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Impact of varying levels of mental stress on phase information of EEG Signals: A study on the Frontal, Central, and parietal regions

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ABSTRACT

Mental stress is a commonly occurring phenomenon that impacts people from diverse backgrounds and is associated with numerous physical and psychological illnesses. The brain plays a vital role in how individuals perceive and react to stress, including their physiological and behavioral responses. In this study, our objective was to investigate the impact of varying levels of induced stress, ranging from mild to severe, on brain activity. Our primary interest was to determine if mental stress would influence neural coordination, as assessed through intertrial phase clustering (ITPC). Furthermore, we hypothesized that an increase in perceived mental stress would result in reduced regional connectivity as measured via phase-lag index (PLI). EEG data from 41 participants (20 females, 21 males, age range 18 to 46; mean = 26.1; SD = 7.06) were collected while they were exposed to three levels of mental stress, using a parametric modulation study design. Following pre-processing, we extracted the two mentioned features and performed statistical analysis. As an additional analysis, we assessed the discriminatory power of these features using a Random Forest classifier. Statistical analysis revealed a significant decrease of ITPCs over frontal, central, and parietal regions accompanying increased levels of stress. The results obtained from the PLI analysis showed that the increase in levels of stress were associated with a decrease in the brain connectivity over the frontocentral, frontoparietal, and centroparietal regions. The classification result showed that the Random Forrest classifier predict three levels of stress with 83.78% accuracy. These findings indicate that phase-based EEG features could serve as a novel neurometric for quantifying *in vivo* stress levels. Furthermore, this study could contribute to developing more precise tools to measure mental stress objectively.

1. Introduction

Stress is a widespread phenomenon that affects individuals from various walks of life [1]. It has been linked to various physical and mental health problems [2] such as depression [3] anxiety [4] and cancer [5] to name a few. The brain plays a crucial role in the experience and physiological and behavioral responses to stress [6,7]. Stress can impact brain activity by altering the way the brain processes information and affects neurotransmitter levels [8–10]. Chronic stress has been linked to changes in the prefrontal cortex, which is involved in executive functions such as decision-making, working memory, and attention modulation [11–13]. It can also lead to changes in the hippocampus, a structure long known to be involved in declarative memory and learning [14,15]. These changes can result in a decreased ability to focus and retain information, as well as an increased risk for mental and physical health problems. The mental stress experienced by people can vary greatly from low to high stress depending on the person, the context and situation [16–18]. High stress levels can evoke feelings of anxiety, discomfort, and increase cognitive load, affecting the emotional and cognitive responses of the individuals [19–21]. These pieces of evidence imply the necessity and importance of an objective and precise tool for an early detection of mental stress.

Assessing mental stress is a difficult task because it affects individuals differently and there exist multiple methods for stress evaluation [22]. Electroencephalography (EEG) is a commonly used non-invasive technique that measures the electrical activity of the brain and is useful in

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studying the effects of stress [23–25] It provides real-time information on how the brain processes stress [23,26]. There have been numerous studies assessing the effect of stressors on brain responses using EEG. Power spectral density [27], frontal asymmetry [28], time–frequency features [29], and entropy [30,31] are some of the metrics that have been utilized to detect different levels of stress from EEG data [32].

During a stressful event, the brain typically responds by increasing its overall level of activity [33,34] An increase in beta activity has been found in stressful conditions, which is associated with alertness, focus, and concentration [35]. At the same time, the brain also typically exhibits a decrease in alpha wave activity during stress, suggesting that stress can suppress the alpha rhythm. An increase in Alpha band activity is associated with relaxation and calmness [36]. A decrease in alpha activity may be due to the fact that the brain is directing its resources toward the more immediate demands of the situation, such as focusing on a threat or planning a response [37]. This suppression may reflect a shift in the brain's state from a passive or relaxed state to an active or alert state [38] For this reason, most of the previous research has been focused on alpha activities, with some research on beta.

However, there is a lack of consistency in the literature regarding the effect of mental stress on different EEG features. For instance, [39] reported an increase in alpha power and a decrease in beta band activity during stressful conditions. [40] reported an increase in beta and theta frontal and parietal midline regions during stress conditions compared to control and baseline conditions. Therefore, it is important to note that the relationship between stress and changes in the brain activity is complex and can vary among individuals [36,41]. Some individuals may exhibit suppression of alpha power in response to stress, while others may exhibit an increase [27,33,42,43]. This variability may reflect differences in the brain's response to stress and individual differences in stress-coping mechanisms [44,45]. In addition, since the current EEG metrics on mental stress suffer from high false positivity and low sensitivity (especially in fast oscillation activity), a robust metric that is associated with reproducible results in mental stress detection is missing in the field.

