Development of a wearable monitor to identify stress levels using internet of things

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Article Info

Article history:

Received Oct 20, 2023
Revised Nov 17, 2023
Accepted Jan 11, 2024

Keywords:

Healthcare
Heart rate
Internet of medical things
Respiratory rate
Skin conductivity
Stress

ABSTRACT

Modern life's ubiquitous component of stress has a significant impact on many facets of human existence. This article presents the development of a wearable device integrated with internet of things (IoT) technology, aiming to identify and quantify stress levels in real-time. This technology provides a possible means of improving stress assessment, enabling prompt treatments and individualized stress management techniques. ESP32-PICO computation platform was used as part of wearable stress monitor. The developed wearable monitor also includes a high-sensitivity pulse oximeter and heart-rate sensor (MAX30102) and galvanic skin response (GSR) sensors to acquire physiological signals associated with stress status. The wearable monitor device delivers data to the firebase platform via Wi-Fi. The benefits and prospective uses of the IoT-enabled wearable device are also covered in the article. It demonstrates the mobile wearable monitor adaptability in a variety of scenarios, such as offices, classrooms, and healthcare facilities, where stress management is vita and required for activity optimization. Continuous monitoring capabilities allow users to learn about their stress levels and take proactive self-care measures. During the validation experiments, the accuracy of measurement capabilities of the developed wearable monitor were evaluated reduced errors of heart rate and respiratory rate being observed.

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1. INTRODUCTION

"Stress" is a loaded word. It has a lot of negative implications and is frequently utilized in advertising and the media as a "boogeyman" that needs to be driven out of people's lives. The role of stress and the stress response in the preservation of health and survival, however, is completely overlooked by this too simplified viewpoint when the environment places tremendous strain on the brain and body [1].

Any scenario can be stressful. Stress first affects the feeling, which leads to psychological illnesses. Early indicators of stress include anxiety, distracting anxiety, excessive worry, changes in sleep patterns, impatience, anger, melancholy, intolerance, thoughts of harming oneself or others, palpitation, stress headache, and internal pressure. Other symptoms include headaches, severe fatigue, nausea and vomiting, diarrhea, tachycardia, chest discomfort, increased blood pressure, flushing or disorientation, shortness of breath, restlessness, choking sensation, or hyperventilation [2].

The ability of the human body to react to stress and mobilize resources to deal with difficult circumstances is truly astounding. However, prolonged or excessive stress can have a number of physiological and psychological side effects that have a big impact on how people feel physically. Unmanaged stress can have a wide range of negative effects on a person's quality of life, including immune system deterioration, anxiety disorders, and depression. Stress comes in several forms, including eustress, distress, acute stress, and chronic stress. When we are stressed, our bodies go into fight or flight mode [3].

A vital action in the pursuit of ideal health is the monitoring of stress levels. It is possible to recognize triggers, comprehend the impact on various physical systems, and create efficient coping mechanisms by obtaining insight into personal stress patterns. This proactive approach gives people the power to take charge of their health and make wise decisions to lessen the negative impacts of stress. Monitoring stress levels is essential for protecting mental and emotional health in addition to physical health. Cognitive impairment, anxiety disorders, sadness, and a lower quality of life can all be influenced by psychological stress. Regular stress assessments provide people a better understanding of their mental and emotional states, empowering them to seek out the right help, put stress-reduction strategies into practice, and develop resilience. Monitoring stress levels also makes it easier to spot negative behavioral tendencies and lifestyle decisions. Stress can interfere with sleep cycles, decrease cognitive abilities, and trigger unhealthy coping strategies like binge eating or social withdrawal. By keeping track of their stress levels, people can acquire insight into how stress affects their behavior, enabling them to make educated decisions, form better habits, and create stress-reduction plans.

Internet of things (IoT) technology is currently becoming more widely available. Recent developments in the technology of embedded processors, diverse sensors, and wireless communication systems had a major role in the development of this field. As a result, it was possible to create inexpensive, tiny, and ultra-low power embedded devices that may be networked and serve as essential elements of the IoT [4], [5]. Many of the mobile health platforms reported in the literature are using a variety of sensors, including heart rate sensors, to gather information on the patient's vital signs and overall health inside of internet of medical things (IoMT). Through the use of a platform, a collection of sensors, and other devices, interaction between people and things is ensured [6], [7]. Latest technologies has made it easier and more convenient to monitor stress levels. Thus, people now have the ability to track and analyze their stress responses in real-time thanks to wearable technology, smartphone apps, and online platforms. These tools combine physiological measurements, activity monitoring, and self-reported data to deliver individualized insights and actionable recommendations, empowering people to actively participate in stress management and improve their health outcomes.

Chronic ailments include cardiovascular problems, diabetes, autoimmune diseases, and mental health issues place a heavy load on people and healthcare systems worldwide. Recent studies have illuminated the complex relationship between chronic disease and stress, emphasizing the crucial part that stress plays in the onset, progression, and management of disease. Healthcare providers can get important insights that guide individualized interventions, increase disease management, and ultimately improve the quality of life for those with chronic diseases by precisely quantifying and monitoring stress levels. Understanding the complex link between stress and chronic disease has made accurate and reliable stress measurement even more important. Traditional clinical evaluations and self-reported questionnaires offer only a limited amount of information about the subjective experience of stress, frequently depending on recollections from the past that could be biased and inaccurate. However, improvements in stress measuring methods, including wearable technology, biomarker analysis, and physiological monitoring, have created new opportunities for the objective and in-the-moment assessment of stress. Stress is a normal response to the pressures of our constantly shifting world. Even though demands and change are continuous companions, how we perceive these internal and external changes directly affects how much stress we feel. Stress can accelerate the development of brain lesions, which can worsen Alzheimer's disease. Reducing stress may aid in slowing the disease's progression, according to some studies [8].

