Towards a Closed-Loop Neurostimulation Platform for Augmenting Operator Vigilance

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***Abstract*—*Vigilance* is a primary job-performance requirement for human operators in domains that demand sustained attention, including air traffic control (ATC), surveillance, emergency response and many others. In this pilot study we introduce the prerequisites and conditions that facilitate a novel closed-loop, adaptive neurostimulation system to alleviate vigilance decrements during prolonged time-on-task efforts. Here, we investigate the use of transcranial Direct Current Stimulation (tDCS) with preset stimulation parameters – intensity (I), duration (t), and, probe location to augment the operators' vigilance state during an under-arousing task. To this end, we employ an app-based psychomotor-vigilance test (PVT), where performance metrics are analyzed along with physiological and cognitive bio-markers to explore opportunities toward a predictive framework. Initial observations ($N = 19$) suggest that – (1) a prolonged version of the PVT ($40\ min.$) can function both as a diagnostic and an inductive mechanism for vigilance loss, (2) tDCS can serve to restore/ improve operator vigilance states relative to baseline performance levels, and (3) short-term heart rate variability (HR/V) features ($3\ min.$) and the fNIRS signal are sensitive to state changes during the PVT, and to the effects of stimulation.**

***Index Terms*—tDCS, neuromodulation, fNIRS, heart rate variability**

I. Introduction

Vigilance in operators within safety-critical socio-technical systems is a primary job performance requirement [1]. With increasing *time-on-task* demands, operator cognitive states are compromised as *vigilance decrements* begin [2]. There are varied definitions for vigilance, and the associated diminution, but there is some precision in characterizing it as the ability to sustain attention for an extended duration of time while maintaining optimal task performance. Therefore, contingent on the nature of the task, the observed decrease in attention state over a given time period is ascribed to vigilance loss [3], [4]. The consequence of vigilance decrements within these systems is not trivial, with operator lapses or error identified as a contributor to several well-researched case studies for example, Three Mile island, and Chernobyl [5]. Some studies attribute their cause to sleep deprivation, monotony, and (or) boredom [6], while others explore underlying cognitive factors that prime these states [7]. The ability to predict the onset of vigilance loss, and to compliment the user's cognitive deficits through intervention remains an active research effort [8]–[10].

Studies have identified theoretical models, and measures for the quantitative, and qualitative estimation of vigilance in human operators. These include the *arousal theory* which posits cortical arousal as a causal indicator for vigilance performance. Successive investigations with functional magnetic resonance imaging (fMRI), and electroencephalography (EEG) suggest that vigilance is correlated with cortical arousal however the causal relationship remains suspect [11], [12]. In contrast, the *underload* theory suggests that vigilance loss is due to the observer's withdrawal of focused attention to a task due to task monotony [13], and it is this perspective that informs our current direction.

The underlying neural basis for vigilance, and vigilance states is an important consideration in this investigation, and it is a complex issue. There are multiple constructs and neural systems elementary to the relatively non-specific alertness and activation states associated with vigilance, implying that the phenomenon is not uni-dimensional [14]. Some attempts have been made on using EEG workload indices as predictors for monitoring vigilance states, with the measured *Task Load Index*, and *Engagement Index* from lower-frequency *alpha* as an objective diagnostic measure for operator vigilance loss [15]. However, this and related metrics need further investigation on the variability associated with altering task demands. fMRI studies report that attentional performance is correlated with *BOLD-signals* especially in the parietal and pre-frontal cortices [16], [17], nevertheless, these methods are not optimized for everyday use-cases. Another study reports the responsiveness of cerebral hemodynamics to operator fatigue, and vigilance states using near-infrared spectroscopy (NIRS) [18] – this non-invasive ambulatory technique shows promise in providing correlates for vigilance decrement but is limited by its spatio-temporal resolution, and operating constraints [19]. On the subject of deficit prediction, there is also emphasis on the need for *wearables* that are unobtrusive to task performance requirements, while remaining sensitive to the physiological, and cognitive triggers that capture operator lapses. For the systems discussed thus far, this remains an impediment, however, recent efforts suggest that HR/V is a sensitive metric for predicting the cognitive demands of sus-

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tained attention tasks [20], in particular, spectral power ratios, time-domain, and some non-linear parameters derived from the inter-beat interval (IBI). These metrics can be obtained using electrocadiography (ECG) enabled wearables that are easy-to-use, inconspicuous, and self-contained.

