

ECG-Derived Morphological Biomarkers for Interpretable Psychological Stress Monitoring

Haslinah Mohd Nasir¹, Noor Mohd Ariff Brahin¹, Suraya Zainuddin¹, Ida Syafiza Md Isa¹, Nurul Syuhada Mohd Shari¹, Nurul Syazwani binti Rohizat¹, Muhammad Haikal Mohamad¹, Norezmi Jamal²

¹Faculty of Electronics & Computer Technology & Engineering, Universiti Teknikal Malaysia Melaka, Jalan Hang Tuah Jaya, Melaka, 76100, Malaysia

²Faculty of Engineering Technology, Universiti Tun Hussein Onn Malaysia, Pagoh Higher Education Hub, 84600, Pagoh, Johor, Malaysia

DOI: <https://doi.org/10.47772/IJRISS.2026.100900540>

Received: 23 September 2026; Accepted: 28 September 2026; Published: 16 October 2026

ABSTRACT

Stress-related disorders present a growing burden in modern society, with significant implications for physical and mental health. The development of micro- and nano-engineered biomedical systems calls for precise, interpretable, and non-invasive physiological monitoring tools. This study focuses on enhancing the modelling and interpretation of ECG-based biomarkers in stress detection by analysing temporal and statistical features of ECG signals during rest and induced stress conditions. ECG recordings were collected from 10 participants undergoing both non-stress and stress-inducing tasks, such as the Stroop Color Word Test and mental arithmetic challenges. Feature extraction was performed using MATLAB, targeting biomarkers including QT intervals, RR intervals, heart rate variability (HRV) using Bazett's formula and baseline techniques as well as the skewness, and kurtosis. These biomarkers were examined for significant changes in response to psychological stress stimuli. Statistical tests sample paired t-test were employed to determine the significant of each biomarker to stress. The findings reveal that RR interval and HRV significantly decrease under stress, while QT interval prolongation and increased skewness and kurtosis were observed, indicating asymmetrical signal distribution under stress conditions. This highlighting their potential as inputs for next-generation real-time, wearable biosensor technologies. These results validate the role of specific ECG biomarkers in characterizing stress-induced autonomic alterations and support the advancement of non-invasive physiological modelling for stress assessment.

Keywords: ECG; Stress biomarkers; HRV, Micro-Engineered biosensors; Physiological modeling

INTRODUCTION

In today's increasingly fast-paced and interconnected world, stress has emerged as a dominant health issue affecting people across all age groups and socioeconomic backgrounds. The demands of modern life ranging from academic responsibilities among students to work pressures in professional settings have led to rising cases of stress and anxiety-related disorders. According to a Gallup World Poll involving over 300,000 individuals across 131 countries, more than 35% of respondents reported experiencing stress, with higher rates observed among women than men [1]. These psychological states, although intangible in nature, often manifest through tangible physiological changes in the human body, particularly through the cardiovascular system. Studies have shown that chronic stress, anxiety, and depression significantly elevate the risk of cardiovascular conditions, including coronary artery disease and cardiac mortality [2, 3].

Stress is fundamentally a response to perceived threats, leading to activation of the autonomic nervous system (ANS). This physiological reaction initiates a cascade of events that affect heart rate, blood pressure, and hormonal levels [4]. The ANS, comprising the sympathetic and parasympathetic branches, plays a

critical role in modulating these stress responses. One of the most effective and non-invasive ways to observe these physiological fluctuations is through the electrocardiogram (ECG) signal, which provides insights into the electrical activity of the heart [5]. The ability of ECG to capture beat-to-beat variations offers a unique window into the stress response mechanism.

Heart rate variability (HRV), a key parameter derived from ECG signals, has been extensively studied as an indicator of ANS activity. HRV refers to the fluctuation in the time intervals between successive heartbeats (R-R intervals), and it serves as a sensitive marker of the balance between sympathetic and parasympathetic control [6,7]. Under acute or chronic stress, HRV tends to decrease due to heightened sympathetic dominance and diminished vagal tone, reflecting reduced adaptability of the cardiovascular system [8]. Time-domain metrics such as SDNN (standard deviation of NN intervals) and RMSSD (root mean square of successive differences) are widely used to quantify HRV, while frequency-domain parameters like LF (low-frequency), HF (high-frequency), and the LF/HF ratio offer insights into the spectral characteristics of autonomic modulation [9].