Previous studies have primarily focused on the frequency-domain features and differential asymmetry features, and as mentioned earlier there is a lack of consistency in the results driven form these features for assessing stress. The investigation of stress through time–frequency (TF) features has yet to be investigated. TF analysis enables the examination of dynamic changes in amplitude and phase across frequencies, differentiating between phase-locked and non-phase-locked signals [32]. TF analysis also estimates the consistency of phase across multiple trials of a specific event, known as inter-trial phase synchrony (ITPC) or intertrial phase clustering (ITPC/ITC). ITPC evaluates the consistency of EEG activity with a particular event of interest at a specific time and frequency. In this method, individual trials of an EEG experiment cluster together based on their similarities in waveform or spectral characteristics. ITPC has been shown as a well-suited measurement of attention, information processing, and executive function by representing the rhythmicity of cortical activation, especially in alpha [46,47].

Another lacking evidence in the literature is the effect of mental stress on the regional connection of the brain. A limited number of studies have investigated the relationship between stress and functional connectivity in EEG [48,49] and contradictory results have been reported. The main drawback of interpreting connectivity result in EEG, is the common source problem and volume conduction effect which result in false positivity and showing spurious connectivity [50]. With this regard, other connectivity metrics such as phase-lag index (PLI) has been introduced [51] which is capable of reducing the effect of common source problem and detecting "real" connectivity in EEG. Unlike other measures of connectivity, PLI specifically targets phase synchronization, thereby eliminating the confounding effects of volume conduction. PLI demonstrates high specificity and sensitivity while minimizing false positivity, thus enhancing the reliability of the obtained results [51,52].

In this paper, as illustrated in Fig. 1, we aim to unravel how different levels of stress (induced by task difficulty) ranging from mild to severe while watching video materials (i.e., documentary) affects brain activity. The degree of mental stress was assessed through the use of EEG features, ITPC and PLI. Additionally, by applying a Random Forest predictive model, we classify three levels of stress using mentioned EEG features and show their relative contribution to the final decision of the model. The outcome of the present research could contribute to providing a better measurement with high sensitivity and specificity for mental stress detection. Additionally, the classification results show that we can improve the efficiency of mental stress detection methods with varying levels of intensity considering those metrics. Finally, the implications of this research for commercialization are also noticeable, especially considering the limited number of EEG channels analysed in the study.

2. Materials and method

2.1. Participants

A total number of 41 (20 female, 21 male) participants (age range 18 to 46; mean = 26.1; SD = 7.06) without any reported psychiatric or neurological conditions were recruited in the experiment via the Neurons Inc. online recruitment system. All participants were informed about the experiment and had read and signed the consent form prior to the experiment, following the Declaration of Helsinki. The experiment was approved by the local ethical committee and all data were analysed and reported anonymously.

2.2. Experimental procedure

The experiment consisted of three different conditions, named respectively low, medium, and high stress conditions. The main stimulus was a documentary video ("The Reality of Van Life", Different Media © 2018) which was around 4 min. All participants went through all three conditions in the same order as depicted in Fig. 2. The "low stress" condition consisted of just watching the video. After 1 min of rest, in the "medium stress" condition, participants watched the documentary and simultaneously were required to perform a Digit Span task. In this mental task, a sequence of numbers is presented for 5 s, followed by 4 s of a blank screen, and afterwards the subjects are required to repeat the sequence out loud (Fig. 2A). Following 1 min of rest, participants passed the "high stress" condition. While watching the video, in this condition

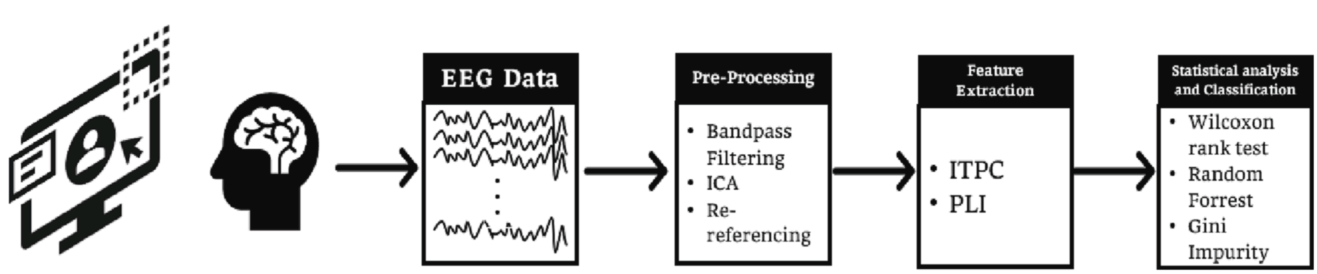

Fig. 1. Flow Diagram of the study.

