Investigating Frontal Neurovascular Coupling in Response to Workplace Design-Related Stress

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ABSTRACT This research seeks to examine the impact of workstation types on the coupling of neural and vascular activities of the prefrontal cortex (PFC). The design of the workstations was found to impair the performance, physical and mental health of employees. However, the mechanism underlying cognitive activity involved during workstation design-related stress effects in the PFC has not been fully understood. We used electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) to simultaneously measure electrical activity and hemoglobin concentration changes in the PFC. The multimodal signal was collected from 23 healthy adult volunteers who completed the Montreal imaging stress task in ergonomic and non-ergonomic workstations. A supervised machine learning method based on temporally embedded canonical correlation analysis (tCCA) was utilized to obtain the association between neural activity and local changes in hemoglobin concentrations to enhance localization and accuracy. The results showed deactivation in alpha power rhythms and oxygenated hemoglobin, as well as declined activation pattern of the fused data in the right PFC at the non-ergonomic workstation. Additionally, all participants at the non-ergonomic workstation experienced a substantial rise in salivary alpha-amylase activity in comparison with the ergonomic workstation, indicating the existence of high-stress levels. The proposed tCCA approach obtains excellent results in discriminating workstation types achieving accuracies of 98.8% and a significant improvement of 8.0% \((p < 0.0001)\) and 9.4% \((p < 0.0001)\) over EEG-only and fNIRS-only, respectively. Our study suggests the use of functional neuroimaging in designing the workplace as it provides critical information on the causes of workplace-related stress.

INDEX TERMS Electroencephalography (EEG), ergonomic, functional near-infrared spectroscopy (fNIRS), oxygenated hemoglobin, prefrontal cortex (PFC).

I. INTRODUCTION

Stress has progressively become a part of daily life and is one of the health and safety issues at work. It could affect the well-being of workers and contribute to health problems; it has been documented as the second most common workplace health issue in Europe [1], and more than half of all job absences are due to stress effects [2]. The consequences of stress, such as presenteeism, absenteeism, and staff turnover, lead to productivity loss and increase the cost burden of enterprises [3]. Consequently, it is necessary to determine the causes of stress in the workplace (for example, psychological and physical stressors) to eliminate the levels of stress as much as possible. This study highlights the workplace environment and psychosocial stressors, and their interactions and effects on the severity of mental stress. Evidence has emerged that uncomfortable working conditions could affect workers’ comfort and increase their stress symptoms [4]–[6], resulting in disorders related to hypothalamic-pituitary-adrenal (HPA) axis activation, such as cardiovascular and hypertensive diseases [7]–[9].

The use of functional neuroimaging has contributed to a better understanding of the neural correlates of stress and other mental states. Recent studies have revealed...
that combining electrophysiology and hemodynamics could further improve our understanding of cognitive function [6], [10], [11] and enhance medical diagnostics [12]. The localized neural activity is followed by dynamic and complex biological functions, such as the generation of electrical activity and synchronized metabolic variation [13]. The underlying relation between neural activity and hemodynamic fluctuations resulting from the metabolic responses is commonly referred to as the neurovascular coupling (NVC) phenomenon [14], [15]. Given that neurons do not possess internal reserves of energy in the shape of glucose and oxygen, their firing results in a need for oxygenated blood supply. Over-compensatory oxygenated blood is supplied through vasodilatory processes to the activated brain regions, causing an increase in local oxygenated hemoglobin and a decrease in deoxygenated hemoglobin.

Neuroimaging modalities can be categorized into two groups: one measures the electrophysiological response of the brain, and the second measures the hemodynamic changes related to neural activity [16]. The former group includes electroencephalography (EEG), magnetoencephalography (MEG), and transcranial magnetic stimulation (TMS), and the latter group comprises functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), positron emission tomography (PET), and single-photon emission computed tomography (SPET). Each of these modalities measures various aspects of neural correlates, but no individual method is best suited for mapping the underlying neural activity linked to brain function. However, the combined EEG and fNIRS are increasingly gaining attention in this contest.

Both techniques, EEG and fNIRS, are complementary in nature. EEG is a psychophysiological technique that assesses the electrical activity of the brain with high temporal resolution via measuring scalp voltages caused by a synchronized activation of cortical neurons. EEG devices are designed to monitor brain function and to diagnose disorders in clinical and research settings [17], [18]. fNIRS is a hemodynamic-based neuroimaging tool used to assess the functional activity of the brain. It offers small size, good temporal and spatial resolution, portability, is less prone to motion artifacts, is relatively inexpensive, and allows for natural recording conditions [19], [20].

To date, little research explored the influence of workstation design on the NVC and executive function of the brain. Further, the underlying mechanism in the prefrontal cortex (PFC) during workplace design-related stress has not been fully characterized. The evidence showed that NVC is affected by traumatic brain injury [21], mental states [22], and aging [23], [24]. However, multimodal coupling reflects an ongoing research endeavor that still needs plenty of work. According to the literature, there are a growing number of studies that have used canonical correlation analysis (CCA) in multivariate analysis [25]. The CCA is one of the effective multivariate methods for investigating jointly relationships among multiple data sets. Recent studies have used CCA to uncover and quantify the environmental effects in the EEG and fNIRS modalities concurrently and characterize brain changes during stress, aging, and other cognitive impairments [25]–[27]. Despite the non-instantaneous coupling between EEG and fNIRS modalities, temporally embedded CCA (tCCA) [28] offers instantaneous electrovascular coupling, which might help to increase the detection rate of workstation types and to a better understanding of the mechanisms of neurovascular coupling.