With the onset of vigilance decrements there is the need to sustainably reverse or otherwise delay the condition using some active, adaptive mechanism. Research in this space dwells on the use of both conventional and unconventional solutions. Conventional paradigms include – meditation, yoga, caffeine, and nicotine among others; with each showing varying levels of success, and some inherently limited by their mechanism of action [10]. Unconventional solutions include pharmacological agents such as *D-Amphetamine*, and *Modafinil* among others, with each having unique pharmacodynamics, activations, and long-term addiction potentials [21]. Some of these modalities are used on a spontaneous, ad-hoc basis, with no clear statistical validation of their efficacy (e.g., coffee in the workplace). Moreover, there is a need for tools that can act prior to symptomatic expression, and also those that are mapped to the operator's "real-time" cognitive state.

Neuromodulation techniques that use non-invasive mechanisms show promise in enabling some form of preemptive action, and in eliciting the desired response. In particular, the use of transcranial direct current stimulation (tDCS) has been explored by multiple research groups [22], [23]. In these studies, a small current (1 to 2 mA) is applied to the user's scalp for a short duration of time (up to $40\ min.$). These small currents are stated to influence levels of cortical excitability, thereby altering user vigilance states. Research by Nelson et al. showed promise in vigilance enhancement via tDCS when administered over the dorsolateral prefrontal cortex (dlPFC), while performing a simulated air traffic control task [9]. Similar findings have been reported with participants subject to a psycho-motor vigilance Test (PVT), and the Mackworth clock test [24].

For the scope of this investigation, we explore a closed-loop, adaptive approach to tDCS administration. In the studies prior, including those related to vigilance, and those in other applications, tDCS dosages were based on arbitrary, sequential time-intervals with non-specific relationships to user cognitive states [9], [24]. In this study, we investigate the pre-requisites for a system that is explicitly, and concurrently informed by physiological triggers/ thresholds that determine the onset of vigilance loss. There are several unknowns relevant to this proposition, and this pilot study aims to disambiguate some among them – **(1)** the characteristics of vigilance decrements, and its representation within PVT performance-metrics across individuals, **(2)** the correlation between traditional HR/V features, the fNIRS signal and operator vigilance state, **(3)** the predictive-potential for HR/V as a sufficient measure to infer operator vigilance trends, and **(4)** the effects of tDCS on restoring/ augmenting operator task performance levels relative to baseline.

This paper is organized into the following sections – *Section II* provides an overview of our data collection methodology, analysis techniques, and proposed system architecture. In *Section III* we present our observations, and discuss their significance within the context of the proposed closed-loop system, and current literature. Finally, in *Section IV* we conclude with a discussion of the relevance of this effort within the current body of literature, foreseeable limitations, and future directions.

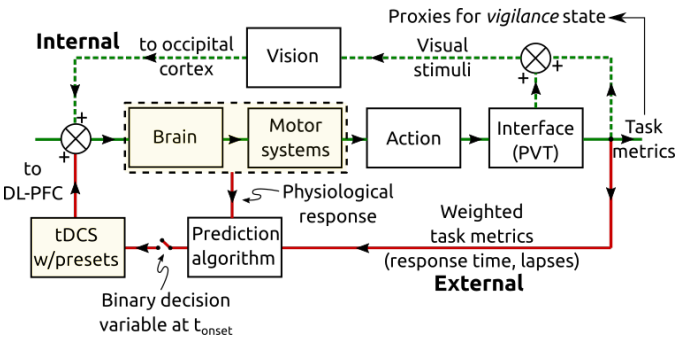

Fig. 1. A block diagrammatic representation of the proposed closed-loop system. The internal feedback loop (dashed, green) consists of the visual pathway, and is mediated by the *occipital cortex* of the brain. The external feedback loop (solid, red) is mediated by a prediction algorithm informed by operator physiological/ cognitive states, and provides electrical stimulation to the *dorsolateral prefrontal cortex* (dlPFC). A binary decision variable determines the activation of this neuromodulation (tDCS) system.

II. Methods

A. Overview

The overall system's architecture is represented by the graphic in **Fig. 1**. Human-visual-information processing, as it relates to the PVT, relies on an internal feedback loop (dashed, green). This feedback loop is mediated by the *visual system* which receives cues (visual stimuli) from the interface, and commands action via the occipital, and posterior parietal cortices – a button-press event [25]. This interaction influences task-performance metrics, and is underscored by operator vigilance state. The PVT however is an under-arousing task, that elicits minimal cognitive activity [26], therefore, with extended *time-on-task*, there is an expected performance decline attributed to vigilance decrements arising from monotony, and boredom. Further, our hypothesis relies on the evidence that the markers for vigilance state are captured within HR/V and fNIRS metrics. Together with weighted performance measures, these neurophysiological indices inform a prediction algorithm that can determine the onset of vigilance loss (t_{onset}). Which then enables the secondary, external feedback loop (solid, red), that relies on a binary decision variable from the prediction algorithm to administer tDCS with preset stimulation parameters (intensity, I and probe position). For the scope of this investigation, we independently analyze – **(1)** performance decline associated with the PVT, **(2)** HR/V features as prediction metrics for vigilance decline, **(3)** the efficacy of tDCS in improving task performance levels, and **(4)** the role of cognitive biomarkers during stimulation.

