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Depression Evaluation via Heart Rate Variability and Body Temperature

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Abstract

Mental status tasks influence several neurophysiological measures. Biomedical instrumentation is widely used to measure the behavior of the human body and calculate the relative physiological responses to cognitive tasks. There is a common connection between heart rate variability (HRV) and ANS activity. In addition, the skin conductance peak characteristics (SC) from electrodermal activity (EDA) and skin temperature (SKT) modifications can also affect ANS activity As such, the autonomic nervous system (ANS) can easily influence depression. Previous efforts to study and apply HRV features as biomarkers of depression are encouraging. This study includes HRV analysis and temperature measurements during a depression task and is designed to explore the connection between electrocardiography (ECG) and body temperature. Regarding HRV analysis, previous research has shown a decrease in high-frequency (HF) features, as well as body temperature decreases during the day, in patients with depression. Five healthy college students with no health issues participated in the study. An ECG was recorded while relaxing and while performing the Stroop Color-Word task; body temperatures were recorded periodically. Results showed that there were six significant relationships between HRV features and body temperature associated with depression. In addition, short-term meditation had a positive influence, and this protocol could be useful in depressive disorders.

Disciplinary: Biomedical Instrumentation, Signal Processing, Mental Disorder.

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1 Introduction

Depression is a serious disease with considerable problems that can affect individuals [1]. Normally, the autonomic nervous system (ANS) is balanced. However, when depression occurs, heart rate variability (HRV) is used as a biomarker and is linked with depression [1]. The relationship between HRV and depression-influencing factors is still debatable [2]. In general, HRV features are recommended as a diagnostic tool and biomarker for depression; however, essential research examining the connection between HRV and depression is limited [3].

2 Literature Review

The heart rate is the simplest biological signal to analyze. The electrocardiogram (ECG) records the heart rate, i.e. two heartbeats, on a skin-surface level [4]. The difference appears meaningful in the functional circumstances. Earlier findings have proven the variability in heart rate (HRV) and measurement potential [5]. Instant instability in HRV can signify modifications in sympathetic and parasympathetic systems. In practical usage, HRV is a noninvasive marker of the autonomic nervous system, especially the heart [6]. It is also involved in the regulation of the cardiovascular system [7]. Patients with severe myocardial infarction demonstrated changes in HRV index assessments [8].

HRV analysis can be achieved through short- and long-term recordings. The short-term is a useful approach for estimating the autonomic stage and can follow alterations in cardiac autonomic performance within minutes [9]. However, long-term autonomic function changes over hours [9]. HRV analysis researchers can easily choose a suitable time window for data collection.

HRV can be measured using linear and nonlinear analysis [4]. Time-domain features, such as the standard deviation of NN intervals (SDNN), are the simplest method for calculating HRV. These are statistical estimates of repeated RR intervals and are usually correlated with each other [4,10]. Frequent domain features include very low frequency (VLF), low frequency (LF), high frequency (HF), and HF/LF ratio; these are indicators established using spectral analysis. This is commonly used to evaluate the impact of HRV on the autonomic nervous system [4,10]. Nonlinear features are promising methods to measure HRV and utilize power-law exponents, approximate entropy, and detrended fluctuation analysis. These methods exhibit complex ANS interfaces [4].

Depression is correlated with decreased intracellular serotonin (5-HT) levels [11]. The serotonin reuptake transporter (SERT) is a regulator of serotonin neurotransmission and a major target of antidepressants. [11]. Conversely, increases in extracellular 5-HT have been associated with enhanced temperature changes [11]. Do not change any format of this file. Section break and page break are not allowed.

Previous research has shown lowered HRV features through lower estimates of time-domain features (SDNN, RMSSD), frequency-domain features (HF), and enhanced importance of (LF) power for subjects with depression compared with healthy control subjects [1,12,13]. Additionally, the LF/HF ratio has repeatedly been observed to reduce depression [14]

In this study, depression was evaluated using two different instrumentation methods: ECG and body temperature. HRV analysis includes both linear and nonlinear features. In addition, the correlation between HRV features and body temperature was evaluated.

The goal was to increase measurements to deeply consider the correlation between human body systems and unforeseen relationships between the nervous and cardiovascular systems. The Stroop Color-Word Test is often used to assess psychological depression [15].

