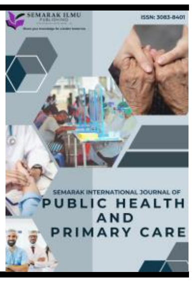
SEMARAK ILMU PUBLISHING

Semarak International Journal of Public Health and Primary Care

Journal homepage: https://semarakilmu.my/index.php/sijphpc/index
ISSN: 3083-8401



Development and Evaluation of the Inner Peace Meter: A Galvanic Skin Response-Based Stress Monitoring System

Siti Nursyuhadah Mohammad Affendi[1,*], Norsyifa Nadhirah M. Nasril[1], Izzah Aidilla Azman[1], Kuhan Raj Saravanan[1], Kumaresan Morgan[1], Mohd Kamal Kamarulzaman[1, 2], Sakinah Hisham[3, 4], Qayyum Halim[5, 6], Mohammad Mehedi Hasan[7]

[1] Faculty of Engineering, Universiti Malaysia Sabah, 88400 Kota Kinabalu, Sabah, Malaysia
[2] Faculty of Engineering, Universiti Pertahanan Nasional Malaysia, Kem Sungai Besi, 57000 Sungai Besi, Kuala Lumpur, Malaysia
[3] Faculty of Manufacturing and Mechatronic Engineering Technology, Universiti Malaysia Pahang, Al-Sultan Abdullah, 26600 Pekan, Pahang, Malaysia
[4] Faculty of Engineering, Built Environment and Information Technology (FOEBEIT), MAHSA University, Bandar Saujana Putra, 42610 Jenjarom, Selangor, Malaysia
[5] Ecosystem, MRANTI Corporation Sdn. Bhd., 57000 Kuala Lumpur, Malaysia
[6] Faculty of Mechanical and Automotive Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, 26600 Pekan, Pahang, Malaysia
[7] School of Engineering and Technology, Central Queensland University, Rockhampton, Queensland 4701, Australia

ARTICLE INFO

Article history:
Received 21 April 2025
Received in revised form 16 May 2025
Accepted 1 June 2025
Available online 30 June 2025

Keywords:
Stress monitoring; Galvanic Skin Response (GSR); Electrodermal Activity (EDA); wearable health technology; biofeedback therapy

ABSTRACT

Stress is a critical physiological and psychological response that affects individuals across various domains, including healthcare, workplaces and academic settings. Conventional stress assessment methods, such as self-report surveys and heart rate monitoring, often lack objectivity or require complex instrumentation. This necessitates the development of alternative, non-invasive stress monitoring techniques. This study aims to develop and evaluate a portable Galvanic Skin Response (GSR) sensor prototype for real-time stress monitoring. The device is designed to improve the accuracy and accessibility of stress detection through continuous skin conductance measurements. The Inner Peace Meter prototype was developed using a GSR sensor, an Arduino Uno microcontroller and LED indicators to visualize stress levels. The system was tested on volunteers under controlled conditions, including relaxation and stress-inducing tasks. A moving average filter was applied to stabilize sensor readings and calibration was performed to account for individual differences in skin conductivity. The device successfully detected stress fluctuations, with red LEDs indicating heightened stress, green LEDs signalling relaxation and yellow LEDs representing stable conditions. Quantitative analysis showed a strong correlation between stress-inducing activities and increased GSR readings. Challenges related to environmental factors and individual variability were addressed through calibration and optimized sensor placement. The Inner Peace Meter demonstrates a reliable and cost-effective approach to stress monitoring, with potential applications in mental health, biofeedback therapy and wearable health technology. Future enhancements, such as smartphone integration and wireless data logging, could further improve usability and expand its practical applications.

* *Corresponding author.*
E-mail address: siti_nursyuhadah_bk20@iluv.ums.edu.my

https://doi.org/10.37934/sijphpc.4.1.1426

1. Introduction

Stress is an unavoidable aspect of modern life, affecting individuals across various settings such as workplaces, academic institutions and healthcare environments [1,2]. It has profound physiological and psychological consequences, contributing to conditions like anxiety, cardiovascular diseases and cognitive impairments [3,4]. With increasing awareness of stress-related health risks, there is a growing demand for non-invasive, real-time stress assessment tools that can provide objective and continuous monitoring.

Traditionally, stress has been assessed through self-reported questionnaires and physiological indicators such as heart rate variability and cortisol levels. However, these methods often suffer from subjectivity, delayed response times and invasiveness, limiting their effectiveness for real-time applications. To overcome these limitations, Electrodermal Activity (EDA) has emerged as a promising physiological marker for stress assessment due to its direct link to autonomic nervous system responses, particularly changes in sweat gland activity [5,6]. Among EDA-based techniques, Galvanic Skin Response (GSR) has gained attention due to its non-invasiveness, cost-effectiveness and ability to capture stress-related variations in skin conductivity in real time [7,8].

