Enhancement of Physiological Stress Classification using Psychometric Features

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Abstract: Psychological data features are underutilized in many acute stress studies since they are challenging to replicate and validate due to their inherent subjectivity. However, psychology and perception play essential roles in stress research according to the well-established allostatic load model. Therefore, we demonstrate the importance of accounting for psychological data in acute stress research in an ambulatory setting through a joint analysis. We enhanced stress classification by combining psychometric features with standard physiological signal features. We used the publicly available Wearable Stress and Affect Database (WESAD), from which we obtained physiological signals and psychological self-assessments from 15 participants. For each participant, a set of physiologically relevant features were extracted from each signal type. In parallel, we adapted psychometric features, positive emotion (PE_{score}) and negative emotion (NE_{scores}) scores, by calculating the weighted average of self-evaluation scores. Using a stepwise feature selection and a linear-discriminant-analysis-based classifier, we found that PE_{scores}, along with select physiological signal features, could enhance cross-validated stress classification accuracy by 8%, higher than a previous benchmark study using the same dataset. More importantly, we found that such a classification accuracy could be achieved with significantly fewer physiological signal features (by 20 times) with the aid of a psychometric feature. Finally, we found that psychometric features could indicate the type of perceived stress relating to an individual's mood descriptor scores. Thus, a combination of psychometric and physiological data could be beneficial towards improving the detection and management of stress and support the development of holistic stress models.

1 INTRODUCTION

Stress is a complex physiological, and psychological response of the human body towards perceived or actual threats to its well-being (O'Connor et al., 2021). Stress has been reported to cause many medical and mental health issues experienced by workers in highly demanding jobs, such as personal support workers and healthcare practitioners (Pappa et al., 2020). In addition, prolonged stress could induce many long-term health issues like cardiovascular disease and depression (Legault et al., 2017; O'Connor et al., 2021). Therefore, persistent or chronic stress without proper and regular intervention could be detrimental to an individual's well-being.

Some stress studies on workers in harsh environments primarily focused on using commercial-grade wearables(Choi et al., 2011; Runkle et al., 2019) or building wireless body area networks (WBANs)(de Fazio et al., 2020; Wu et al., 2019) to monitor and detect physiological and environmental indicators of stress. Studies cited above are crucial for developing stress studies standards, such as experimental protocols and devices, in a dynamic setting such as the workplace. However, the psychological correlates of stress, such as affect, perception, and past experiences have been under-represented.

Evidence of the dynamic interaction of human physiology and psychology in response to stressors has been long established (Guidi et al., 2021; McEwen and Rasgon, 2018). The interaction of different physiological and psychological systems in the human body is the building block of the allostatic model(Guidi et al., 2021; Fava et al., 2019; McEwen and Rasgon, 2018). The allostatic model provides a framework to elucidate the physiological and psycho-

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logical mechanisms that contribute to the overall wear and tear of the body (allostatic load) as a result of prolonged exposure to stressors. Although administering psychological evaluations in a dynamic environment is challenging, accounting for psychological biomarkers along with physiological biomarkers of a stress response could be beneficial to improve stress classification tasks.

The disjunct in methods of measurement or assessment of the stress response is apparent in some studies. While some have focused on characterizing stress through physiological signal features(Schmidt et al., 2018; Choi et al., 2019), others solely relied on evaluating its psychological effects through observational studies and self-reports analysis(Vitale et al., 2021; Edmondson et al., 2014). A previous study by (Schmidt et al., 2018) called for accounting psychological data from self-reports to improve physiological characterization of stress and affective states for individuals. The importance of psychological data to stress modeling using ambulatory data has been previously shown (Hovsepian et al., 2015; Sarker et al., 2016; Plarre et al., 2011) however, a joint quantitative analysis of raw psychological and physiological stress factors has been underutilized.

Our work highlights the importance of accounting for psychological correlates of stress, such as affect and perception, along with physiological signals from wearable devices. We jointly analyze the physiological signal and psychometric features to enhance stress classification. In addition, we introduce new psychometric features, the emotion scores, translated from an established psychological questionnaire, and assess their relevance in improving stress classification, consistent with the allostatic load model. Outlined in Figure 1 is the overall organization of our work presented in this paper.