Knowing how stress affects chronic disease can guide focused interventions and individualized treatment plans. Healthcare professionals can lessen the harmful impacts of stress by designing therapies that target stress management, which may improve disease outcomes, lessen symptom burden, and improve overall quality of life for people with chronic diseases. Additionally, stress assessment offers a way to monitor the success of lifestyle changes and interventions that aim to reduce stress, enabling ongoing therapy monitoring and adaptation.

An important step forward in the measurement and treatment of stress is the developments of a wearable device that is IoMT-enabled for stress level recognition. This gadget has the potential to empower people, healthcare providers, and researchers in understanding and reducing the impact of stress on human well-being by giving real-time and tailored stress data. It creates new opportunities for early stress-related disorder detection, preventive interventions, and the creation of specialized stress management techniques.

By transmitting data to medical experts via IoT and mobile technology, technologies make patient health monitoring easier. Professionals would benefit from employing the intermediate storage strategy to retain and gather patient data so that it is always accessible. On the basis of the integration of data from multiple functional health sensors, we suggest a wearable device that may also be utilized for monitoring the patient's status with a chronic disease. Numerous IoT devices are used for health monitoring, according to the literature [9], [10]. Long-term patient monitoring is necessary in many medical conditions, such as those involving chronic illnesses, and cardiac conditions. The IoMT device should be capable of doing real-time monitoring in such circumstances [11].

A Brazilian University's undergraduate students who are enrolled in health sciences courses were profiled and their levels of stress were examined in the work [12] to see how these factors affect their health and academic performance. Higher levels of stress had a negative impact on students' academic performance, socializing, relationship with the university, learning, sleep, and perceived health. Stress levels were connected to gender, course, and semester. According to the current study, stress has a negative impact on academic performance and health status for Brazilian undergraduate students majoring in health sciences.

The aim of the study [13] was to investigate how stress and coping mechanisms in university students are related. Data were gathered using a quantitative study that used a cross-sectional non-probability sample research approach. A questionnaire was used to gather the data, and it also included the adolescent coping scale (ACS) and the perceived stress scale (PSS). The study's findings showed that the majority of college students experience moderate levels of stress. Among undergraduates, there was a substantial in-verse link between stress level and coping mechanisms.

Yikealo *et al.* [14] was to ascertain how stressed the college of education (CoE) students at the Eritrea Institute of Technology were. To determine the degree of stress among the pupils, descriptive research was conducted. A self-created questionnaire that measured participants' levels of stress across five domains (physiological, social, psychological, academic, and environmental) was completed by randomly selected participants (N=123). The findings showed that the kids' levels of stress were moderate. Academic and environmental stressors were discovered to be the two that contributed most to the students' degree of stress out of the five domains. Additionally, it was shown that there were no statistically significant correlations between the students' stress levels and their gender or grade point average (GPA).

Surantha *et al.* [15], discuss using wearable technology to address issues with healthcare, such as disease detection, monitoring, and treatment. In addition, this review paper described how wearable device architecture was used. Chopra and Singhal [16] discuss the most popular wearable technology and sensors, wearable computing, wearable functioning and architecture, diverse applications, user preferences, and major wearable difficulties. The data under analysis revealed that the majority of consumers use wearables on a daily basis.

The creation of an IoT physical rehabilitation system based on smart walkers is discussed in Nave and Postolache [17]. IMU, load cells, and an ultrasound sensor were used in the design and implementation of a multimodal sensing solution. The Arduino Mega computation platform, which calculates walking data throughout a rehabilitation session and stores them in the cloud, is what makes a walker smart. An established website and mobile app facilitate data analysis and data visualization.

Using a smart wearable wristband, machine learning algorithms, and a dexterous robot hand that was three-dimensional (3D) printed, Yang *et al.* [18] introduced an IoT-enabled stroke rehabilitation system. The wearable device measures biopotential signals, and the robot hand receives the processed data remotely. In order to provide users with knowledge and feedback on their muscle movements, the received signals are then translated using a machine learning algorithm.

To detect and track user cardiac abnormalities, Majumder *et al.* [19] devised and created an integrated smart IoT system. In order to help consumers better understand how they could feel about their electrocardiography (ECG), this research offers them a non-invasive technology. Brezulianu *et al.* [20] offer a system for tracking heart activity parameters utilizing wearable ECG devices and fabric-integrated sensors. Respiration and heart rate are the parameters that are measured.

For patients with asthma, a smart IoT system to measure their respiratory rate is suggested in [21]. The patient's data is examined after the measured data is safely uploaded to the cloud. Mazgelytė *et al.* [22] looked at the dynamics of various stress indicators before, after, and during a quick session of respiratory biofeedback using virtual reality. In the study, 39 healthy participants took part. Before and after the session, participants appraised their mood status, level of weariness, and degree of strain using saliva samples. Throughout the session, measurements of the subjects' heart and respiratory rates, heart rate variability, and galvanic skin reaction were taken. The findings demonstrated a significant reduction in skin conductance values, heart and respiratory rates, and salivary cortisol levels following a single 12-minute relaxing session.

