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TIME SEGMENT ANALYSIS OF HEART RATE VARIABILITY TO EVALUATE DAILY STRESS USING WEARABLE DEVICE TECHNOLOGY

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ABSTRACT

Present studies have successfully evaluated psychological properties such as mental health and stress by using physiological data from the cardiovascular system. Most studies established specific interventions and ambiguous heart rate properties according to homeostatic conditions. We proposed a study evaluating mental stress based on daily activities dataset. Twenty-two healthy men were observed in this study. We employed two approaches based on the time segments, while extracting the HRV parameters. We discovered that there was no significant difference between the parameters corresponding to the daily stress score groups (low- and high-stress) when we used whole-day recording in one segment HRV parameter measurement ($p > 0.05$). However, by extracting the HRV parameters based on multi time segments (phases 1, 2, and 3), we found parameters that were able to properly distinguish the two groups (low- and high-stress). The frequency domain parameters are the most sensitive features, especially the LF and HF ($p < 0.01$), followed by the total power ($p < 0.05$). In the time domain measurement, the RMSSD, StdHR, SD1, and SD2 are able to differentiate the participants based on the daily stress scores ($p < 0.05$). As a result, this study proposed that by continually monitoring biological signals based on time segment and employing the given parameters, it is possible to appropriately and meaningfully measure the daily stress condition for future classification studies.

Keywords*: daily stress, heart rate variability, wearable, time segment.*

I. INTRODUCTION

IN many countries, including the United States, where mental health remains a significant issue, citizens have committed suicide as a result of extreme mental duress, which can occur in a variety of professions [1]. Due to the intense problems, researchers have learned and acknowledged a significant connection between a person's physical, mental, and psychological health over the past 20 years [2]. Based on this, numerous stress detection methods are used to prevent future chronic illnesses [3].

Since detecting stress has become essential, psychological methods have been considered less effective since the subjective perspective is unavoidable during the surveys. Studies have suggested that it is possible to monitor changes in emotion and stress using electronic devices by attaching them to the body as physiological signals with specific sensors [4, 5]. Thus, the next issue is finding the most appropriate sensors to represent psychological changes as an objective measurement tool.

The devices that incorporate the study of objective psychological instrumentation instruments, such as HR, ST, GSR, RR, ACC, and BP sensors, are known as wearable sensors, and the studies that apply to them are briefly listed [6]. Due to their close connection to the autonomic nervous system, heart rate sensors become beneficial in representing rest, physical, and mental states [7, 8]. By utilizing the heart rate sensor, extracting the heart rate variability (HRV) features considerably contributes to physiological and psychological metrics. Thus, conventional devices are not suitable for wearable and mobile purposes. To overcome the issue, wearable devices are considered daily trackers.

Since the development of wearable technologies and sensors have become important, the issue of daily comfort remains. Today, researchers use commercially available wearables like watches and smartphones to monitor these physiological signal activities [9-12]. When the wearable device's comfort is attained, its use to monitor daily activities and physiological properties becomes more promising. Promising outcomes have been obtained from earlier research on detecting human psychological conditions in specific environments. However, based on the current situation, researchers are aware that the development of stress detection systems in experimental design studies does not accurately reflect the actual human situation, which is highly variable and influenced by daily activities [2]. Research on identifying stress and emotions concentrated primarily on the workplace and just for specific times initially. However, as time progressed, the focus of this research shifted to identifying emotional changes and stress in routine activities, or what we refer to as daily stress [13]. The stimulated or altered psychological state does not always reflect a person's natural response and can sometimes have an effect on the participants' emotions after the experiment has concluded. For this reason, it is essential to conduct research and studies on how a person's mental tension changes as a result of their daily activities, and to carefully observe these changes over time. Validation of this research is still required for further investigation, as its limitations still concentrate on recognizing stress at specific times or in specific situations, and it can be ambiguous with other bodily conditions or physical activities.

Previously, a significant amount of research on a person's stress level during a specific short-term event focused on physiological signals, which some argue is not a reliable method for measuring stress. Specifically, our proposed study aims to determine the physiological response properties, such as the heart rate, based on how the changes in the biological signal during a person's daily activities correspond to their subjective psychological assessment, which is measured by different extracted features over the course of a full day (24 hours). Then, this study must determine if it is possible to use segmentation in time series analysis to determine and enhance how stressed a person is at a specific time, based on the extracted features, and if so, whether this is possible. We conclude by examining how time-segment analysis can be used to classify a person's daily stress so that it can be measured more accurately and meaningfully using standard or well-known wearable devices.

Previous studies continue to focus on identifying stress at specific times or in specific environments, and it can be difficult to distinguish stress from other physiological conditions or physical activity. Then, we noted that our contributions to the study included 1) using a quantitative method to measure physiological properties from a typical wearable device biosensor that correspond to psychological changes; 2) identifying the significant HRV parameter(s) to represent daily stress; and 3) verifying an efficient pipelining technique to measure daily stress based on time segment analysis on HRV properties by using a well-known wearable device on the market. This study significantly contributes to our comprehension of how to monitor daily stress using a standard smartwatch or other wearable device, which can be integrated into any mobile app by pairing the device via Bluetooth.

II. RESEARCH METHODS

A. Dataset

The research data comes from secondary data under the Open Database License (ODbL) v1.0, an MIT Physionet data collection repository, with twenty-two male university students as the participants. The data consists of user_info data, peak-to-peak heart rate interval data, questionnaires, and supporting data that is produced by the device, such as activity (number of steps) and saliva to measure the biochemical properties before and after sleep. All participants were in good health. As this is an exploratory pilot study, it was important to seek a sample of subjects that was as homogeneous as possible in order to limit inter-individual variables and maintain a small number of subjects [14]. Before the research started, the subjects were confirmed to have understood the research procedures, signed informed consent consciously, and understood the research protocol. The research protocol that was carried out complied with ethical reviews according to the rules and regulations of the Helsinki Declaration regarding human involvement in this research.