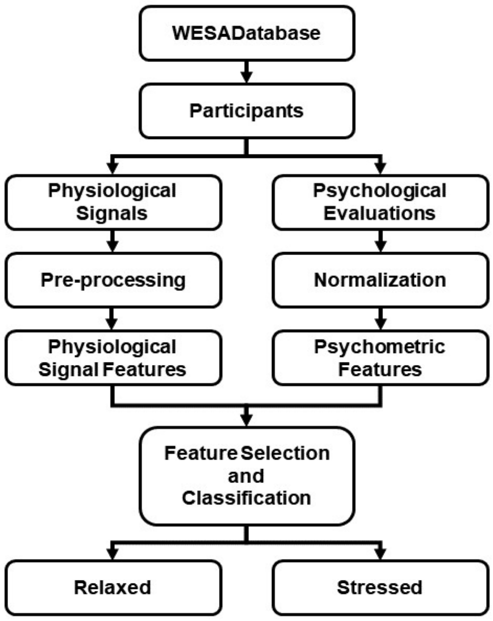

Figure 1: Overall organization of proposed study to improve stress classification accuracy using both physiological and psychometric data features.

2 METHODS

2.1 Database

Data used in this work was obtained from the Wearable Stress and Affect Database (WESAD) as part of the study done by (Schmidt et al., 2018), made available through the University of California Irvine's machine learning repository (Asuncion and Newman, 2007). Below, we briefly describe WESAD and summarize its authors' data collection methods relevant to our proposed work. Then, we direct the reader to (Schmidt et al., 2018) for a detailed description of the data acquisition and validation of WESAD.

WESAD provides a standard multi-modal dataset for stress and affect detection in an ambulatory setting. In addition, the authors of WESAD offered benchmark classification results using standard data features and machine learning methods for comparison against future stress and affect studies.

WESAD consists of physiological and psychological data collected from 15 participants, 12 males and 3 females, with an average age of 27.5 ± 2.4 years old. Physiological data from each participant were obtained from two wearable devices, one strapped around the chest (RespiBAN professional) and the other around the wrist (Empatica E4). In this work, we limited our data source to the chest device due to its superior signal quality compared to the wrist device. Therefore, from the chest device, only accelerometer (ACC), plethysmograph (RESP), electrocardiograph (ECG), electrodermal activity (EDA), and temperature (TEMP) data were included for feature extraction.

Moreover, from all of the questionnaires used in the Schmidt study, we chose only the Positive Affect and Negative Affect Schedule (PANAS)(Crawford and Henry, 2004) as the source of our psychometric features since it was consistently used throughout that study. The authors of WESAD added affect state descriptors (i.e., Stressed, Frustrated, Happy, and Sad) to the original PANAS questionnaire to suit the goals of the original study. We used the 'Stressed' descriptor as ground truth for later classification. Finally, we included data only from neutral/relaxed and stressed states to perform binary classification.

2.2 Physiological Signal Feature Extraction

Due to the length of both baseline (20 mins) and stress (6.5 mins) conditions, we calculated signal features within a sliding one-minute window on increments of 10 seconds for all signal types. The set of signal features for each signal type were ensured to have been proven in the literature to be physiologically relevant in stress research. The median of sliding window increments for each physiological signal feature was calculated for baseline and stress conditions. Table 1 summarizes physiological signal features used in this study.

2.2.1 Electrocardiograph (ECG)

Standard beats per minute (BPM), heart rate variabilities (HRV), and its root mean squared (HRV_{rms}) were calculated from the ECG data. Moreover, features of the HRV spectrum were calculated. HRV features are critical because they can relate psychological processes to physiological processes (Grossman and Taylor, 2007). Therefore, to indicate physiological response to stressful situations, we calculated the ratio (HR_{ratio}) of the area under the curve of low-frequency bands (0.05 – 0.15 Hz) over high-frequency bands (0.15 – 0.5 Hz), the HRVratio (Healey and Picard, 2005).