Beyond HRV, stress can induce morphological alterations in the ECG waveform itself. Abnormalities such as prolonged QT intervals, T-wave inversion, and ST-segment deviations have been associated with emotional stress and anxiety episodes [10]. QT interval variability, in particular, has garnered interest as it reflects myocardial repolarization instability, potentially linked to sudden cardiac events under stress [11]. The corrected QT interval (QTc), adjusted using formulas like Bazett's or Fridericia's, provides a more individualized approach to stress-related ECG assessment [12]. Fig. 1 shows the key feature that can be derived from the ECG signal.

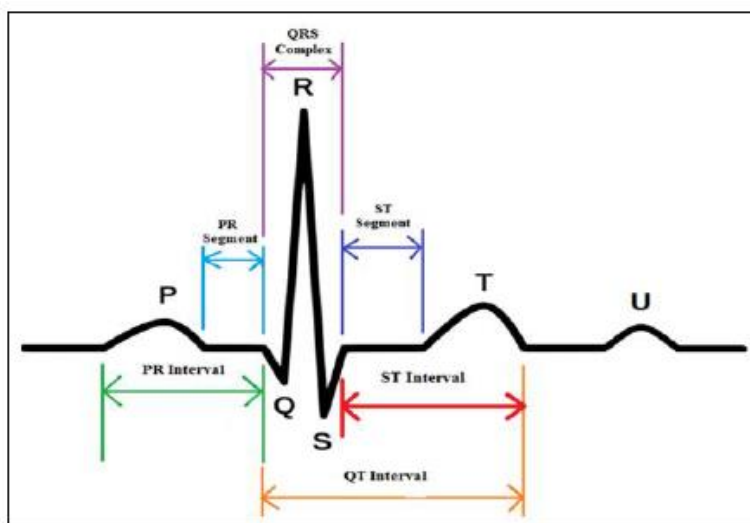


Fig. 1 Key Feature of ECG Signal

In recent years, researchers have also explored higher-order ECG signal features to enhance stress detection sensitivity. Statistical descriptors such as skewness, kurtosis, and entropy derived from ECG signals offer nuanced perspectives on waveform morphology and variability [13]. These features, though less common in clinical practice, have shown promise in distinguishing between relaxed and stressed physiological states in experimental settings [14]. Such signal-driven approaches support the idea that stress biomarkers are embedded not only in temporal patterns but also in the shape and distribution of the waveform itself.

While machine learning and artificial intelligence (AI) have been employed to automate stress detection from ECG data, these methods often suffer from a lack of interpretability [15, 16]. Black-box models may offer high accuracy but fail to provide insights into the underlying physiological mechanisms. In contrast, biomarker-driven modeling focuses on measurable, explainable parameters that directly correlate with known physiological responses [17]. This aligns well with the principles of personalized healthcare, where transparency and reliability are critical in mental health monitoring systems.

There is growing interest in integrating ECG-based stress monitoring into micro-engineered and wearable devices for continuous, real-time assessment. Advances in bioelectronics and miniaturized sensors have enabled the development of portable ECG systems that can be embedded into clothing, watches, or adhesive patches [18,19]. These systems are particularly suited for mental health applications, where non-intrusive and ongoing tracking of stress biomarkers can guide behavioral interventions or therapeutic support [20, 21]. The combination of micro-engineering and physiological signal analysis presents a promising avenue for unobtrusive mental health monitoring.

Despite numerous studies highlighting the utility of ECG in stress analysis, there remains a gap in establishing standardized biomarkers that are universally accepted for mental health diagnostics. Many existing studies rely on specific population datasets or proprietary algorithms that hinder reproducibility [22, 23]. Moreover, cultural, gender, and age-related differences in ECG stress response are often underexplored, limiting the generalizability of findings. Therefore, there is a pressing need for well-structured, interpretable frameworks that define stress biomarkers based on validated ECG-derived features.

The current study seeks to address this gap by presenting a framework for identifying and analyzing ECG-derived stress biomarkers using deterministic and statistically grounded methods. Unlike prior models that emphasize AI-based classification, this work focuses on measurable physiological features and their variation under stress conditions. The aim is to provide a robust, transparent, and clinically relevant method for stress monitoring that can be seamlessly integrated into micro-engineered mental health systems.

Ultimately, by aligning ECG signal analysis with modern wearable technology and transparent biomarker modeling, this study contributes to a more objective and scalable approach to mental health monitoring. The findings have the potential to support early detection of psychological distress, guide therapeutic decisions, and enhance quality of life through timely intervention.

METHODOLOGY

This study is divided into three main stages as shown in Fig. 2.