B. Experimental Design

The dataset aimed to determine the body's psychological and physiological conditions while performing activities for 24 hours (1 day). This dataset was obtained by asking the participants to carry

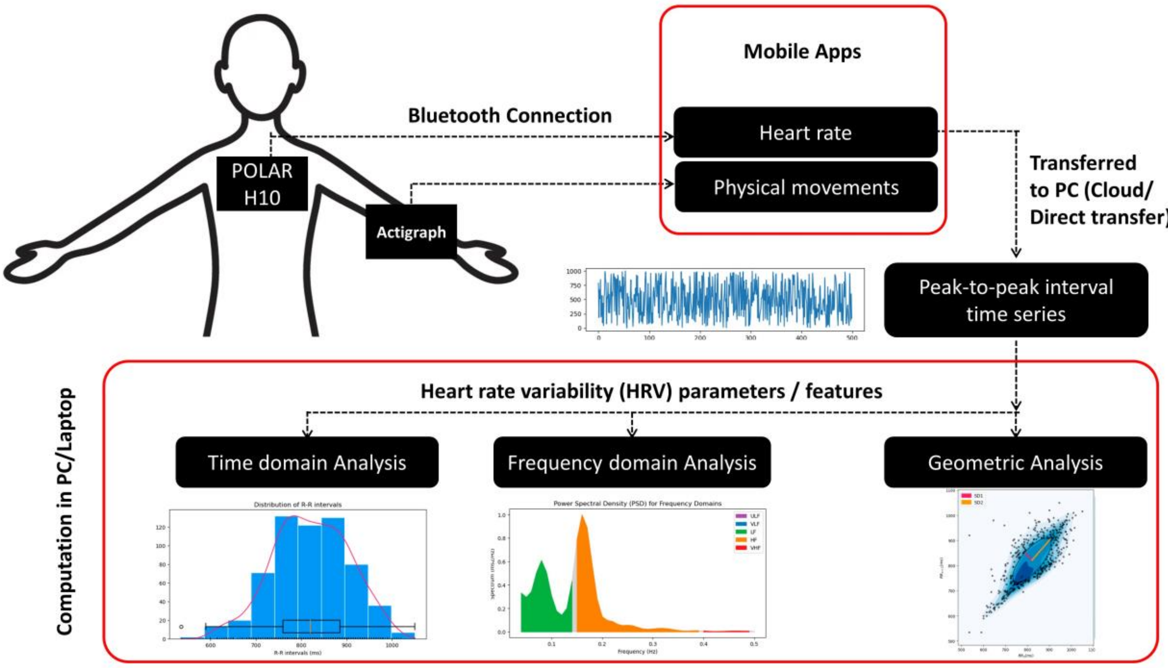


Figure 1. Data acquisition and features extraction schema

out their daily activities as usual without any specific treatment or intervention. After their daily activities, all participants filled out their daily score inventory (DSI) before going to sleep to summarize the magnitude of stressful events that they had engaged in during the day. Utilized wearable devices continuously recorded all body activities, including cardiovascular activity (heart) and movement (accelerometer). For this study, we utilized the dataset to focus only on the heart's activity by decomposing the heart rate variability parameters.

C. Data Acquisition

Heart activity and body movements, including the number of steps and the body's vector magnitude, provide physiological data extracted from the human body. The dataset retrieved data from a common wearable device for measuring cardiac activity, the Polar H10, a pulse sensor worn all day without interfering with the subject's activities. An actigraph device is utilized for body movements, which is a device similar to a smartwatch that records data on a person's pulse rate, number of steps, and vector magnitude for body movements over a specified period. Bluetooth connectivity was used to attach each of these tools to mobile devices. However, this study focused on the cardiac rhythm properties, as they reflect the autonomic nervous system and correspond to the stress state. The dataset collected data for 24 hours, beginning with morning routines and ending before bedtime. As the main raw data, we extracted each participant's peak-to-peak interval time series from the dataset. The detailed schema of data acquisition can be found in Figure 1.

D. Signal Processing and Features Extraction

The signal obtained has been recorded and extracted in CSV format. The Polar H10 device generated the RR interval time series data, which is the time interval between two consecutive heart rate peaks in seconds. For Polar H10 data, the extracted features were Heart Rate Variability (HRV) time domain parameters, which included linear and non-linear data features. The linear features consisted of MeanRR (ms), SDRR (ms), NN50, pNN50 (percentage), RMSSD (ms), MeanHR (beats per minute), and StdHR (beats per minute) parameters. As for the non-linear parameters, the extracted parameters were SD1 (ms), SD2 (ms), SD ratio (SDrat), and elliptical area (Ellip_area) (ms^2). In addition to time-domain analysis, we also demonstrated frequency-domain analysis that includes very low frequency (VLF; ms^2/Hz), low frequency (LF; ms^2/Hz), high frequency (HF; ms^2/Hz), LFHF ratio (LFHFrat), and total power (ms^2/Hz) [15]. As depicted in Figure 1, we illustrated the procedures.