This work aims to find the relationship between the bandwidth of EEG with the dynamics of the fNIRS in response to induced stress of workstation types. We propose a supervised machine learning method based on multimodal source power co-modulation [29], [30] to extract stress-related sources from both modalities to estimate the coupled electrophysiological and hemodynamic signals. In addition, using the proposed method, we obtain multimodal fused feature vectors based on the conventional and temporally embedded CCA (mCCA and mC\textsubscript{CCA}, respectively) [28], [31] for classifying the workstation types. Salivary alpha-amylase (sAA) is employed in this study to measure the participants’ stress level since it has gained rapid popularity as a non-invasive biomarker for the sympathetic nervous system (SNS) activity [32]–[34].

II. MATERIALS AND METHODS

A. SUBJECTS

Twenty-three healthy adult volunteers with no history of psychological illness, musculoskeletal problems, or substance dependence took part in this study (mean age 28.6 ± 3.4 years, males, right-handed, mean height 1.7 ± 0.038 m, BMI > 18 and < 25). The research was approved by the Medical Research Ethics Committee (MREC) of Universiti Kuala Lumpur Royal College of Medicine Perak (UniKL RCMP). All procedures were conducted following the approved regulations and guidelines. All subjects signed informed consent under the MREC approval stipulations.

B. STUDY DESIGN

The experiment was developed to examine the impact of the environmental (workstation type) and psychosocial (including mental workload and time constraints) stressors on mental stress severity. Two types of workstations, ergonomic (SE) and non-ergonomic (SNE), were investigated in this study (Fig. 1(c)). The SE workstation was established based on a well-designed ergonomic chair with an effective position as suggested by [35], [36], whereas the SNE was designed with an ineffective working position and a non-ergonomic chair. Besides, the Montreal Imaging Stress Task (MIST), in the form of a stressful mental arithmetic task (MAT) with social-evaluative threats and time constraints, has been used to induce psychosocial stress [37]. The MAT comprised of three random integers between 0 and 99 and random operators such as subtraction ‘−’ or addition ‘+’ (example: 37 - 54 + 21). Before the experiment, all respondents had a practice
session that included a series of computer-operated MATs without social-evaluation threats or time restraints, even though participants were commanded to answer the questions as correctly and as fast as possible. To further increase the stress levels of participants, 90% of the estimated average time was used as a time limit, and 85% of their average actual performance was displayed on the screen. The timeline of the experiment and workstation types are illustrated in Fig. 1.

As part of the protocol timeline, participants were first given a brief introduction about the experiment, before signing the informed consent, to enable them to become habituated to the environment. Subsequently, a combined EEG-fNIRS probe was put on the participants to start recording vascular and electrophysiological signals. A sequence of 20 s of baseline or rest followed by 30 s of MAT condition continued for 10 trials, as illustrated in Fig. 1(a). During baseline and rest conditions, participants were asked to sit quietly while looking at a fixation cross displayed on the screen. The total recording time was 17 minutes, with two separate sessions of 8.5 minutes for each experiment and a gap of about one hour between them. The sAA activity was determined with a COCORO meter (Nipro Co., Osaka, Japan) [38], [39] before and immediately after each experiment.

C. EEG-fNIRS PROBE ARRANGEMENT

Our multi-modal recording system consists of 17 EEG electrodes and 37 fNIRS channels (Fig. 2). The source-detector distance was fixed at 3 cm, which could provide a good signal quality as stated in the literature [40]. A flexible material was designed as a base to hold the optode sockets and EEG electrodes to obtain good contact with the scalp and provide a comfortable fit for the subject. The EEG electrodes were placed in the fNIRS channel locations to attain the same channel configuration. Seventeen gold cup EEG leads, 12 detectors, and 12 dual-wavelength LED emitters were arranged. For added stability, the EEG electrodes were assembled on a BrainMaster Discovery (BrainMaster Technologies Inc., Bedford, USA) while fNIRS optodes were mounted on an OT-R40 system (Hitachi Medical Corporation, Japan). Brain activity was recorded over the PFC with a combined EEG-fNIRS probe according to the 10/10 system (Fpz, Fp1, Fp2, AF7, AF8, F7, F8, AFz, AF3, AF4, F5, F6, Fz, F1, F2, F3, and F4). The EEG ground and reference electrodes were placed, respectively, at Fz and earlobes.

D. DATA ACQUISITION

The EEG-fNIRS data were simultaneously acquired with our customized probe at a sample rate of 256 Hz and 10 Hz for EEG and fNIRS measurements, respectively. The fNIRS system uses dual-wavelength at about 695 and 830 nm. The
fNIRS system control software was used to test calibration and check the strength of the signal before each recording. The EEG electrode impedances were kept below 10 kΩ. For EEG and fNIRS synchronization, event trigger signals were simultaneously sent to both devices using a splitter cable through parallel and serial ports accessed by MATLAB.

E. DATA PREPROCESSING

The data from the EEG and fNIRS were analyzed and filtered separately to achieve the desired output signals. The signals were initially passband filtered with a fifth-order Butterworth from 0.5 Hz to 70 Hz for EEG data and from 0.02 to 0.5 Hz for fNIRS data. Noting that, cortical contributions to the scalp EEG are small to negligible in the gamma frequency and beyond [41].