When high levels of stress were experienced, Can *et al.* [23] recommended appropriate relaxation techniques (e.g., traditional or mobile) utilizing their automatic stress detection system and Empatica-E4 smart-bands. The authors' technology uses contextual data based on physical activity to analyze high stress levels and provide the best relaxing technique. While traditional approaches may be helpful in free environments, more constrained contexts may include less physical activity and be better suited for mobile relaxing techniques.

The proposed work is a continuation of the research work [24], which was aimed at creating an mHealth monitoring system based on IoT, including sensors, medical bracelets, mobile devices with applications. Zholdas *et al.* [24] used a ready-made Xiaomi Mi Band 5 fitness bracelet to measure the patient's stress levels and physical activity, which includes: heart rate and steps. The primary disadvantage of utilizing Xiaomi Mi Band 5 is that it is impossible to get real-time data from a fitness wristband. The decision to develop a wearable health monitor was considered.

The scientific novelty of this research is that the wearable monitor device consists of the main ESP32-PICO-KIT microcontroller computation platform, photoplethysmography (PPG) sensor (MAX30102), galvanic skin response (GSR) sensor, light-emitting diode (LCD) organic LED (OLED), battery and power bank module. The operation of a wearable device is carried out using the human hand. From the human pulse, impulses are sent to the pulse sensor and galvanic skin sensor. Next, the sensors process impulses from the hand and the human skin. Next, the signals enter ESP32-PICO-KIT microcontroller, where the blood flow is processed.

The hypothesis of this study is model (1) to (4), developed by Gonçalo Ribeiro, Octavian Postolache in work [25]. Based on this hypothesis, a wearable device is proposed. The theoretical significance of the study is to determine the values of a person’s health status when assessing the level of stress based on (1) to (4). The practical signif-icance of this study is that the developed wearable device can be used for patients with chronic diseases, since the level of stress affects a person’s health.

The proposed wearable device has differences from the developed devices in [26]–[28]. In the proposed wearable device the following were used: ESP32-PICO-KIT as the main unit and PPG and GSR sensors. Sentilkumar *et al.* [26] in the development of the device the following were used: Arduino Mega as the main unit and the pulse sensor. Ragupathi *et al.* [27] in the development of the device following were used: Raspberry Pi, pulse sensor, temperature and blood pressure sensor. Valsalan *et al.* [28] develop body temperature sensor, pulse rate sensor were used for health monitoring. Due to the fact that the proposed device is wearable and this device uses ESP32-PICO computation platform with higher autonomy, it is convenient for monitoring human health stress for long periods during daily activities that recommend this prototype versus reported systems such as [26]–[28].

This paper is organized as follows. Section 2 describe and discusses the proposed wearable device to identify the existing solutions and to analyze the novelty and originality of the proposed solution. Section 3 presents the stress monitor validation results obtained for different scenario, as well as some considerations and comparisons. Conclusion and future work follow in section 4.

