Available online at : http://josi.ft.unand.ac.id/

Jurnal Optimasi Sistem Industri

| ISSN (Print) 2088-4842 | ISSN (Online) 2442-8795 |

Research Article

Cognitive Load Assessment in Multitasking: An fNIRS Study of Prefrontal Cortex Activation for Ergonomic Insight

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DOI: 10.25077/josi.v24.n1.p305-323.2025 **Submitted:** September 7, 2025 **Accepted:** November 29, 2025 **Published:** December 30, 2025

ABSTRACT

Although traditional neuroimaging techniques like fMRI and EEG have yielded insightful results, their rigid movement limitations restrict their practical use. Functional near-infrared spectroscopy (fNIRS) offers a practical alternative by allowing researchers to measure cortical activity during more natural task performance, particularly in the prefrontal cortex (PFC)—a key region for attention and executive control. This study uses fNIRS to investigate how multitasking demands affect PFC activation. An eight-channel fNIRS system recorded the brain activity of thirty participants as they completed tasks from the Multi-Attribute Task Battery (MATB). Oxygenated hemoglobin (HbO) signals were the main focus of data preprocessing, and AtlasViewer was used to visualize cortical projections. The superior and middle frontal gyri, which are linked to the dorsolateral prefrontal cortex (dlPFC), showed a significant increase in HbO responses when multitasking. On the other hand, lower activation levels were produced under less demanding circumstances. These results are consistent with resource-based models of attention, which postulate that the brain allocates more cognitive resources, especially in the right PFC, as task complexity increases. Beyond theoretical ramifications, this study shows that fNIRS can be used to detect cognitive load in real time. In high-stakes settings like aviation, healthcare, and mission-critical operations, this capability has potential uses in adaptive systems intended to monitor and reduce mental overload. This study emphasizes fNIRS as a useful tool for comprehending and managing multitasking in today's dynamic work contexts by bridging laboratory research and real-world settings.

Keywords: multitasking, functional near-infrared spectroscopy, prefrontal cortex, cognitive load

INTRODUCTION

The study of multitasking presents considerable challenges. Although traditional neuroimaging techniques—such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG)—have significantly advanced our understanding, their applicability is limited by susceptibility to motion-related artifacts. In contrast, functional near-infrared spectroscopy (fNIRS) offers a promising alternative, enabling the investigation of multitasking within ecologically valid and dynamic environments.

The ability of the human mind to effectively distribute and manage cognitive resources while carrying out tasks with various requirements simultaneously is thought to be connected to multitasking behavior [1]. The primary cognitive mechanisms that allow people to multitask in this situation are executive functions (EF). The EFs coordinate several higher cognitive functions, such as working memory, inhibitory control, and cognitive flexibility. Together, these cognitive functions support goal-directed behavior, which in turn enables individuals to adapt to complex or unfamiliar situations, to respond to environmental requirements and to interact with others in a controlled way [2]. Among these functions, working memory plays an important role by providing temporary storage and manipulation of information, which is necessary for switching tasks and retaining details associated with those tasks. Greater working memory capacity is correlated with generally more successful multitasking, as individuals have greater capacity to retain information and to manage the distraction of tasks [3].

Another component of EFs, i.e., inhibitory control, allows humans to hold automatic, habitual, or irrelevant responses in an attempt to optimize focused, goal-directed performance. This kind of ability is crucial in a multitasking workplace where maintaining focus requires cognitive control due to frequent distractions. By controlling attention between tasks, adapting to shifting priorities, and offering new tactics when necessary, cognitive flexibility can also sustain performance while performing multiple tasks. This adaptability not only facilitates efficient task switching but also fosters adaptive responses in the face of conflicting or unforeseen demands [4].

The mechanism by which the brain prioritizes simultaneous tasks is still the subject of debate. According to conventional wisdom, tasks can only be completed sequentially, not simultaneously. This is because of a cognitive bottleneck which prevents large amounts of information from being transmitted at the same time during multiple tasks of a high intensity [5], [6]. On the contrary, recent evidence suggests that parallel processing may occur in the early stages of perceptual and response preparation, although this occurs within the range of 100 milliseconds [7]. Moreover, in complex and continuous tasks such as those in MATB, a more dynamic mechanism can be used in which temporary parallel processing can support rapid environmental assessment while continuous sequential control is used to coordinate tasks over time. Although fNIRS has time constraints to capture this millisecond-level dynamic, it may provide continuous cortical activation, an indicator of overlapping cognitive task and effort priorities across competing cognitive resources. Moreover, the prioritisation of tasks in a multi-tasking environment is influenced by context factors such as instructions, urgency and conflict, which indicate the allocation of scarce attentional resources [8].