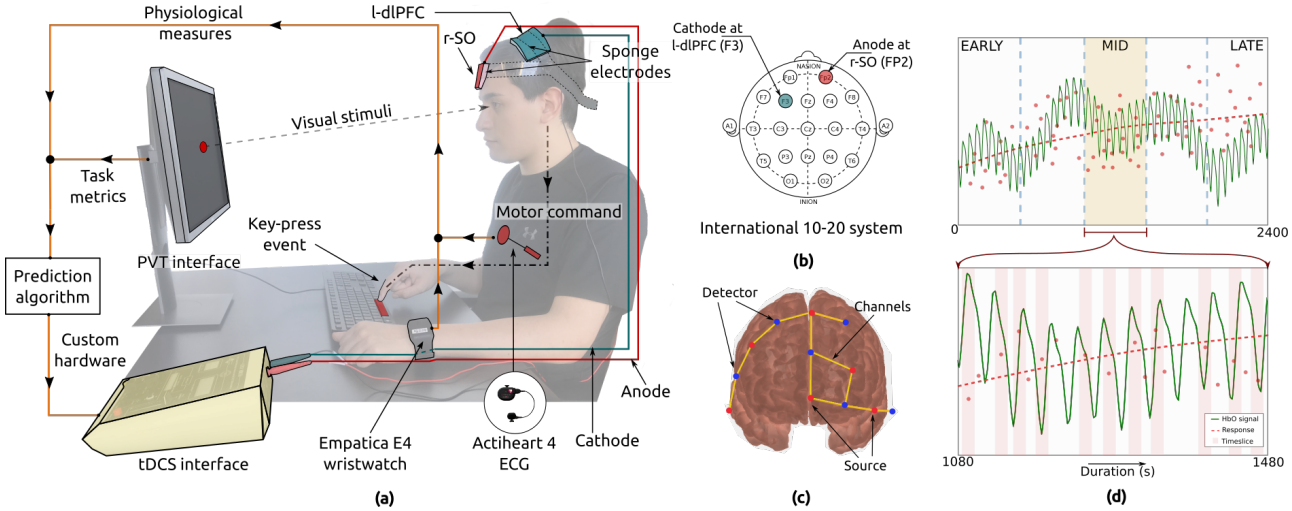

Fig. 2. **(a)** A schematic representation of the participant engaging with the PVT interface while under the *reversed* tDCS condition, i.e. anode at the left-dlPFC, and cathode at the right-SO regions respectively. Physiological data is monitored by the chest-worn, two-lead ECG device, and the research-grade smartwatch. A custom hardware interface transfers activation commands from the prediction algorithm to the tDCS device. **(b)** The 10-20 international system representing the electrode montage for the *reversed* stimulation condition, with anode at **FP2**, and cathode at the **F3** positions. **(c)** fNIRS probe map for the tDCS experiments showing source (red), detector (blue) and channel positions over the regions of interest. **(d)** Schematic representation of the processing pipeline for extracting temporal features from the fNIRS signal.

B. The onset of vigilance decrements

For phase one, we had participants ($N = 19$; $18 - 30$ age group) engage with a computer-based, custom, PVT application, while monitoring their physiological indices. An important distinction in this study is that the PVT is used both as a tool to induce vigilance decrements (with extended duration of task exposure), and as a diagnostic tool to evaluate user cognitive state, the motivation for this is to use an interface that is standardized, and analogous to other metrics for vigilance/ cognitive impairment (E.g. blood alcohol content). The PVT entails users responding to objects (circles, and crosses) that are randomly sequenced to appear on screen, with a button-press (see schematic in **Fig. 2 (a)**). The users are instructed to press the button only on seeing a circle, and to do so as soon as they can. The inter-stimulus interval (ISI) is randomized, with a screen refresh loop running every three seconds (i.e. min. $ISI = 3s$), the stimuli objects are probabilistically sampled with unequal weights ($P_{circ} = 0.4, P_{cross} = 0.2, P_{null} = 0.4$) from a random distribution. This experiment lasted a duration of $40\ min.$. The application reports user-response time, response correctness, and lapses as metrics that relate to their vigilance state, where response time is defined as the time between stimulus projection, and user key-press events. A correct response is when the user responds to a circle object or disregards a non-circle object, and a lapse is any key-press event that occurs beyond $500ms$ since stimulus display [26].