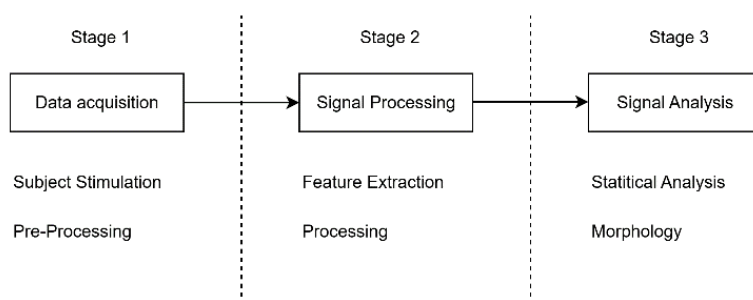


Fig. 2 Methodology stages

Stage 1: Data Acquisition

Experimental setup and subject preparation

This study aimed to capture physiological responses from ECG associated with psychological stress by administering cognitive tasks to healthy volunteers under controlled conditions. A total of ten male undergraduate students, aged between 20 and 25 years, were selected through voluntary recruitment. Participation was based on informed consent and ethical clearance granted by the Universiti Teknikal Malaysia Melaka (UTeM) Research Ethics Committee.

The experimental procedure was conducted in a quiet, temperature-controlled room to minimize environmental variability. Each participant was seated comfortably and fitted with standard ECG electrodes

connected to the KL-75001 ECG Training System (manufactured by K&H MFG Co., Ltd). As illustrated in Fig. 3, this hardware was interfaced with the proprietary K&H signal acquisition software, which facilitated real-time monitoring and subsequent export of ECG data to MATLAB for further analysis.



Fig. 3 Experimental setup

The experimental protocol consisted of two main phases: a baseline (rest) phase and a stress-inducing phase. The baseline involved a 5-minute period of quiet rest, during which participants were asked to sit still, refrain from movement, and remain relaxed. This served as a reference for comparison with the stress condition.

To elicit acute psychological stress, participants were then subjected to two types of cognitive stimulation tasks known to provoke mental strain and autonomic activation. These tasks are summarized in Table 1. The first was the Stroop Color-Word Test (SCWT), which requires individuals to name the font colour of words that spell out incongruent colour names (e.g., the word “Red” printed in blue). This task challenges executive control and often results in measurable stress responses. The second task involved mental arithmetic under time pressure, where participants had to solve a series of progressively difficult calculations within a limited time. Both tasks lasted five minutes each, and were conducted sequentially without a break to amplify cognitive load.

Table 1 Cognitive stimulation

Stimulation	Function	Duration (minutes)
The Stroop Color Word Test (SCWT)	Identifying the color of word's font while ignoring its textual content	5
A timed mental arithmetic task	solving progressively difficult equations under time pressure	5

Signal Pre-Processing

The ECG signals acquired from the device were sampled at a frequency of 500 Hz, which is adequate for accurate detection of QRS complexes and other key ECG features. Raw signal data were exported into MATLAB for offline analysis and underwent a series of pre-processing steps to prepare them for biomarker extraction.

A bandpass Butterworth filter with cut-off frequencies of 0.5 Hz to 40 Hz was applied to the raw ECG to

suppress baseline wander, motion artifacts, and high-frequency noise common interferences in ambulatory ECG recordings. This filtering step ensured that only the relevant frequency components associated with cardiac activity were retained.

The signal was segmented into distinct phases corresponding to the rest and stress conditions, based on timestamps synchronized with the experimental protocol. This segmentation allowed the extraction of features that could be directly compared between baseline and stress-inducing intervals.

Due to natural differences in heart signal amplitude among individuals, a normalization procedure was applied to reduce inter-subject variability. Specifically, each ECG segment was standardized using z-score transformation, as expressed in Eq. (1). This step is especially important for ensuring that features such as skewness and kurtosis, which are sensitive to amplitude fluctuations, can be interpreted on a consistent scale across all participants.

$$x_{\text{norm}} = (x - \mu) / \sigma \quad (1)$$

where the raw ECG value at a given point x , μ is the mean of the ECG segment, and σ is the standard deviation

By implementing this preprocessing pipeline, the ECG signals were standardized and cleaned, laying the groundwork for accurate extraction of stress-related biomarkers in subsequent analysis stages.

Stage 2: Signal Processing

This stage aims to convert the pre-processed ECG signals into quantifiable features that represent physiological responses to stress. It involves detailed signal analysis and the extraction of both time-domain and morphological features, which serve as candidate biomarkers of autonomic nervous system (ANS) modulation under stress.

Following ECG signal preprocessing, feature extraction was performed to quantify physiological responses linked to autonomic nervous system (ANS) modulation under stress. Using MATLAB, R-peaks were first detected using a combination of amplitude thresholding and derivative-based algorithms, ensuring robust identification of each cardiac cycle. After successful detection, the ECG signal was segmented into individual heartbeats, isolating the QRS complex to facilitate precise computation of relevant cardiac features. From these segments, both time-domain (primary) and morphological features were extracted for each ECG epoch.