Despite these advantages, current research on GSR-based stress detection faces several critical challenges. First, there is a lack of standardization in data acquisition, signal processing and classification methodologies, leading to inconsistencies in stress detection across different studies [9,10]. Second, GSR measurements are highly sensitive to environmental and individual variations, such as humidity, temperature and skin properties, which affect the reliability and generalizability of findings. Third, existing studies have not fully explored the integration of GSR-based stress assessment into wearable technology and clinical applications, limiting its practical implementation for continuous monitoring in real-world settings [11,12].

A key limitation in current GSR-based stress studies is the inadequate control of environmental factors. Temperature, humidity and ambient conditions directly influence sweat gland activity and skin conductivity, which may introduce variability in GSR readings [13,14]. For instance, increased humidity can cause excessive sweating unrelated to stress, leading to potential false positives, whereas dry conditions may reduce sweat gland activity, resulting in false negatives. Similarly, temperature fluctuations affect skin hydration levels and electrical conductivity, altering GSR responses. Without proper environmental controls, inconsistencies in data collection may compromise the reliability and validity of stress classification models [15,16].

To address these concerns, future studies should incorporate additional environmental sensors, such as temperature and humidity sensors, to measure and compensate for these external influences. By integrating these environmental control mechanisms into stress assessment frameworks, researchers can account for external variations, improving the accuracy and robustness of GSR-based stress detection [17,18]. Moreover, developing adaptive signal processing techniques that dynamically adjust for environmental conditions will enhance the reliability of stress monitoring in different settings. This approach is particularly crucial for real-world applications, including wearable stress monitoring devices, where environmental fluctuations are inevitable.

While short-term studies can demonstrate proof of concept and initial feasibility, long-term studies and user trials are essential to assess the sustained reliability, accuracy and user acceptance of GSR-based stress monitoring devices. Conducting extended user trials across diverse populations and varying real-world conditions would help identify potential device degradation, signal drift and user adaptation over time. Additionally, long-term studies would provide insights into the psychological and behavioural impact of continuous stress monitoring, fostering trust among users and increasing adoption rates. By evaluating the device’s long-term performance, researchers can refine hardware and software components to enhance durability, minimize calibration requirements and improve overall user experience [19,20].

To bridge these gaps, this study aims to develop and validate a pilot portable GSR-based stress-monitoring device that enhances accuracy and reliability while remaining cost-effective and user-friendly. By integrating real-time feedback mechanisms, this research seeks to advance stress monitoring applications in healthcare, psychology and everyday wellness practices. The proposed system intends to bridge the gap between research-grade stress analysis tools and accessible, practical solutions for personal and clinical use.

2. Methodology

2.1 Research Approach

The Inner Peace Meter is a prototype designed to measure stress levels by analysing Galvanic Skin Response (GSR), which reflects physiological changes due to emotional states. The research methodology consists of three main phases: hardware development, software development and testing and calibration. The overall methodological approach is illustrated in Figure 1. Compared to traditional stress assessment methods such as heart rate variability or EEG-based systems, this approach offers a more accessible, cost-effective and portable solution for real-time monitoring in everyday environments.

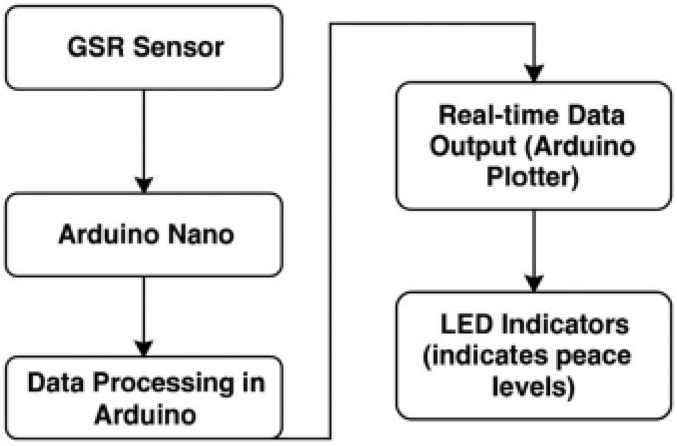


Fig. 1. Block diagram of inner peace meter method approach

2.2 Hardware Development

The hardware development phase involved assembling essential components to measure GSR and provide real-time feedback. The primary components include a GSR sensor to detect changes in skin conductance, an Arduino Uno microcontroller to process data from the sensor, LED indicators (red, green and yellow) for real-time visualization and resistors and wiring to ensure circuit stability. The circuit was initially constructed on a breadboard for flexibility during testing and debugging, as shown in Figure 2. The GSR sensor was attached to the user's fingers using adhesive patches to ensure consistent skin contact. Power was supplied via the Arduino's USB connection, which also facilitated real-time data visualization on the serial monitor. The LED indicators were programmed to function as follows: the red LED illuminated when stress levels increased, the green LED indicated relaxation and the yellow LED signalled stable conditions.