In addition to task performance metrics, we monitored the participant's physiological response using a wearable ECG device (Actiheart 4, CamNtech Ltd., Cambridgeshire, UK), and a research-grade smart-watch (Empatica E4, Empatica Inc., Boston, MA). The goal of this model building exercise is to find correlation between HR/V indices, and reported task metrics, that could identify the onset of vigilance decrements.

1) Measured physiological indices: The ECG data is captured continuously during the experiment at a sampling rate of 128 Hz. The embedded hardware estimates the Inter-beat Interval (IBI) with a temporal resolution of approximately $\pm 1ms$. Heart Rate (HR) is measured internally as an average of the last 16 valid IBI measures. The raw ECG signal is filtered for motion artifacts using the accelerometer on the device, and normalized for measured HR. The automated experiment protocol provides event markers that determine the start and finish of the PVT. Of the indices that define HR/V characteristics, we are interested in those that are congruent with the goal of reducing latency in the overall system's response to operator physiological state. Prior research on ECG in vigilance tasks report the use of conventional spectral parameters [27], [28], including the RR-interval, spectral power across frequency regimes: very-low (VLF), low (LF), and high (HF), i.e. $\leqslant 0.04Hz$, $0.04 - 0.15Hz$, and $0.15 - 0.40Hz$ respectively, normalized LF and HF power, and the ratio of LF to HF power. Our preliminary analysis relies on similar primitives, including time-/frequency-domain, and non-linear parameters (see **Fig. 3 (b)**).

2) Correlations between HR/V and performance: Heart rate and its variability are complex, non-linear phenomena. The variability of this chaotic system allows individuals to adapt to changing environments/ task-demands [29]. For example, higher levels of resting vagally-mediated HR/V are linked to attention and emotional processing by the prefrontal cortex, while, afferent information processing can modulate frontocortical activity and impact higher-level functions [30]. Therefore, given that regulators of the cardiovascular system interact in a non-linear way, HR/V analysis using non-linear methods would best predict or reflect these mechanisms. Previous

studies that focus on prediction with HR/V have relied on testing the strength of a linear relationship between each HR/V parameter and the performance metric [27], fuzzy clustering [28], and feature extraction methods. For this investigation we use a combination of 34 time/ frequency-domain, and non-linear features of the HR/V signal [29]. The autonomic control of HR/V fits the classical description of a non-linear, dynamical/ chaotic system, however the overarching goals for this project necessitate simplistic architectures or algorithms that are functional, and compatible with the online frameworks. The threshold to determine the time-of-onset (t_{onset}) of vigilance decrements rely on existing literature, and observations during the pilot data collection effort.

C. Evaluation of the closed-loop system

The second phase of this investigation is centered on evaluating the efficacy of tDCS in augmenting or restoring task performance levels relative to the participant's baseline. Here participants ($N = 3$) engage with the PVT interface described in the preceding section, while their physiological, cognitive, and performance data are logged during multiple sessions (15 sessions in total). The tDCS platform (1×1 tDCS system, Soterix Medical, NY, NY) with presets (current intensity, $1mA$, and probe position), as represented in **Fig. 2 (a)** is enabled during the course of the experiment during a pre-determined time instant. Prior research on vigilance enhancement with tDCS has explored the role of the frontal cortex in mediating attentional states, in particular the dlPFC region was identified as a potential candidate for anodal stimulation [9], we adopt a similar arrangement in this pilot study with the reference electrode over the right supra-orbital (r-SO) region.

Participants in this second phase engage with the PVT interface over five sessions – active (anodal), reversed (cathodal), sham (anodal), pre-stimulation (anodal) or null (no stimulation) spread across multiple days. During active stimulation, the anode is placed over the left dlPFC (electrode center over F3 on the 10–20 system), and the cathode over the right supra-orbital (electrode center over FP2 on the 10-20 system) region, under the reversed conditions, the anode was placed over the left dlPFC and the cathode right supra-orbitally (shown in **Fig 2 (c)**). During sham, the active electrode positions will be retained, however the stimulation waveform will have a brief ($30s$) up-ramp to set point ($1mA$), a plateau at set point for 15 s and a subsequent down-ramp to $0mA$, which is retained for the rest of the experiment duration. Under pre-stimulation, the anodal electrode positions are retained, but stimulation is provided prior to the start of experiment for a duration of $5\ min.$. During the no stimulation condition, participants wear the required peripherals, but no tDCS is provided. In addition to ECG, participants ($N = 1$) wear an fNIRS device (NIRSport2, NIRx Medical Technologies, LLC, Los Angeles, CA) during the stimulation experiment to better understand the neural basis for vigilance changes across the five experiment conditions.

