2 level Before</th>
<th>Average SpO2 level After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>110</td>
<td>110</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Female</td>
<td>77.5</td>
<td>82.5</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

![Figure 13](image1.png)

Figure 13. Sporty and non-sporty heart rate before and after activities: (a) sporty person heart rate BPM before activities, (b) sporty person heart rate BPM after activities, (c) non-sporty heart rate BPM before activities, and (d) non-sporty heart rate BPM after activities

### Table 2. Sporty and non-sporty heart rate before and after activities

<table>
<thead>
<tr>
<th>Group</th>
<th>Average heart rate BPM Before exercise</th>
<th>Average heart rate BPM After exercise</th>
<th>Average SpO2 level Before exercise</th>
<th>Average SpO2 level After exercise</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sporty</td>
<td>91.5</td>
<td>94</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Non-sporty</td>
<td>90</td>
<td>110</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

4. **CONCLUSION**

In conclusion, our study proposes a real-time monitoring tool that incorporates MAX 30100 sensor to collect BPM and SpO2 data and connects to a visualization platform such as InfluxDB and Grafana. Our findings show interesting differences in resting heart rates and changes in heart rate after activity between male and female participants. Specifically, some male participants had a higher resting heart rate compared to female participants, while a few female participants had a lower resting heart rate. Additionally, the average heart rate slightly increased for female participants after activities. We plan to validate these findings by conducting further research with a larger and more diverse sample population. We also aim to enhance the monitoring tool by incorporating additional sensors to provide a more comprehensive picture of the body’s physiological state. Moreover, we intend to explore machine learning algorithms to analyze the collected data and provide personalized health recommendations based on individual patterns and trends.

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