The EEG data was then notch filtered at 50 Hz to suppress powerline interference. Independent Component Analysis (ICA) was used to remove any ocular artifacts on the EEG signals, and the obtained signals were then filtered into the delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) bands. The oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) concentrations from the fNIRS signals were determined by the modified Beer-Lambert law [42]. The low-pass cut-off of the fNIRS filter was applied at 0.5 Hz to remove heartbeat effects while obtaining the underlying hemodynamics activity. The data from EEG and fNIRS were divided into epochs starting 20 s before the MAT task and ended 30 s after.

F. MULTIMODAL DATA ANALYSIS

The correlation between the neural activity and the NVC was studied through the multimodal co-modulation [29], [30] based on tCCA (mCtCCA). This technique finds the components which offer maximal functional coupling between EEG band-power modulations ($\hat{S}_{EEG}$) and the fNIRS hemodynamic response ($\hat{S}_{fNIRS}$) (Fig. 3(c)). The EEG band was filtered based on the frequency range of interest selected from the primary results, and then epoched to match the fNIRS data samples (Fig. 3(b)). In other words, the fNIRS data samples were equal to the EEG data epochs as the extracted source modulations of fNIRS are related to the power modulations of the EEG source. The EEG data were down-sampled to 200 Hz, while the fNIRS data down-sampled to 4 Hz. Additionally, a spatio-spectral decomposition (SSD)-based dimensionality reduction was performed to increase the SNR on the chosen band [43]. The extracted source components of EEG and fNIRS are given by:

$$\begin{align*}
(w^{EEG})^\top X^{EEG}(t) & = \hat{S}_{EEG}(t) \\
(w^{fNIRS})^\top Y^{fNIRS}(t) & = \hat{S}_{fNIRS}(t)
\end{align*}$$

where $w^{EEG}$ and $w^{fNIRS}$ donate the spatial filters for EEG and fNIRS, respectively. The epoch-wise power of EEG sources is defined by the variance computed over the epoch $(e)$, and equal to:

$$\hat{p}_{EEG}(e) = \text{Var} \left[ \hat{S}_{EEG}(t) \right](e) = (w^{EEG})^\top C^{EEG}(e) w^{EEG}$$

where $C^{EEG}(e)$ represents the EEG covariance matrix in the epoch $(e)$. Next, the temporal filter $(w^{T})$ is used to model the time-delayed coupling between EEG and fNIRS using a finite impulse response (FIR) filter [28]. The FIR-filtered power time-series are therefore computed by:

$$\hat{h}(\hat{p}_{EEG})(e) = \sum_{m=0}^{M} w^{T} \hat{p}_{EEG}(e - m)$$

By substituting Eq. (3) into Eq. (4), we get:

$$\hat{h}(\hat{p}_{EEG}) = \sum_{m=0}^{M} w^{T} (w^{EEG})^\top C^{EEG}(e - m) w^{EEG}$$

where $w^{T}$ represents the element $m$th of the vector $w^{m} = (w^{T}_{1}, w^{T}_{2}, \ldots, w^{T}_{M-1})^\top$, $m$ is a set of relevant pre-selected time-lags, and $M$ is the total number of time-lags to be considered. Further alternative expressions can be obtained for Eq. (5) to simplify the optimization problem.

$$\begin{align*}
\hat{h}(\hat{p}_{EEG})(e) & = (w^{EEG})^\top \sum_{m=0}^{M} \left( w^{T} C^{EEG}(e - m) w^{EEG} \right) \\
& = \text{h}(C^{EEG}(e))
\end{align*}$$

The functional coupling between two modalities with different temporal resolutions:

$$\text{max}_{w^{EEG},w^{fNIRS},w^{T}} \text{Cov} \left( \hat{h}(\hat{p}_{EEG}), \hat{S}_{fNIRS} \right)$$

Subject to the following normalization constraints:

$$\begin{align*}
(w^{EEG})^\top C^{EEG} w^{EEG} & = (w^{fNIRS})^\top C^{fNIRS} w^{fNIRS} \\
& = (w^{T})^\top C^{\hat{p}_{EEG}} w^{T} = 1
\end{align*}$$

The Lagrange multipliers method is used to incorporate the constraints into the Lagrange function $L$.

$$L \left( w^{EEG}, w^{fNIRS}, w^{T} \right)$$

$$\begin{align*}
= \hat{h}(\hat{p}_{EEG}) \hat{S}_{fNIRS} - \alpha \left( (w^{EEG})^\top C^{EEG} w^{EEG} - 1 \right) \\
- \beta \left( (w^{fNIRS})^\top C^{fNIRS} w^{fNIRS} - 1 \right) \\
- \gamma \left( (w^{T})^\top C^{\hat{p}_{EEG}} w^{T} - 1 \right)
\end{align*}$$
where $\alpha$, $\beta$, and $\gamma$ are unknown Lagrange variables. Then we calculate the partial derivatives of $L$ with respect to $w^{EEG}$, $w^{NIRS}$, and $w^\tau$.