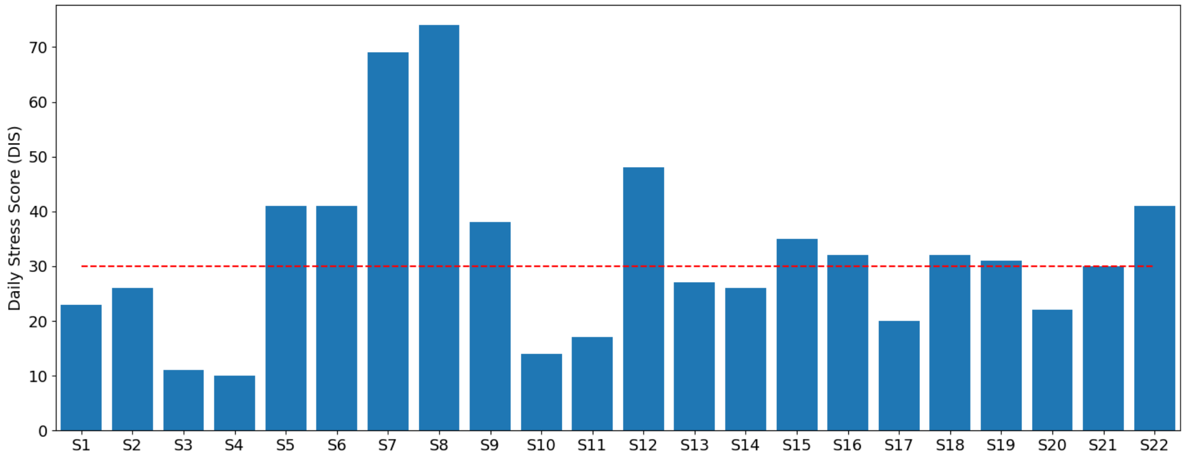


Figure 2. The daily stress inventory assessment score from the overall subjects

E. Daily Stress Inventory (DSI)

As a subjective evaluation, we used a daily stress inventory (DSI) from the dataset to assess the daily stress score of each participant throughout the day. The daily stress assessment used a 58-question daily stress questionnaire as a self-report assessment after 24 hours of activity. The scoring system uses a Likert scale of 1 (not stressed) to 7 (stress or panic), with a total accumulated score of all questions ranging from 0 to 406. The higher the score, the higher the daily stress experienced [14]. The complete DSI questionnaire is already attached to the attachment of this manuscript.

F. Data Analysis

Even though the data was collected from 22 participants, it did not meet the normal distribution. Since it did not come from a normal distribution, the statistical tests use non-parametric techniques. We employed the Kruskal-Wallis test to analyze the heart rate variability parameters based on group stress and time-segment factors to investigate any significant difference between the low and high daily stress groups. All data analysis techniques used a 95% confidence level (p-value of 0.05), where we called the data significantly different from the groups if the p-value was less than 0.05. We performed the single and multi-time segments for analysis purposes. Initially, we focused on the regular analysis that utilized the whole data recording as the primary scenario of data being recorded.

The single time-segment analysis was conducted from 9:00 a.m. to 9:00 p.m. before bedtime. The multi-time segment analysis was performed in the same time interval and separated into three segments: before lunch (phase 09.00 a.m.-12.00 p.m.), after lunch or the second phase working hours (01.00 p.m.-04.00 p.m.), and before bedtime (05.00 p.m.-09.00 p.m.). In addition, we conducted a correlation analysis to determine the connection between heart rate variability analysis and daily stress assessment.

