Published Online: 2026 April 25

Research Article

Identifying Anger Emotion Using BVP Sensor: Heart Rate Variability (HRV)

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Received: 7 June, 2025; **Revised:** 16 November, 2025; **Accepted:** 2 February, 2026

Abstract

Background: Accurate measurement tools are crucial for the early detection of emotional problems and dysregulation.

Objectives: This study aimed to identify the emotion of anger using heart rate variability (HRV) as a biomarker. The diagnostic accuracy of five HRV-related subscales — HR, RR, HF, LF, and LF/HF — was evaluated among individuals with high and low anger.

Methods: This descriptive (exploratory) quantitative study included adults aged 20 - 45 years living in Tehran. A total of 100 participants were initially recruited, but 24 were excluded due to insufficient or inaccurate HRV recordings, leaving a final sample of 76. Participants completed the Positive and Negative Affect Schedule (PANAS), and HRV data were collected via a blood volume pulse (BVP) sensor. Descriptive statistics and independent-sample *t*-tests were performed using SPSS, while receiver operating characteristic (ROC) and sensitivity analyses were conducted using MedCalc.

Results: Significant differences were found between high- and low-anger groups in HR ($P < 0.05$) and RR ($P < 0.001$) scales, with higher mean scores in the high-anger group. Among the five HRV subscales, the RR scale had the highest discriminative accuracy (AUC = 0.71), performing significantly better than HR, HF, LF, and LF/HF.

Conclusions: Heart rate variability, particularly the RR subscale, can serve as a reliable biological indicator for anger detection. These findings support the potential application of physiological markers in identifying emotional states.

Keywords: Anger, Biomarkers, Emotion Dysregulation, Heart Rate Variability

1. Background

Humans see the world through a perceptual filter and emotions that are formed by a wide and diverse range of personality-oriented thoughts and behaviors (1). Contemporary researchers consider emotions as the foundation of human development and relationships (2). Since emotions are social in nature, they are a basic means of communication for humans. Unfortunately, there are people who do not know what their emotions are, let alone how to express them (3). Emotion is often defined as a complex feeling that results in physical and psychological changes that affect thought and behavior (4).

Despite the fact that in recent years, psychologists have paid a lot of attention to emotions, few clinical and objective recommendations have been provided to deal effectively with specific emotions (5). In fact, if we can accurately identify emotions and measure them objectively, we can greatly help reduce emotional problems and increase people's mental health. Therefore, the methods of identification and evaluation of emotions presented in the research literature can be classified into two main groups according to the basic techniques used in the detection of emotions: Based on self-evaluation of emotions by completing different questionnaires (6, 7); and machine evaluation techniques based on measuring different parameters of the human body (8, 9). It is difficult to assess emotions in clinical settings, which must be obtained by periodic self-reports by patients. Self-reporting always depends on people's willingness to tell and is subject to intra-subject variation in reporting due to other contextual factors such as environment, people, situation, etc. (3).

How to Cite: Dehghanizadeh Z, Dolatshahi B, Nosratabadi M, Moradi H. Identifying Anger Emotion Using BVP Sensor: Heart Rate Variability (HRV). Iran J Psychiatry Behav Sci. 2026;20(2):e162423. doi: https://doi.org/10.5812/ijpbs-162423

However, one of the most distinctive of these ways is the monitoring of human physiological changes. There are signals that the human body shows involuntarily, such as heart rate variability (HRV), skin/muscle tension, facial expressions, pupil dilation, and micro-movements. Most of them have a bioelectrical impulse which in turn can be recorded by sensors (10). These signals can identify and regulate emotions using the biofeedback method, which has been widely investigated in many studies (10, 11). Considering the large number of available biological signals, one of the problems is the selection of the most appropriate biological signals, which are used as a method to convert signals into emotions (12, 13). Therefore, it is very important to use appropriate sensors to measure biosignals, and high precision is required to obtain good reliability (14).