2.2.2 Plethysmograph (RESP)

Several relevant features were calculated from RESP data. Respiration cycle features could provide clues on blood-oxygen saturation, which is essential in maintaining proper organ function (Schmidt et al., 2018). We calculated inhalation and exhalation duration (RESP_{indur} & RESP_{exdur}) and ratio (RESP_{ratio}), respiration duration (RESP_{dur}), chest stretch ($\text{RESP}_{stretch}$), inhalation volume (RESP_{invol}), and respiration rate (RESP_{rate}).

2.2.3 Respiratory Sinus Arrhythmia (RSA)

Respiratory sinus arrhythmia (RSA) describes irregularity in heart rate due to cardiac vagal efferent discharge and time-alignment to breath cycles (Grossman and Taylor, 2007). It has been observed that during inhalation, the heart beats faster and slower during exhalation. In a highly stressful situation, hyperventilation could occur therefore increasing the occurrence of RSA (Campbell and Wisco, 2021; Tavel, 2021). Therefore, RSA is a multimodal feature, dependent on both the ECG and RESP signals. The RSA feature was calculated using the peak-valley method(Grossman and Taylor, 2007) such that the shortest beat interval during inhalation was subtracted from the longest beat interval during exhalation. We also calculated the beat number ratio between exhalation over inhalation segments (RSA_{ratio}). The respiration window was extended 750 ms forward to account for phase shifts between respiration and heart rates in sync with respiratory rates (Grossman and Taylor, 2007).

2.2.4 Electrodermal Activity (EDA)

Skin conductance level (SCL) and skin conductance response (SCR) are two components of the EDA signal. While SCL reflects general changes in autonomic arousal, SCR indicates autonomic responses specific to external stimuli (Boucsein, 2012). We separated these components via regularized least-squares detrending method used by (Choi et al., 2011) in a previous study. However, no particular startle events were noted in the Schmidt study; therefore, we included only the statistical features from EDA's SCL components in our analysis.

2.2.5 Accelerometer (ACC) and Skin Temperature (TEMP)

From ACC, we calculated an approximation of the energy expenditure of each subject through the integral of the modulus of acceleration (IMA)(Karantonis et al., 2006). Finally, we calculated the average skin temperature (TEMP) for each subject within each condition.

2.3 Psychometric Features

We calculated psychometric features, positive (PE_{score}) and negative (NE_{score}), from each subject based on their self-reported perceptions of emotional descriptors within the PANAS questionnaires. Each item in the questionnaire was scored using a 5-point scale. A score of 1 indicates descriptor perception as 'Very Slightly' or 'Not at All' while 5 as 'Extremely.' First, we grouped the questionnaire items into 10 positive and 10 negative adjectives associated with positive and negative emotions. Second, we normalized the participants' scores for each adjective using min-max normalization, where 0 is the lowest and 1 is the highest. We implemented a weighted average (ρ_{ij}, η_{ij}) on the normalized scores (s_{ij}) for each subject (i) to calculate their PE_{score} and NE_{score} features such that

Table 1: Summary of physiological signal features calculated from wearable data (Schmidt et al., 2018) for stress classification.

Summary of physiological signal features		
Signal type	**Feature**	**Description**
ECG	BPM	Beats per minute
	HRV	Heart rate variability
	HRV_{rms}	Root mean squared of HRV
	HR_{ratio}	Ratio of low and high frequency bands of HRV spectrum
RESP	$RESP_{indur}$	Inspiration duration
	$RESP_{exdur}$	Expiration duration
	$RESP_{ratio}$	Ratio of $RESP_{indur}$ and $RESP_{exdur}$
	$RESP_{dur}$	Overall respiration duration
	$RESP_{stretch}$	Chest stretch due to respiration
	$RESP_{invol}$	Inspiration volume
	$RESP_{rate}$	Respiration rate
ECG & RESP	RSA	Respiratory sinus arrhythmia
EDA	SCL_{mean}	Average skin conductance level
	SCL_{std}	Standard deviation of SCL
	SCL_{var}	Variance of SCL
ACC	IMA	Integral of modulus of acceleration (energy expenditure)
TEMP	TEMP	Skin temperature

$$PE_{score,i} = \sum_{j=1}^{10} \rho_{ij} s_{ij} \tag{1}$$

and

$$NE_{score,i} = \sum_{j=1}^{10} \eta_{ij} s_{ij}. \tag{2}$$

The weights were calculated according to the adjective groupings from a mood checklist(Crawford and Henry, 2004). Based on the mood checklist, negative emotions are weighed equally while positive emotions have different subgroups hence have their unique weights, and so a distinction between ρ_{ij} and η_{ij} was made.