$$h \left( C^{EEG} \right) \left( w^{EEG} \right) \left( w^{NIRS} \right)^T Y^{\text{NIRS}} (e) = \alpha \left( C^{EEG} w^{EEG} \right)$$  \hspace{1cm} (10)

and,

$$\hat{h} \left( \hat{p}_{\text{EEG}} \right) \left( w^{NIRS} \right)^T Y^{\text{NIRS}} (e) = 2\beta \left( C^{\text{NIRS} \times w^{NIRS}} \right)$$  \hspace{1cm} (11)

and,

$$P_{\text{SEEG}} (e) \left( w^{NIRS} \right)^T Y^{\text{NIRS}} (e) = 2\gamma \left( C^{\hat{p}_{\text{SEEG}} \times w^\tau} \right)$$  \hspace{1cm} (12)

since $w^{EEG}$ is dependent on $w^{NIRS}$ and $w^\tau$, we initially compute these weighted vectors. By multiplying $(w^{NIRS})^T$ and $(w^\tau)^T$ into Eq. (10), Eq. (11), and Eq. (12), respectively, we obtain:

$$h \left( C^{EEG} \right) \left( w^{NIRS} \right)^T \left( w^{NIRS} \right) Y^{\text{NIRS}} (e) = 2\beta \left( C^{\text{NIRS} \times w^{NIRS}} \right)$$  \hspace{1cm} (13)

and

$$P_{\text{SEEG}} (e) \left( w^{NIRS} \right)^T Y^{\text{NIRS}} (e) = 2\gamma \left( C^{\hat{p}_{\text{SEEG}} \times w^\tau} \right)$$  \hspace{1cm} (14)

since $(w^{NIRS})^T C^{\text{NIRS} \times w^{NIRS}} = 1$, $(w^\tau)^T C^{\hat{p}_{\text{SEEG}} \times w^\tau} = 1$.

$$h \left( \hat{p}_{\text{SEEG}} \right) \left( e \right) Y^{\text{NIRS}} (e) = 2\beta \left( C^{\text{NIRS} \times w^{NIRS}} \right)$$  \hspace{1cm} (15)

$$P_{\text{SEEG}} (e) \left( w^{NIRS} \right)^T Y^{\text{NIRS}} (e) = 2\gamma \left( C^{\hat{p}_{\text{SEEG}} \times w^\tau} \right)$$  \hspace{1cm} (16)

It is seen that $\lambda = 2\beta = 2\gamma$. Substituting $\lambda$ into Eq. (11) and (12), we can get the following:

$$h \left( \hat{p}_{\text{SEEG}} \right) \left( e \right) Y^{\text{NIRS}} (e) = \lambda \left( C^{\text{NIRS} \times w^{NIRS}} \right)$$  \hspace{1cm} (17)

$$P_{\text{SEEG}} (e) \left( w^{NIRS} \right)^T Y^{\text{NIRS}} (e) = \lambda \left( C^{\hat{p}_{\text{SEEG}} \times w^\tau} \right)$$  \hspace{1cm} (18)

since $h \left( \hat{p}_{\text{SEEG}} \right) \left( e \right) = (w^\tau)^T P_{\text{SEEG}} (e)$, we rewrite Eq. (17) as

$$P_{\text{SEEG}} (e) \left( w^{NIRS} \right)^T Y^{\text{NIRS}} (e) = \lambda \left( C^{\text{NIRS} \times w^{NIRS}} \right)$$  \hspace{1cm} (19)

Hence, Eq. (18) and Eq. (19) can be transformed into the following generalized eigenvalue problem:

$$\left[ \begin{array}{cc} 0 & C^{\text{SEEG} \times \text{NIRS}} \\ C^{\text{NIRS} \times \text{SEEG}} & 0 \end{array} \right] \left[ \begin{array}{c} w^\tau \\ w^{NIRS} \end{array} \right] = \lambda \left[ \begin{array}{c} C^{\hat{p}_{\text{SEEG}} \times w^\tau} \\ 0 \end{array} \right] \left[ \begin{array}{c} w^\tau \\ w^{NIRS} \end{array} \right]$$  \hspace{1cm} (20)
Besides, we further add a regularization term [44] to the covariance matrices on the right-hand side of Eq. (20) to avoid overfitting issues, which may occur due to the complexity of the solution. With the case of regularization, the solution obtained by Eq. (20) becomes:

\[
\begin{bmatrix}
0 & C^{\text{EEG}, \text{fNIRS}} \\
C^{\text{fNIRS}, \text{EEG}} & 0
\end{bmatrix}
\begin{bmatrix}
w^{\text{EEG}} \\
w^{\text{fNIRS}}
\end{bmatrix}
= \lambda
\begin{bmatrix}
C^{\text{EEG}} + I\kappa^{\text{EEG}} & 0 \\
0 & C^{\text{fNIRS}} + I\kappa^{\text{fNIRS}}
\end{bmatrix}
\begin{bmatrix}
w^{\text{EEG}} \\
w^{\text{fNIRS}}
\end{bmatrix}
\]

(21)

where \(\kappa^{\text{EEG}}\) and \(\kappa^{\text{fNIRS}}\) are the regularizers for EEG and fNIRS modality, respectively. The output of Eq. (21) consists of \(w^{\text{EEG}}\) and \(w^{\text{fNIRS}}\) vectors which can be used to compute the \(h(C^{\text{EEG}})(e)\) and \(S^{\text{fNIRS}}\). Moreover, to compute \(w^{\text{EEG}}\), we apply a generalized eigenvalue problem to Eq. (10) with \(\lambda = \alpha\).