For automatic detection and assessment, most emotion assessment studies focus on other classifications (15), which include emotion dimensions, in most cases valence (activation-negative/positive) and arousal (high/low) (16, 17), and analyze only basic emotions such as anger, fear, sadness, happiness, surprise, disgust, and contempt, which can be easily defined and provide an assessment of their intensity. Among the different emotions that we experience, anger has the most negative effect on human health (18); therefore, this issue may become a complicated issue for the individual, in which case, the need for medical help to deal with it is necessary (19). On the other hand, continuous expression of anger and nervousness and inability to control it may also lead to failure in social relations and interpersonal interactions (18, 19). Accordingly, the most important benefit of being aware of and paying attention to angry feelings is the opportunity we get to regulate or inhibit our reactions, reassess the situation, and plan actions that are most likely to remove the source of the anger (20). The ability to recognize emotions early can help us deal with people in various situations and manage our emotional responses to their feelings. Furthermore, the actions we take to develop impulse awareness can be useful for what almost all of us can achieve—being aware of emotional behavior, or recognizing our emotional state as soon as it begins to express itself in words or actions. If you can become aware that an emotion has started to guide your behavior, you can consciously check whether your emotional reaction is appropriate for the situation you are in, and if so, whether it has the right intensity and expresses itself in the most constructive way (20).

Recently, Huang et al. (21) extracted features from facial expressions and electroencephalography (EEG) of 27 subjects. They integrated these methods and obtained the highest accuracy of 66.28% for capacity and 63.22% for arousal using decision-level fusion. Zhang et al. (22) collected respiration (RSP), electromyography (EMG), and skin conductance (SC) from 20 subjects. They obtained the highest detection rate of 80% for arousal and 76.67% for capacity by combining these three methods. When the four categories were arbitrarily adjusted to account for the arousal and valence dimensions, the highest accuracy of 50% was achieved with single-modality RSP or EMG rather than modality fusion. In well-documented works, "individual differences" have been raised as a matter of widespread concern. Humans may show different emotions for the same emotion and have different physiological patterns when exposed to an emotional stimulus. This issue was raised for the first time by Picard et al. (23). The main motive of using physiological signals as opposed to subjective personal reports in the detection of emotions was to discover the internal connection of signal patterns with human emotional states and finally to accurately detect emotions (24).

Valenza et al. suggested that HRV can be an objective tool to assess emotional responses (25). Also, Lane et al. reported the relationship between the subject's emotional state and HRV (26). Although HRV is now used sporadically in experiments designed to assess human emotional states, no research has yet confirmed its validity as a tool for assessing human emotion (27).

2. Objectives

In the present study, the goal of the researchers is to be able to identify anger using the heart rate sensor — BVP. This research is the first phase of a research based on the design of an emotional smart wristband that is able to identify emotions in real time and give feedback to the person so that they are aware of their emotional state and type of emotion and then can deal with the situation appropriately. Among the strategies of emotion regulation, it is shown that this leads to better and more adaptation. Therefore, the obtained diagnostic accuracy helps us to know if heart rate can be the right tool to evaluate and detect emotions in real time.

3. Methods

The study is descriptive (exploratory) and quantitative analysis. The current research population includes all adults (age range 20 - 45 years selected based on research literature) living in Tehran. The statistical sample of the current research, which was selected using the available sampling method based on the entry and exit criteria, was 100 people. After reviewing the data obtained from their heart rate sensors, 24 participants were excluded because their recordings contained less than 5 minutes of valid, artifact-free data, which is below the minimum duration recommended for reliable HRV analysis (Task Force, 1996). The remaining sample in the present study was 76. Baseline comparisons (age, gender, baseline PANAS scores) between excluded (n = 24) and included participants (n = 76) revealed no significant differences (all $P > 0.05$), indicating that the exclusion procedure did not introduce sampling bias. The final sample size (n = 76) is consistent with previous HRV-based emotion detection where comparable or even smaller sample sizes were used successfully. For example, Suzuki et al. conducted an HRV-based emotion study with 48 participants, and Quintana et al. investigated emotion recognition and HRV in 65 participants, both reporting reliable classification results (28, 29) and is sufficient for robust receiver operating characteristic (ROC) and sensitivity analyses.