1) fNIRS processing stream: The fNIRS data is acquired using the NIRSport device, a modified probe-map was designed to accommodate the concurrent use of the fNIRS system along with the tDCS sponge electrodes (see **Fig. 2 (c)**). The probe-map was optimized to focus on the active region of interest for the vigilance task i.e. the *l-dlPFC*. There were a total of 12 channels with 6 sources, and 6 detectors respectively. The fNIRS data was acquired at a frequency of $10Hz$. The processing pipeline employs the *Homer2* software tool to convert the raw intensity data from the NIRS device into a differential optical density measure, from thereon the modified Beer-Lambert is applied to obtain changes in haemoglobin concentration relative to baseline ($dConc$), which provides information related to brain activity within the region of interest [31]. Further, this signal is de-trended to account for sensor drift, filtered to correct for motion artifacts, and band-pass filtered for instrumental and physiological noise. The time series change in concentration ($dConc$) for each signal (HbO/T/R) is then imported into a post-processing script for subsequent analysis.

The experiment protocol includes a $5\ min.$ baseline prior to the start of the PVT, the $dConc$ data is partitioned into five phases post baseline – early, pre, mid/stim, post, and late with each phase broken into two sections e.g., E1 and E2 for the early stage. Given that the PVT entails randomized stimulus events these partitions where chosen in such a way to ensure an equitable distribution of response events within each phase. With this constraint, each phase entailed roughly 50 response events over a period of $4\ min.$. For the fNIRS signal, we use epoch-peaks (p_i) averaged over the entire phase as a representative measure for that interval ($\bar{x}_{ph}$). Here the epoch size was defined as $15s$ which is consistent with the latency of hemodynamics in the human brain [32]. The stimulus time stamps were used to slice the phase interval into smaller $15\ s$ epochs (n) where each epoch constitutes at least one unique stimulus event, care was taken to ensure that no interval had overlapping stimulus events (see **Fig. 2 (d)**).

$$\bar{x}_{ph} = \frac{\sum_{i=1}^{n} p_i}{n} \tag{1}$$

Since the fNIRS signal measures relative change in concentration, the representative statistic for each phase is cumulative such that for k phases, the k^{th} phase has an amplitude as given by the below expression,

$$[\bar{x}_{ph}]_k = [\bar{x}_{ph}]_k + [\bar{x}_{ph}]_{k-1} \tag{2}$$

III. Observations and Discussion

A. Vigilance decrements with time-on-task

In *Phase-1* upon consent, we had 19 participants undertake the PVT while their physiological indices (HRV) and performance was monitored as described in *Section II-B*. The response delay as a function of time across all participants is reported in **Fig. 3 (a)**. The dashed trend-line shows the average performance profile in the form of a regularized cubic spline, while the scatter plot represents the epoch-averages