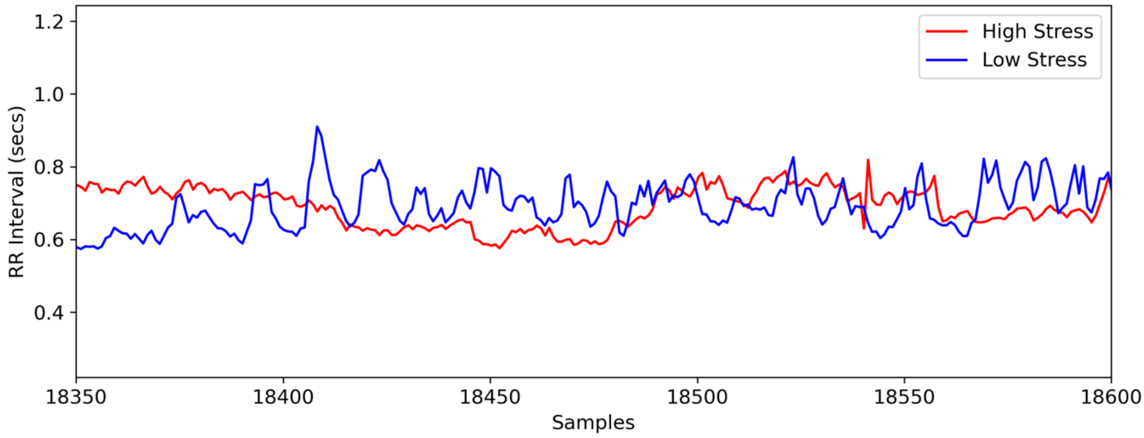
III. RESULTS

A. Daily Stress Assessment

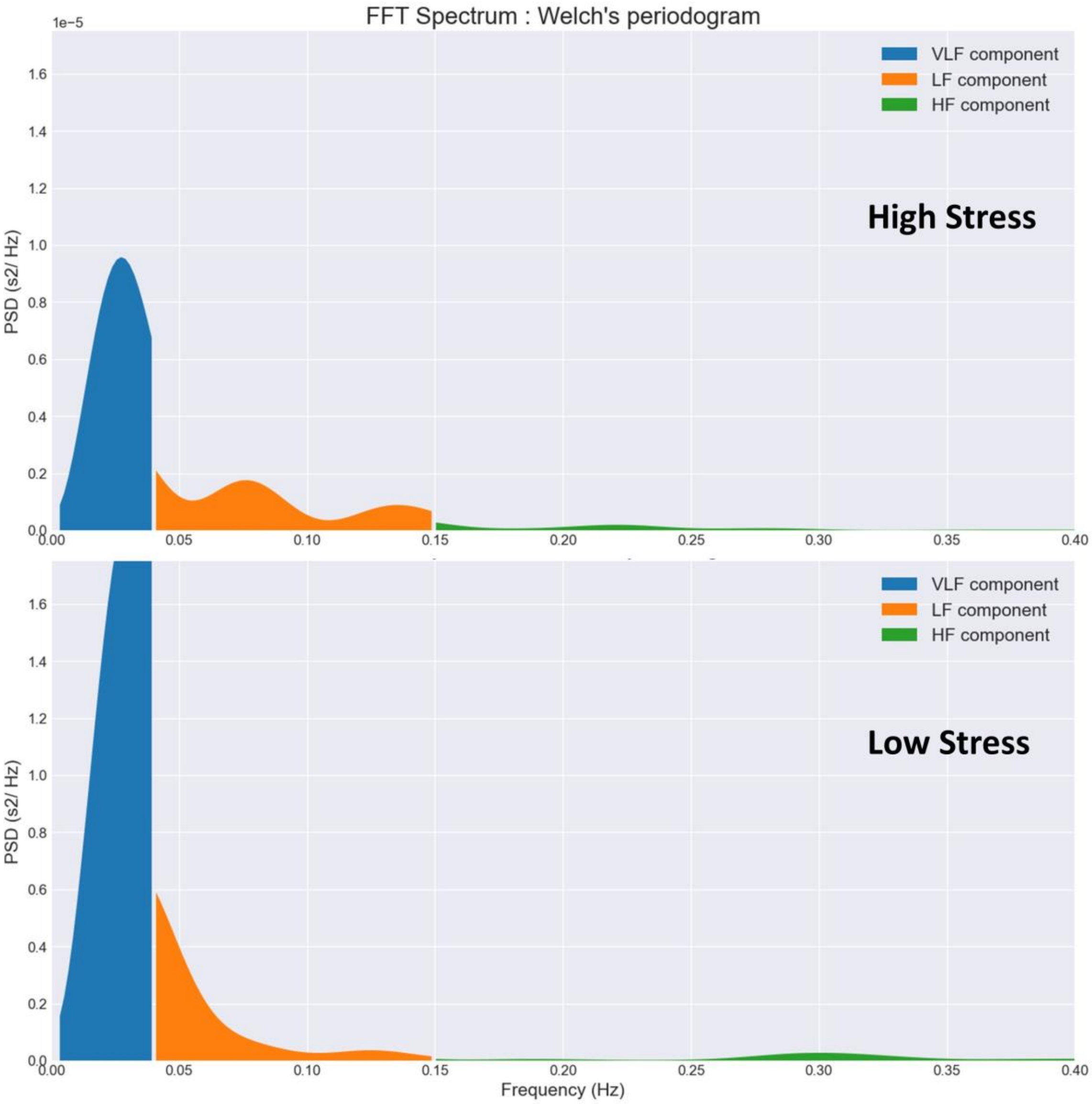
We divided the stress score into two groups based on the scores obtained after using the daily stress assessment for everyday activities based on the median data of the daily stress inventory analysis [14]. Figure 2 shows that twelve of the 22 participants had daily stress levels greater than 30, indicating that the subject felt stressed while performing regular tasks. Subjects were considered less stressful if their daily stress score was less than 30. The findings showed that roughly half of the individuals encountered the stressor while engaging in daily activities. Based on the stress level, the data were deemed balanced.

B. Peak-to -peak Interval Time Series Characteristic

By utilizing the physiological data obtained by the wearable device, we obtained their heart rate variability data by extracting the peak-to-peak interval from the heart rate (RR interval time series). We visualized the RR interval time series between subjects during the high- and low-stress scoring assessments to initiate the insight. Figure 3 shows that the RR interval's variance is lower during high-



(a)



(b)

Figure 3. The comparison between subjects who had a lower and higher stress level: (a) The peak-to-peak interval time series (RR interval); (b) the power spectral density in the frequency domain

stress compared to the low-stress condition. During high stress, the RR interval's changes are between 0.6 and 0.8 seconds. Thus, the RR interval's changes during low stress are between less than 0.6 and 0.9

TABLE 1
PHYSIOLOGICAL PROPERTIES BETWEEN LOW AND HIGH STRESS USING A SINGLE TIME SEGMENT (09.00 A.M. – 09.00 P.M.)

Parameter	High Stress		Low Stress	
	Mean	SE	Mean	SE
Linear Analysis: Time Domain				
MeanRR (ms)	808.3226	18.0773	806.1854	22.6981
SDRR (ms)	172.1650	7.7873	183.2966	14.7385
NN50	13735.3333	1575.5983	15156.8500	2176.5363
pNN50 (%)	17.1771	1.8232	19.2909	3.1594
RMSSD (ms)	62.6382	6.3494	89.7002	32.1799
MeanHR (bpm)	78.8446	2.2515	79.5154	2.4539
StdHR (bpm)	19.8257	2.0436	20.7586	2.0379
Linear Analysis: Frequency Domain				
LF (ms^2/Hz)	1988.3882	192.8258	2532.2421	715.8425
HF (ms^2/Hz)	908.2172	154.4051	2769.2522	2478.7103
LFHFrat	2.8255	0.4222	2.3960	0.4453
LFnu	70.6674	2.6856	66.1963	4.1206
HFnu	29.3326	2.6856	33.8037	4.1206
TotPow (ms^2/Hz)	4774.1035	392.9658	7326.6289	3442.4176
VLF (ms^2/Hz)	1877.4982	109.5240	2025.1345	282.5244
Time Domain: Non-Linear Analysis				
SD1 (ms)	44.2919	4.4897	63.4276	22.7547
SD2 (ms)	238.8492	11.1705	246.3502	13.3353
SDrat	6.1146	0.6967	5.5008	0.8178
Ellip_area (ms^2)	33251.7484	3672.8274	53481.6267	24735.3316

seconds. According to the findings, high stress causes a low RR interval time series, which means the heart rate beats faster than under low stress.