The entry criteria included agreeing to participate in the project and use the BVP sensor, age range of 20 - 45 years, living in Tehran, and not suffering from heart diseases, blood pressure issues, or blood phobia. Exclusion criteria included discontinuing participation in the research or the occurrence of illness restricting participation. In the first stage, among 20 films approved in scientific articles, three films that induced the emotion of anger were selected; 5-minute clips in which anger moments were clearly perceived were used. Volunteers were invited to perform the test steps. The experiment was conducted in an emotion induction phase by showing the anger content on the Parand Clinic test room TV screen. HRV data recording was synchronized with the onset of each anger-inducing film clip. The BVP sensor automatically started recording at the beginning of each clip and continued throughout its duration (approximately 6 minutes), ensuring that HRV measures corresponded precisely to the anger induction phase. Participants were instructed not to consume caffeine on the day of the experiment. To minimize stress, all participants underwent guided relaxation exercises before and during the experiment, and the testing environment was quiet and temperature-controlled. The heart rate of each subject was recorded by the BVP sensor for 6 minutes. Immediately after viewing the film clips, participants completed the online PANAS to report the quantity and quality of emotions perceived.

Operational Definition of Anger: In line with Spielberger's State-Trait Anger Theory (STAXI), anger was defined as a subjective emotional state rather than aggressive behavior. Participants' anger was measured using selected PANAS items capturing feelings of anger, irritation, or hostility immediately after viewing the anger-inducing film clips. This operationalization ensures that HRV changes reflect emotional experience (anger) rather than behavioral manifestations. The study included 76 participants (19 males, 57 females; age range 20 - 49 years, mean ± SD: 27.87 ± 7.49).

3.1. Research Instrument

3.1.1. Positive and Negative Affect Schedule

To measure the concurrent validity, the Positive and Negative Affect Schedule (PANAS) prepared and presented by Watson, Clark, and Telgen in 1988 was used. This scale measures 20 items (10 positive feelings and 10 negative feelings) in the majority of words and is generally evaluated on a five-point Likert scale (from strongly agree to strongly disagree) (30). Research on the psychometric properties of the Persian version of this scale provides evidence with high internal consistency (Cronbach's $\alpha = 0.85$) (31).

3.1.2. Blood Volume Pulse Sensor

The blood volume pulse (BVP) sensor and Bioline biofeedback device (manufactured by Medinateb, Iran) were used to record heart rate.

Heart rate variability is an emotional state assessment technique based on the measurement of HRV, which means the beat-to-beat changes over time during a given period of sinus rhythm. Unlike average heart rate variance, which is expressed over a 60-second period, HRV analysis examines the fine-grained time variance within each heart rate cycle and its regularity (32). The change in heart rate is regulated by the synergistic action of the two branches of the autonomic nervous system, i.e., the sympathetic and parasympathetic nervous systems. The heart rate reflects the net effect of the parasympathetic nerves, which slow the heart rate, and the sympathetic nerves, which speed it up. These changes are influenced by emotions, stress, and physical exercises. In addition, HRV depends on age and gender, and additional factors include physical and psychological stress, smoking, alcohol, coffee, overweight, and blood pressure, as well as glucose levels, infectious agents, and depression (33).

3.2. Statistical Methods

Data were collected using the specified scales and recorded on a computer for analysis. Descriptive statistics, including means and standard deviations, were calculated for all variables. To compare the mean scores of HR, RR, HF, LF, and LF/HF between the high-anger and low-anger groups, a two-independent-samples t-test was performed using SPSS software. Additionally, ROC analysis and sensitivity analysis were conducted using MedCalc software to evaluate the diagnostic accuracy of the HRV subscales. Receiver operating characteristic analysis, derived from signal detection theory, is used to assess the diagnostic performance of tests (34) and to compare two or more diagnostic tests (35). The ROC curve plots sensitivity (vertical axis) against 1-specificity (horizontal axis). A higher area under the curve (AUC) indicates better discriminative ability of the test, ranging from 0.5 (classification by chance) to 1.0 (perfect classification). Values above 0.9 are generally considered to indicate excellent diagnostic accuracy (34).

4. Results

One of the key biological variables examined as a potential biomarker for anger in previous studies is heart rate and its derived measures. In the present study, participants' anger levels were assessed using the PANAS while they watched a standardized anger-inducing film clip ("My Bodyguard"), selected based on prior research. Based on their PANAS scores, participants were categorized into high- and low-anger groups. Simultaneously, heart rate data were recorded using a BVP sensor to analyze physiological responses associated with anger.

Figure 1 presents the ROC curves for the five physiological indices (RR, HR, HF, LF, and LF/HF), allowing a comparative evaluation of their diagnostic performance in distinguishing high- and low-anger groups.