The Stroop Color-Word Test (SCWT) has long been an accepted experiment for neuropsychological evaluations, including depression. [16]. The Stroop Color-Word Test was developed because subjects can figure out words significantly faster than identify and name colors [16]. The experiment was used for subjects in four conditions: base, rest, performing the SCWT task, and meditation.

Table 1: Experiment Protocol.

Session	Protocol	Time (min)
Base	Do Nothing	5
Relaxed	Close-Eye State	5
Depression	Open-Eye State (Perform SCWT)	5
Meditation	Watching Ocean Waves Video and taking a Deep Breath Every Minute	5

3 Method

This study proposed the measurement and calculation of HRV and body temperature during four separate sessions (base, relaxation, SCWT task, and meditation) (Table 1). The relaxed session was closed eyes for the subject, while the task session performed the SCWT task [17].

3.1 Subjects

The total number of subjects was five. The ECG and temperature records were obtained from five right-handed subjects. There were two male and three female graduate and undergraduate students with mean ages of 24.4 ± 6.0 years. The participants signed written informed consent.

3.2 Signal Condition and Features Extraction

Several filters were employed to eliminate physiological and nonphysiological artifacts from the ECG. ECG was recorded using a Bio Radio drive at a sampling rate of 960 Hz. Electrocardiogram (ECG) and body temperature were recorded simultaneously for 20 min. Body temperature was taken every two and a half minutes and eight data points were obtained by using a skin temperature device.

3.3 Statistical Analysis

One-way ANOVA and Pearson's correlation were applied to determine the significance between ECG features and body temperatures. The statistical analyses were performed using MATLAB R2017a software.

4 Result and Discussion

Biometric information from five subjects is shown in Table 2. Tables 3 and 4 demonstrate the ECG estimation for four recording sessions: base, relax, SCWT task, and meditation.

Table 2: Subject Information

Information	Data
Gender	Male: 2: Female: 3
Age	24.4±6.0
Weight	75±8.0 kg
Height	168±8.2 cm
BMI	26.6±1.0 kg/m^2

Table 3: HRV Features Calculation

Features	Base	Relax	SCWT	Meditation
Mean RR	944±75	964±115	902±91	884±87
STD HR	13.2±7.0	17±7.1	14.6±7.7	23.7±7.6
NN50	142±34	127±34	140±38	170±50
LF	1282±456	2078±818	860±307	4917±1384
HF	1364±560	3042±828	941±691	4808±2435
LF/HF	0.92±0.2	1.16±0.2	0.96±0.5	0.56±0.2
SD1	133±81	143±86	145±89	184±70
SD2	177±89	202±87	197±106	253±75
D2	2.9±0.7	2.8±0.7	2.7±0.68	1.8±0.7

Table 3 justifies the estimation for 9 features that were changeable during the four sessions of the base, relaxed, SCWT, and meditation, in twenty-minute recordings. For HRV analysis in relaxing sessions, mean RR, STD HR, LF, HF, LF/HF, SD1, and SD2 increase, while NN50 and D2 decrease, showing the relax session's impact. In the SCWT session, NN50 and SD1 increase while mean RR STD HR, LF, HF, LF/HF, SD2, and D2 decrease in the depression task. Finally, though STD HR, NN50, LF, HF, SD1, and SD2 increased; mean RR, LF/HF, and D2 decreased in the subsequent mediation session.

In Table 4, the mean body temperature gradually rises until it reaches 31.8 ℃ at 7:30 min, then falls when the depression task starts at 10:00 min, and the body temperature reaches 31.7 °C. The meditation session showed progressively decreasing temperature.

Table 4: Body Temperature Measurements

Time	Body Temperature (Celsius)
0:00	31.2±0.57
2:30	31.5±0.57
5:00	31.7±0.59
7:30	31.8±0.62
10:00	31.7±0.64
12:30	31.6±0.7
15:00	31.6±0.7
17:30	31.5±0.7
20:00	31.5±0.7

Figures 1-6 show the correlations between HRV features and body temperatures. The results confirmed six correlations between HRV analysis and body temperature. There was a positive correlation between mean RR and body temperature ($p = 0.000012$ and $r = 0.4$), a positive correlation between NN50 and body temperature ($p = 0.02$ and $r = 0.17$), a negative correlation between body temperature and LF ($p = 0.02$ and $r = -0.8$), a positive correlation between body temperature and HF

(p =0.04 and r =0.5), and a positive correlation between body temperature and LF/HF (p = 0.00001 and r = 0.04). Finally, there was a negative correlation between body temperature and D2 (p =0.00001 and r =-0.5).