When we carefully observed the RR time series, we found that the time series variance or the variability data differed between the low- and high-stress participant. The component frequency can be seen in Figure 3, where a high-stress participant had a lower frequency component, whereas the low-stress had a higher one. Instead, a high-stress participant's very low frequency is also lower than the low-stress subject.

C. Single Time-Segment Analysis

As shown in Table 1, we present the single time-segment analysis of the features extracted from the overall data from the beginning to the end of data collection (09.00 a.m. – 09.00 p.m.). We focus on linear analysis using time domain analysis first. Based on the mean values of all individuals, the heart rate is comparable under low and high-stress levels. When under high stress (808.3226 ms), the MeanRR is marginally higher than when under low stress (806.1854 ms), having a marginally smaller impact on the heart rate's beats per minute. Regardless, the features derived from the variance or deviation of the RR interval time series data plainly distinguish between high and low stress. As can be seen, the percentages differ between the two levels of stress and are 9 to 10% lower in the high stress condition. The SDRR, RMSSD, and StdHR show that the variation of RR interval properties is completely lower between those two conditions, especially the SDRR and RMSSD were lower in high-stress participants. The SDRR and RMSSD differentiate between high- and low-stress daily assessments, which were around 11.1316 and 27.062 ms, respectively. During low stress, the standard deviation of the heart rate is slightly higher, but it does not exceed one beat per minute. In addition, the NN50 and pNN50 represent the number and proportions of the RR interval with a value greater than 50 ms are lowers in the high-stress group.

According to the frequency decomposition, most frequency components are lower in the high-stress condition compared to the low-stress condition. The lower frequency components (VLF and LF) have more than 100 ms^2/Hz higher differences, whereas the high frequency (HF) shows the highest difference, which is more than 1000 ms^2/Hz. Based on that, sympathetic activity is affected during stressful conditions.

Additionally, we demonstrated the nonlinear analysis that calculates the geometrical properties of RR interval time series (SD1 and SD2). Because the features' characteristics are identical to the variation of the RR time series in the linear method, the properties had similar tendencies, with SD1 and SD2 being higher during high stress. The SD1 had a lower value (44.2919 ms) in the subjects with high-stress

TABLE 2
PHYSIOLOGICAL PROPERTIES USING MULTI TIME-SEGMENT - PHASE 1 (9.00 A.M. TO 12.00 P.M.)

Parameters	Phase 1 (09.00 a.m. - 12.00 p.m.)			
	Low		High	
	Mean	SEM	Mean	SEM
Linear Analysis: Time Doman				
MeanRR (ms)	753.8494	20.9301	752.9757	27.2462
SDRR (ms)	129.0765	20.6378	101.0621	5.7438
NN50	2363.6000	516.0530	1612.0833	252.1246
pNN50 (%)	18.0562	4.0651	13.6383	2.7687
RMSSD (ms)	101.7647	39.1280	56.2636	7.1293
MeanHR (bpm)	82.6021	1.7687	82.5727	2.9303
StdHR (bpm)	15.2828	1.1187	13.2042	1.2412
Linear Analysis: Frequency Domain				
LF (ms^2/Hz)	3059.4835	961.7391	1727.7687	203.5162
HF (ms^2/Hz)	3818.2910	2875.1836	693.5721	144.4575
LFHFrat	2.7496	0.5288	3.7445	0.6750
LFnu	67.4713	5.2936	74.3777	3.2128
HFnu	32.5287	5.2936	25.6223	3.2128
TotPow (ms^2/Hz)	8730.3817	4233.7402	4033.8992	384.5834
VLF (ms^2/Hz)	1852.6072	410.6654	1529.2251	165.1358
Time Domain: Non-Linear Analysis				
SD1 (ms)	71.9585	27.6676	39.7844	5.0412
SD2 (ms)	161.5687	17.6572	136.5704	7.5786
SDrat	3.4714	0.5474	3.9578	0.4613
Ellip_area (ms^2)	47230.7584	25757.6893	17796.7562	3098.6018

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TABLE 3
PHYSIOLOGICAL PROPERTIES USING MULTI TIME-SEGMENT - PHASE 2 (1:00 P.M.– 4:00 P.M.)