4.1. Descriptive Statistics Calculations

Descriptive statistics, including mean, standard deviation, skewness, and kurtosis, for the five scales (HR, RR, LF, HF, LF/HF during task) are presented in Table 1. As all skewness and kurtosis values were below 2, consistent with Tabachnik and Fidell (1996), the distributions of these scales can be considered approximately normal.

Independent samples t-tests were conducted to examine differences between the high- and low-anger groups for each scale (Table 2). Significant differences were observed for the HR and RR scales. Specifically, the HR scale showed a statistically significant difference between groups (t = 2.56, $P < 0.05$), and the RR scale also showed a statistically significant difference (t = -2.99, $P < 0.05$). No significant differences were found for the LF, HF, and LF/HF scales.

4.2. Investigating the Diagnostic Accuracy of Scales

Descriptive statistics indicated that the HR, HF, LF, and LF/HF scales had approximately normal distributions, while the RR scale exhibited moderate negative skewness (skewness = -1.22), suggesting caution in interpreting normality assumptions for this scale.

Receiver operating characteristic analyses were conducted to examine the discriminative ability of the five scales (HR, RR, LF, HF, LF/HF). Results are presented in Table 3. The RR scale demonstrated the highest Youden index (0.71), followed by the HR scale (0.69). Statistical comparison indicated that the RR scale performed significantly better than the HR scale (Z = 0.01 vs. Z = 0.06). The remaining scales (HF, LF, LF/HF) showed lower discriminative ability and limited clinical relevance.

As shown in Table 3, the RR scale demonstrated the highest AUC (0.71, 95% CI: 0.60 - 0.81, SE = 0.06), indicating its superior ability to detect anger. DeLong's test was performed to compare the AUCs of other HRV scales against RR. The results confirmed that RR significantly outperforms HF (P = 0.040), while differences with HR, LF, and LF/HF were not statistically significant ($P > 0.05$). These findings highlight RR as a clinically relevant and reliable biomarker for anger detection.

Given its superior performance, the RR-TASK scale was further examined separately in the subsequent analyses, and its values are reported accordingly.

As seen in Figure 2, the area under the ROC curve (AUC) for the RR scale was 0.71 (P = 0.001), indicating that the RR subscale has a good discriminative ability to differentiate between individuals with high and low anger levels. The sensitivity and specificity are also explained in the following tables.

Sensitivity analysis was conducted to determine the optimal cut-off scores for the five HRV scales (RR, HR, HF, LF, and LF/HF), taking into account sensitivity, specificity, positive likelihood ratio, and negative likelihood ratio. An optimal cut-off was defined as the score that maximizes sensitivity and specificity while minimizing the negative likelihood ratio. As shown in Figure 3, the ROC curves for these scales provide a comparative assessment of their discriminative performance in identifying high- and low-anger individuals, with P-values from DeLong's test indicating statistically significant differences between the AUCs.

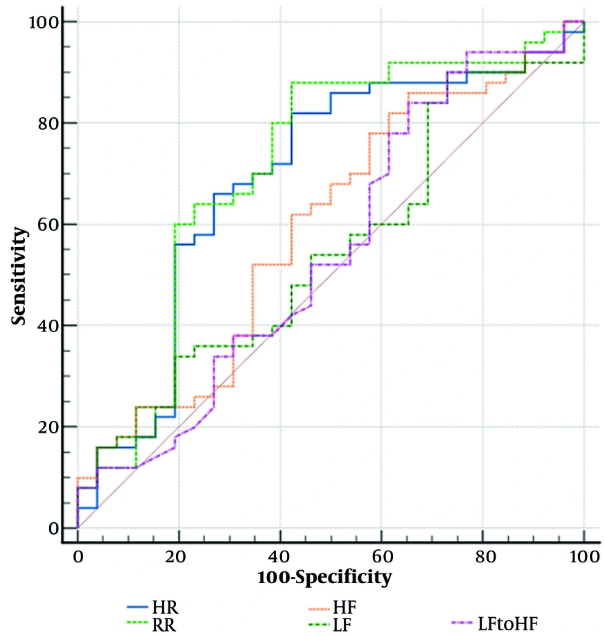

Figure 1. Receiver operating characteristic (ROC) curves diagram for five scales RR, HR, HF, LF, LF/HF