However, multitasking is usually measured in terms of cognitive load, i.e. the mental effort required to process information and perform tasks [9]. It should be noted that just performing a few tasks does not necessarily mean an increased cognitive load [10]. When individuals perform a series of tasks without significant cognitive involvement, such as routine or automatic behaviour, the cognitive load associated with these tasks may be minimal. In this context, multitasking is considered to be important in situations where there are significant demands on cognitive resources and involves the constant attention, decision making and switching of tasks. As a result, we can associate increased cognitive workload with increased multitasking, as reduced allocation of resources in the brain to meet competing demands [11]. Increased workload may result in reduced performance, especially in complex tasks or tasks with the same cognitive processing [12], [13].

From a neurocognitive standpoint, elevated cognitive load has been linked to PFC activation [14]. Prior research has shown that PFC activation in various brain regions responds to increased cognitive load. The lateral PFC is activated when completing a task with a high cognitive load, according to fMRI research [15]. This area has been linked to a number of EFs, including future planning [19], working memory [16], behavioral flexibility [17], and attentional control [18]. The ventromedial PFC (vmPFC), on the other hand, exhibits reduced activation in situations with high cognitive load and strong motivation [20], indicating a connection between areas linked to emotional and cognitive processing [21]. Dorsolateral PFC (dlPFC) activation in response to increased memory loads has been repeatedly demonstrated by a popular task paradigm, such as the n-back task [22], [23]. This illustrates the function of the dlPFC in preserving and combining task-related data. Additionally, the dlPFC is crucial for coordinating high-order

 DOI: 10.25077/josi.v24.n2.p305-323.2025

control procedures and multiple task rules, both of which are necessary for multitasking performance [24], [25]. Interference and conflict between competing subtasks may be handled simultaneously by the ventrolateral prefrontal cortex (vlPFC), which regulates semantic and contextual information [26] and aids in response inhibition when cognitive control is high [27]. In complex multitasking settings, such as MATB, these regions are likely to work together under the coordination of dlPFC for executive control across tasks and vlPFC for conflict monitoring. A key inquiry, then, is whether increased difficulty in multitasking activates PFC broadly or selectively in subregions such as dlPFC. Together, this evidence points to the functional activation within the PFC and its dynamic involvement in responding to various cognitive demands.

Given that the PFC is the region that processes cognitive load, it is therefore technically possible to produce an image of the cognitive load changing using neuroimaging techniques. The physiological basis of neuroimaging depends on the brain's functional changes in response to the cognitive load captured by various sensors [28]. For example, it is evident that cognitively active regions in the brain are associated with electrical impulse changes at the cellular level [29]. Because of this, it is possible to use EEG to record changes in brain electrical activity, which can reveal variations in cognitive load and, consequently, multitasking behavior [30]. The same idea holds true for fMRI and fNIRS, particularly when it comes to using their capacity to record variations in blood oxygenation to signify shifts in cognitive load [31], [32]. In conclusion, higher blood oxygenation in the PFC indicates higher neural activation, which may be linked to higher cognitive load, such as when multitasking.

Although fMRI's high spatial resolution and ability to capture deep brain regions make it the gold standard for neuroimaging [33], there are a number of disadvantages. Because fMRI technically requires participants to refrain from making even small movements of their bodies, the types of tasks that can be completed are restricted [30]. Similarly, EEG has good temporal resolution and can capture rapid changes in neural activity [34], [35]. It can't be used for tasks that require quick body movements or natural interactions, though, because it is extremely sensitive to motion artifacts and eye blinks [36]. Alternatively, fNIRS provides a low-cost, portable, motion-insensitive measurement method [37]. These characteristics give fNIRS a technical advantage over fMRI and EEG in that it can be used for a variety of dynamic multitasking scenarios, including coordinated attention, motor response, and performance monitoring. Therefore, fNIRS offers the best possible balance between ecological validity, portability, and spatial resolution, enabling researchers to show cortical changes during multitasking in authentic environments.