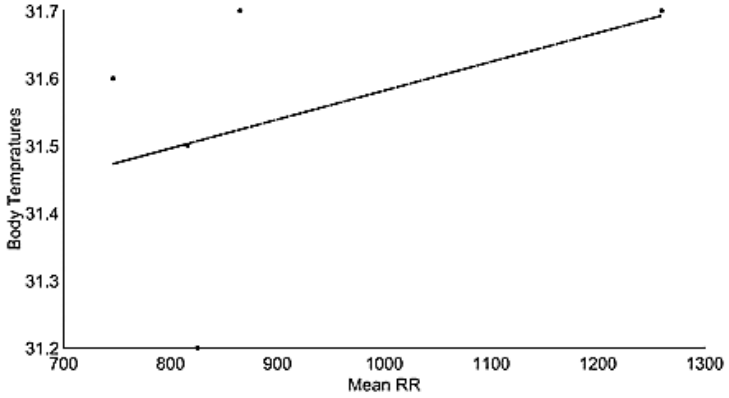

Figure 1: Relationship between body temperatures and Mean RR among the five subjects (r =0.4, p<0.05).

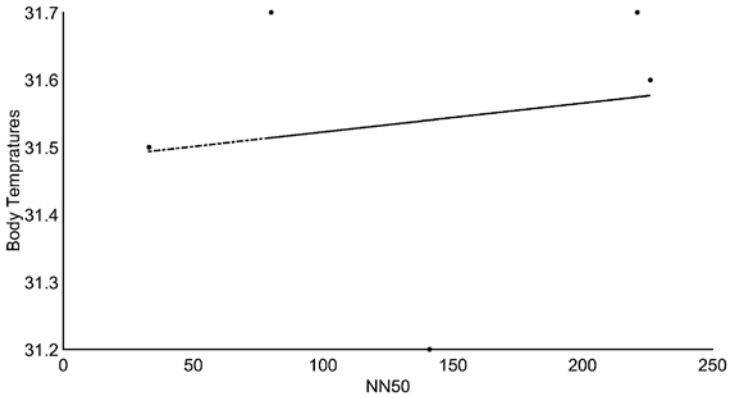

Figure 2: Relationship between body temperatures and NN50 among the five subjects (r =0.17, p<0.05).

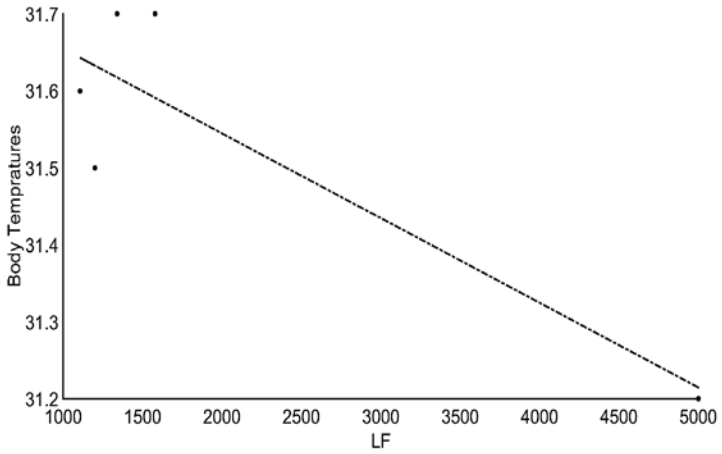

Figure 3: Relationship between body temperatures and LF among the five subjects (r =-0.8, p<0.05).

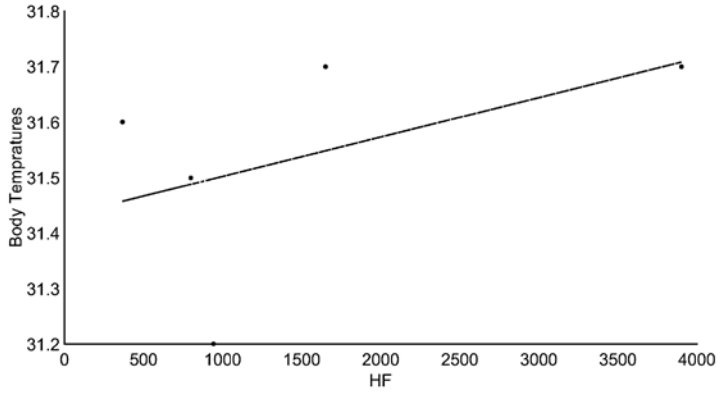

Figure 4: Relationship between body temperatures and HF among the five subjects (r =0.5, p<0.05).