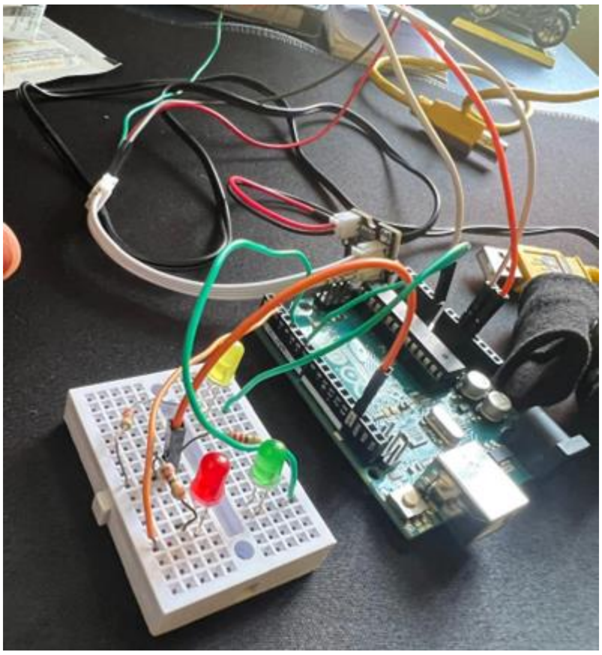


Fig. 2. Hardware setup of the components

The Arduino Uno was selected due to its affordability, compatibility with various sensors and ease of programming, making it an ideal choice for rapid prototyping. While the LED indicators provide a simple and immediate stress response visualization, future iterations could integrate an OLED display or mobile application interface for more detailed feedback. This setup ensures practical usability in various environments, such as workplaces and clinical settings, where real-time stress monitoring can enhance mental well-being interventions.

2.3 Software Development

The software for the Inner Peace Meter was developed using the Arduino Integrated Development Environment (IDE), which controlled data acquisition, processing and LED outputs. Figure 3 presents a snapshot of the coding process, while Table 1 outlines the key code structure. To ensure signal stability, a moving average filter was implemented. The system continuously read and averaged ten consecutive GSR values, reducing noise and fluctuations. A threshold-based method was used to classify stress levels. A significant increase in GSR readings above a predefined threshold activated the red LED, a significant decrease activated the green LED and minor fluctuations resulted in the activation of the yellow LED. The optimized threshold was determined through calibration experiments to improve sensitivity and minimize false readings.


```
// Define GSR sensor pin
const int GSR_PIN = A0;

// Define LED pins
const int RISE_LED_PIN = 2;
const int FALL_LED_PIN = 4;
const int STABLE_LED_PIN = 6;

// Variables to store GSR readings
int currentGSRValue = 0;
int previousGSRValue = 0; // Initialize to avoid initial false trigger
int gsr_average = 0;

// Threshold for change detection (adjust as needed)
const int THRESHOLD = 5; // ######Experiment with this value

void setup() {
  // Initialize serial communication for debugging
  Serial.begin(9600);

  // Set LED pins as outputs
  pinMode(RISE_LED_PIN, OUTPUT);
  pinMode(FALL_LED_PIN, OUTPUT);
  pinMode(STABLE_LED_PIN, OUTPUT);

  // Initialize LEDs off
  digitalWrite(RISE_LED_PIN, LOW);
  digitalWrite(FALL_LED_PIN, LOW);
  digitalWrite(STABLE_LED_PIN, LOW);
}

void loop() {
  // Read GSR value
  long sum=0;
  for(int i=0;i<10;i++){
  currentGSRValue = analogRead(GSR_PIN);
  sum += currentGSRValue;
  delay(5);
  }
  gsr_average = sum/10;


  // Print GSR value to serial monitor for debugging
  Serial.print("GSR Value: ");
  Serial.println(gsr_average);
```

Fig. 3. A snapshot of coding from Arduino IDE

While the system successfully reduces noise, future enhancements could integrate machine learning algorithms to dynamically adjust threshold levels based on individual user patterns, making the device even more adaptive to different users. Additionally, incorporating an automatic threshold adjustment mechanism based on environmental conditions could further refine stress detection accuracy.