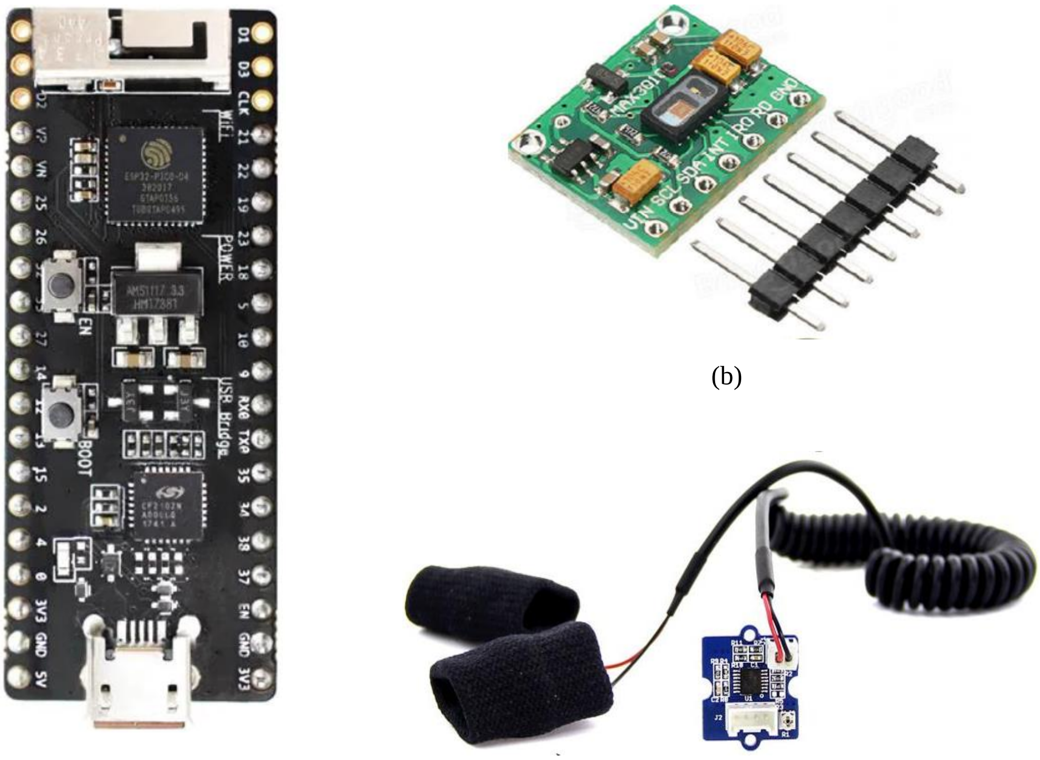
2. METHOD

2.1. Hardware components of the system

Figure 1 shows the ESP32-PICO-KIT microcontroller, MAX30102 and GSR sensors. The ESP32-PICO-KIT Figure 1(a) is powered by the ESP32-D0WDQ6 microcontroller, a dual-core Tensilica LX6 32-bit processor with a clock speed of up to 240 MHz. It supports IEEE 802.11 b/g/n Wi-Fi with a range of features like WPA/WPA2 and WEP encryption, station mode, access point mode, and Wi-Fi direct peer to peer (P2P). It has a 12-bit SAR ADC with up to 18 channels, making it suitable for analog sensor interfacing. The ESP32 features two 8-bit DACs for analog signal generation. Combining a PPG sensor Figure 1(b) and a GSR sensor Figure 1(c) into a wearable device allows for the monitoring of physiological reactions to stress and the evaluation of general well-being. The GSR sensor detects fluctuations in the skin's electrical conductivity, whereas the PPG sensor analyzes changes in blood volume using visual methods. The PPG sensor measures blood flow and oxygen saturation levels using light-emitting diodes (LEDs) and photodetectors. The PPG sensor illuminates the skin in order to detect variations in reflected light intensity brought on by variations in blood volume, giving important information on cardiovascular function.

The GSR sensor, on the other hand, gauges the electrical conductance of the skin, which is impacted by sympathetic nervous system arousal and sweat gland activity. Stress causes the sympathetic nervous system to become active, which increases sweat production and changes the electrical conductivity of the skin. A measure of emotional arousal and stress response is provided by the GSR sensor, which recognizes these changes. Figure 2 shows the wiring diagram of the proposed wearable device.

Individuals can acquire the PPG, and GSR signals that can be used for a better understanding of their physiological reactions to stress. The developed monitor device can continually track changes in daily GSR as well as heart rate and respiration rate. Using optical methods, the MAX30102 sensor, a combined pulse oximeter and heart-rate sensor module, is intended to monitor a range of physiological indicators. It is frequently used to track heart rate and blood oxygen saturation levels (SpO2) in wearable technology, healthcare software, and fitness trackers.



(b)

(a) (c)

Figure 1. Main sensors of a wearable monitor: (a) ESP32-PICO-KIT, (b) MAX30102 sensor, and (c) grove GSR sensor

On the basis of the PPG principle, the MAX30102 sensor functions. Depending on the blood's oxygenation level, some of the light that the LEDs produce into the skin is absorbed by the blood vessels beneath the skin. The photodetector gauges how much light is being reflected or transmitted. The sensor can calculate the oxygen saturation level and heart rate by observing variations in light intensity. Analog-to-digital converters (ADCs) and digital signal processing (DSP) algorithms are integrated into the sensor module to help improve the precision and dependability of the measured signals. It offers configurable sample rates and resolution, enabling customisation based on the demands of the individual application.

The MAX30102 sensor also has a number of built-in noise-reduction and ambient light-cancellation capabilities that guarantee reliable measurements even in difficult conditions. It offers adjustable LED timing and current management, making it possible to customize for various skin kinds and situations. Typically, microcontrollers or development boards are used to communicate with the MAX30102 sensor. The inter-integrated circuit (I2C) interface used by the sensor and host device for communication makes it simple to integrate the sensor into a variety of platforms.

The GSR sensor, also known as the electrodermal activity (EDA) sensor, is a device used to measure the electrical conductance of the skin. It is commonly employed in applications related to stress monitoring, emotional arousal assessment, and biofeedback training. The GSR sensor works on the premise that fluctuations in sweat gland activity, which is controlled by the sympathetic nervous system, modify the electrical conductance of the skin. The sympathetic nervous system is engaged when a person feels emotional or physiological stimulation, such as stress or excitement, which results in an increase in sweat production. The electrical conductivity of the skin is changed by the increase of perspiration on the surface.

Two electrodes that are in touch with the skin, often on the fingers or palm, make up the GSR sensor in most cases. The "measurement electrode" tracks the electrical current produced by the "excitation electrode," which uses one electrode to apply a little voltage to the skin. The measured current is a reflection of the skin's conductivity, which is impacted by sweat.

Skin conductance response (SCR) and skin conductance level (SCL) measurements are also possible with the GSR sensor. SCL is the normal level of skin conductance, and it varies with temperature and humidity, among other things. SCR, on the other hand, describes brief variations in skin conductance that happen in reaction to events or stimuli. SCR is frequently employed to evaluate stress reaction or emotional arousal.