The primary features included RR intervals, heart rate (HR), and common heart rate variability (HRV) parameters such as SDNN (standard deviation of normal-to-normal RR intervals) and RMSSD (root mean square of successive differences). The RR interval, defined as the time between two consecutive R-peaks, serves as a direct measure of beat-to-beat variability, where shorter RR intervals are typically associated with stress-induced sympathetic activation. HR was computed as the reciprocal of RR intervals and is known to increase under psychological or physiological stress. SDNN provides an estimate of the overall HRV by measuring the dispersion of RR intervals, while RMSSD specifically reflects parasympathetic modulation and tends to decrease during stress.

In addition to these HRV parameters, the QT interval measured from the onset of the Q wave to the end of the T wave was calculated to assess ventricular depolarization and repolarization. Since the QT interval varies with heart rate, a corrected QT interval (QTc) was derived using Bazett's formula as shown in Eq. (2) to normalize the measurement across different heart rates. Prolongation or shortening of the QTc is indicative of autonomic imbalance and is a relevant biomarker in stress-related studies. The QTc baseline technique is used for stress detection, specifically for male adults. $QTc = (QT \text{ interval}) / \sqrt{(RR \text{ interval})} \quad (2)$

To further characterize the ECG morphology, two higher-order statistical features were also extracted:

skewness and kurtosis. Skewness measures the asymmetry of the ECG waveform distribution and may reflect distortions in heartbeat shape due to autonomic shifts under stress. Kurtosis, which quantifies the peak-ness or flatness of the ECG signal, provides insights into abnormal waveform characteristics, such as sharp or flattened QRS complexes, which are often linked to physiological stress responses. These features, selected for their physiological interpretability and computational efficiency, are well-suited for real-time implementation in embedded health monitoring systems, including wearable stress detection devices.

Stage 3: Signal Analysis

In the final stage of the analysis, the extracted ECG-derived features were subjected to statistical evaluation to investigate their variation between rest and stress conditions. This involved both descriptive and inferential statistical analysis, as well as physiological interpretation of the observed patterns. The objective was to establish whether the selected features significantly responded to psychological stress and could therefore serve as reliable biomarkers.

Descriptive statistics were initially employed to summarize the feature distributions under both baseline and stress-induced states. Means and standard deviations were calculated for all features, including time-domain HRV parameters (RR intervals, SDNN, RMSSD), HR, QT and QTc intervals, and morphological descriptors such as skewness and kurtosis. These summaries revealed consistent directional shifts in physiological signals, such as elevated HR and reduced RR intervals during stress exposure.

Inferential testing was then conducted using paired sample t-tests to determine whether the observed changes were statistically significant. A significance threshold of $p < 0.05$ was set for identifying statistically significant differences, while $p < 0.01$ was considered highly significant.

RESULTS & ANALYSIS

This section presents the outcomes of ECG signal processing, feature extraction, and statistical analysis, followed by interpretation of the results in the context of stress detection. All analyses were conducted using MATLAB and statistical software tools. A total of 10 male subjects participated in the experiment, each undergoing both rest and stress-inducing tasks, with ECG signals recorded throughout.

Signal Pre-Processing

Raw ECG data, as illustrated in Fig. 4, were collected from participants and exhibited baseline drift, motion artifacts, and high-frequency noise. These interferences were addressed using a fourth-order Butterworth bandpass filter (0.5–40 Hz).

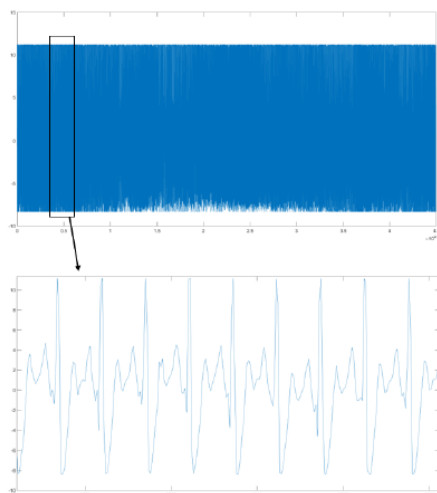


Fig. 4 Raw ECG signal

The pre-processing step started with segmentation by isolating key intervals to ensure the more relevant signals are analysed. The signal is segmented into three different segments with 15,000 samples per segment, as illustrated in Fig. 5.