Table 1
Code structure on Arduino IDE for monitoring stress

Code structure

// Define GSR sensor pin
const int GSR_PIN = A0;
 	
// Define LED pins
const int RISE_LED_PIN = 2;
const int FALL_LED_PIN = 4;
const int STABLE_LED_PIN = 6;
 	
// Variables to store GSR readings
int currentGSRValue = 0;
int previousGSRValue = 0; // Initialize to avoid initial false trigger
int gsr_average = 0;
 	
// Threshold for change detection (adjust as needed)

```
const int THRESHOLD = 5; // #######Experiment with this value

void setup() {
 // Initialize serial communication for debugging
 Serial.begin(9600);

 // Set LED pins as outputs
 pinMode(RISE_LED_PIN, OUTPUT);
 pinMode(FALL_LED_PIN, OUTPUT);
 pinMode(STABLE_LED_PIN, OUTPUT);

 // Initialize LEDs off
 digitalWrite(RISE_LED_PIN, LOW);
 digitalWrite(FALL_LED_PIN, LOW);
 digitalWrite(STABLE_LED_PIN, LOW);
}

void loop() {
 // Read GSR value
 long sum=0;
 for(int i=0;i<10;i++){
 currentGSRValue = analogRead(GSR_PIN);
 sum += currentGSRValue;
 delay(5);
 }
 gsr_average = sum/10;
 // Print GSR value to serial monitor for debugging
 Serial.print("GSR Value: ");
 Serial.println(gsr_average);

 // Check for rise or fall
 if (abs(gsr_average - previousGSRValue) > THRESHOLD) { // Use absolute value
  if (gsr_average > previousGSRValue) {
   // Rise detected
   Serial.println("Rise detected!");
   digitalWrite(RISE_LED_PIN, HIGH);
   digitalWrite(FALL_LED_PIN, LOW); // Turn off the other LED
   digitalWrite(STABLE_LED_PIN, LOW);
  } else {
   // Fall detected
   Serial.println("Fall detected!");
   digitalWrite(FALL_LED_PIN, HIGH);
   digitalWrite(RISE_LED_PIN, LOW); // Turn off the other LED
   digitalWrite(STABLE_LED_PIN, LOW);
  }
 } else {
  // No significant change, turn off both LEDs. This is important to avoid LEDs staying on.
  digitalWrite(RISE_LED_PIN, LOW);
  digitalWrite(FALL_LED_PIN, LOW);
  digitalWrite(STABLE_LED_PIN, HIGH);
 }

 // Update previous GSR value
 previousGSRValue = gsr_average;

 delay(50); // Small delay for stability (adjust as needed)
}
```

2.4 Testing and Calibration

Testing and calibration were crucial steps to verify the system’s accuracy and reliability. Volunteers participated in controlled experiments involving relaxation activities such as deep breathing and stress-inducing tasks like solving complex problems under time constraints. The GSR readings were continuously recorded and visualized, as illustrated in Figure 4. To ensure accurate measurements, baseline calibration was performed for each volunteer, accounting for individual variations in skin conductivity. The detection threshold was fine-tuned through iterative trials to enhance sensitivity and minimize false readings.

To ensure consistency, calibration was repeated across multiple sessions to assess sensor drift over time. Additionally, external factors such as room temperature and humidity were monitored to determine their impact on sensor readings. Implementing an automatic recalibration feature in future versions would further enhance accuracy.

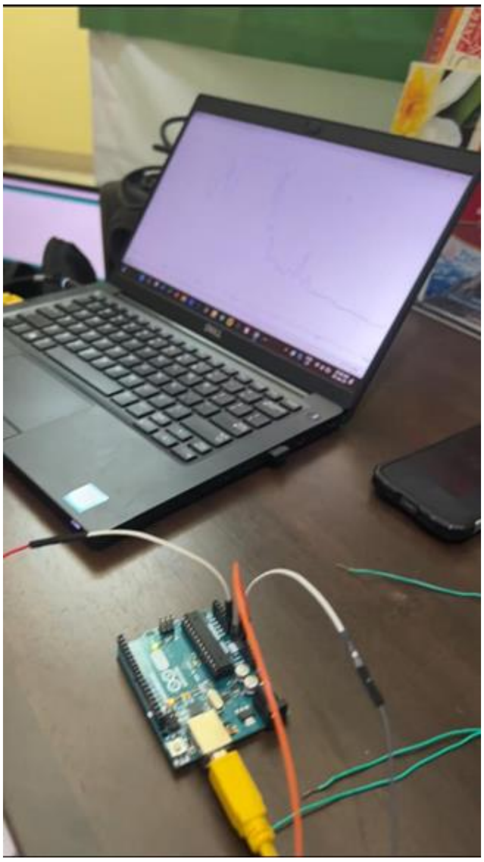


Fig. 4. Testing and calibrating the sensors

2.5 Data Collection and Analysis

The data collection phase systematically recorded GSR responses to assess stress levels. The procedure involved ensuring proper sensor placement for consistent skin contact, calibrating each individual's baseline GSR levels and conducting real-time monitoring using LED indicators for visual feedback. Stress trends were quantified by analysing the frequency of LED activations over a one-minute interval. If a volunteer experienced multiple red LED activations, they were categorized as experiencing high stress. Conversely, if green LED activations dominated, the individual was classified as being in a relaxed state. Figure 5 illustrates the recorded GSR variations over time, highlighting the system's responsiveness to changing stress levels.