Signal conditioning circuits can amplify and process the GSR analog output signals. These circuits clean up the signal, amplify variations in skin conductance, and prepare it for future analysis or system integration. Real-time or postponed study of the GSR sensor's data are also options. It frequently works in tandem with additional physiological sensors or biofeedback devices to offer a thorough understanding of a person's emotional or stress response.

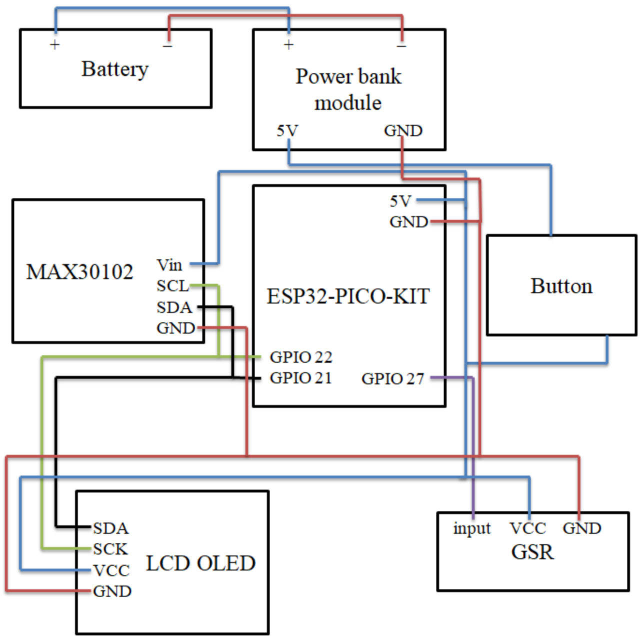


Figure 2. Block diagram of wearable stress monitor

Stress management, mental health monitoring, biofeedback training, and studies of human-computer interactions are among the applications of GSR sensors. The GSR sensor provides invaluable insights into a person's mental state and physiological reactions to diverse stimuli by tracking variations in skin conductance, enabling tailored interventions and stress-reduction approaches. Figure 3 shows design of proposed wearable device. The wearable device has a battery and a charger that provide 5 to 6 hours of operation for the device.

2.2. Measured physiological parameters

The cardiovascular, pulmonary, endocrine, gastrointestinal, neurological, muscular, and reproductive systems are just a few of the biological systems that are typically impacted by stress. Acute stress affects the cardiovascular system by raising heart rate, intensifying heart muscle contractions, expanding the heart, and diverting blood flow to big muscles. The circulatory system and respiratory system collaborate to deliver oxygen-rich blood to body cells while eliminating carbon dioxide waste [29].

Heart rate refers to the number of times a person's heart beats per minute (BPM). It is a vital physiological parameter that reflects the rate at which the heart pumps blood throughout the body to supply oxygen and nutrients to tissues and organs. Heart rate is commonly used as a measure of cardiovascular health and fitness and can provide valuable insights into an individual's overall well-being. The National Institutes of Health have included the average heart rate for each age group, as shown in Table 1. Heart rate and stress are directly related because when a person is under stress, their body briefly generates adrenaline, which raises heart rate and consequently blood pressure. Additionally, having high blood pressure increases the risk of heart attacks by damaging the arteries, resulting in blood clots.

The respiratory rate is a basic vital sign that can be affected by a variety of pathological disorders, such as pneumonia, unfavorable cardiac events, and clinical deterioration, as well as stresses including emotional stress, cognitive load, heat, cold, physical effort, and exhaustion from exercise. The increased sensitivity of respiratory rate to these situations compared to most other vital signs, as well as the variety of appropriate technological solutions monitoring respiratory rate, have significant implications for healthcare, workplace environments, and sport [30].

The term "respiratory rate", frequently abbreviated as "RR", refers to how many breaths a person takes in a minute. Given that it offers crucial details regarding a person's respiratory function and general health, it is one of the vital indicators that is frequently examined in hospital settings. A person's respiratory rate is a critical measure of how effectively their respiratory system is working and can provide information about any potential medical issues or changes in their state of health.

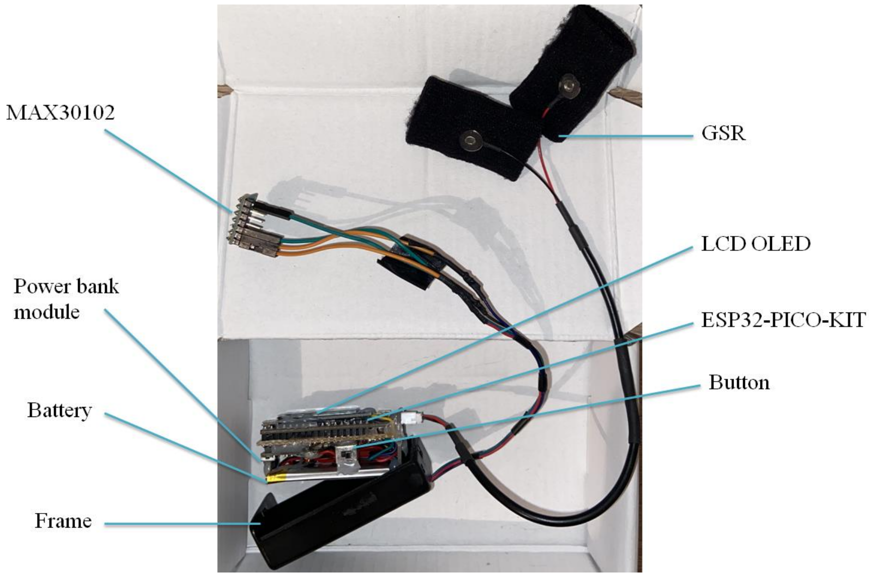


Figure 3. Design of wearable device

Table 1. Levels for heart rate [31]