2.4 Feature Selection and Classification

Using SPSS®(George and Mallery, 2019), we performed stepwise feature selection, with a 95% confidence interval ($\alpha = 0.05$), to determine a set of inputs to a linear discriminant analysis (LDA) based classifier that will yield the best cross-validated (CV) classification accuracy.

Selected features were served as inputs to the LDA-based classifier to separate stressed individuals from those relaxed. Subject data was labeled as 'stressed' if they graded the corresponding descriptor in the PANAS questionnaire between 2 and 5. Subjects with a score of 1 for the same descriptor were labeled as 'relaxed' or 'baseline.' In total, 7 LDA models were generated, i.e., physiological only (Φ), psychometric PE_{score} (Ψ_P), psychometric NEscore (Ψ_N), psychometric only (Ψ), physiological and psychometric PE_{score} (Φ, Ψ_P), physiological and psychometric NE_{score} (Φ, Ψ_N), and finally, physiological and psychometric (Φ, Ψ). Due to sample size, prior probabilities were adjusted based on the number of participants in each group. We validated each classifier model using the leave-one-out cross-validation (LOOCV) method (George and Mallery, 2019).

3 RESULTS

Eight (8) participants experienced some degree of stress during a controlled stress test, while 7 participants minimally experience stress. Participant reports served as the ground truth for classification. Both physiological and psychometric feature types were fed to the LDA-based classifier. Table 2 shows the detailed classification results and the confusion tables for only 5 LDA-based models since only the combinations of PE_{score} with physiological signal features improved classification accuracy.

Classification accuracy of 93.3% can be achieved with only 3 physiological features, while 86.7% can be achieved using the PE_{score} feature. Furthermore, when stepwise feature selection was applied to the combined physiological and psychometric features, 3 physiological features and PE_{scores} improved to a perfect classification (100%), improving the previous results presented by the benchmark study (Schmidt et al., 2018) using the same binary classification

Table 2: Evaluation of stress classification performance via leave-one-out cross validation (LOOCV) of linear discriminant analysis-based classifier models. O: original, P: predicted, Φ: physiological only, Ψ: psychometric only, Ψ_P: psychometric PE_{score}, Ψ_N: psychometric NE_{score}, and PE_{score} (Φ, Ψ_P): physiological and psychometric PE_{score}.

Model	Confusion Matrix O \ P	R	S	**LOOCV** (%)
Φ	R	7	0	93.3
	S	1	7	
Ψ	R	6	1	86.7
	S	1	7	
Ψ_P	R	6	1	86.7
	S	1	7	
Ψ_N	R	6	1	80.0
	S	2	6	
Φ, Ψ_P	R	7	0	100.0
	S	0	8	

method by 8% [1]. In addition, our results show that such classification accuracy could be achieved with 20 times fewer physiological signal features compared to the same study above. Although the results obtained are from a small dataset, our results demonstrate potential in the joint analysis of physiological and psychometric features to enhance stress classification.

Table 3 shows the descriptive statistics of the selected features, RSA_{ratio}, HRV_{ratio}, IMA, and PE_{score}. We also show in Figure 2 the comparison of the distribution of values of a physiologically dominant signal feature, RSA_{ratio}, and the dominant psychometric feature PE_{score}.

We demonstrate that stressful conditions increase an individual's RSA_{ratio} values. Specifically, the average number of beats during exhalation was higher than during inhalation in stressed individuals, which explains their higher RSA_{ratio} values.