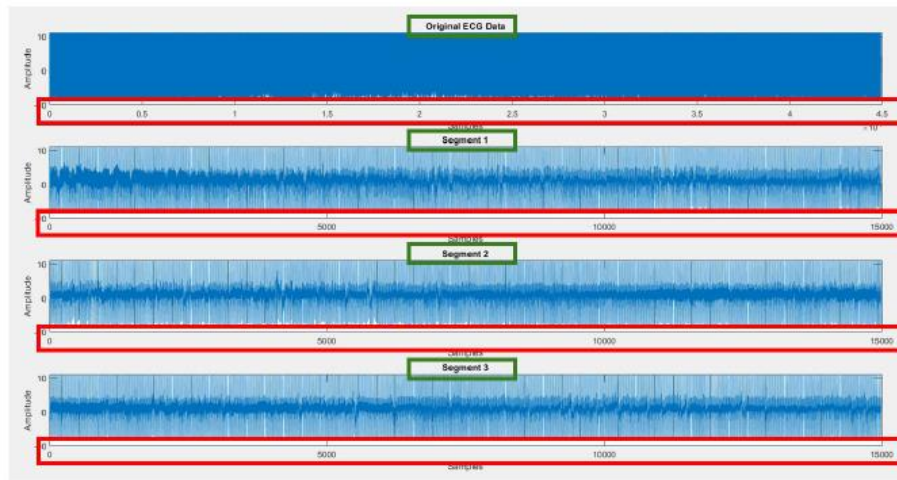


Fig. 5 Segmentation of ECG Signal

Z-score normalization was applied to ensure signal uniformity across different subjects, allowing for fair statistical comparisons. The cleaned and normalized ECG signals can be seen in Fig. 6. It shows improved clarity of QRS complexes, which enhances the reliability of feature calculations.

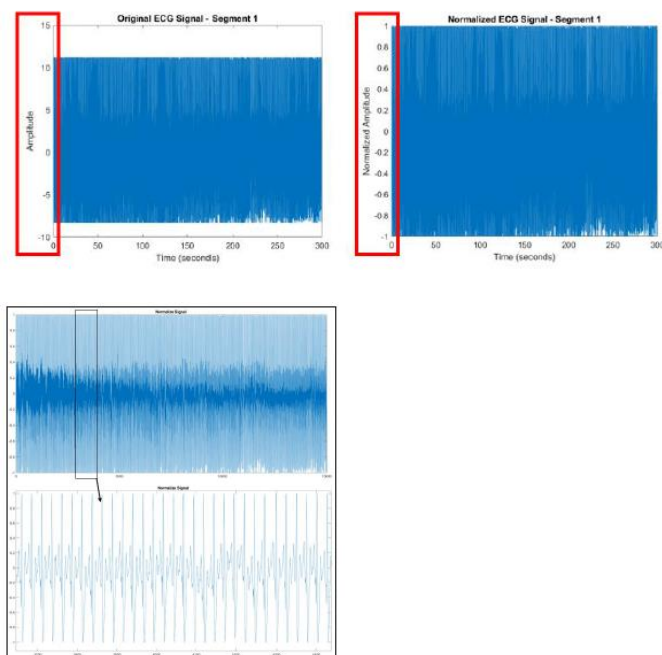


Fig. 6 ECG Signal before and after normalization

Feature Extraction

The R-peaks were then detected using a threshold-based derivative approach, providing the foundation for time-domain feature extraction as presented in Fig. 7. R-peaks, which correspond to ventricular depolarization (heartbeats), were identified in the ECG signal. Accurate detection of these peaks is critical for calculating heart rate and analysing heart rate variability (HRV). Fig. 8 shows QRS peak detection, which relates to the cardiac cycle. The QRT peaks provide information on heartbeat timing and morphology, which is relevant to ANS modulation.