To improve data interpretation, statistical analysis methods such as standard deviation and variance in GSR readings could be introduced to offer deeper insights beyond simple LED frequency counts. Additionally, integrating self-reported stress levels from participants alongside sensor data could help validate the system's accuracy.

2.6 Challenges and Solutions

Several challenges were encountered during the development and testing phases. One major challenge was noise in GSR readings due to sweat and environmental factors. This was mitigated by instructing volunteers to dry their hands before testing. Another challenge was inconsistent sensor contact, which resulted in erratic readings. This issue was addressed by ensuring the sensor was properly positioned on the fleshy part of the finger for optimal contact. Additionally, determining an appropriate threshold for detecting stress level changes required multiple calibration trials to refine sensitivity. Initially, thresholds that were too high or too low resulted in false triggers or missed detections, but through systematic refinement, the detection threshold was optimized for accurate stress monitoring.

Despite these improvements, further refinements could involve integrating additional environmental sensors to account for temperature and humidity fluctuations, which can impact skin conductivity and GSR readings. Future studies should also explore variations in skin properties among different individuals, as hydration levels and skin texture can influence measurement accuracy.

2.7 Future Enhancements

While the Inner Peace Meter successfully achieves real-time stress detection, there is room for further improvements to enhance its usability, accuracy and adaptability. One of the key enhancements would be the integration of machine learning algorithms to dynamically adjust stress detection thresholds based on long-term user data, making the system more personalized and responsive. Additionally, incorporating wireless connectivity through Bluetooth or Wi-Fi would allow real-time data transmission to mobile applications, enabling users to visualize trends and monitor their stress levels over extended periods. Environmental compensation is another important aspect that could be improved by integrating additional sensors to measure external factors like humidity and temperature, which can influence GSR readings. Further validation studies could incorporate self-reported stress assessments to refine detection algorithms and improve reliability. Lastly, redesigning the device into a more compact, wrist-worn format would enhance wearability and enable continuous stress monitoring without requiring finger attachments. By implementing these enhancements, the Inner Peace Meter has the potential to evolve into a more sophisticated, user-friendly tool for both clinical and personal applications, further solidifying its role in biofeedback therapy and mental health monitoring.

3. Results and Discussion

The Inner Peace Meter effectively measures stress levels by detecting changes in Galvanic Skin Response (GSR). The real-time feedback mechanism, utilizing LED indicators, provides an intuitive means for users to assess their stress states. The results from controlled testing demonstrate that the device reliably differentiates between varying stress conditions, reinforcing its potential as a practical stress monitoring tool.

3.1 Stress Level Detection Accuracy

The experimental results confirm that the Inner Peace Meter accurately captures fluctuations in stress levels. Participants subjected to stress-inducing activities, such as solving complex puzzles under time constraints, exhibited noticeable increases in GSR values. These changes were reflected in the activation of the red LED, indicating heightened stress levels. Conversely, relaxation exercises like deep breathing resulted in a decrease in GSR readings, which corresponded with the activation of the green LED. In cases where no significant variations in stress levels were observed, the yellow LED remained illuminated, signifying a stable emotional state.

The graphical representation of GSR readings over time, as shown in Figure 5, illustrates the system's responsiveness. The increasing segments of the graph indicate heightened stress responses, aligning with red LED activations. Conversely, declining segments correlate with a reduction in stress levels, validated by green LED responses. This trend demonstrates the device's ability to provide real-time stress monitoring in a user-friendly manner.