\[
(h(C^{\text{EEG}})(e)w^{\text{fNIRS}})^{\top}y^{\text{fNIRS}}(e)w^{\text{EEG}} = \lambda(C^{\text{EEG}, \text{fNIRS}})
\]

(22)

G. STATISTICAL SIGNIFICANCE

Data statistical analysis was performed (\(p < 0.05\) indicates the significance level) using the Statistical Package for Social Sciences (SPSS), together with MATLAB. The effect of the workstation types on EEG bands and fNIRS chromophores were examined using a two-factor analysis of variance (ANOVA) with Bonferroni post hoc. The factors were divided into two ‘groups’ (SE and SNE workstation groups) and four features (delta, theta, alpha, and beta) for EEG and two features (HbO and HbR) for fNIRS. For the results of mCtCCA analysis, a two-sample t-test was used to investigate the differences between the activation pattern of fused data for the two groups.

H. MULTIMODAL DATA CLASSIFICATION

In addition to studying the activation patterns of estimated EEG components coupled with their corresponding fNIRS components, we further evaluated the feature sets from both modalities and their fusion based on mCtCCA and mCtCCA approaches. The EEG-only feature set included ten subsets obtained from the 16 channels, where one subset belonged to the frequency domain and the rest to the time domain. The one from the frequency domain was: mean power spectral density and the ones from the time domain were: mean, peak, maximum, minimum, skewness, variance, kurtosis, Shannon entropy, and log energy entropy. On the other hand, the fNIRS-only feature set included nine HbO-based subsets (such as mean, peak, maximum, minimum, skewness, variance, kurtosis, Shannon entropy, and log energy entropy) acquired from the 37 channels. To this end, a sliding window of 0.5 ms was used to extract the corresponding feature values. All features from EEG-only, fNIRS-only, and the fusion ones were then normalized by the z-score. The MATLAB function “sequentialfs” was applied in this study to determine the best subsets for EEG-only and fNIRS-only classification.

A support vector machine (SVM) was used to classify the workstation types for each subject. The objective of SVM is to create a hyperplane that optimizes the margins between the classes [45]. The SVM with radial basis function (RBF) kernel has been shown to model both linear and more complex decision boundaries [26], [46], [47]. It was performed using the fitcsvm and predict functions in MATLAB. In this study, a 5-fold cross-validation method was employed to avoid the issue of overfitting. Each dataset was segmented randomly into five similarly sized subsets. Four of the subsets were used as a training set, and the remaining one was used as a testing set.

The optimal penalty parameter (C) and kernel parameters (\(\gamma\)) were determined to obtain maximum accuracy for the fold. The classification accuracy, sensitivity, and specificity for each subject were evaluated separately using the four types of feature sets for comparison; EEG-only feature set, fNIRS-only feature set, mCtCCA-based fusion feature set, and mCtCCA-based fusion feature set.

III. RESULTS

The use of functional neuroimaging has led to a deeper understanding of the neural correlates of stress and other mental disorders. Previous findings have shown that integrating electrophysiology and hemodynamics could increase our understanding of NVC [48], [49] and improve diagnostics [12]. Nevertheless, the essential mechanism behind the electro-vascular coupling associated with stress-related workstation type has not been fully characterized. The current study examines neural activity (EEG), vascular changes (fNIRS), and their coupling in the SE and SNE groups. Besides, we further evaluated the feature sets from both modalities and their fusion/coupling set. The neural and cerebral activities in this study were concurrently collected over the frontal region. The findings of this study highlighted: (1) the effect of the workstation type on sAA level; (2) the effect of stress-related workstation type on EEG frequency bands and fNIRS chromophores; (3) the associations between EEG and fNIRS modalities to enhance localization and precision; (4) whether the coupled EEG and fNIRS feature set can improve classification performance compared to singular EEG and fNIRS.

A. sAA DATA ANALYSIS

Measurements of sAA were collected before the experiment as a baseline and promptly after the experiment. The findings, shown in Fig. 4, indicate a substantial increase in sAA levels in subjects under stress conditions in both workstations, SE (\(t(1,22) = 15.6, p < 0.001\)) and SNE (\(t(1,22) = 13.8, p < 0.001\)), relative to their baselines. Higher stress levels, as shown by sAA activity, were observed in the SNE workstation group (\(t(1,22) = 6.5, p < 0.001\)), as compared with subjects who used the SE workstation, while no substantial difference was reported between their baseline conditions (\(t(1,22) = 0.3, p = 0.4\)).
Subsequently, the post-hoc tests showed that there was a statistically significant reduction in the alpha power, high cortical activation, of the SNE users (mean (M) = −1.522, standard deviation (SD) = 1.738) in comparison with the SE users (M = −0.152, SD = 0.783). This significant reduction in the power of the SNE users was also observed in the theta rhythm (M = −1.477, SD = 1.959) and the beta rhythm (M = −1.516, SD = 1.726) in comparison with the theta (M = −0.206, SD = 0.921) and beta (M = −0.146, SD = 1.043) powers of the SE users. However, there was also a reduction in the delta power of the SNE users, but not significant compared to the SE users. Among all EEG frequency bands, alpha was the most influenced by the variation in workstation types and selected for further analysis.