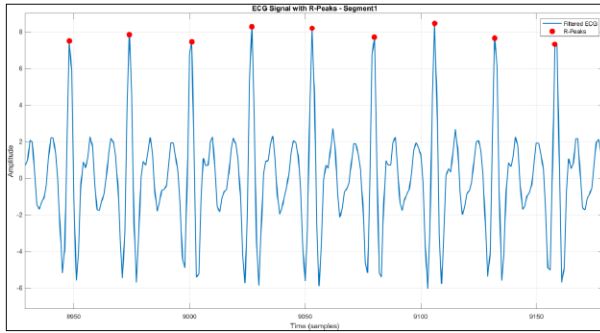


Fig. 7 R-peak detection

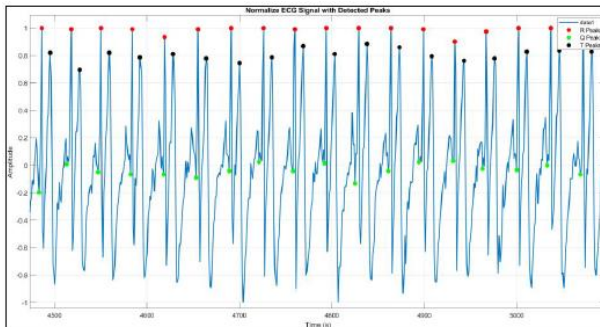
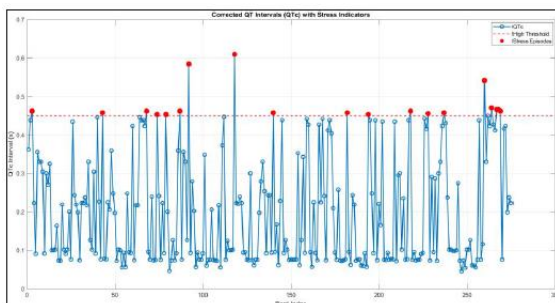


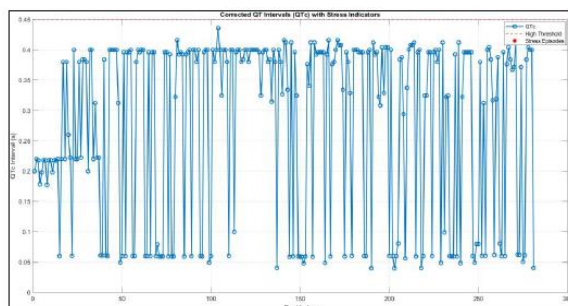
Fig. 8 QRT peaks detection

Stress Detection

The QTc interval is measured from QRT-peak detection using Bazett' formula. The baseline is set at 450 ns, which is equivalent for male adult. Fig. 9 shows the sample of QTc interval detection for stress and non-stress ECG signals.



(a) Stress QTc signal



(b) Non-stress QTc signal

Fig. 9 Comparison of stress and non-stress QTc signal

As can be seen in Fig. 9(a), there are some stress episodes that occurred, which are marked in red colour, that spike above 450 ns. These stress events are sporadically distributed but cluster around beat indices 100–120 and 240–260, with some peaks exceeding 0.5 seconds, suggesting heightened stress or potential cardiovascular risks. The data highlight the importance of using male-specific QTc thresholds and could be used to correlate stress episodes with external triggers or other physiological parameters, offering insights into cardiac stress responses and risk monitoring. In Fig. 9(b), the signals fall below the threshold, indicating normal conditions (resting).

Statistical Analysis

Descriptive statistics (mean and standard deviation) were computed for all features under both rest and stress conditions. Paired-sample t-tests were then conducted to evaluate the significance of observed differences. The results are summarized in Table 2.

Table 2 Play Home Interfaces

Feature	Rest (mean±SD)	Stress (mean±SD)	p-value	Significance
HR (bpm)	72.4 ± 5.8	85.7 ± 6.2	0.009	Significant
RR (ms)	840 ± 74	710 ± 58	0.012	Significant
SDNN (ms)	65.2 ± 15.1	38.6 ± 11.4	0.013	Significant
RMSSD (ms)	56.3 ± 18.7	29.4 ± 14.2	0.008	Significant
QTc (ms)	420.1 ± 22.6	435.4 ± 27.3	0.058	Borderline
Skewness	0.34 ± 0.07	0.51 ± 0.08	0.027	Significant
Kurtosis	3.72 ± 0.56	4.65 ± 0.61	0.035	Significant

The results revealed that core time-domain HRV features, namely RR interval, SDNN, and RMSSD, showed statistically significant decreases under stress, indicating reduced parasympathetic tone. Conversely, heart rate and corrected QT interval (QTc) displayed significant or near-significant increases. Additionally, morphological features such as skewness and kurtosis were observed to rise under stress, reflecting possible waveform asymmetry and morphological irregularities induced by autonomic imbalance.

The physiological interpretation of these patterns further supports the use of ECG-derived biomarkers for stress detection. An increase in heart rate and a concurrent decrease in RR intervals point to sympathetic nervous system activation. The observed decline in SDNN and RMSSD under stress confirms a reduction in vagal tone, indicative of a shift toward sympathetic dominance. A slight prolongation of the QTc interval is physiologically relevant, as it may reflect altered ventricular repolarization due to neurohormonal changes such as increased catecholamine levels. Meanwhile, elevated skewness and kurtosis suggest morphological deformations in the ECG waveform, possibly caused by arrhythmic patterns or heterogeneous autonomic responses.