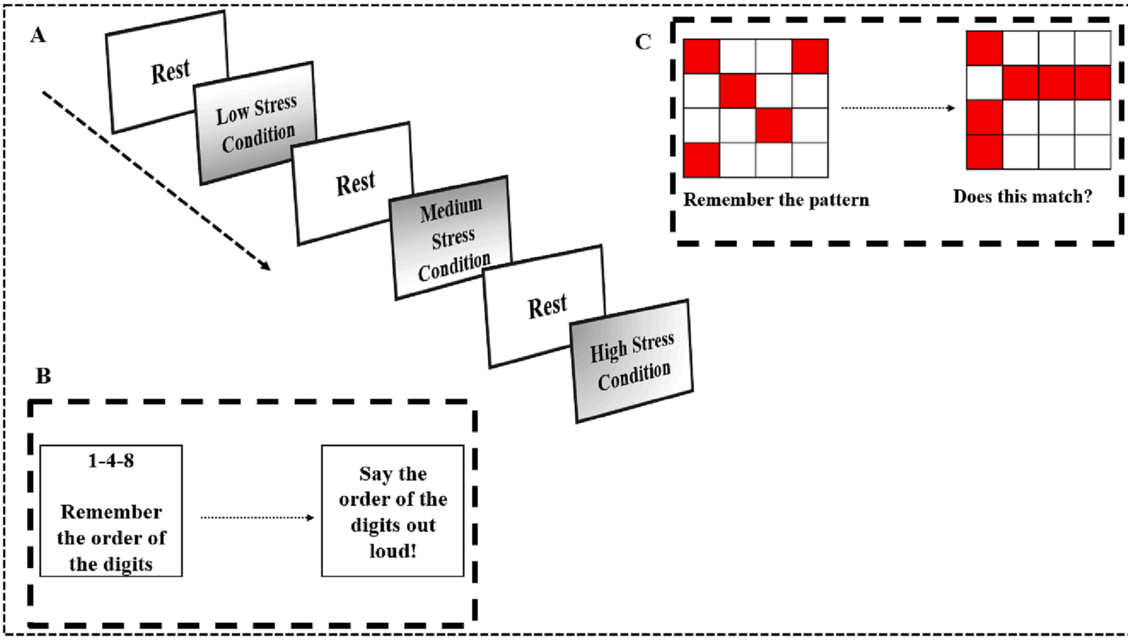

Fig. 2. The general procedure of the experiment is presented in section A. and section B, the details of Digit Span task are depicted. The red box task is shown in section C.

participants performed the Digit Span task of the previous conditions and were additionally required to remember patterns of squares. For this, the subjects were presented with a 4 by 4 white and red square matrix for 3 s followed by three digits task for 5 s. After 4 s of a blank screen, they were required to say the digits out loud, and consecutively they needed to approve whether the pattern that was presented to them in a box and on the screen matches the pattern that they previously saw (Fig. 2B). Finally, we asked each participant to rate their level of stress on a 7-point scale for each condition.

2.3. EEG recording and processing

The EEG data were recorded via Biopac B-Alert with 9 channels (Fz, F3, F4, Cz, C3, C4, POz, P3, P4). The ground and reference electrodes were placed at AFz, and mastoid, respectively. EEG data were sampled at 256 Hz and exported to MNE Python library [53] for further analysis. For pre-processing, first, the data were filtered with an upper and lower band of 0.1 to 45 Hz, respectively using a FIR bandpass filter with hamming window. Independent Component Analysis (ICA) [54] was used to removed eyeblink and eye movement components. On average, 3.1 components were removed for each subject through ICA. Thereafter, common average refencing was utilized as the reference point of the data. At last, the EEG data were segmented to 3 s epochs (without overlapping) for further analysis.

2.4. Inter trial phase clustering

ITPC is a measure of phase synchrony for EEG signals across trials. To compute ITPC for a given signal, we applied Morlet wavelets to extract time–frequency features. The number of cycles (time–frequency trade-off) for the wavelets was set to 5 which means the frequency resolution was 1 Hz (from 8 to 13) and the length of time-windows was to 70 ms on average. Then, the ITPC was computed as follows:

$$ITPC(f,t) = \frac{1}{N}\sum\nolimits_{1}^{N}\frac{E_k(f,t)}{|E_k(f,t)|} \quad (1)$$

In which E_k (f,t) is the spectral estimate of the signal at time and frequency of t and f. ITPC represents the phase alignment cross trials and it is normalized between 0 and 1 with 0 meaning no phase locked trials and 1 indicating a near-perfect EEG phase coherence across trials [55,56]. The ITPC values of channel ×, have been averaged over the frequency bins ad time-samples, then, to represent ITPC of region y, those values have been averaged for all channels within region y. This procedure was repeated for each condition and each subject.