Furthermore, we see in Fig. 5(b) a large difference in alpha power between the SE and SNE groups, especially in the right PFC. The topographic map of F-values (ANOVA) for each channel is depicted in Fig. 5(c), representing the main effects of the workstation type on the power of the alpha band. Compared to the SE users, a significant reduction in alpha power was observed in the right dorsolateral prefrontal cortex (DLPFC), right ventrolateral prefrontal cortex (VLPFC), and right orbitofrontal cortex (OFC) of the SNE users.

### C. fNIRS Analysis

The mean concentration of HbO and HbR for SE and SNE groups is illustrated in Fig. 6(a), and the corresponding statistical results are listed in Table 1. The ANOVA with Bonferroni post-hoc test was performed to examine the main effects of workstation type on the HbO and HbR concentrations. Considering the HbR, the ANOVA demonstrated a remarkable effect of the workstation type (F(1,44) = 4.485, p < 0.05, η² = 0.093), with a significant decrease in HbR values of the SNE group (M = −0.001, SD = 0.004), in comparison with the SE group (M = 0.001, SD = 0.003). Likewise, for the HbO, the ANOVA showed a highly noticeable effects of the workstation type (F(1,44) = 11.507, p < 0.001, η² = 0.207) than the HbR, with a significant decrease in HbO values of the SNE group (M = −0.001, SD = 0.013), in comparison with the SE group (M = 0.014, SD = 0.018). Based on these findings, HbO was selected for further analysis as it was most significantly influenced by the workstation type compared to the HbR.
TABLE 1. Results of two-way ANOVA for EEG bands and fNIRS chromophores at SE and SNE workstations.

| Modality | Feature | SE Mean | SE Std. Deviation | SNE Mean | SNE Std. Deviation | F | Sig. | Partial Eta Squared (η²) |
|----------|---------|---------|------------------|---------|------------------|---|------|------------------------|
| EEG      | Delta   | -0.618  | 1.335            | -1.586  | 1.836            | 4.184 | 0.051 | 0.087                  |
|          | Theta   | -0.206  | 0.921            | -1.477  | 1.959            | 7.936 | 0.007** | 0.153                  |
|          | Alpha   | -0.152  | 0.783            | -1.522  | 1.738            | 11.881 | 0.001*** | 0.213                  |
|          | Beta    | -0.146  | 1.043            | -1.516  | 1.726            | 10.614 | 0.002** | 0.194                  |
| fNIRS    | HbO     | 0.014   | 0.018            | -0.001  | 0.013            | 11.507 | 0.001*** | 0.207                  |
|          | HbR     | 0.001   | 0.003            | -0.001  | 0.004            | 4.485  | 0.040* | 0.093                  |

Note: two-way ANOVA with Bonferroni post hoc analysis: *p < 0.05, **p < 0.01, and ***p < 0.001.

FIGURE 7. Correlations between alpha and HbO in the SE (grey) and SNE (orange) groups resulted from mCtCCA. The error bars represent the standard error (SE).

In addition, a large difference in HbO values was observed between the SE and SNE groups in the right PFC and parts of the left PFC (Fig. 6(b)). The F-value topographic map of ANOVA values for each channel is shown in Fig. 6(c), which represents the main effects of the workstation type on the HbO. A significant reduction in HbO values was highly observed, in order, in the right VLPFC, left DLPFC, and right DLPFC of the SNE users in comparison with that of the SE users.

D. CORRELATION BETWEEN ALPHA OSCILLATIONS AND HBO RESPONSES

The attempt to integrate multiple neurophysiological signals obtained from EEG and fNIRS is known as multimodal fusion. In this study, we employed the mCtCCA method that finds spatial filters such that their corresponding power dynamics of the alpha signal maximally covary with the time-course of the HbO signal. Fig. 7 shows the mCtCCA - based correlations between the alpha power dynamics and HbO for the SE and SNE groups, as the significant features from EEG and fNIRS, respectively. Eight regions of interest were chosen, including the entire PFC area and seven subregions localized in the right hemisphere (R-DLPFC, R-VLPFC, and R-OFC), middle PFC at the frontal polar area (FPA), and the left hemisphere (L-DLPFC, L-VLPFC, and L-OFC). Based on Table 2, each subregion contains EEG electrodes and fNIRS channels. For example, channels 1, 2, 3, 8, 9, and 10 and electrodes F2 and F4 are corresponding to R-DLPFC subregion.

The obtained signals from electrodes and channels for all ROIs were separately fused to assess the multimodal fusion performance. The results in Fig. 7 reveal a stronger correlation between alpha power and HbO in the both SE (mean ($r_M$) = 0.920, standard error ($r_SE$) = 0.044) and SNE ($r_M$ = 0.896, $r_SE$ = 0.0694) groups, particularly when considering the entire PFC regardless of the ROIs. Therefore, further analysis based on all the channels and electrodes across the PFC was performed in the next section.

E. ELECTRO-VASCULAR COUPLING ANALYSIS INTERHEMISPHERIC ASYMMETRY

The cross-correlation between the alpha power of EEG components with the temporal activation of the corresponding HbO component is shown in Fig. 8. It shows maximal correlation at a time lag of 5 seconds (Fig. 8(a)), which is evident for all subjects from the coupled EEG components with temporal filter and corresponding fNIRS ones with the R-OFC.