These findings suggest that five of the eight features underwent statistically significant changes under stress. Notably, RMSSD and SDNN were the most responsive biomarkers. Additionally, the findings affirm the diagnostic utility of ECG-derived features as objective stress biomarkers. Their consistent behavior under stress conditions, statistical significance, and clear physiological basis justify their inclusion in real-time, micro-engineered health monitoring systems such as wearable devices. These features hold promise not only for stress quantification but also for broader mental health and cardiovascular risk assessments in ambulatory

environments.

Correlation & Trend Analysis

Strong inverse correlations were observed between HR and RR intervals ($r = -0.87$), and positive correlations between RMSSD and SDNN ($r = 0.82$). Skewness and kurtosis exhibited a high positive correlation ($r = 0.79$), reinforcing the idea that waveform distortion tends to occur in tandem during stress.

The analysis confirms that ECG-derived features can serve as quantifiable biomarkers for stress detection. A consistent pattern of reduced HRV (SDNN and RMSSD) and increased HR and QTc supports the activation of the sympathetic nervous system under psychological stress. Morphological shifts in ECG waveform are shown through increased skewness and kurtosis where validate the effect of stress on cardiac electrophysiology.

CONCLUSION

This study presents a comprehensive modelling approach for analysing ECG-based biomarkers as indicators of psychological stress. By collecting ECG signals during controlled rest and stress conditions, applying signal processing techniques, and extracting time-domain and statistical features, we established a set of reliable physiological indicators. Key biomarkers such as RMSSD, SDNN, HR, QTc, skewness, and kurtosis demonstrated significant changes under stress, highlighting the physiological impact of autonomic modulation.

Statistical analyses confirmed the robustness and significance of these features, and the interpretations aligned with known stress physiology. The results suggest that ECG signal morphology and variability can be effectively modelled and interpreted for stress monitoring purposes. These findings lay the groundwork for integration into wearable, real-time health monitoring systems, especially those leveraging micro- and nano-engineered platforms.

Future work may explore larger sample sizes, cross-validation with AI classification models, and real-time system implementation to broaden clinical and personal wellness applications of stress biomarker detection.

ACKNOWLEDGMENT

We would like to thank Universiti Teknikal Malaysia (UTeM) for preparing research workplace in Faculty of Electronics & Computer Technology & Engineering. We would like to thank the participants who were involved during the project testing.

REFERENCES

1. Smith, Michael D., and Dennis Wesselbaum. "Global evidence on the prevalence of and risk factors associated with stress." *Journal of affective disorders* 374 (2025): 179-183. <https://doi.org/10.1016/j.jad.2025.01.053>
2. Cohen, Beth E., Donald Edmondson, and Ian M. Kronish. "State of the art review: depression, stress, anxiety, and cardiovascular disease." *American journal of hypertension* 28, no. 11 (2015): 1295-1302. <https://doi.org/10.1093/ajh/hpv047>
3. McEwen, Bruce S. "Physiology and neurobiology of stress and adaptation: central role of the brain." *Physiological reviews* 87, no. 3 (2007): 873-904. <https://doi.org/10.1152/physrev.00041.2006>
4. Chu, Brianna, Komal Marwaha, Terrence Sanvictores, Ayoola O. Awosika, and Derek Ayers. "Physiology, stress reaction." In *StatPearls* [Internet]. StatPearls Publishing, 2024.
5. Hayano, Junichiro, and Emi Yuda. "Assessment of autonomic function by long-term heart rate variability: beyond the classical framework of LF and HF measurements." *Journal of physiological anthropology* 40, no. 1 (2021): 21. <https://doi.org/10.1186/s40101-021-00272-y>