2.5. Phase lag index

PLI is a connectivity measurement of two signals which reflects consistent phase lag (or lead) between two nodes [51]. The idea behind PLI is to remove the phase differences around 0 or π which is induced by shared sources and keep the phase difference between 0 and π which is less probable to be affected by volume conduction [51,57]. The PLI between two signals is computed as follows:

$$PLI = |\langle \mathrm{sign}(\Delta\varnothing(t_k)) > | \quad (2)$$

In which $\Delta\varnothing$ indicates phase difference and the <.. > operation is the average over time. The PLI varies between 0 and 1; PLI at 0 represents no phase coupling or coupling with phase difference of zero or π, and PLI at 1 indicates perfect coupling of the two given signals which $0 < \Delta\varnothing < \pi$ or $0 < \Delta\varnothing < -\pi$. The Fourier method was used to transform the data to frequency domain with 256 points (~256 ms) in the alpha frequency band (8–13 Hz). Thereafter, by applying the sign function to the phase difference between two given signals (imaginary part of the cross spectrum of two signals), we averaged these values over frequency bins to represent the connectivity values for each of the two channels. Lastly, by averaging pairwise connectivity over Frontal, Central and Parietal regions (both within and between regions) the final PLI values are computed.

2.6. Statistical analysis

Since ITPC and PLI values have non-normal distributions [58], a non-parametric Wilcoxon signed rank test was utilized for the comparison of ITPC and PLI between conditions, since it does not take the assumption of having normal distribution for the data. For both ITPC and PLI, the statistical test was applied over the averaged regional values to compare the three given conditions. The significance level was set to 0.05 and Bonferroni correction was applied for multiple comparisons. For the mentioned parameters, in order to have a statistical power of at least 0.8, it is required to have a sample size of 25.

2.7. Random Forrest classifier

A Random Forrest classifier [59] was implemented to classify the ITPC and PLI features from the three given classes: low, medium, and high stress. Random Forest uses an ensemble of uncorrelated decision trees to vote for the output label. By randomly sampling (with replacement) from the data and training each decision tree, the model would result in a relatively low variance [59].

$$H(x) = \frac{1}{B}\sum_{b=1}^{B} h_b(x) \quad (3)$$

In which B indicates number of estimators (decision trees), and h(x) is the decision tree classifier which averaging over all of them will yield the Radom Forrest classifier H(x). In addition, by using Gini Impurity, we could evaluate the explainability power of each feature for the target class [60].

Gini Impurity $= \sum_{c=1}^{C} f_c(1 - f_c)$ **(4).**

In which C indicates the number of classes and fc shows the frequency of class c in a node. Gini impurity is a metric used to measure the level of similarity among a set of samples, indicating the difficulty of classifying them based on their labels. The importance of each feature is determined by computing the average Gini impurity across all nodes and trees, which reflects the reduction in impurity achieved by using that feature.

3. Results

RainCloud plots of the participants' self-response on the stress-level questions are presented in Fig. 3. The average response and standard deviation of the participant for low, medium, and high stress conditions were 1.78 ± 1.17, 3.68 ± 1.47, and 4.68 ± 1.57, respectively. There was a significant difference (p-value < 0.00001) between all conditions regarding the self-report stress level.

3.1. ITPC analysis

The distribution of ITPC values over the scalp is represented in Fig. 4A. The averaged values of ITPC over the Frontal region (0.098 ± 0.006) in low stress condition was significantly higher than high stress condition (0.087 ± 0.006). No significant difference was observed comparing low and medium stress condition (0.094 ± 0.006) in the Frontal lobe. However, comparing medium and high stress conditions, a significant decrease was found. The averaged ITPC values over the central region in low stress condition was 0.096 ± 0.006, which, compared to the ITPC in high stress condition 0.087 ± 0.005, which showed a significant decrease. No significant difference was found in the comparison of ITPC values over the central region between low and medium stress (0.092 ± 0.006) condition. In the parietal lobe, there was also a significant decrease in ITPC from low (0.097 ± 0.005) to high (0.087 ± 0.005) stress condition. ITPC values of parietal lobe in the medium stress condition (0.092 ± 0.006) was not significantly different from the low or high stress conditions. The distribution of ITPC values in different regions is presented in Fig. 4B.