The main working principle of fNIRS is the utilization of near infrared to reach cortical brain areas [38]. The penetrated light captures changes in blood concentration in the brain containing both oxygen (HbO) and less oxygen (HbR), using the ability of hemoglobin in absorbing lights in the range of near infrared spectrum. Changes in oxygen concentration can subsequently indicate neural activation or deactivation based on neurovascular coupling mechanisms [39]. When near-infrared light is emitted into the brain, it is absorbed and scattered by the tissue. Hemoglobin absorbs this light differently depending on its oxygenation state. The changes in light intensity are converted into hemoglobin concentration using the modified Beer-Lambert law, which accounts for the path length and absorption characteristics of the tissue [12]. fNIRS shares several methodological and conceptual similarities with fMRI. Both fNIRS and fMRI measure changes in cerebral blood oxygenation related to neural activity. fNIRS detects changes in oxygenated and deoxygenated hemoglobin using near-infrared light, while fMRI measures blood-oxygen-level-dependent (BOLD) signals [40]. Furthermore, studies have shown a good spatial correspondence between fNIRS and fMRI, particularly in regions of the cortex adjacent to the scalp. For example, fNIRS can overlap up to 68% of fMRI-detected activity in group analyses [40]. In addition, both modalities exhibit high temporal correlation in detecting brain responses, with fNIRS showing moderate-to-strong temporal correlation with fMRI signals [41].

In addition, with these features, fNIRS emerges as a promising technique to provide neurofeedback [42]. Specifically, changes in cortical oxygenation may be presented as a form of real-time feedback indicating performance [43]. Since fNIRS can target PFC regions involved in executive control, attention, and emotion regulation, training these functions is technically possible through guided practice [42]. This is relevant for multitasking, since neurofeedback based on PFC activation could allow individuals to practice their executive control during high cognitive load. In the practical domain, the usefulness of neurofeedback can include strengthened attentional control, reduced performance errors, and improved resilience to mental fatigue during multitasking conditions. If self-regulation of brain activation can be reinforced, neurofeedback may improve immediate task performance and long-term adaptability in high-demand work environments. The portability and motion tolerance of fNIRS further increase its suitability for such training in naturalistic settings. Recent advances in wearable and portable fNIRS systems further increase the feasibility of applying neurofeedback outside controlled laboratory environments, thereby enhancing ecological validity [44].

Although numerous studies have investigated the phenomenon of multitasking, most rely on behavioral data or common neuroimaging methods such as fMRI and EEG [45], [46], which are limited by high cost and sensitivity to motion. However, a few fNIRS studies have employed complex, aviation-derived multitasking paradigms like the MATB to systematically compare cortical activation between precisely calibrated levels of task difficulty. Consequently, the specific patterns of PFC recruitment and their sensitivity to gradual increases in multitasking load remain unclear. Therefore, this study employs fNIRS to investigate how multitasking demands modulate PFC activation, thereby addressing a gap in ecologically valid neuroimaging evidence and showcasing fNIRS as a viable tool for real-world cognitive load assessment.

METHODS

Experiment task and design

This study employed a repeated-measures design, with the independent variable manipulated by exposing participants to two levels of multitasking demand (low and high). The dependent measures consisted of fNIRS-derived brain activation data recorded across channels 1 to 8. To generate tasks for each demand level and ensure randomized configurations, a MATB was programmed. The possible sequence orders were generated by the program, resulting in six counterbalancing combinations to avoid order effect: ABAB, AABB, ABBA, BABA, BBAA, and BAAB (where 'A' represented low demand and 'B' represented high demand). Participants were asked to roll a die before the experiment session to determine the sequence of their task.

Participants

Participants in the current study were chosen from among staff members and students. The experiment involved 30 participants (M = 32.04 years, SD = 4.74), including 7 university employees and 23 students. The majority of participants (n = 28) were men. Two participants had an undergraduate degree, fourteen had a master's degree, and fourteen had a doctorate or were working toward one. Every participant had normal or corrected-to-normal vision and no history of neurological or psychiatric conditions. G*Power 3.1 power analysis. With parameters of medium effect size ($d = 0.50$), $\alpha = 0.05$, and power $(1-\beta) = 0.80$, 9.7 [47] showed that a total sample size of 30 participants was sufficient to obtain sufficient statistical power.