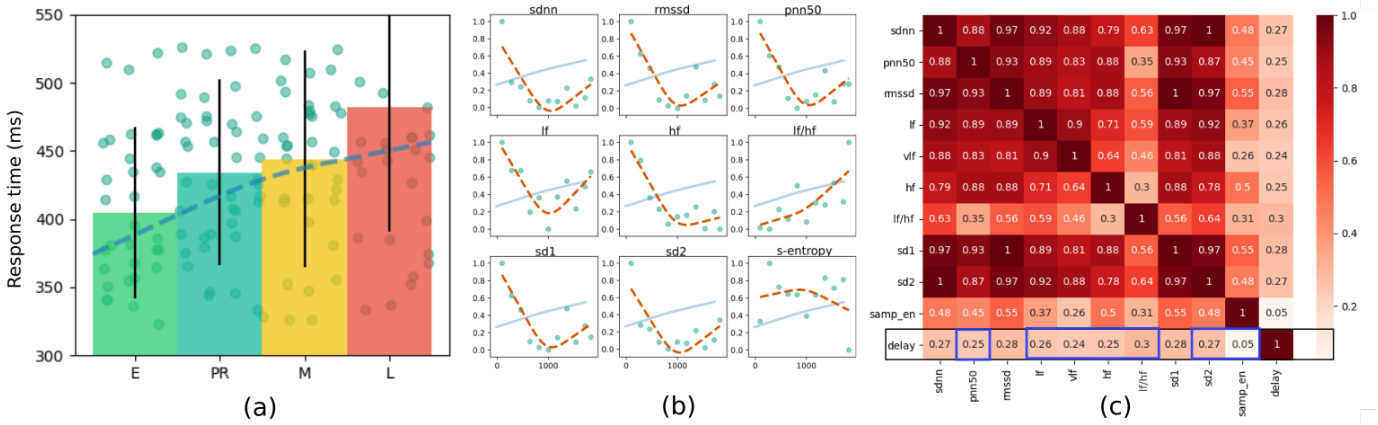

Fig. 3. **(a)** PVT response times across all participants ($N = 19$) during *Phase-1*. The dashed line represents a regularized cubic spline fit to the epoch-averages of response time across all participants. The super-imposed bar graph represents the changes in response time over four stages consistent with *Phase 2* – early (E), pre (PR), mid (M), and late (L), along with the standard deviations for each segment. **(b)** Short-term ($3\ min.$), time-domain, spectral, and nonlinear HR/V features for the proposed algorithm, normalized and derived from a $30\ min.$ PVT on a single participant. Feature trend is shown in dashed lines, performance trend represented by the solid line. The raw HR/V data was filtered for outliers and ectopic beats. Linear interpolation was used for missing values. **(c)** Pearson correlation metrics across all HRV features derived from participant response data.

of response time for all participants. From these observations it is evident that response delay increases as a function of time, with more than 80% of the participants sharing this behavior. However, there were significant baseline differences in response times, and some subjective variability in response behavior. Notably, most participants who begin with relatively good response times ($< \ 400ms$) show sharper increases in response delay until midway, where they plateau or show a more gentle decay. Those participants who begin with poor baselines ($> 500ms$) tend to show no significant change in response behavior over the entire experiment duration. This observation is significant in that it highlights the subjective variability in vigilance decrements and therefore underscores the need for an adaptive framework.

1) Heart rate variability as a prediction mechanism: From the response data in *Phase-1*, we processed the IBI signals to generate temporal, spectral, and non-linear features that characterize the ECG signal. We adopt a short-term feature epoch of five minutes resulting in approximately 8 feature samples for each participant. The IBI signal was filtered for outliers and ectopic beats, adjusted for motion artifacts, and linearly interpolated for missing beats [33]. Performance data was normalized across the whole experiment by participant, while HR/V features were normalized by epoch. The performance data is contrasted against the HR/V features for one participant as shown on the graphic in **Fig. 3 (b)**. At the outset, HR/V as a predictor is impeded by the recommended epoch window, and our sample size ($N = 19$). Our data set was too sparse for any robust prediction paradigm, while further data collection is on pause given the global crisis. However, we do notice that some features appear to show stronger correlations with performance trends in those participants who begin with better baseline response times ($< 400ms$), they are as highlighted in **Fig. 3 (c)**, we believe that with a larger participant pool HRV measures could help account for individual variability in response behaviors, and function as a priming mechanism for the proposed closed loop system. However, it is our belief that such a system will have to work in combination with a sensing modality that has better temporal resolution, and is sensitive to changes at the point-of-origin of such cognitive responses, this lead us to investigate the effectiveness of fNIRS as a sensing mechanism when incorporated along with the tDCS experiments as reported in the sections to follow.

B. Effects of stimulation on PVT performance

In *Phase-2* upon consent, we had participants ($N = 3$; 15 sessions) engage the PVT interface, while under varying stimulation conditions, over multiple experiment sessions. The working hypothesis here borrows from the evidence reported in *Section III-A*, where we observed that PVT performance levels diminish over time, however it is also noted that the performance trends are subjective and do show some patterns of variability. Here we hypothesized that tDCS should alter the vigilance state of the participant, and this can either result in a return to baseline response times or an improvement in response time altogether. Across the five experiment conditions, we notice an upward trend in response time (delay) as a function of the experiment duration. Further, in experiments that involve a stimulation event (*ACT, REV, SHA*) we see level changes (improvements) in performance behaviors across all participants and these changes appear concomitant with the stimulus interval ($18 - 25\ min.$). However, the amplitude of change remains varied across participants and conditions. Notably the slope of response time decrease during the *ACT* condition was the highest across all stimulation events (see **Fig. 4 (a)**), with the average response time showing a 16% decrease from the MID to LATE stages of experiment.