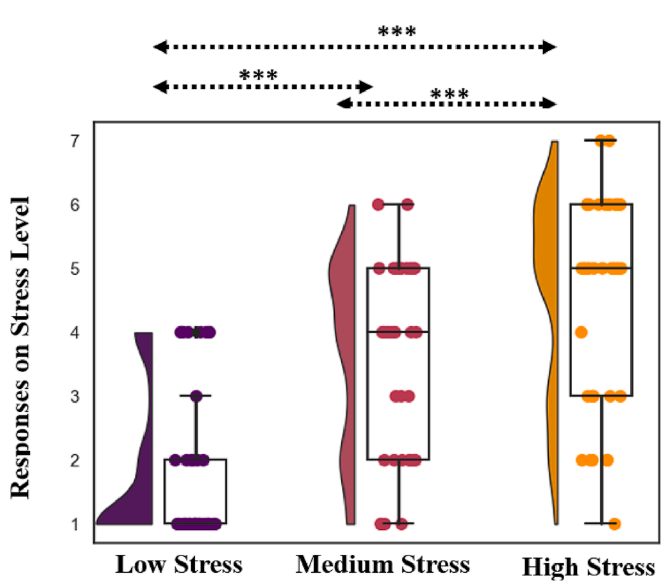

Fig. 3. Survey responses of perceived stress level for three conditions. *** indicates significant difference (p-value < 0.00001).

3.2. Connectivity analysis (PLI)

In Fig. 5, the circle of averaged PLI values between and within the frontal, central, and parietal lobes are represented. A decrease in network synchronization was observed from low to high stress condition. In Table 1, PLI values of inter- and intra- regional pairs for each condition are reported.

In Fig. 6, the p-values resulted from statistical comparison are illustrated. Comparing low and medium stress condition, we found a significant decrease of frontal-central PLI values. A significant decrease was observed in frontal-central, frontal-parietal, and central-parietal PLI values when comparing low and medium stress conditions. In the medium and high stress comparison, the frontal-central PLI values decreased significantly.

3.3. Classification results

The results of the Random Forrest classifier are reported in Fig. 7A. 70 percent of the input features was used for the training split and 30 percent as the test. The predictive model showed a balanced performance among the three classes using a subject-independent scheme. Additionally, the contribution of each input feature to the final decision of the model was computed via Gini criteria and is presented in Fig. 7B. These features were ranked based on Gini importance (reducing node impurity) and even though there is not a huge difference (<10%) it is worthed to show the discriminatory power of each feature.

4. Discussion

This study expands on the current research regarding the effects of mental stress on brain activity, specifically examining how stressors with varying levels of intensity can modulate the phase information of EEG signals. The results of the study indicate that as the level of stress increases, the brain loses its synchronized activity, as measured through the computation of ITPC in the frontal, central, and parietal regions. Additionally, our study found that there was a decrease in the coupled activity of the brain, as measured through the phase lag index (PLI) metric, across the three levels of stress. These results demonstrate the potential of phase-based EEG features as a discriminatory tool for classifying different levels of mental stress. Overall, these findings have important implications for our understanding of the impact of mental stress on brain activity. They suggest that even moderate levels of stress can disrupt the synchronized activity of the brain, leading to decreased coupling between brain regions. Furthermore, the predictive model used in this study highlights the potential utility of EEG signals as a means of objectively measuring stress levels. This study provides important insights into the neural underpinnings of stress and underscores the need for further research in this area. The results of this study could have important implications for the development of interventions and treatments aimed at reducing the negative effects of stress on brain function.