Before the experiment session began, participants signed an informed consent. Adhering to university ethical policies, participants were briefed that their anonymity and confidentiality were assured, and the data were solely used for academic purposes. Monetary compensation was given to participants after completing the whole experiment session. Ethical approval was obtained from the faculty's internal review board. It is important to note

 DOI: 10.25077/josi.v24.n2.p305-323.2025

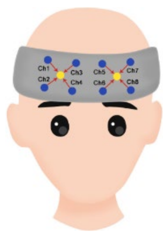


Figure 1 illustrates the layout of fNIRS sensors on the participants' PFC areas

that the generalizability of the findings to a broader population might be limited due to the homogenous nature of the participants, which resulted from convenience sampling from a single academic institution.

Instruments

The fNIRS Device

The Artinis OctaMon (Artinis Medical Systems, Elst, Netherlands) was utilized to capture changes in blood oxygenation concentrations in the PFC. The sensors consist of eight channels and work at the sampling rate of 10 Hz. Two different wavelengths, i.e., 760 Hz and 850 nm, to capture deoxygenated and oxygenated hemoglobin, respectively. The device has four light emitters and one receiver in each hemisphere, with a distance separating each pair of emitter-receivers of 35 mm. When putting the sensors on the participants' foreheads, they were centered at Fpz and aligned exactly above the eyebrows. This positioning extends laterally to Fp1 and Fp2 to cover bilateral prefrontal areas across BA10 and BA45 [48], [49]. Figure 1 illustrates the positioning of the sensors.

Multi-Attribute Task Battery (MATB)

In this experiment, MATB served as the main platform to simulate multitasking conditions and evaluate multitasking performance. The MATB was developed by NASA [50] and consists of four subtasks that simulate the demands of multitasking conditions. System Monitoring (SYSMON), the first subtask, required quick responses to rapid changes in system indicators. The second subtask, Tracking (TRACK), simulated a target that continuously moves and must be maintained inside certain boundaries. The third subtask, Resource Management (RESMAN), simulated virtual fuel consumption and failures that must be managed over time to ensure the system is not running out of fuel. The fourth subtask, Communication (COMM), simulates verbal communication between air traffic control and pilots.

In this study, the overall task demand was adjusted by manipulating the difficulty and event rate of each MATB subtask. For the low-demand condition, the TRACK component was kept at the 'default-low' level, the SYSMON display generated only two deviations per minute, and the RESMAN panel triggered a single pump failure per minute. In the high-demand condition, the TRACK component was raised to the 'default-medium' setting, the SYSMON task produced up to 30 deviations per minute, and the RESMAN task generated one to two pump failures per minute, each lasting around 15 seconds. The COMM subtask was deliberately omitted to avoid excessive sensory load and potential interference between modalities. This decision was also informed by the characteristics of our sample, which consisted of non-expert participants rather than highly trained multitaskers such as pilots. Previous studies indicate that auditory tasks may cause confusion and reduce motivation in non-expert participants [51]

To check the success of demand manipulation, scores for each subtask and the total scores of MATB performance were calculated using methods proposed by Kim and Yang [52]. For the TRACK subtask, performance scores were defined as the average distance of the target from the center participants can maintain throughout the session, with scores decreasing if the target fails to be maintained near the center. Performance scores in the SYSMON subtask were calculated as a ratio of accuracy to the number of stimuli; scores dropped if participants frequently failed to correctly identify the stimuli. The success of keeping fuel within a specific range was used to calculate scores for the RESMAN; greater deviations from this range were indicative of subpar performance. Negative values received a score of zero and were regarded as a complete performance failure. In order to enable direct comparison between participants and conditions, all subtask scores were normalized to a 0–1 scale. After that, scores were evaluated using a 2 (easy vs. difficult) × 4 within-subject ANOVA with Bonferroni correction (TRACK, RESMAN, SYSMON, TOTAL).