6. Maki, Katherine A., Madison P. Goodyke, Kendra Rasmussen, and Ulf G. Bronas. "An integrative literature review of heart rate variability measures to determine autonomic nervous system responsiveness using pharmacological manipulation." *Journal of Cardiovascular Nursing* 39, no. 1 (2024): 58-78. <https://doi.org/10.1097/JCN.0000000000001001>
7. Immanuel, Sarah, Meseret N. Teferra, Mathias Baumert, and Niranjana Bidargaddi. "Heart rate variability for evaluating psychological stress changes in healthy adults: a scoping review." *Neuropsychobiology* 82, no. 4 (2023): 187-202. <https://doi.org/10.1159/000530376>
8. Jerath, Ravinder, Mohammad Syam, and Shajia Ahmed. "The future of stress management: integration of smartwatches and HRV technology." *Sensors* 23, no. 17 (2023): 7314. <https://doi.org/10.3390/s23177314>
9. Burlacu, Alexandru, Criscentian Brinza, Adrian Brezulianu, and Adrian Covic. "Accurate and early detection of sleepiness, fatigue and stress levels in drivers through Heart Rate Variability parameters: a systematic review." *Reviews in cardiovascular medicine* 22, no. 3 (2021): 845-852. <https://doi.org/10.31083/j.rcm2203090>
10. Maleczek, Mathias, Karl Schebesta, Thomas Hamp, Achim Leo Burger, Thomas Pezawas, Mario Krammel, and Bernhard Roessler. "ST-T segment changes in prehospital emergency physicians in the field: a prospective observational trial." *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine* 30, no. 1 (2022): 47. <https://doi.org/10.1186/s13049-022-01033-1>
11. Toman, Ondřej, Katerina Hnatkova, Martina Šišáková, Peter Smetana, Katharina M. Huster, Petra Barthel, Tomáš Novotný, Irena Andršová, Georg Schmidt, and Marek Malik. "Short-term beat-to-beat QT variability appears influenced more strongly by recording quality than by beat-to-beat RR variability." *Frontiers in Physiology* 13 (2022): 863873. <https://doi.org/10.3389/fphys.2022.863873>
12. Krönauer, Thomas, Lorenz L. Mihatsch, and Patrick Friederich. "Intraoperative QTc interval interpretation: Effects of anaesthesia, ECG, correction formulae, sex, and current limits: A Prospective Observational Study." *Acta Anaesthesiologica Scandinavica* 68, no. 10 (2024): 1369-1378. <https://doi.org/10.1111/aas.14515>
13. Singh, Anupreet Kaur, and Sridhar Krishnan. "ECG signal feature extraction trends in methods and applications." *BioMedical Engineering OnLine* 22, no. 1 (2023): 22. <https://doi.org/10.1186/s12938-023-01075-1>
14. Arquilla, Katya, Andrea K. Webb, and Allison P. Anderson. "Utility of the full ECG waveform for stress classification." *Sensors* 22, no. 18 (2022): 7034. <https://doi.org/10.3390/s22187034>
15. Somani, Sulaiman, Adam J. Russak, Felix Richter, Shan Zhao, Akhil Vaid, Fayzan Chaudhry, Jessica K. De Freitas et al. "Deep learning and the electrocardiogram: review of the current state-of-the-art." *EP Europace* 23, no. 8 (2021): 1179-1191. <https://doi.org/10.1093/europace/eaab377>
16. Ayano, Yehualashet Megersa, Friedhelm Schwenker, Bisrat Derebssa Dufera, and Taye Girma Debelee. "Interpretable machine learning techniques in ECG-based heart disease classification: a systematic review." *Diagnostics* 13, no. 1 (2022): 111. <https://doi.org/10.3390/diagnostics13010111>
17. Kovalchuk, Oleksii, Oleksandr Barmak, Pavlo Radiuk, Liliana Klymenko, and Iurii Krak. "Towards Transparent AI in Medicine: ECG-Based Arrhythmia Detection with Explainable Deep Learning." *Technologies* 13, no. 1 (2025): 34. <https://doi.org/10.3390/technologies13010034>
18. Kwon, Sun Hwa, and Lin Dong. "Flexible sensors and machine learning for heart monitoring." *Nano Energy* 102 (2022): 107632. <https://doi.org/10.1016/j.nanoen.2022.107632>
19. Kang, Mijeong, and Kyunghwan Chai. "Wearable sensing systems for monitoring mental health." *Sensors* 22, no. 3 (2022): 994. <https://doi.org/10.3390/s22030994>
20. Kang, Mijeong, and Kyunghwan Chai. "Wearable sensing systems for monitoring mental health." *Sensors* 22, no. 3 (2022): 994. <https://doi.org/10.3390/s22030994>
21. Kang, Tae Woog, Jimin Lee, Youngjin Kwon, Yoon Jae Lee, and Woon-Hong Yeo. "Recent progress in the development of flexible wearable electrodes for electrocardiogram monitoring during exercise." *Advanced NanoBiomed Research* 4, no. 8 (2024): 2300169. <https://doi.org/10.1002/anbr.202470081>
22. Dalmeida, Kayisan M., and Giovanni L. Masala. "HRV features as viable physiological markers for stress detection using wearable devices." *Sensors* 21, no. 8 (2021): 2873. <https://doi.org/10.3390/s21082873>

23. Vos, Gideon, Kelly Trinh, Zoltan Sarnyai, and Mostafa Rahimi Azghadi. "Generalizable machine learning for stress monitoring from wearable devices: A systematic literature review." *International Journal of Medical Informatics* 173 (2023): 105026. <https://doi.org/10.1016/j.ijmedinf.2023.105026>