TABLE 2. Component pairs of the fNIRS channel and EEG electrodes.

| No | Brain region | Component pair | EEG |
|----|--------------|----------------|-----|
| 1  | Entire PFC   | All channels   | All electrodes |
| 2  | Right DLPFC  | Ch1, Ch2, Ch3, Ch8, Ch9, and Ch10 | F2 and F4 |
| 3  | Left DLPFC   | Ch5, Ch6, Ch7, Ch13, Ch14, and Ch15 | F1 and F3 |
| 4  | Right VLPFC  | Ch16, Ch17, Ch23, Ch24, and Ch31 | F6 and F8 |
| 5  | Left VLPFC   | Ch21, Ch22, Ch29, Ch30, and Ch37 | F5 and F7 |
| 6  | FPA          | Ch11, Ch12, Ch18, Ch19, Ch20, Ch26, and Ch27 | AF4, AFz, and AF3 |
| 7  | Right OFC    | Ch25, Ch32, and Ch33 | Fp2 and AF8 |
| 8  | Left OFC     | Ch28, Ch35, and Ch36 | Fp1 and AF7 |
maximum in the cross-correlation at lag zero (Fig. 8(b)). This reflects the dynamics of coupling between the EEG sources and the fNIRS, allowing a more comprehensive study of neurovascular coupling.

The alpha band power of EEG was fused with the concentration changes of HbO. The activation patterns of estimated EEG components coupling with their corresponding fNIRS components underlying stress effects at SE and SNE workstations are shown in Fig. 9. The SNE group revealed a frontal interhemispheric asymmetry of the coupled EEG alpha pattern, particularly in the right PFC. It showed a deactivation in the right subregions between DLPFC, FPA, and VLPFC in comparison with the SE group. Furthermore, a two-sample t-test was conducted to statistically compare the activation of the coupled EEG alpha pattern between the two workstation groups, as shown in Fig. 9(b). In this regard, a noticeable reduction in the activation pattern was observed in the SNE group ($p < 0.05$) across channels localized in the right DLPFC, right VLPFC, and right FPA.

**F. CLASSIFICATION ACCURACY: EEG, fNIRS, AND THEIR FUSION**

The classification accuracies in the form of a scatter plot for the alpha, HbO, and their fusion based on mCtCCA and mCtCCA are shown in Fig. 10. Green circles above the diagonal line indicate that classification accuracies are increased by the combination of alpha and HbO based on the mCtCCA and mCtCCA approaches in comparison with alpha and HbO alone (Fig. 10(a) and 10(b)). Furthermore, mCtCCA exhibited an increase in classification accuracy when compared with the mCtCCA approach (Fig. 10(c)). More than 91.3%, 95.7%, and 100% of the subjects exhibited improved classification accuracies by the mCtCCA based fusion against mCtCCA, alpha, and HbO, respectively. Furthermore, a statistically significant increase in classification accuracy was revealed between the mCtCCA approach and mCtCCA ($p < 0.001$) and between mCtCCA and alpha or HbO ($p < 0.0001$).

The classification results of the sole alpha signals showed high performance in discriminating workstation type with an average of 90.8% accuracy, 94.0% specificity, and 88.9% sensitivity. Likewise, the classification performance of sole HbO signals indicated 89.4% accuracy, 87.7% specificity, and 91.8% sensitivity. Note that alpha signals achieved a relatively better performance over HbO signals with an improvement of 1.4% in accuracy. Additionally, the combination of the EEG data (alpha) with the fNIRS signal (HbO) offers a performance increase in classification. The result showed that combined information of alpha and HbO outperforms the information of the alpha and HbO alone. The classification performance of the mCtCCA approach achieved 97.0% accuracy, 95.3% specificity, and 96.7% sensitivity, while the mCtCCA approach achieved 98.8% accuracy, 97.6% specificity, and 100.0% sensitivity. In that, higher classification performance was observed with mCtCCA as compared to the mCtCCA approach. For the mCtCCA, the classification performance was significantly improved compared to alpha alone by 6.2% in the accuracy, 1.3% in specificity, and 7.8% in sensitivity, while compared to HbO alone by 7.6% in the accuracy, 7.6% in specificity, and 4.9% in sensitivity. In contrast, mCtCCA showed a significant classification improvement with respect to alpha by 8.0% in the accuracy, 7.6% in specificity, and 4.9% in sensitivity; HbO by 9.4% in the accuracy, 9.9% in specificity, and 8.2% in sensitivity; mCtCCA approach by 1.8% in the accuracy, 2.3% in specificity, and 3.3% in sensitivity.

**IV. DISCUSSION**

Our study aimed to evaluate the precision and localization of stress-related to workstation types on the frontal cortex. To those aims, twenty-three healthy volunteer subjects completed MIST in SE and SNE workstations, while EEG and fNIRS signals were synchronously recorded. The results indicated that working at SE versus SNE workstations provoked different neural and cerebral activities within the PFC cortex. More specifically, these differences were observed with a higher reduction in the alpha power in the right PFC of the SNE group, indicating increased cortical activity in this area (Fig. 5; Table 1), which is responsible for processing negative emotions.

However, the SE group showed an increased alpha power in the right PFC, which may owe to the internal processing...
of the MAT. This implies that stress exposure associated with SNE workstation adversely affects selective attention to the relevant task [50], [51]. Our findings in this study are consistent with prior studies, which found a reduction in alpha power with an increase in stress levels [52], [53]. We suggest that assessing psychological stress on its own without considering the surrounding stressors may not give a clear interpretation of stress pathways.