Table 1. The Results of Descriptive Statistics for Five Scales HR, RR, LF, HF, LF/HF

Scales	Mean ± SD	Skewness	Kurtosis
HR	81.46 ± 9.32	-0.19	-0.75
RR	754.90 ± 108.04	-1.22	7.15
LF	1592.78 ± 3017.16	4.05	17.24
HF	3154.59 ± 5651.46	2.68	6.63
LF/HF	0.79 ± 0.56	1.49	1.88

Table 2. The Results of *t*-Test (*t*) of Independent Groups

Scales	df	*t*	Sig	Means Difference	SE
HR	74	2.56	0.012	5.57	2.17
RR	74	-2.99	0.004	-74.40	24.83
LF	74	-1.35	0.17	-984.35	725.45
HF	74	-1.42	0.15	-1935.19	1357.14
LF/HF	74	1.29	0.19	0.17	0.13

Among the five scales, only RR demonstrated a favorable Youden index (0.71). Based on the combined results of ROC and sensitivity analyses (Table 4), a cut-off score of 690.66 on the RR scale was identified as optimal. This indicates that the RR scale is the most discriminative measure for distinguishing individuals with higher anger levels, consistent with prior research. These results support the potential use of heart rate sensors as reliable tools for anger detection. The RR subscale demonstrated the highest discriminative

Table 3. Receiver Operating Characteristic Analysis of heart rate variability-Derived Scales for Distinguishing High vs. Low Aggression Groups, Including Comparison with RR Scale Using DeLong's Test

Scales	AUC	95% CI	SE	Comparison vs. RR (P-Value)
RR	0.71	0.60-0.81	0.06	-
HR	0.69	0.57-0.79	0.06	0.078
HF	0.59	0.47-0.70	0.07	0.04
LF	0.54	0.42-0.66	0.06	0.94
LF/HF	0.55	0.43-0.66	0.07	0.99

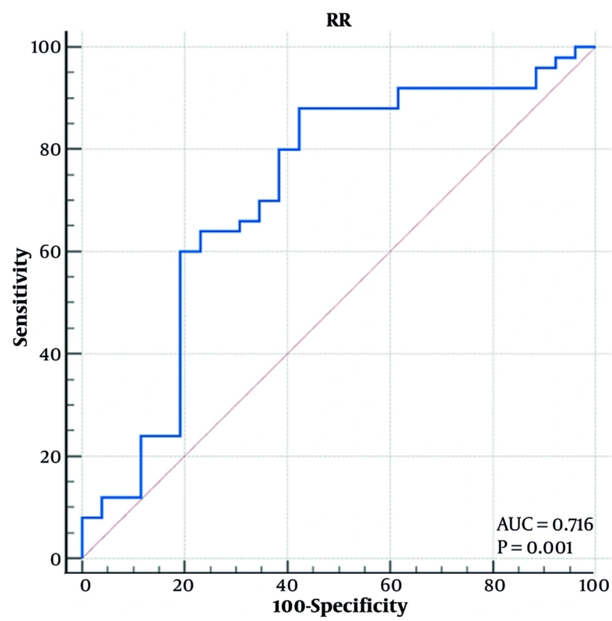

Figure 2. Receiver operating characteristic (ROC) curve diagram for RR Scale

ability among the HRV indicators, with a Youden index of 0.45, indicating that it effectively differentiated between individuals with high and low anger levels.

5. Discussion

Undoubtedly, the existence of accurate measurement tools is an important step toward the early diagnosis of emotional problems and dysregulation. In the present study, we aimed to identify anger emotion using HRV as a biomarker. In the present study, anger was treated as a subjective emotional state rather than a behavioral outcome. Consistent with Spielberger's State-Trait Anger Theory (STAXI), participants' experience of anger was operationally defined through PANAS items assessing feelings of anger, irritation, and hostility. This distinction clarifies that HRV changes observed in this study reflect emotional experience (anger) rather than aggressive behavior, addressing potential conceptual confusion. While PANAS is a general affect measure, these selected items closely align with STAXI anger-specific constructs, ensuring that physiological responses recorded via HRV can be interpreted as correlates of emotional states, not behavioral manifestations. Among five HRV-related measures (HR, RR, HF, LF, LF/HF), the RR scale showed the highest AUC = 0.71, indicating modest but acceptable predictive ability.