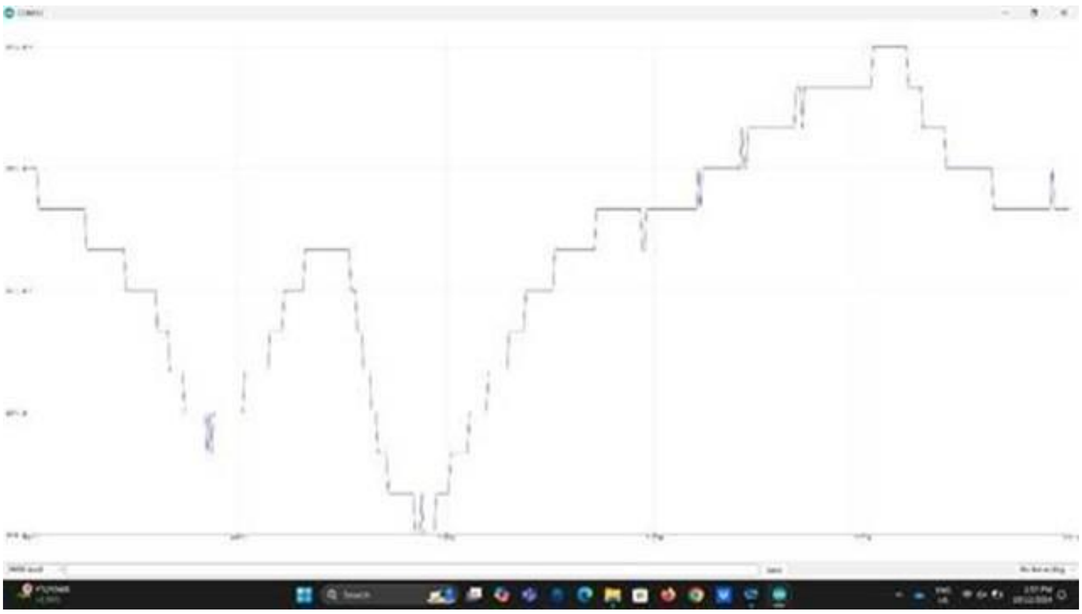


Fig. 5. Reading of graph GSR (microsiemens) against time (milliseconds)

3.2 Statistical Validation and Performance Analysis

To validate the performance of the Inner Peace Meter, a quantitative analysis was conducted by examining the frequency of LED activations over a one-minute interval. Additionally, statistical methods such as standard deviation and variance were applied to assess the consistency of GSR readings across different users. Participants experiencing multiple red LED activations were classified as having high stress levels, while those with frequent green LED activations were categorized as being in a relaxed state. The inclusion of a moving average filter in the software significantly improved the stability of the readings, mitigating noise and enhancing data reliability.

A correlation analysis between GSR fluctuations and self-reported stress levels was performed to ensure the reliability of the device. Further analysis of individual baseline GSR readings highlighted the necessity of calibration for each user, as variations in skin conductivity due to hydration levels and ambient temperature affected stress detection accuracy. Variability in skin conductivity, influenced by factors such as hydration levels and environmental conditions, necessitated personalized baseline adjustments. This finding underscores the importance of an adaptive threshold mechanism, which could be incorporated into future iterations of the device to improve accuracy.

3.3 Challenges Encountered During Testing

Several challenges emerged during the testing phase, primarily related to environmental influences and user variability. One significant issue was noise interference caused by humidity and temperature fluctuations, which affected GSR readings. This challenge was addressed by instructing participants to dry their hands before sensor placement, reducing inconsistencies caused by excess moisture.

Another challenge was inconsistent sensor contact, as variations in finger placement affected data accuracy. To mitigate this, participants were guided to position the sensor on the fleshy part of the finger, ensuring stable and consistent readings. Additionally, differences in individual baseline GSR values required customized calibration, highlighting the necessity for automated recalibration mechanisms in future developments.

3.4 Potential Improvements and Future Applications

Despite the promising results, further enhancements could be implemented to refine the Inner Peace Meter's performance. One key improvement would be the integration of machine learning algorithms to adapt stress detection thresholds dynamically based on user-specific trends. This would enhance the system's ability to account for variations in skin conductivity and improve accuracy across diverse populations.

Additionally, wireless connectivity via Bluetooth or Wi-Fi could enable real-time data logging on a mobile application, allowing users to track long-term stress patterns. Another valuable upgrade would be the inclusion of environmental sensors to compensate for external factors such as humidity and temperature variations, further stabilizing GSR readings.

From an application standpoint, the Inner Peace Meter has considerable potential in fields such as mental health monitoring, biofeedback therapy and workplace stress management. The ability to provide real-time insights into stress levels makes it a valuable tool for healthcare professionals, allowing them to monitor patients' emotional states more effectively. Moreover, the device's portability and ease of use could make it a practical addition to wellness programs aimed at reducing workplace stress.

Not to forget, to add more promising results, future studies may involve a six months' trial with varied of participants, where they will be using Galvanic Skin Response device daily, to assess its long-term reliability. Statistical analyses like ANOVA and regression modelling will be used in future research to measure how environmental factors affect GSR readings. This will increase the validity of our results and offer a more thorough comprehension of the effectiveness of the device.