Age	Normal resting heart rate (bpm)
0-1 month	70 to 190
1-11 months old	80 to 160
1-2 years old	80 to 130
3-4 years old	80 to 120
5-6 years old	75 to 115
7-9 years old	70 to 110
10 years and older and adults (including seniors)	60 to 100
Athletes in top condition	40 to 60

The average resting respiratory rate for a healthy adult is between 12 and 20 breaths per minute. However, it may differ according to elements including age, level of physical activity, emotional stability, and general health. As an illustration, babies and infants often have higher respiratory rates than adults do, and people who are physically active or under stress may have brief increases in their respiratory rates.

For patients with respiratory diseases such asthma, chronic obstructive pulmonary disease (COPD), or pneumonia, monitoring respiratory rate is a crucial part of patient assessment. Any appreciable difference from the average respiration rate could be a symptom of respiratory distress or other serious problems, demanding further testing and medical attention. Typically, respiratory rate is determined by counting breaths for one minute, watching a person's chest or abdomen, or measuring it during a shorter time frame and then extrapolating it to one minute. In order to assess the overall respiratory health and direct appropriate medical care when required, an accurate measurement of respiratory rate is essential. The normal respiratory rate as a function of age is established as shown in Table 2.

Table 2. Normal respiratory rate by age [32]

Age	Breaths per minute
Newborns	70 to 190
Infants	80 to 160
Preschool children	80 to 130
Older children	80 to 120
Adults	75 to 115
Adults exercising	70 to 110

Stress and breathing have a direct relationship because while under stress, a person breathes more quickly in order to quickly circulate oxygen-rich blood throughout their body. Stress can make breathing more challenging for someone who already has a breathing condition like asthma or emphysema. The condition of the skin's sweat glands affects skin conductivity. The sympathetic nervous system regulates sweating, and skin conductivity is a sign of either psychological or physical arousal. Sweating gland activity increases when the sympathetic branch of the autonomic nervous system is significantly activated, which in turn raises skin conductivity. Figure 4 shows measured physiological parameters with proposed wearable device: heart rate, respiratory rate and skin conductivity. As a result, skin conductivity can be used as a gauge of emotional and sympathetic reactions in categories, which are shown in Table 3.

Figure 4. Implemented werable stress monitor with measured physiological parameters display

Table 3. Levels for skin conductivity [25]

Skin conductivity	Information	Symptoms/Consequences
0% to 31%	Low levels	Does not pose a problem or risk to human health
32% to 82%	Normal levels	Does not pose a problem or risk to human health
83% to 100%	High levels	It does not pose any problem or risk to human health, however, there is a high psychological stimulation (increased emotional response) and greater sweat production

Finding the greatest possible value for this parameter, which is done using (1) [25], is a crucial step in converting heart rate from beats per minute to %. Knowing each subject's age is important to calculate their maximal heart rate, hence it was made necessary to provide it when new users registered for the mobile application.

$$MAX_{Heart\_Rate} = 220 - age \quad (1)$$

Once the subject's maximal heart rate is known, (2) [25] may be used to calculate the heart rate in percentage using the heart rate data gathered by the sensor, as this equals 100%.

$$Heart\_Rate\ [\%] = (Heart\_Rate * 100) / MAX_{Heart\_Rate} \quad (2)$$

The maximum value for the respiratory rate must also be established, but unlike the heart rate, this does not depend on age, in order to convert it from breaths per minute to %. However, it is common for many athletes who engage in sports requiring significant physical exertion to present maximum values for respiratory rate in the range of 70 breaths per minute, and as such, it was admitted as a maximum value in this system, i.e., this equals 100%. Using the respiratory rate recorded by the sensor, the respiratory rate in percentage is obtained using (3) [25].

$$Respiratory\_Rate\ [\%] = (Respiratory\_Rate \times 100) / MAX_{Respiratory\_Rate} \quad (3)$$

The algorithm developed in this system for the estimation of stress levels can then be used. It is based on the weighted average of the 3 parameters obtained by the sensory system and is defined by (4) [25].

$$\text{Stress}[\%] = (\text{Heart\_Rate}[\%]+\text{Respiratory\_Rate}[\%]+\text{SC}[\%])/3 \quad (4)$$

This algorithm can be applied after determining the heart rate and respiratory rate, both in percentage, and getting the skin conductivity value, also in percentage, directly from the sensor.

3. RESULTS AND DISCUSSION

3.1. Firebase Web App to display sensors readings

To create a web app that displays sensor readings from an ESP32-PICO computation platform, firebase was as the backend for storing and synchronizing the data. Firebase is a comprehensive platform offered by Google that provides a set of backend services and tools to help developers build and scale web and mobile applications quickly and efficiently. Firebase is known for its ease of use, real-time capabilities, scalability, and seamless integration with other Google services. It is popular among both small startups and large enterprises as it simplifies many backend tasks, enabling developers to focus more on building great user experiences. The Figure 5 shows a high-level overview of the application.