Furthermore, we observed a significant increase in HRV_{ratio} values in stressed individuals, which reflects the degree of sympathetic over parasympathetic nervous activity, respectively. A closer ex-

Table 3: Selected features for stress classification and features descriptive statistics.

Features	Relaxed (n = 7)	Stressed (n = 8)
RSA_{ratio}	0.59 ± 0.06	0.67 ± 0.04
HRV_{ratio}	2.77 ± 1.77	5.28 ± 4.43
IMA	$53,575 \pm 8,625$	$50,484 \pm 5,428$
PE_{score}	0.28 ± 0.11	0.56 ± 0.16

[1] (Φ, Ψ_N) and (Φ, Ψ) are not shown in table 2 since they do not improve LOOCV results beyond (Φ, Ψ_P) provided, therefore are redundant.

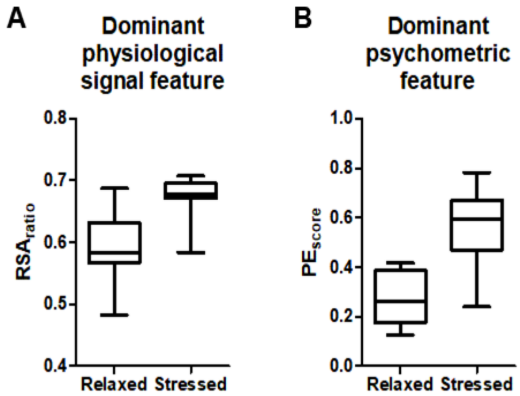

Figure 2: Distribution comparison between relaxed and stressed states of a dominant physiological signal feature, RSA_{ratio}(A), and a psychometric feature, PE_{score} (B), for stress classification.

amination of the area under the low-frequency HRV spectrum reveals that, while it remained higher than its high-frequency component for both states, there was a significant increase in its median values in stressed individuals compared to those who were relaxed (stressed: 74% vs. relaxed: 56%). Such an observation indicates that individuals under stress have a greater sympathetic nervous response (i.e., fight-or-flight) than those in a neutral state, as corroborated by earlier studies(Choi et al., 2011; Healey and Picard, 2005).

Energy expenditure, as approximated by IMA, decreased in individuals under stress. Due to the nature of IMA calculation (i.e., the sum of integrals of each accelerometer axis channel), a decrease in an individual's IMA indicates a reduction in an individual's overall movement during stress, decreasing their energy expenditure. This observation could be due to an evolutionary tendency to conserve energy when faced with challenges (Pontzer, 2015); however, this warrants further investigation within the scope of stress research in an ambulatory setting as well as an examination of the stress protocol of a study.

Interestingly, one of our psychometric features, PE_{score}, is also an important feature for stress classification. Although PE_{score} and NE_{score} increased for individuals during stress, 78% and 50% more than baseline values, respectively, PE_{score} remained higher than NE_{score} in both states suggesting participants experienced eustress (positive stress) through a stress protocol indicating an overall positive engagement. Naturally, as they were subjected to stressful situations, individuals' distress (negative stress) became more prominent. Different stress types have been previously described (Le Fevre et al., 2003), and the trend shown from our psychometric features is concordant to their observations.

It is important to note that PE_{score} are based on the weighted average of the positive mood descriptors as assessed by each individual. While we achieved a perfect classification with the inclusion of this psychometric feature, we did not include in its calculation a participant's perceived stress score. Many versions of the PANAS questionnaire have been previously introduced (i.e., PANAS-C(Laurent et al., 1999), I-PANAS-SF(Thompson, 2007), and PANAS-X(Watson and Clark, 1999)) however no version of the PANAS questionnaire include a 'Stressed' descriptor. A 'Stressed' descriptor was added by the authors of WESAD in their PANAS questionnaire to suit the goals of the original classification study. Therefore, the perceived stress score of a subject was not accounted in the calculation of our psychometric features and was used only as a label for binary classification as described above.

4 DISCUSSIONS

We introduced new psychometric features to enhance stress classification using physiological data from wearable technologies obtained from WESAD. Our psychometric features, derived from traditional questionnaires from psychological evaluations, were used to perform a joint analysis with physiologically relevant features for stress research. More importantly, we demonstrated that stress classification could be improved when both the physiological and psychological components of stress are considered.