Parameters	Phase 2 (01.00 p.m. - 04.00 p.m.)			
	Low		High	
	Mean	SEM	Mean	SEM
Linear Analysis: Time Doman				
MeanRR (ms)	753.4009	25.7220	754.7852	27.3677
SDRR (ms)	132.3879	22.3689	109.4473	5.9591
NN50	4871.7000	1066.6439	3407.5000	560.1314
pNN50 (%)	18.0302	4.4570	13.2267	2.5428
RMSSD (ms)	105.5826	43.7918	54.0254	5.8603
MeanHR (bpm)	83.0739	2.2843	82.5787	2.9801
StdHR (bpm)	15.9211	1.1969	13.7213	0.9389
Linear Analysis: Frequency Domain				
LF (ms^2/Hz)	3067.9929	975.1824	1719.5969	163.9203
HF (ms^2/Hz)	4176.4570	3244.1516	638.2639	105.3322
LFHFrat	2.6668	0.4673	3.4957	0.5497
LFnu	67.5073	5.2563	74.1266	2.8882
HFnu	32.4927	5.2563	25.8734	2.8882
TotPow (ms^2/Hz)	9075.8821	4593.7336	3859.1900	347.0084
VLF (ms^2/Hz)	1831.4322	401.0520	1501.3292	163.8958
Time Domain: Non-Linear Analysis				
SD1 (ms)	74.6582	30.9655	38.2017	4.1439
SD2 (ms)	164.5720	17.5357	149.5174	8.1593
SDrat	3.5992	0.5518	4.4210	0.5014
Ellip_area (ms^2)	51636.5292	30068.6256	18561.4364	2847.2135

daily scores compared to the lower one (63.4276 ms). The ratio between SD2 and SD1 is slightly higher under high stress compared to low stress. By utilizing the SD1 and SD2 values, we also calculated the elliptical area (ellipse_area). Obviously, people with a higher daily stress score represent a 38% lower elliptical area than those with lower scores.

Finally, we employed a statistical test between the two groups. We found no significant differences between the groups using the previously extracted features. As a result, we concluded that the measurement of overall heart rate variability features in a one-day time segment could not represent mental stress changes during daily activities ($p > 0.05$). Thus, we demonstrated the multi-time-segment analysis (phases 1, 2, and 3) to broaden our findings.

D. Multi Time-Segment Analysis

When the entire set of daily data was compared to the daily stress score, there was no difference between the stress and non-stress conditions ($p > 0.05$). We extracted the heart rate variability based on

TABLE 4
PHYSIOLOGICAL PROPERTIES USING MULTI TIME-SEGMENT - PHASE 3 (5.00 P.M.–09.00 P.M.)

Parameters	**Phase 3 (05.00 p.m. - 09.00 p.m.)**			
	Low		**High**	
	Mean	**SEM**	**Mean**	**SEM**
Linear Analysis: Time Doman				
MeanRR (ms)	757.9977	28.7026	740.9159	21.7175
SDRR (ms)	145.0982	21.4723	122.3943	13.7073
NN50	7532.7000	1495.1191	4963.4167	758.3917
pNN50 (%)	18.3999	4.3530	11.9282	1.9958
RMSSD (ms)	109.0497	45.2958	50.9604	4.8841
MeanHR (bpm)	83.2907	2.8357	84.9186	2.7679
StdHR (bpm)	17.3870	1.3814	16.6475	2.7538
Linear Analysis: Frequency Domain				
LF (ms^2/Hz)	3107.6685	996.1253	1647.8823	175.6088
HF (ms^2/Hz)	4435.5138	3454.4195	571.3710	80.1594
LFHFrat	2.5620	0.4618	3.5885	0.5608
LFnu	66.5416	5.3009	74.7117	2.7742
HFnu	33.4584	5.3009	25.2883	2.7742
TotPow (ms^2/Hz)	9395.9262	4814.4764	3643.0710	315.4667
VLF (ms^2/Hz)	1852.7439	391.0585	1423.8177	141.6251
Time Domain: Non-Linear Analysis				
SD1 (ms)	77.1098	32.0290	36.0345	3.4536
SD2 (ms)	182.3732	14.7743	168.8011	19.4664
SDrat	3.9168	0.5803	5.0677	0.6230
Ellip_area (ms^2)	56695.9950	31832.5279	19702.4382	3122.5311

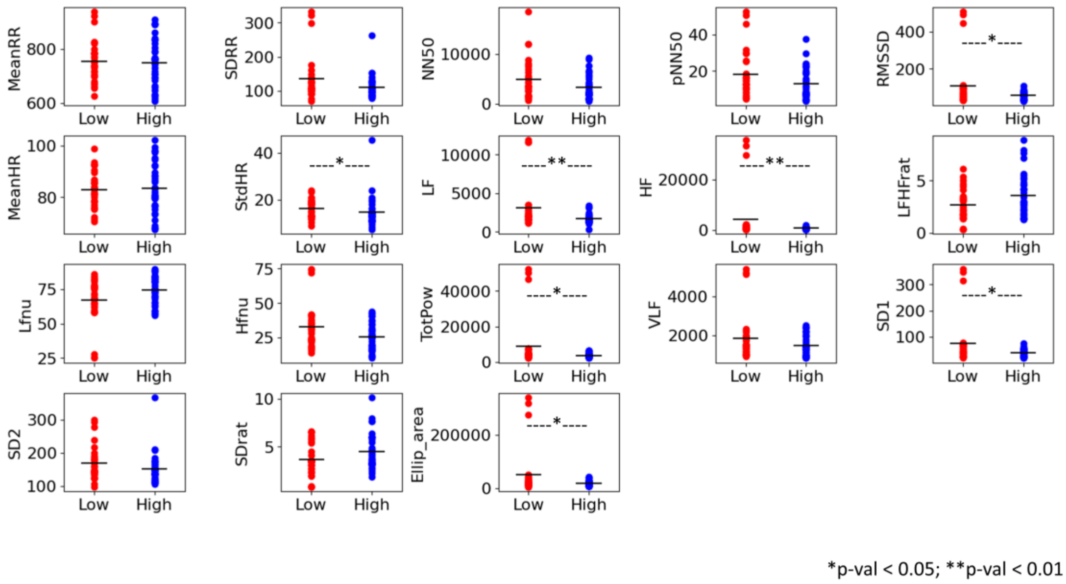

Figure 4. The distribution and mean value of physiological measurements in the groups with low and high-stress daily scores

time segments into three phases: phase 1 (09.00 a.m.–12.00 p.m.), phase 2 (01.00 p.m.–04.00 p.m.), and phase 3 (05.00 a.m.–09.00 a.m.). We grouped the extracted features based on the multi time-segment corresponding to the daily stress inventory scores. The results can be summarized in Tables 2, 3, and 4.