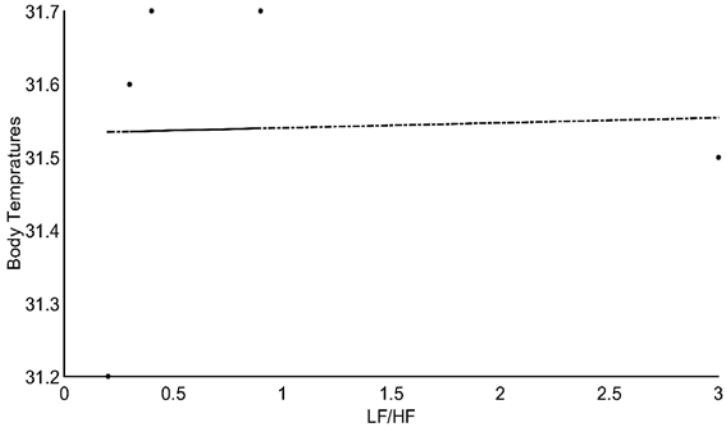

Figure 5: Relationship between body temperatures and LF/HF among the five subjects (r =0.04, p<0.05).

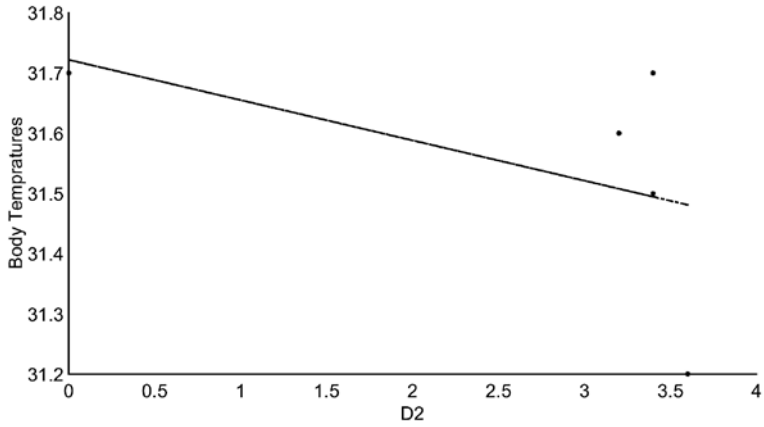

Figure 6: Relationship between body temperatures and D2 among the five subjects (r =-0.5, p<0.05).

In this study, advanced instrumentation analysis implants were used to compare the data from several biosignals. Biometric results are shown in Table 2. Table 3 shows HRV analysis for the linear and nonlinear analyses. The linear calculation includes the time- and frequency-domain features such as mean RR (mean RR interval- ms), STD HR (Standard Deviation of Heart Rate-

1/min), NN50 (the number of successive heartbeat intervals that exceed 50 ms-%), LF (low frequency-ms2), HF (high frequency- ms2), LF/HF (ratio of low frequency to high frequency), SD1, SD2 (Poincaré plot indices), and D2 (correlation dimension, which evaluates the minimum number of variables required to construct a model of system dynamics).

This study demonstrated six relationships between HRV features and body temperature associated with depression. The mean RR correlated with body temperature. The three HRV frequency domain features (LF, HF, and LF/HF) were also linked with body temperature in depression sessions. In linear features, D2 correlated with body temperature. These results confirm that temperatures with lower activation follow cardiac stimulation during the depression. The HF decreases with depression [18], and the body temperature drops [11]; these results are consistent with previous studies. Depressed mood is related to decreased parasympathetic cardiac control during the depression in both healthy men and women. These findings extend those of earlier studies by including HRV nonlinear analysis and body temperature measurements.

5 Conclusion

This study explored the correlation between HRV parameters and body temperature. HRV parameters are used as biomarkers for depression. Other measurements could be useful in identifying depression levels in patients. This study presents a new method for discovering the relationship between depression and various biomedical physiological measurements. Many factors affect the results, and we will increase the sample size to analyze more deeply in the future. Studies that review the variations in HRV features and depression over time are vital to better understand the link between HRV and disease situations.

6 Availability of Data and Material

Data can be made available by contacting the corresponding author.