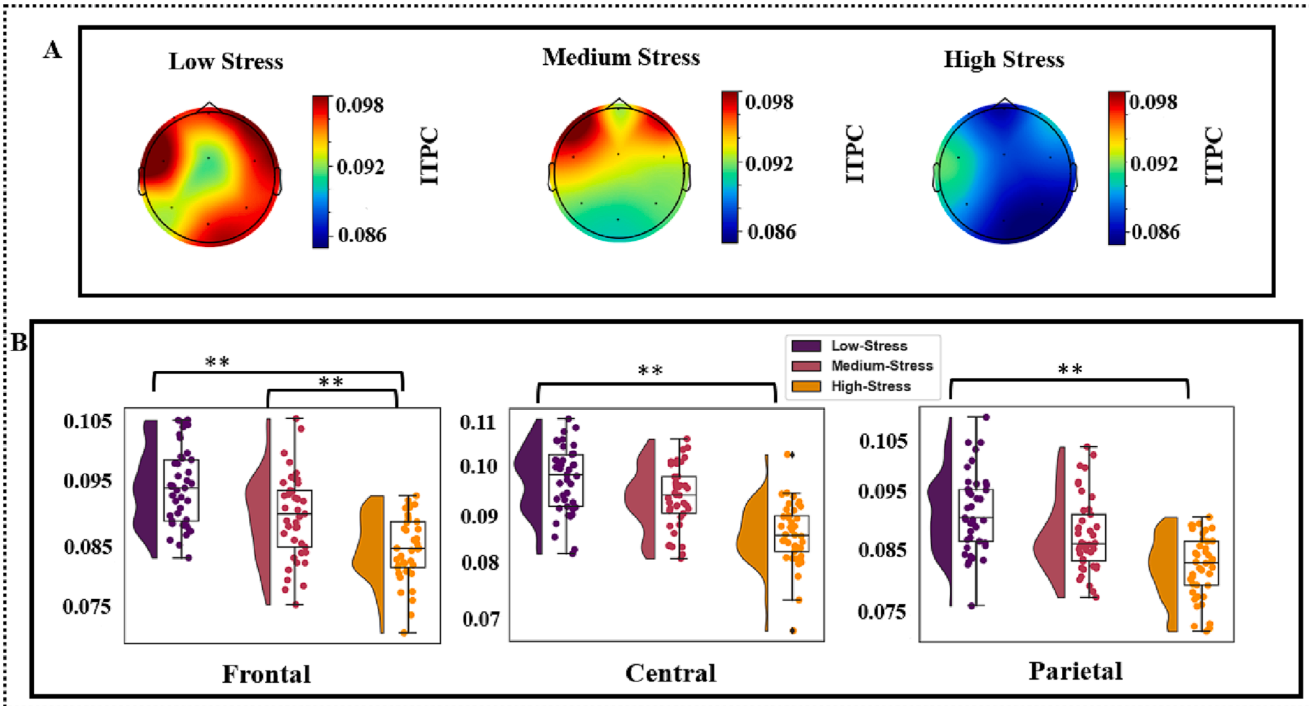

Fig. 4. The distribution of the ITPC values is presented in section A. In section B, the RainCloud plots of the averaged ITPC over each region is depicted. ** indicates significant differences (P-value < 0.0001).

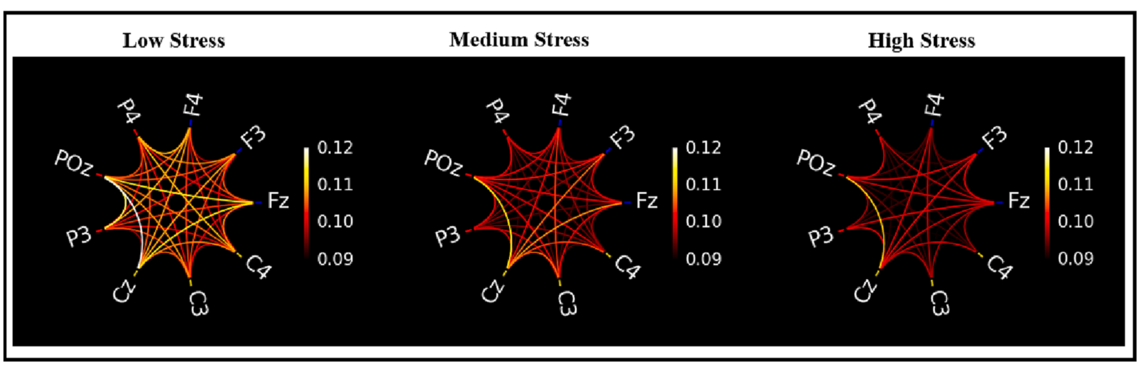

Fig. 5. Connectivity circles of PLI values for the three conditions.

Table 1
PLI values (mean ± std) for inter- and intra-regional of each condition.

Phase-Lag Index Values	*Frontal-Frontal*	*Central-Central*	*Parietal-Parietal*	*Frontal-Central*	*Frontal-Parietal*	*Central-Parietal*
Low Stress	0.397 ± 0.009	0.399 ± 0.009	0.399 ± 0.010	0.100 ± 0.011	0.099 ± 0.011	0.099 ± 0.012
Medium Stress	0.396 ± 0.011	0.398 ± 0.012	0.396 ± 0.010	0.094 ± 0.016	0.093 ± 0.012	0.094 ± 0.012
High Stress	0.393 ± 0.013	0.393 ± 0.015	0.393 ± 0.012	0.088 ± 0.018	0.088 ± 0.013	0.088 ± 0.014