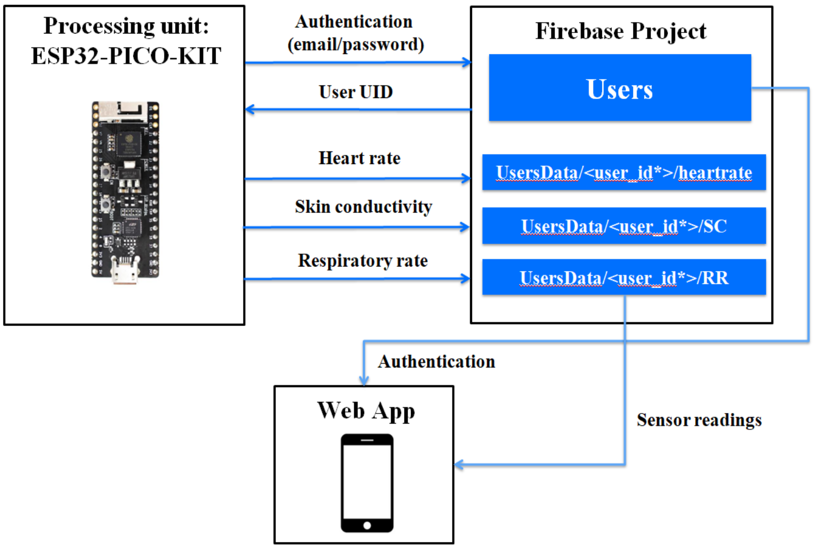


Figure 5. Structure of the web application

- The ESP32-PICO computation platform verifies a user's identity using their email address and password (the user must be configured for Firebase authentication methods);
- The ESP receives the user ID (UID) following authentication;
- Security guidelines secure the database. The user's user UID is the sole way for them to access the database nodes underneath the node. The ESP can publish data to the database once it has obtained the user's UID;
- The ESP sends measured parameters to the database.

Using firebase hosting and a worldwide content distribution network (CDN), firebase hosts developed web application and offers an SSL certificate. The domain name established by firebase can be used to access your web app from any location. You must authenticate with a valid email address and password the first time you visit the online app. You can access a web app page that displays the sensor readings kept on the real-time database after logging in. Once logged in, you can always log out. You will have to log in again the next time you access the application. Figure 6 shows measured parameters in the firebase platform.

3.2. Data analysis and assessment of stress levels

An important development in the field of stress management and individual wellbeing is the measurement of stress levels using data from a proposed wearable device, such as heart rate, respiratory rate and skin conductivity. Utilizing the capabilities of these tools allows users to get a deeper understanding of their stress patterns and reactions, resulting in more intelligent and proactive approaches to stress reduction. Checking the correctness of the heart rate results from a proposed wearable device using a reliable reference device, such as the MEDLAB P-OX 100 pulse oximeter, is essential to ensure the accuracy and validity. This verification process helps to establish the wearable device's credibility and its ability to provide trustworthy data to users and healthcare professionals. In this research the comparison was carried out by simultaneous measurement: to ensure accurate comparison, both the proposed wearable device and the pulse oximeter should be worn or used simultaneously on the same individual. This means that the heart rate data from both devices is recorded simultaneously during the same period.

As we Figure 7, the heart rate readings from the proposed wearable device and MEDLAB P-OX 100 are the same, they are equal to 97 (because only the heart rate was measured and the sensor was not worn, the GSR value is 0). In the proposed device, deviations by an average of 3 to 5 beats per minute are observed in some seconds for heart rate. Figure 8 shows values of parameters measured during 15 minutes: heart rate Figure 8(a), respiratory rate Figure 8(b) and skin conductivity Figure 8(c).

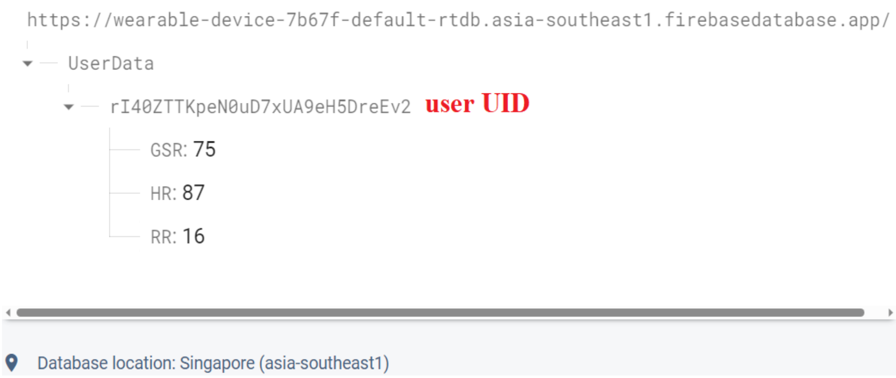


Figure 6. Sensor data sent from ESP32-PICO-KIT to firebase

Figure 7. Comparison of heart rate readings of the proposed wearable device and MEDLAB P-OX 100

Checking the stress level accuracy of a proposed wearable device is a crucial step in ensuring its reliability and effectiveness in stress management applications. To check and compare the results, the Mi Band 5 fitness bracelet was used, which has its own method for tracking the level of stress and the ability to monitor it on a mobile application. Several different conditions for the experiment were considered: the state of rest and stressful situations. According to the results of the experiments, it was known that at rest the stress level does not exceed the low stress levels and normal stress levels in Table 4. In the Mi Band 5 fitness bracelet, stress levels are divided as follows: relaxed (0 to 39%), mild (40 to 59%), moderate (60 to 79%) and high (80 to 100%). In the proposed device, deviations by an average of 5 to 10 % are observed in some intervals for stress levels.