3.5 Key Findings and Implications

The findings highlight that the Inner Peace Meter effectively detects stress levels, offering a reliable and cost-effective approach to real-time stress monitoring. The system successfully differentiates between stress levels through LED indicators, aligning with GSR fluctuations. While challenges such as environmental noise and user variability were encountered, the device's accuracy was significantly improved through calibration and sensor placement optimization.

Incorporating additional statistical validation, such as regression analysis between sensor data and physiological stress markers, could further substantiate the accuracy of the device. These findings suggest that further enhancements, such as machine learning-based threshold adjustments, wireless data logging and environmental compensation mechanisms, could significantly improve the system's adaptability and accuracy in various conditions. With its practical applications spanning healthcare, psychology and personal wellness, the Inner Peace Meter demonstrates potential as an accessible and impactful tool for stress management and emotional health monitoring.

4. Conclusions

The development and evaluation of the Inner Peace Meter confirm its effectiveness as a real-time stress monitoring tool. By leveraging Galvanic Skin Response (GSR) measurements and a simple LED-based feedback system, the device provides an accessible and cost-efficient alternative to traditional stress assessment methods. The results demonstrate that the system accurately distinguishes between different stress levels, reinforcing its potential use in various personal and clinical applications.

While the device successfully detects stress fluctuations, challenges related to environmental influences, individual skin conductivity differences and sensor placement variability were identified. These limitations emphasize the need for continuous improvement, particularly in refining calibration mechanisms, enhancing data stability and integrating automated threshold adjustments. Future advancements, such as machine learning-driven stress classification, wireless data logging and environmental compensation, could further optimize performance and usability.

Overall, the Inner Peace Meter represents a promising step toward non-invasive, real-time stress monitoring. Its ease of use and potential for integration with mobile health applications highlight its value in mental health management, workplace wellness programs and biofeedback therapy. Further research and iterative development will be essential in expanding its capabilities, ensuring broader adoption and maximizing its impact on stress assessment and emotional well-being.

Acknowledgement
The authors wish to express their sincere gratitude to Universiti Malaysia Sabah (UMS) for their unwavering support, resources and research funding through Geran Penyelidikan Dana Kluster (DKP) Fasa 1/2024, UMS – Kod Projek DKP0173. The authors extend their deepest appreciation to Dr. Mohd Kamal Kamarulzaman for his invaluable mentorship, insightful guidance and continuous encouragement throughout this research. His expert advice and constructive feedback have been instrumental in refining the methodology and overall execution of this project. His expertise has been instrumental in shaping the development and execution of this project. The authors also acknowledge the contributions of all research participants whose involvement in testing and feedback played a crucial role in validating the Inner Peace Meter's functionality. The authors also acknowledge the efforts of the laboratory staff and research assistants who facilitated data collection and experimental procedures. Lastly, appreciation is extended to colleagues and peers for their invaluable feedback, which significantly contributed to the refinement and overall impact of this research.

References

[1] Maqsood, Aneela, Seema Gul, Nazia Noureen and Arooj Yaswi. "Dynamics of perceived stress, stress appraisal and coping strategies in an evolving educational landscape." *Behavioral Sciences* 14, no. 7 (2024): 532. https://doi.org/10.3390/bs14070532

[2] Sylvester, Derry Dexler, Aiman Idris, Noor Dian Eka Wahyu Mohamad, Nurhafiza Lokman, Nur Nabila Syafiqah Sufian, Mohd Kamal Kamarulzaman, Sakinah Hisham and Qayyum Halim. "Development and Control Method for a Six-Wheeled Robot with a Bogie Structure." *Malaysia Journal of Invention and Innovation* 4, no. 3 (2025): 9-21.

[3] Rashid, Sarim, Aniqa Gulfam Qureshi, Tayyiba Ahmed Noor, Khizer Yaseen, Muhammad Abdullah Amir Sheikh, Maria Malik and Jahanzeb Malik. "Anxiety and depression in heart failure: an updated review." *Current problems in cardiology* 48, no. 11 (2023): 101987. https://doi.org/10.1016/j.cpcardiol.2023.101987

[4] Boehm, Julia K. "Positive psychological well-being and cardiovascular disease: Exploring mechanistic and developmental pathways." *Social and Personality Psychology Compass* 15, no. 6 (2021): e12599. https://doi.org/10.1111/spc3.12599

[5] Kafková, Júlia, Pavol Kuchár, Rastislav Pirník, Michal Skuba, Tomáš Tichý and Jiří Brož. "A New Era in Stress Monitoring: A Review of Embedded Devices and Tools for Detecting Stress in the Workplace." *Electronics* 13, no. 19 (2024): 3899. https://doi.org/10.3390/electronics13193899

[6] Xu, Changhao, Samuel A. Solomon and Wei Gao. "Artificial intelligence-powered electronic skin." *Nature machine intelligence* 5, no. 12 (2023): 1344-1355. https://doi.org/10.1038/s42256-023-00760-z