Previous studies achieving higher predictive performance have typically integrated multiple physiological signals, including EEG, blood pressure, respiration, or facial features. For instance, studies based on the DEAP dataset have reported classification

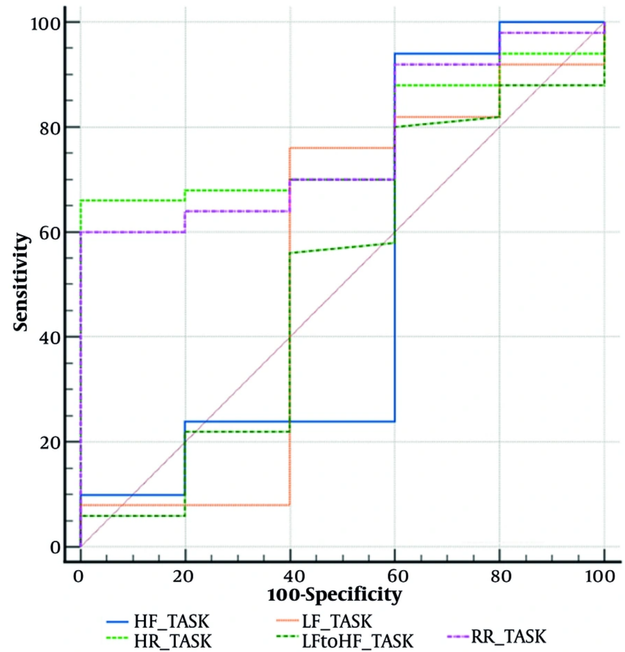

Figure 3. Receiver operating characteristic (ROC) curves for HRV-derived scales (RR, HR, HF, LF, LF/HF) in distinguishing high and low aggression groups. P-values from DeLong test are indicated

Table 4. Receiver operating characteristic Analysis for the RR Scale: Full Sample and Cross-Validated Test Set

Dataset	AUC	Cutoff	Sensitivity	Specificity
Full Sample	0.768	727.735	0.70	0.60
Test Set	0.958	727.735	0.71	1.00

accuracies ranging from approximately 80% to over 90% (36). In contrast, studies relying solely on heart rate variability (HRV) generally report more moderate performance, typically in the range of 65 - 75% (37). In line with these findings, the present study achieved an AUC of 0.71 for the RR interval, indicating acceptable but limited predictive performance. Nonetheless, the findings demonstrate the feasibility of HRV-based anger detection and provide a baseline for future research.

For practical applications, such as wearable emotion recognition devices, combining HRV with additional physiological or behavioral signals (e.g., video analysis, motion detection, or speech emotion recognition) may enhance diagnostic accuracy and overcome limitations of single-modality systems.

Finally, due to the small sample size, these results cannot be generalized to all populations. Future studies should confirm the validity and reliability of HRV-based anger detection with larger and more diverse samples. Overall, this study represents a preliminary investigation into the diagnostic accuracy of HRV measures for anger identification.

Although this study primarily serves as a foundational validation of HRV for anger detection, the results clearly demonstrate that HRV can reliably differentiate between high and low anger states. These findings provide a robust basis for future applications, including real-time monitoring of emotional states in wearable devices, which could support individuals in becoming aware of their emotions as they occur and facilitate subsequent emotion regulation strategies.

To contextualize these findings, descriptive analyses confirmed the normal distribution of HRV indices, supporting the robustness of subsequent statistical comparisons. Descriptive calculations in order to investigate the distribution of people's scores in these five scales showed that all five scales have relatively normal distribution and do not have any problems in terms of skewness and kurtosis. Preliminary studies on the difference between the mean scores of two groups of people with high and low anger in five scales HR, RR, HF, LF, and LF/HF showed that the difference between the mean scores of the two groups in the HR scale (at a significant level of less than 0.05) and RR (at a significance level of less than 0.001) is statistically significant. In both scales, the average scores of people with high anger were higher than the average of people with low anger. Determining the optimal cut-off score for these scales based on the observed differences, in addition to being associated with many errors, does not have strong statistical support; therefore, ROC and sensitivity analysis were used to determine the optimal cut-off score and also to examine the diagnostic accuracy of these scales.