Consent for Publication: The author gives consent for publication in the above Journal. Therefore, anyone can read material published in the Journal.

Conflict of Interests: The author declares no conflict of interest concerning this study.

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Authors' Contributions: Eyad Attar: collection, organizing, review of the literature, preparing the manuscript, manuscript review, modification, editing, and revision.

Patient Permission: All participants permit the author to collect the data and sign the consent form.

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8 References

[1] R. Hartmann, F. M. Schmidt, C. Sander, and U. Hegerl, “Heart rate variability as indicator of clinical state in depression,” *Front. Psychiatry*, vol. 10, 2019.

[2] K. W. Choi and H. J. Jeon, “Heart Rate Variability for the Prediction of Treatment Response in

Major Depressive Disorder," *Front. Psychiatry*, vol. 11, 2020.

[3] F. A. Jain *et al.*, "Heart rate variability and treatment outcome in major depression: A pilot study," *Int. J. Psychophysiol.*, vol. 93, no. 2, pp. 204–210, 2014.

[4] B. Francesco *et al.*, "Linear and nonlinear heart rate variability indexes in clinical practice," *Comput. Math. Methods Med.*, 2012.

[5] Y. Yaniv and A. E. Lyashkov, "The Fractal-like Complexity of Heart Rate Variability beyond Neurotransmitters and Autonomic Receptors: Signaling Intrinsic to Sinoatrial Node Pacemaker Cells," *Cardiovasc. Pharmacol. Open Access*, vol. 2, no. 3, 2013.

[6] T. Laitio, J. Jalonen, T. Kuusela, and H. Scheinin, "The role of heart rate variability in risk stratification for adverse postoperative cardiac events," *Anesth. Analg.*, vol. 105, no. 6, pp. 1548–1560, 2007.

[7] Z. He, "The control mechanisms of heart rate dynamics in a new heart rate nonlinear time series model," *Sci. Rep.*, vol. 10, no. 1, 2020.

[8] H. V. Huikuri and P. K. Stein, "Clinical application of heart rate variability after acute myocardial infarction," *Front. Physiol.*, vol. 3 FEB, 2012.

[9] K. Li, H. Rüdiger, and T. Ziemssen, "Spectral Analysis of Heart Rate Variability: Time Window Matters," *Front. Neurol.*, vol. 10, 2019.

[10] F. Shaffer and J. P. Ginsberg, "An Overview of Heart Rate Variability Metrics and Norms," *Front. Public Heal.*, vol. 5, 2017.

[11] J. L. Rausch *et al.*, "Depressed Patients Have Higher Body Temperature: 5-HT Transporter Long Promoter Region Effects," *Neuropsychobiology*, vol. 47, no. 3, pp. 120–127, 2003.

[12] R. M. Escorihuela *et al.*, "Reduced heart rate variability predicts fatigue severity in individuals with chronic fatigue syndrome/myalgic encephalomyelitis," *J. Transl. Med.*, vol. 18, no. 1, 2020.

[13] C. Dell'Acqua, E. Dal Bo, S. Messerotti Benvenuti, and D. Palomba, "Reduced heart rate variability is associated with vulnerability to depression," *J. Affect. Disord. Reports*, 2020.

[14] D. Jangpangi, S. Mondal, R. Bandhu, D. Kataria, and A. Gandhi, "Alteration of heart rate variability in patients of depression," *J. Clin. Diagnostic Res.*, vol. 10, no. 12, pp. CM04–CM06, 2016.

[15] J. Markela-Lerenc, S. Kaiser, P. Fiedler, M. Weisbrod, and C. Mundt, "Stroop performance in depressive patients: A preliminary report," *J. Affect. Disord.*, vol. 94, no. 1–3, pp. 261–267, 2006.

[16] F. Scarpina and S. Tagini, "The stroop color and word test," *Front. Psychol.*, vol. 8, 2017.

[17] C. E. Englund, D. L. Reeves, C. A. Shingledecker, D. R. Thorne, and K. P. Wilson, "Unified Tri-

Service Cognitive Performance Assessment Battery (UTC-PAB). 1. Design and Specification of the Battery," 1987.

[18] J. W. Hughes and C. M. Stoney, "Depressed Mood Is Related to High-Frequency Heart Rate Variability During Stressors," *Psychosom. Med.*, vol. 62, no. 6, pp. 796–803, 2000.

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