4.1. A decrease in brain synchronised activity associated with mental stress.

Considering the frontal lobe, we found a significant decrease in ITPC values when comparing low to high, and medium to high stress conditions. However, for the central and parietal lobes, this decrease only occurred significantly from low to high stress conditions. Even though the extreme level of stress will modulate ITPC in all regions, this modulation on ITPC could not be observed in moderate levels of stress. ITPC provides information in time and frequency, which in that sense, has advantages over time-only or frequency-only features. Despite numerous studies demonstrating the functional significance of ITPC in various cognitive processes [61], research on mental stress has until now not included ITPC as an analytical approach. ITPC is believed to indicate the coordination and synchronization of neural activity among distinct brain regions involved in a specific task [62,63]. The study by [46], provides a comprehensive overview of the impact of ITPC modulation in information processing, attention deficiency, and behavioral performance. Given that mental stress can negatively impact our ability to maintain attention or process information, while also disrupting brain-

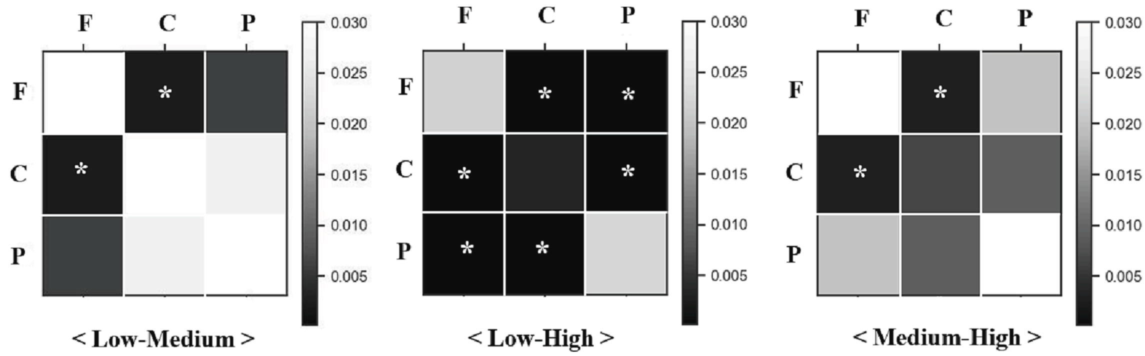

Fig. 6. P-value representation for the PLI comparison. Each cell shows the P-value resulted from the statistical comparison of PLI of the two connections between the two given stress condition.

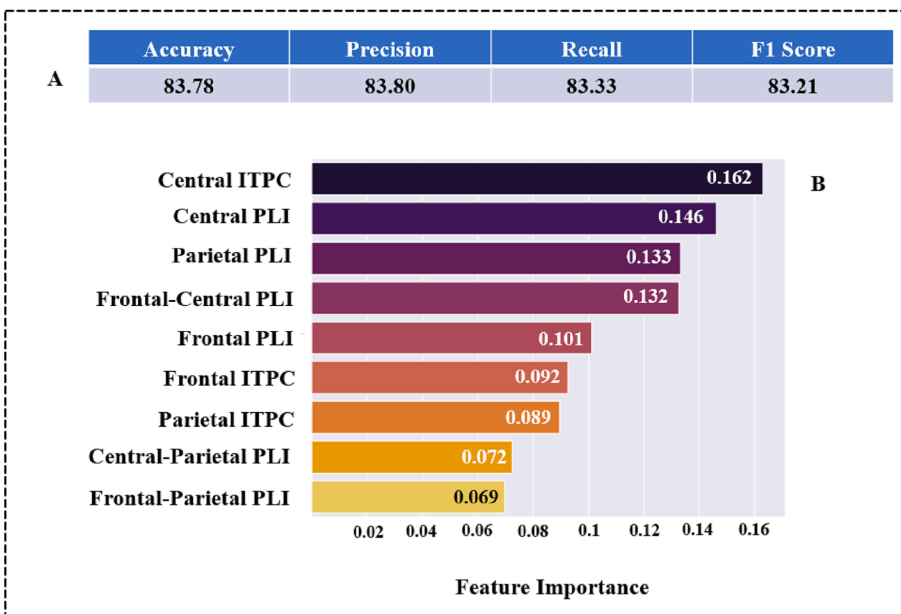

Fig. 7. In section A four diffeent metrics of the predictive mdoel is represented. All of the input features were ranked based on their relative contibituon to the final deicson of the classifer (section B).

wide network functions in creativity, empathy, and other important mental functions, ITPC could be utilized as a potential marker to detect mental stress.