Among the five scales, the RR scale showed the highest purity index (AUC = 0.71), significantly outperforming HR, HF, LF, and LF/HF. In clinical practice, a purity index above 0.70 is generally considered acceptable, and thus, only the RR scale meets this criterion in the present study. To further assess the stability and reliability of the RR scale, a cross-validation analysis was performed using a split-sample approach (70% training, 30% test). The ROC analysis on the test set confirmed high discriminative accuracy, with an AUC of 0.958, supporting the robustness of the RR scale in differentiating between high and low anger groups. The cutoff, sensitivity, and specificity values for both the full sample and test set are summarized in Table 4. These findings strengthen the clinical applicability of the RR scale as a reliable biomarker for anger detection. The HR scale, with an AUC of 0.69, falls slightly below this threshold, yet still outperforms HF, LF, and LF/HF. Based on ROC analysis, the RR scale correctly classifies individuals into high- and low-anger groups in 71% of cases, while the HR scale achieves 69%. These results are consistent with previous research. HRV-based emotion recognition studies have reported moderate performance levels, typically ranging from approximately 65% to 80% depending on feature extraction and classification methods (37). Chen et al. found an average accuracy of 77.57% for detecting four emotions using emotional intelligence devices, with a maximum accuracy of 86.67% (24).

Furthermore, multimodal approaches integrating physiological and affective signals have demonstrated significantly higher performance, often exceeding 80% accuracy on benchmark datasets such as DEAP (36) while Wagner et al. reported 92.05% accuracy (38). More recently, Huang et al. combined EEG and facial expression features and obtained a maximum accuracy of 66.28% (39).

Overall, these findings reinforce the RR scale's reliability as a biomarker for anger detection and highlight its potential for clinical and wearable applications.

Overall, the present study demonstrates that HRV can serve as an objective indicator for emotion identification. However, while biosignals are a valuable tool for emotion detection, it remains unclear whether they are sufficient on their own. Combining multiple sources of information, such as video analysis, motion detection, or speech-based emotion recognition, alongside biosensor signals, appears to be a necessary step to overcome the limitations of single-modality systems.

In the present study, due to the small sample size, the results cannot be generalized to all individuals with certainty. It is also important to consider the influence of cultural norms on emotional expression. Our participants were all adults from Tehran, representing a collectivist cultural context. Previous studies have shown that cultural orientation (collectivist vs. individualist) can influence both anger expression and cardiovascular responses (40, 41). Therefore, HRV-based patterns observed in this study should be interpreted cautiously and may not generalize to populations from other cultural backgrounds. Future research should examine cross-cultural differences in HRV responses to anger and further clarify the validity and reliability of these findings with larger and more diverse samples.

The primary objective of this study was to investigate the feasibility of using HRV as a biomarker to identify anger. Beyond mere identification, the long-term goal is to integrate HRV measurement into a wearable device, such as a wristband, enabling real-time monitoring of emotional states. By providing structured feedback, individuals can gradually develop awareness of their emotions as they occur, and use this information to practice self-regulation strategies. In this context, the wearable device acts as an interactive biofeedback tool, supporting the user in recognizing and modulating emotional responses, thereby facilitating adaptive emotion regulation. This approach emphasizes clinical relevance by offering a non-invasive, continuous method to enhance emotional awareness and self-management, which could complement traditional psychological interventions in subsequent research phases. In general, the present study can be considered a preliminary investigation assessing the diagnostic accuracy of heart rate measurement scales.

Footnotes

AI Use Disclosure: The authors declare that no generative AI tools were used in the creation of this article.

Authors' Contribution: Study concept and design: B. D. and Z. D.; Acquisition of data: Z. D. and M. N.; Analysis and interpretation of data: Z. D. and M. N.; Drafting of the manuscript: Z. D. and M. N.; Critical revision of the manuscript for important intellectual content: H. M.; Statistical analysis: Z. D. and M. N.; Administrative, technical, and material support: B. D. and Z. D.; Study supervision: B. D.

Conflict of Interests Statement: The authors declare no conflict of interest.

Data Availability: The dataset presented in the study is available on request from the corresponding author during submission or after publication.

Ethical Approval: The present study was approved by the Ethics Committee of University of Social Welfare and Rehabilitation Sciences (IR.USWR.REC.1400.293).

Funding/Support: The present study received no funding/support.

Informed Consent: Written informed consent was obtained from the participants.

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