In comparison, the work by Nkurikiyeyezu et al (Nkurikiyeyezu et al., 2019) provided a simple framework for creating person-specific models to predict stress using only physiological signals. Their proposed framework achieved a classification accuracy of 95.2%, comparable to the results of the original WESAD study. Another WESAD-based study by Lai et al (Lai et al., 2021) introduces a stress monitoring assistant that demonstrates a 96.7% binary stress classification accuracy using only features of chest-based physiological signals. However, the above examples do not account for the available psychological data as part of the feature pool for later classification and prediction tasks.

While our work does not introduce any stress models or frameworks, we emphasize the importance of a joint analysis of physiological and psychological data to improve stress classification tasks. As previously described through the allostatic load model, physiological and psychological systems are closely intertwined, if not cascaded. A physiological response could be a result of psychological stressors and vice versa. Moreover, physiological and psychological systems could provide concerted reactions to external stressors. While the relationship of physiological and psychological systems has been previously established in stress research, the contribution of psychological data to stress classification tasks is under-recognized.

Self-reports in a dynamic environment are challenging to validate and replicate due to their inherent subjectivity. Person-specific models and frameworks that consider psychological data also require regular calibration and updates as both physiology and psychology change over time(Nkurikiyeyezu et al., 2019), especially in the context of stress and allostatic load since they are only observed after extended exposure to stressors. However, as we demonstrated in this work, when physiological and psychological data are jointly analyzed, stress classification tasks could be improved, and the number of physiological signal features needed could be greatly reduced. Evidence and recommendations from previous works(Schmidt et al., 2018; Hovsepian et al., 2015; Sarker et al., 2016; Plarre et al., 2011) provide further motivation for the inclusion of psychological data in stress classification tasks.

While we present good stress classification accuracy, we acknowledge that our work has limitations. We recognize that our stress classification task could be affected by choice of features and pre-processing methods. Recommendations for analysis window durations for different physiological signals are in the literature (i.e., HRV (Shaffer and Meehan, 2020) and EDA (Boucsein, 2012)). Our choice of analysis window is in keeping with the WESAD benchmark study (Schmidt et al., 2018), which was based on previous work by (Kreibig, 2010). On the other hand, our choice of features was based on existing literature cited presented in our Methods section. We were careful to select our signal features so that they could adequately represent a stress response. While this strategy naturally decreases the amount of features fed in to an classification algorithm, it ensures sufficient representation of an individual's autonomic activity related to external stressors.

We also recognize that our choice of database limits the sample size on which we could test our new psychometric features. Indeed, a 15-subject cohort is a small sample size. Subject recruitment for human-centric studies in biomedical or biomedical-adjacent fields remains a significant challenge especially for short-term studies such as acute stress. Despite the limited number of subjects, we ensured that our methods for classification and cross-validation were suitable for small sample sizes, such as LOOCV.

Future work aims to collect and analyse data from a larger cohort of subjects to further test and validate our psychometric features. In addition, we aim to use our validated psychometric features to create a holistic predictive model concordant with the established allostatic load model(McEwen and Rasgon, 2018), giving greater focus on chronic stress and its effect on a person's overall well-being.

5 CONCLUSIONS

We demonstrated the importance of including psychological data in an acute stress study. Through a joint analysis of physiological and psychological features, we showed that stress classification could be enhanced. Furthermore, accounting for psychometric data reduces the number of physiological signal features needed stress classification. We also found that our psychometric features could aid in identifying the type of stress (eustress or distress) an individual perceives, as indicated by a self-assessment questionnaire's independent contributions of each mood descriptor (affect). Our work provides an incremental step towards translating affect linked to stress to suitable quantitative measurements similar to those offered by physiological sensors. Joint analysis of psychological and physiological data could be beneficial towards the detection and management of stress. Furthermore, our work could support the future development of holistic stress models consistent with the well-established allostatic load model. Such models could be beneficial for workers in harsh environments like healthcare and personal support workers.

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