Further, we also notice improved baseline performance levels for those participants who begin the experiment with pre-stimulation, with diminished decay in response time as

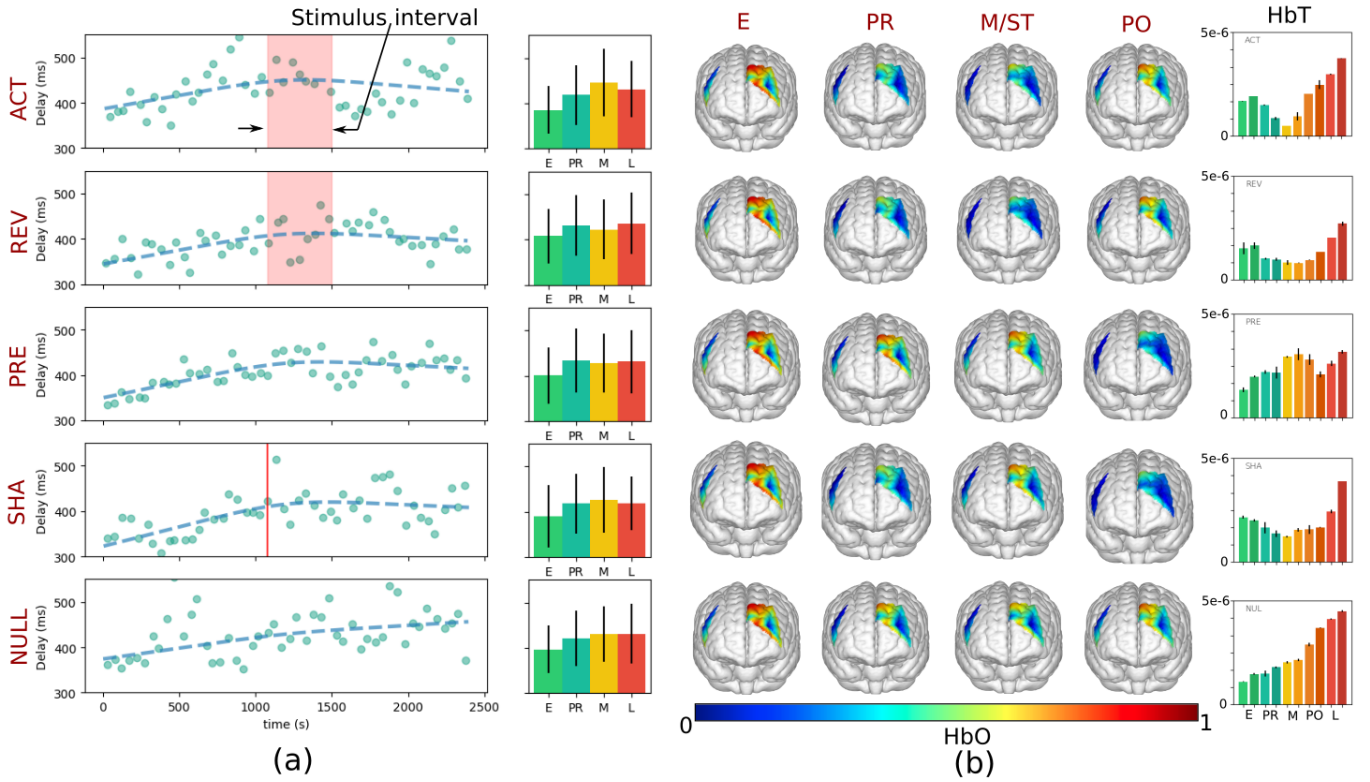

Fig. 4. **(a)** Performance trends across the five experiment conditions for participants in *Phase-2*. The scatter plot represents average response delay (ms) over 180 s intervals, while the dashed line represents a cubic-spline trend line for response delay over the entire experiment. Bar plots represent the response delay during four experiment stages for all participants i.e. early, pre, stim/mid, and late. The error bars depict individual variability. **(b)** Topographic montage depicting changes in peak HbO concentration during different stimulation conditions (see *Section II-C1*) over four stages of the exeperiment – early (E), pre (PR), mid/stim (M/DT), and post (PO). The concentration values were feature scaled across all participants, and conditions. The jet colormap is consistent across each experiment. The bar plots reflect peak averages, and standard deviation of the HbT signal for channels within the region of interest over all phases of the experiment.