4.2. Mental stress will affect between-region connectivity through phase information.

The results indicate a significant reduction in the between-region PLI values from low to high stress conditions for all pairs, while no significant changes occurred for within-region sites. Notably, a significant decrease was observed in the PLI values for the frontal-central connection between low and medium, and medium and high stress conditions, highlighting the critical role of frontocentral inter-dependency in detecting mental stress. Moreover, it is worth mentioning that none of the within-region connections showed a significant change in PLI values in any of the comparisons, emphasizing the significance of long-range synchronization affected by mental stress.

Upon reviewing the literature, only a handful of studies have explored the use of connectivity measurements for detecting mental stress [49,64,65]. For example, [49] reported a decrease in alpha connectivity (coherency) in anterior regions for only one of their stressors (sleep deprivation) compared to rest conditions. In [65] an increase and decrease of coherency under mental stress conditions have been reported over frontal, temporal, and parietal lobes, and further used phase differences of EEG signals to show a decrease in connectivity over frontoparietal and centroparietal sites. In [64] a decrease in phase locking value (PLV) over the frontal region in alpha band has been reported under mental stress conditions.

There are inconsistent findings in the literature regarding the effect of mental stress on connectivity measurements. A recent study by [66] suggests that the volume conduction might be a contributing factor to this issue. The common source problem can lead to spurious connectivity and false positive results, particularly in spectral coherency measurements. Despite recent attempts in addressing this challenge [29], further considerations are still needed regarding the volume conduction effect. The advantage of using phase-based connectivity such as PLI is to reduce the volume conduction effect by ignoring the phase difference in 0, and π which is probably produced by common sources [51].

Another potential issue that should be considered is the multiple comparison effect on the statistical results. Most of the previous studies have used multiple features, multiple frequency bands, and a channel-wise statistical comparison to show their significant results, however, it is unclear whether this significance was affected by multiple-comparison. In contrast, we have reported a significant decrease of phase-based connectivity, at the regional level, in the alpha frequency band under mental stress conditions which addresses both the common source problem and multiple comparison effect.

4.3. ITPC and PLI features showed their discriminatory power to predict mental stress.

The Random Forrest classifier exhibited a reasonably balanced performance in predicting three different mental stress conditions, achieving an accuracy of 83.78%. The Precision, Recall, and F1-score of the classifier suggest that the predictive model has a satisfactory level of sensitivity and specificity. Our model's performance was compared to a recently published study [67] that investigated the brain–heart interaction using the same dataset which achieved an accuracy rate of 77%. Therefore, our model outperformed the previous studies, suggesting the superiority of EEG phase information over brain–heart communication in detecting mental stress.

To examine the contribution of each input feature to the final decision of the model, we analysed the importance of each feature using Gini impurity. We observed that the phase information in the central region had the greatest impact on the model's decision. However, the difference between the features with the highest and lowest importance was<10%, indicating that each feature had a substantial contribution to the final decision of the model.

5. Conclusion

This study demonstrated that mental stress of varying intensity has an impact on the phase information of EEG signals. The findings of the present study confirmed that mental stress can lead to a decrease in neural coordination, as evidenced by a reduction in intertrial phase clustering in multiple regions. Furthermore, the study found a decrease in functional connections between multiple lobes as a result of mental stress. Despite acknowledging that PLI values are less affected by volume conduction, leading to a reduced occurrence of false positives, it is important to emphasize that this advantage is accompanied by the drawback of neglecting actual functional connection, thus increasing the likelihood of false negatives. To address this issue, a multimodal approach integrating EEG with fNIRs or fMRI could be employed as a potential solution. The predictive model used in the study showed promising results in detecting varying levels of mental stress using phase-based information of brain activity. Nonetheless, it should bear in mind that the performance of the model depends on the quality of the EEG data, signifying the importance of meticulous attention to preprocessing procedure. Even though the limited number of EEG channels in this study may not allow us to generalize the interpretation, this study still provides important insights into the neural underpinnings of stress and underscores the need for further research in this area. The results of this study could have important implications for the development of interventions and treatments aimed at reducing the negative effects of stress on brain function. These results suggest that phase-based EEG features could be a new neurometric for measuring stress levels. However, future research should be cautious about the implication of these findings, since there are numerous variables that impact the findings, such as type of stressors, demographic information of participants, and data cleaning methods.

CRediT authorship contribution statement

Farzad Saffari: Project administration, Visualization, Writing – review & editing, Writing – original draft, Resources, Investigation, Validation, Software, Formal analysis, Methodology, Conceptualization. **Kian Norouzi:** Project administration, Writing – review & editing, Data curation, Conceptualization. **Luis E. Bruni:** Funding acquisition, Supervision, Writing – review & editing. **Sahar Zarei:** Writing – review & editing, Writing – original draft. **Thomas Z. Ramsøy:** Funding acquisition, Supervision, Writing – review & editing, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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