In general, Tables 2, 3, and 4 demonstrate that the time domain analysis using both linear and non-linear results is greater, whereas the daily stress evaluation yields a low stress condition as opposed to a high stress condition. We were also able to observe the same trend in frequency domain analysis. As we can see in Tables 2, 3, and 4, the tendency strongly shows the same properties, where the heart variability parameters were lower in the high stress daily score group compared to the lower stress level assessment results.

The linear time-domain HRV parameters show a 20–50% difference in categorizing low- to high-stress daily scores. The non-linear time domain analysis, on the other hand, yields at least a 40% difference between low and high stress on the SD1 parameter. In the frequency domain analysis, the high-frequency components show a big difference, more than 80% of the percentage decrease. In

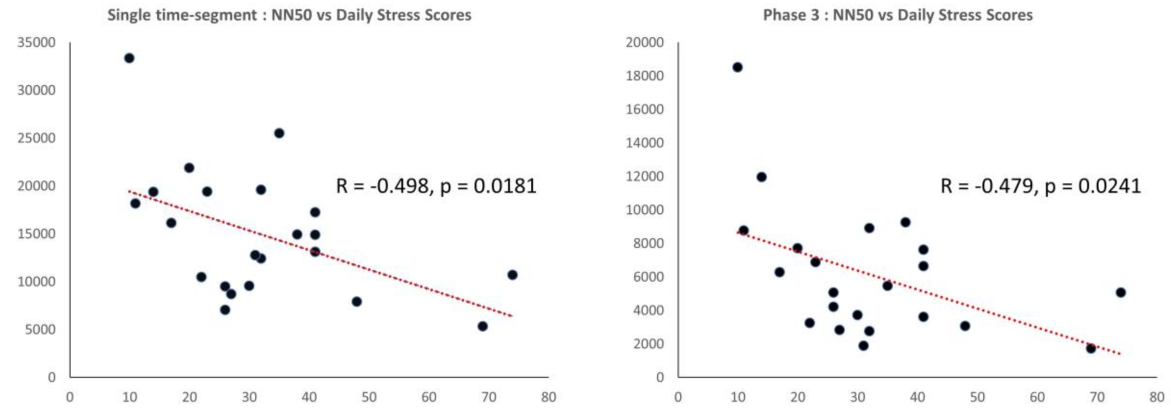

Figure 5. The correlation analysis between HRV parameter (NN50) and the daily stress score

addition, low frequency represents a 40–50% decreasing percentage. The total power also shows a decline from low to high stress (a 50–60% difference) from the three phases of heart rate variability observation. In contrast, the ratio between low frequency and high frequency components indicates that the low stress group is inferior to the high stress group.

On the basis of physiological measurements, the Kruskal-Wallis test was developed to determine the degree to which various groups of daily stress and phases differ from one another. While using the entire data set (one segment features) to differentiate between low and high tension, no evidence of a statistically significant difference was found ($p > 0.05$). The multivariate analysis shows that the time segments or phases are not affecting the difference between low- and high-stress groups where the p-value of all HRV features is 0.5 - 0.9. Based on the daily stress inventory assessment, there is a significant difference in utilizing the time segments only regarding the stress group. When we separated the measurements by the three phases of time, we found that the RMSSD ($p = 0.0432$), StdHR ($p = 0.0211$), LF ($p = 0.0012$), HF ($p = 0.0089$), total power ($p = 0.0242$), SD1 ($p = 0.0432$), and elliptical area ($p = 0.0473$) were all different in a statistically significant way, as shown in Figure 4. The most significant difference came from the two frequency components, LF and HF, where the p-value was less than 0.01. Therefore, we found that frequency components were superior to time domain components for defining low and high stress using time-segment physiological measurements. In addition, the time-segment measurement is better than summarizing the daily measurement to identify the stress level. In addition, we cannot find any interaction between the time-segment factors and the factors that differentiate low- and high-stress scores.

E. Correlation between physiological and psychological assessment

We employ the correlation between each time segment and overall HRV features with the daily stress inventory scores. Not only during a single time segment, but also during multi-time segment analysis in phase 3, we observed the same characteristic and trend. As depicted in Figure 5, the number of pairs of successive N N (R-R) intervals that differ by more than 50 ms negatively correlated with daily stress inventory scores. Using the single time segment, the NN50 correlated with a daily stress score of -0.498 ($p = 0.0181$). In addition, the multi-time-segment indicates that phase 3 (05.00 p.m. - 09.00 p.m.) shows a similar tendency with a correlation value of -0.479 ($p = 0.0241$). According to the correlation results, the NN50 shows that the higher daily stress scores increase the heart rate rhythm, represented by the lower NN50 portion. It shows us that the fewer pairs detected mean higher stress occurred. During the multi-time-segment analysis, only the last time-segment (phase 3) likely affected the scores intensively.

IV. DISCUSSION

This study was proposed to evaluate daily stress assessment using a well-known wearable device (smartwatch and chest strap) as an objective stress detection instrument. This study aims to determine if it is possible to evaluate stress using daily stress without intervention or in the laboratory in order to detect psychological changes. As the essential basis for future research, we discovered that segment time analysis could distinguish stress levels based on physiological data.