the experiment progresses. These performance trends are represented on the graphic in **Fig. 4 (a)**, with the dashed line representing performance trends, while the scatter plots indicate response-time averages over $180s$ intervals. The bar plots in **Fig. 4 (a)** present the level changes in performance across the five experiment conditions for all participants, here the experiment duration is divided into four equal intervals – early, pre, mid/stim, and late, with the bars representing interval averages, and whiskers indicating the extent of individual variability. These observations suggest that the effect of tDCS can serve both to restore operator performance state to baseline levels and also to sustain optimal performance levels for longer periods of time. A question that arises here is whether this improvement in performance is merely a transient return to a state of attention or an underlying improvement in cognitive ability. The pre-stimulation performance behavior when contrasted with the null condition suggests that tDCS can effect changes that are beyond transient effects, an attribute that we intend to investigate further with a larger sample size.

1) Cognitive bio-markers and vigilance state: The activation states of the region of interest can indicate vigilance levels of the participant during an experiment. In **Fig. 4 (b)** we present a topographic map of the activation state of regions within the probe-map as seen in **Fig. 2 (c)**. Here activation state is represented as the peak HbO value for each phase as derived through the process discussed in *Section II-C1*. Further, the color map represents data that is normalized across all experiments to ensure a consistent scale. In the topographic montage we observe a decrease in activation levels as the participants progress through the phases of the experiment, this trend appears to be true for all experiment conditions. However, in experiments that involve an active stimulation event (*ACT, REV, SHA*), we observe a return to activation levels in the phase that follows the stimulation event (*PO*). This change appears stronger in the *ACT* condition than others, as evident from the color intensity on the projection, a fact that was also corroborated in the performance behavior reported earlier. Further, it is also observed that when under pre-stimulation, the activity decay takes a longer time period than in the other experiment conditions, suggesting that tDCS prior to the experiment helps sustain an enhanced vigilance state for longer time periods. These observations signal positively toward recruiting a larger participant pool for an expanded test protocol.

IV. Conclusions

This investigation explored several foundational questions related to the human-factors of sustained-attention tasks in the workplace, and beyond. *Vigilance* is a primary job-performance requirement across domains, and vigilance loss or *vigilance decrements* remain impediments to human task performance. The downstream impact of diminished operator vigilance is non-trivial, and is further amplified within safety-critical socio-technical systems. The neural, and physiological signatures of vigilance/ vigilance decrements remain interesting research themes with nuanced approaches and unexplored regimes. The search for a sufficient, and *fieldable* predictor for operator vigilance state is yet to yield satisfactory results, and as such, it still remains an effort worth pursuing.

Along similar lines, there is the explicit desire for a non-invasive mechanism to restore operator vigilance state. It would be further propitious for this system to exhibit specificity, minimal latency, and no adverse/ long-term reactions while producing the desired effect. tDCS as a platform may fulfill some of these requirements, especially within the context defined in this study. Although we approach this problem with certain optimism we foresee some key limitations to the overall architecture – **(1)** physiological indices may prove insufficient given the desire for *real-time* response, therefore, there might be a need to transition toward cognitive indices sourced from the point-of-origin of neural signals; **(2)** in this framework, tDCS parameters are borrowed from existing literature, but the prior-art reports high variability in outcome due to the observed task-specificity of both tDCS, and the choice of sensing modality. Hence, there is need for more trial-and-error in parameterization; and **(3)** although the study proposes the concurrent use of tDCS with HR/V measures, prior research indicates that tDCS is known to alter autonomic response thresholds, therefore, the current framework cannot enable a *continuous* dose-response mechanism. Importantly, much of this research effort was hindered by the ongoing global pandemic, the evidence reported in this study is derived from as many participants as the study team could recruit prior to the current crisis, and as such these observations signal positively, and demand an expanded participant pool to reaffirm our current direction.

With the above caveats considered, we expect the following contributions upon the completion of this effort – **(1)** an evaluation of PVT in its ability to function *both* as a diagnostic tool that provides quantitative metrics for operator vigilance state, and as an induction mechanism to induce boredom or underload-related vigilance decrements in human operators – this is important given the analogues of the PVT to other standard measures for operator impairment; **(2)** commentary, and statistics on whether heart rate and its variability (HR/V) are sufficient predictors for the onset of vigilance decrements – wearability and functionality in the target workplace remains a conflict for most devices today, and if HR/V proves sufficient, direction on how we could extend this toward a task-agnostic framework; and importantly **(3)** answers to whether a closed-loop neurostimulation platform can produce significant change in task performance abilities, in particular, one that is concurrent and explicitly informed by relevant predictors.

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