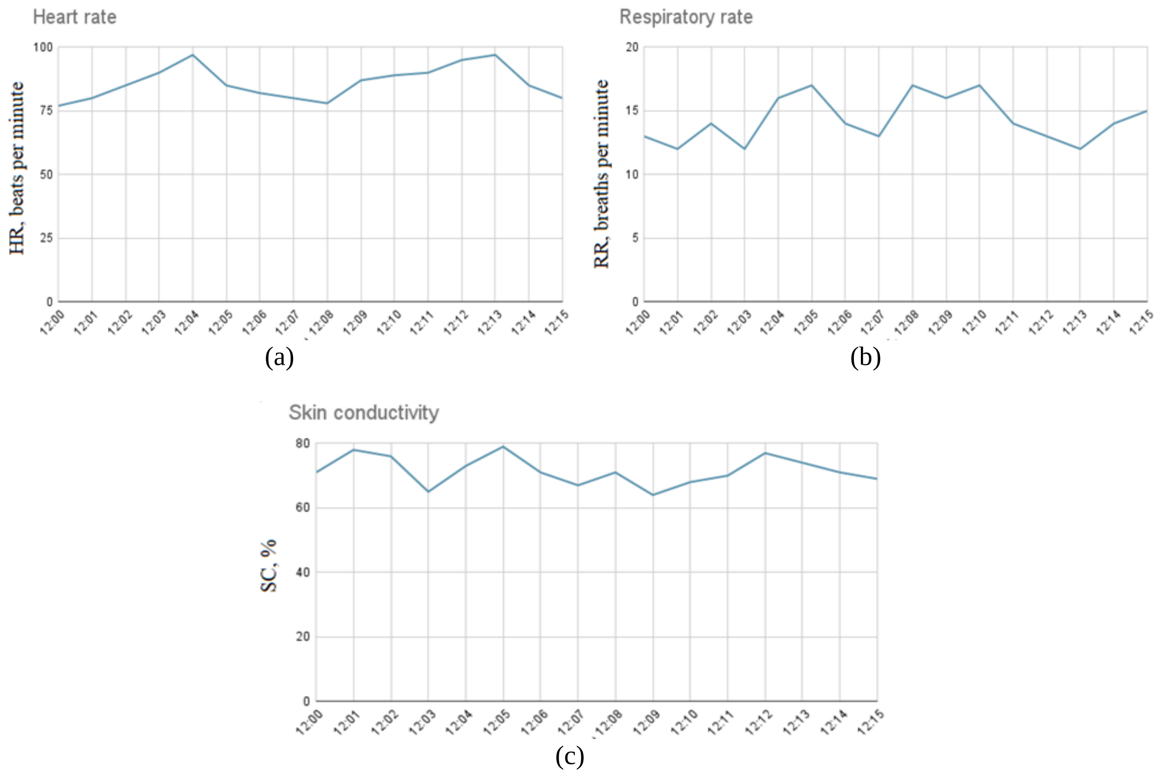


Figure 8. Measured data for 15 minutes: (a) heart rate, (b) respiratory rate and (c) skin conductivity

Table 4. Levels for stress [25]

Stress	Information	Symptoms/consequences
0% to 25%	Resting state	-
26% to 50%	Low stress levels	-
51% to 75%	Normal stress levels	-
76% to 100%	High stress levels	Difficulty controlling emotions, heart problems, teeth and gums problems, weight gain, weakened immune system

4. CONCLUSION

In conclusion, the development of a wearable device to identify stress levels using the IoT holds immense potential in transforming the way we understand and manage stress. The integration of IoT capabilities into wearable devices has unlocked new possibilities for real-time stress monitoring, offering invaluable insights into users' physiological and behavioral responses. By leveraging IoT, these wearable monitor can collect and analyze a vast array of biometric data, including heart rate variability, skin conductance, and sleep patterns, enabling a comprehensive understanding of an individual's stress profile. With this data at their disposal, users can gain self-awareness about their stress triggers, patterns, and responses, empowering them to adopt healthier coping mechanisms and make positive lifestyle changes.

In this study wearable device to identify and quantify stress levels with vital signs was developed. MAX30102 sensor showed values from 76 to 97 beats per minute for heart rate and between 12 and 17 breaths per minute for respiratory rate. GSR sensor showed values from 71% to 79%. Deviations by an average of 5 to 10 % are observed for stress levels. The proposed wearable device can measure, in addition to the heart rate, respiratory rate and skin conductivity in comparison with other wearable devices of researchers that were described in the article. Future studies will examine heart rate variability and the impact of stress on specific chronic disease.

ACKNOWLEDGEMENTS

This work was funded by Committee of Science of Republic of Kazakhstan AP19678998 "Neurocomputer Vision of Smart Traffic Lights in Megacities of the Country" (2023-2025).

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