In addition, substantial differences between the SE and SNE groups in HbO values were observed in comparison with HbR values (Fig. 6; Table 1), which are consistent with the previous studies [6], [54] and indicate that changes in HbO are more apparent under stressful situations. A significant increase in the HbO values was observed in the SE group in comparison with the SNE group, which demonstrated a marked decrease in HbO values in the right PFC (Fig. 6). The right PFC has previously been investigated to be strongly related to psychosocial stress [26], [55] and the findings are consistent with other studies that documented the impact of physical stressor processing on HPA-axis activation and autonomic stress responses [56], [57]. Furthermore, Elbau, et al. [58] observed a rapid impact under psychosocial stress on the peak latency of hemodynamic responses to PFC.

As intended, the MIST showed an improved SNS activity, demonstrated by an increase in sAA levels. Furthermore, the participants showed elevated sAA levels from 55.5 ± 11.5 (kIU/L) at SE workstation to 86.1 ± 14.0 (kIU/L) at SNE workstation, confirming the presence of high-stress levels in the SNE group. Previous studies have reported the significance of sAA as an indicator of stress level [33], [59], [60].

The fused EEG and fNIRS data can be advantageous for understanding brain mechanisms and improving the localization of pathological neuronal networks. The EEG-fNIRS fusion approach here was built on the assumption that homeostasis of the brain microenvironment is preserved by components of the NVC unit (astrocytes, neurons, and blood vessels, and excitation-inhibition balance) in a PFC microcircuit [61], [62]. NVC plays a major role in matching the metabolic supply with regional neural activity and adjusting the cerebral blood flow in accordance with regional metabolic needs [58], [63]. In which, our results (Fig. 8) demonstrated an inverse relationship between alpha cortical activity (direct relationship in the case of alpha power) and the hemodynamic signal (HbO) as well as a maximum peak in correlation at a time delay of 5 seconds.

Notably, in our fusion data (Fig. 9), the interhemispheric asymmetry of the coupled alpha power revealed a profound effect of the workstation type on the PFC. Further, in the right PFC, the power of coupled alpha activity was decreased in the SNE group, indicating an increase in neuronal activity.
These findings may be a consequence of impaired glutamate homeostasis, resulting in a reduction in coupled alpha values in the right PFC compared to the left PFC in the SNE group. Previous studies indicated that both the excitatory glutamatergic system and inhibitory GABAergic system in the PFC are impaired in stress dysregulation [64].

Multi-modal imaging has been reported to improve classification performance over a single modality [65], [66]. This study further investigated the classification performance of EEG-only, fNIRS-only, mCtCCA-based fusion, and mCtCCA-based fusion for discriminating between responses to MIST at SE and SNE workstations. The experimental results revealed an improvement in classification performance using mCtCCA and mCtCCA-based fusion approaches as compared to individual modality data, yielding an average accuracy of 98.8% ± 1.1% and 97.0% ± 1.8%, respectively. It showed an enhanced accuracy of 6.2% and 7.6% over EEG-only and fNIRS-only, respectively, for mCtCCA-based fusion and 8.0% and 9.4% over EEG-only and fNIRS-only, for mCtCCA-based fusion. The effectiveness of these two approaches may be due to the CCA projections serving as a stage of data cleaning, in which a process of reduction of semantic dimensionality occurs. However, the delayed hemodynamic response may hinder the classification performance. The mCtCCA provided better classification accuracy in over 91.3% of considered subjects and increased performance by 1.8% on average (p < 0.001) than that of mCtCCA as the correlation between the two data sets is likely to be highest with a temporal shift.

The overall demonstration results that the proposed approach provides a classification improvement over the existing methods of discriminating stress conditions in the workplace [26], [65] as well as over recent studies that have combined EEG and fNIRS based on motor imagery tasks [67], [68], Alzheimer’s disease [69], and mental workload [70]. Therefore, the combination of EEG and fNIRS using the proposed approach (mCtCCA) has a significant impact on the better analysis of signals.

The current study provides directions for future research. For example, the study focused mainly on body posture, relying on manipulation of the chair and workstation position. Whereas more studies on other aspects of the workplace should be undertaken to regulate stressors and thereby reduce stress in workplace environments. Besides, the sample size was relatively small due to the difficulty of attracting more participants owing to the complexity and length of the experiment. Furthermore, the study was confined to male respondents on their own, leaving the implications for females and other categories of individuals to be determined. Notably, these categories can react to mental and physical stressors differently [71]–[74].

V. CONCLUSION

The current research has concluded that workstation types can have a substantial effect on employees’ brain function, as demonstrated by the deactivation of EEG alpha power and vascular activity (HbO) while working at a non-ergonomic workstation (SNE) compared to an ergonomic workstation (SE). The results of mCtCCA revealed a reduction in the activation patterns of coupled EEG components (alpha) that correspond to fNIRS ones (HbO), particularly in the right PFC, of the SNE workstation group with an increase in sAA activity in comparison with the SE workstation group. The proposed mCtCCA approach identified workstation types with a maximum accuracy of 98.8% with an improvement of 1.8%, 8.0%, and 9.4% over mCtCCA, EEG-only, and fNIRS-only, respectively. These findings demonstrate the ability of multimodal fusion to improve precision and localization by obtaining the associations between EEG and fNIRS modalities.

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