[7] Brooks, Sierra M. and Hal S. Alper. "Applications, challenges and needs for employing synthetic biology beyond the lab." *Nature Communications* 12, no. 1 (2021): 1390. https://doi.org/10.1038/s41467-021-21740-0

[8] Osinga, Sjoukje A., Dilli Paudel, Spiros A. Mouzakitis and Ioannis N. Athanasiadis. "Big data in agriculture: Between opportunity and solution." *Agricultural systems* 195 (2022): 103298. https://doi.org/10.1016/j.agsy.2021.103298

[9] Venables, Peter H. and Margaret J. Christie. "Electrodermal activity." *Techniques in psychophysiology* 54, no. 3 (1980).

[10] Budi, Agus Heri Setya, Sucita, Tasma, Wahyudin, Didin, Saputra, Wasimudin Surya, Adi, Hersyanda Putra, Nasution, Muhammad Fadli and Henny, H. "Heart Rate-Based Fatigue Monitoring System With K-Nearest Neighbor Algorithm for Burnout Prevention". *Journal of Advanced Research in Applied Sciences and Engineering Technology* 61 (1), (2024):165-73. https://doi.org/10.37934/araset.61.1.165173

[11] Sánchez-Reolid, Roberto, Francisco López de la Rosa, Daniel Sánchez-Reolid, María T. López and Antonio Fernández-Caballero. "Machine learning techniques for arousal classification from electrodermal activity: A systematic review." *Sensors* 22, no. 22 (2022): 8886. https://doi.org/10.3390/s22228886

[12] Desai, Usha and Akshaya D. Shetty. "Electrodermal activity (EDA) for treatment of neurological and psychiatric disorder patients: a review." In *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*, vol. 1, pp. 1424-1430. IEEE, 2021. https://doi.org/10.1109/ICACCS51430.2021.9441808

[13] Fowles, Don C. "Mechanisms of electrodermal activity." *Methods in physiological psychology* 1, no. Part C (1974).

[14] Khairul Shah, Alif Haiqal, A Rahman, Khairul Azlan, Goh Thing Thing, Sin Jin Tan, Ritz, Christian and Fuad, Norfaiza. "Investigation of Electroencephalographic (EEG) Brainwave Signal on Mental Stress through Psychomotor Activities". *Journal of Advanced Research in Applied Sciences and Engineering Technology* 62 (2), (2025):245-58. https://doi.org/10.37934/araset.62.2.245258

[15] Williams, Leanne M., Mary L. Phillips, Michael J. Brammer, David Skerrett, Jim Lagopoulos, Chris Rennie, Homayoun Bahramali *et al.,* "Arousal dissociates amygdala and hippocampal fear responses: evidence from simultaneous fMRI and skin conductance recording." *Neuroimage* 14, no. 5 (2001): 1070-1079. https://doi.org/10.1006/nimg.2001.0904

[16] Torkamani-Azar, Mastaneh, Ahreum Lee and Roman Bednarik. "Methods and measures for mental stress assessment in surgery: a systematic review of 20 years of literature." *IEEE Journal of Biomedical and Health Informatics* 26, no. 9 (2022): 4436-4449. https://doi.org/10.1109/JBHI.2022.3182869

[17] Sen, Kausik, Uday Maji and Saurabh Pal. "GSR-Based Auto-Monitoring of Pain Initiation/Elimination Time Using Nonlinear Dynamic Model." *IEEE Sensors Journal* 23, no. 22 (2023): 28120-28128. https://doi.org/10.1109/JSEN.2023.3322206

[18] Patil, Varsha Kiran, Vijaya R. Pawar, Shreiya Randive, Rutika Rajesh Bankar, Dhanashree Yende and Aditya Kiran Patil. "From face detection to emotion recognition on the framework of Raspberry pi and galvanic skin response sensor for visual and physiological biosignals." *Journal of Electrical Systems and Information Technology* 10, no. 1 (2023): 24. https://doi.org/10.1186/s43067-023-00085-2

[19] Gedam, Shruti and Sanchita Paul. "A review on mental stress detection using wearable sensors and machine learning techniques." *IEEE Access* 9 (2021): 84045-84066. https://doi.org/10.1109/ACCESS.2021.3085502

[20] Kaklauskas, Arturas, Ajith Abraham, Ieva Ubarte, Romualdas Kliukas, Vaida Luksaite, Arune Binkyte-Veliene, Ingrida Vetloviene and Loreta Kaklauskiene. "A review of AI cloud and edge sensors, methods and applications for the recognition of emotional, affective and physiological states." *Sensors* 22, no. 20 (2022): 7824. https://doi.org/10.3390/s22207824