According to the most recent evaluations of how wearable sensors and machine learning can be used to detect mental tension [15], most studies prefer to employ laboratory settings over real-world daily activities. Hence, using wearable devices to track users' everyday activities is the greatest approach to learn about daily stress and other physical activities [18]. One of the few publicly available datasets for this type of investigation was the 24-h multi-level physiological responses dataset, which was employed in the proposed study [14].

Stress detection is now widely acknowledged as a vital component of the "fight-or-flight" response. The sympathetic nervous system's "fight-or-flight response" occurs when it releases more cortisol, adrenaline, and noradrenaline in response to a stressor [16]. This survival mechanism enables individuals to respond swiftly to difficult or life-threatening situations. Our study revealed that high-stress subjects generated less band power at a lower frequency than low-stress subjects. Most studies found that short-term sympathetic activity is hyper-activated and low parasympathetic activity, which is characterized by a decrease in the high-frequency band and an increase in the low-frequency band, according to the meta-analysis on HRV to detect mental tension [17]. Throughout the entire day of recording, we discovered that the low frequency is the most distinguishing factor between low- and high-stress individuals. In comparison to the low-stress participant, the high-stress participant tends to have a lower spectrum in low frequency and high frequency. Consequently, future research must still improve and validate the findings, predominantly in terms of how the task and time segments were utilized.

According to the majority of evaluations using heart rate variability parameters, the heart rate is the most frequently reported feature to reflect mental stress changes, with 18 reports of it increasing during stress. It is followed by the RR interval, SDNN/SDRR, RMSSD, NN50, pNN50, total power, and high frequency, which decrease during stress [4]. Our proposed investigation confirmed that, based on the previous studies, the features used for HRV analysis are still valid [24, 25]. Our proposed study concurred that substantial variations and novelty were discovered based on those measures during time segments. On the other hand, we also observed a rise in the low frequency and the low-to-high frequency ratio.

How long and how accurately it takes to do mental stress detection is another crucial factor to consider [19]. The length of time that the smartwatch records your heart rate is, in our opinion, the most essential aspect of accuracy. However, studies have demonstrated that it takes at least 5 to 10 minutes to discern stress with an accuracy of greater than 90%. This is contrary to the fact that most wearable devices detect stress in a very short amount of time [20, 21]. We found that various time-segments, or the amount of time it takes to analyze the heart rate variability data, can offer various indicators of importance between low and high stress. Previous studies reported that to decompose frequency components from the heart variability, one also needs to consider the time segments of recording, such as low-frequency from 5 minutes to 24 hours or high-frequency that can be achieved only for a few minutes of recording [22, 23].

We were able to successfully verify the validity of the duration, and we agree that it must be taken into consideration again when using wearable technology to detect everyday stress, particularly when putting the devices to use. Therefore, the difficulty of this study is figuring out how to subjectively determine the stress condition with varied time segments for future investigations.

V. CONCLUSION

We formulated several questions that need answers from this study. The main query of this study is the possibility of differentiating between low and high-stress conditions with various heart rate variability parameters based on time segments. We discovered that using all physiological measurements in one day (one segment) could not distinguish between low and high-stress conditions ($p > 0.05$). However, we found that by segmenting the time or duration to extract the parameters (three segments: phases 1, 2, and 3), we were able to distinguish the two stress levels (low- and high-stress). We also confirmed that the crucial features are the RMSSD, StdHR, LF, HF, total power, SD1, and elliptical area, as reported in previous studies ($p < 0.05$), and the higher stress increase in the heartbeat rhythm based on the correlation analysis (r $\approx -0.5, p < 0.05$). However, another question remains regarding the best duration for accurately detecting daily stress and how to evaluate it subjectively. We believe that the question should be answered with future studies.

APPENDIX

Scales 1 to 7, they are 1: occurred but was not stressful, 2: caused very little stress, 3: caused a little stress, 4: caused some stress, 5: caused much stress, 6: caused stress very much, 7: caused me to panic.

1. Performed poorly at task
2. Performed poorly due to others
3. Thought about unfinished work
4. Hurried to met deadline activity
5. Interrupted during task/
6. Someone spoiled your completed task
7. Did something you are unskilled at
8. Unable to complete a task
9. was unorganized
10. Criticized or verbally attacked
11. Ignored by others
12. Spoke or performed in public
13. Dealt with rude waiter/salesperson
14. Interrupted while talking
15. Was forced to socialize
16. Someone broke a promise
17. Competed with someone
18. Was stared at
19. Did not hear from someone you expected to hear from
20. Experienced unwanted physical contact
21. Was misunderstood
22. Was embarrassed
23. Had your sleep disturbed
24. Forgot something
25. Feared illness/Pregnancy
26. Experienced illness/physical discomfort
27. Someone borrowed something without your permission
28. Your property was damaged
29. Had minor accident
30. Thought about the future
31. Ran out of food/personal article
32. Argued with spouse/boyfriend/girlfriend
33. Argued with another person
34. Waited longer than you wanted
35. Interrupted while thinking/relaxing
36. Someone "cut" ahead of your in a line
37. Performed poorly at sport/game
38. Did something that you did not want to
39. Unable to complete all plans for today
40. Had car trouble
41. Had difficulty in traffic
42. Money problems
43. Store lacked a desired item
44. Misplaced something
45. Bad weather
46. Unexpected expenses
47. Had confrontation with an authority figure
48. Heard some bad news
49. Concerned over personal appearance
50. Exposed to feared situation or object
51. Exposed to upsetting TV show, movie, book
52. "Pet peeve" violated
53. Failed to understand something
54. Worried about another's problems
55. Experienced narrow escape from danger
56. Stopped unwanted personal habit
57. Had problem with kid(s)
58. Was late for work/appointment

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