Data Collection Procedure

A 10-minute training session was required of the participants prior to the actual session. Participants in this training session practiced and became acquainted with MATB tasks under both high and low demand. During this session, the Instantaneous Self-Assessment (ISA) and NASA Task Load Index (NASA-TLX) scales were also presented. As directed, the actual experiment session started. In order to measure the baseline and resting conditions, participants were told to sit comfortably and stare at the screen for a minute. This baseline measurement technique was chosen because it prevents participants from inadvertently causing mind-wandering or any unintentional brain activation due to extended periods of staring while allowing enough time for brain oxygenation to return to resting levels [53]. The five-minute first block of the session was followed by another baseline of one minute. This order was applicable to the second, third, and fourth blocks. To avoid the aforementioned order effect, a digital die was used to randomly determine the task difficulty order. When the experiment session was over, participants who finished all four blocks were paid.

Data Preprocessing and Analysis

The HomEr program [54] was used to preprocess data using standard pipelines as recommended by earlier research. Initially, the pipeline hmrR_Intensity2OD was used to convert the raw light intensity data to optical density (OD). Motion artifacts were identified using the channel-by-channel method with parameters of 0.5 threshold for standard deviation, 3.0 for amplitude, 10.0 for the motion window, and 5.0 for the pre/post window in order to identify data impacted by excessive movements (pipeline: hmrR_MotionArtifactByChannel). The first components (nSV = 1.0) were eliminated using principal component analysis (PCA) correction (pipeline: hmrR_MotionCorrectPCA) in order to eliminate motion-related data [55]. After that, the optical density data were filtered using a band-pass filter (pipeline: hmrR_BandpassFilt) with a range of 0.001 to 0.1 Hz to remove high-frequency noise and slow drifts. Using the Modified Beer-Lambert Law (MBLL) and a path length factor of 6.0 for both wavelengths, the optical density data were then transformed into HbO and HbR concentration data (pipeline: hmrR_OD2Conc). Lastly, each block's hemodynamic responses were averaged in relation to the stimulus onset, with the main data window being 300 seconds after the onset and the baseline being 5 seconds prior to the onset (pipeline: hmrR_BlockAvg). This technique yields average HbO and HbR concentrations. Our preprocessing pipelines' parameters and thresholds were developed through iterative testing during the initial analysis of pilot data, striking a balance between significant artifact detection and valid data retention. This process adhered to standard fNIRS preprocessing procedures.

HbO concentration data between high- and low-demand multitasking conditions across channels were compared using paired-sample t-tests to evaluate differences across conditions. Because every participant finished both high- and low-demand tasks, direct comparisons were made possible. The multitasking effects were analyzed at the channel

 DOI: 10.25077/josi.v24.n2.p305-323.2025

level because the test was run independently for each channel. Version 4.3 of the R program. The primary statistical tool used for data analysis was 3 [56]. Bonferroni correction was used to manage errors arising from multiple t-test comparisons.

RESULT AND DISCUSSION

Manipulation check

Task-demand manipulation was checked by comparing scores from three measurements: MATB performance scores, NASA-TLX subjective workload ratings, and ISA scores. Each measure was compared between the easy and difficult multitasking conditions.

A significant interaction was found between difficulty level and MATB task type on performance scores, $F(3, 87) = 4.84$, $p = .004$, $\eta^2 g = .02$. Paired-sample t-tests with Bonferroni adjustment showed that performance under high demand was significantly lower than under low demand for the system-monitoring task ($p < .001$), tracking task ($p < .001$), and for the composite overall score ($p < .001$). In contrast, no significant difference was observed for the resource-management task ($p = .292$).

A statistically significant interaction also emerged between demand level and NASA-TLX dimensions in participants' subjective workload ratings ($F(2.96, 85.82) = 5.32$, $p = 0.002$, $\eta^2 g = 0.02$). Pairwise comparisons indicated that subjective workload scores were significantly higher in the difficult condition across all individual NASA-TLX dimensions as well as the overall score, with all $p < 0.001$. The ISA was included as a complementary measure to cross-validate the NASA-TLX results. A paired-samples t-test showed a statistically significant difference in ISA scores between the low-demand ($M = 2.343$, $SD = 0.626$) and high-demand ($M = 3.447$, $SD = 0.723$) conditions ($t(29) = -8.258$, $p < 0.001$).

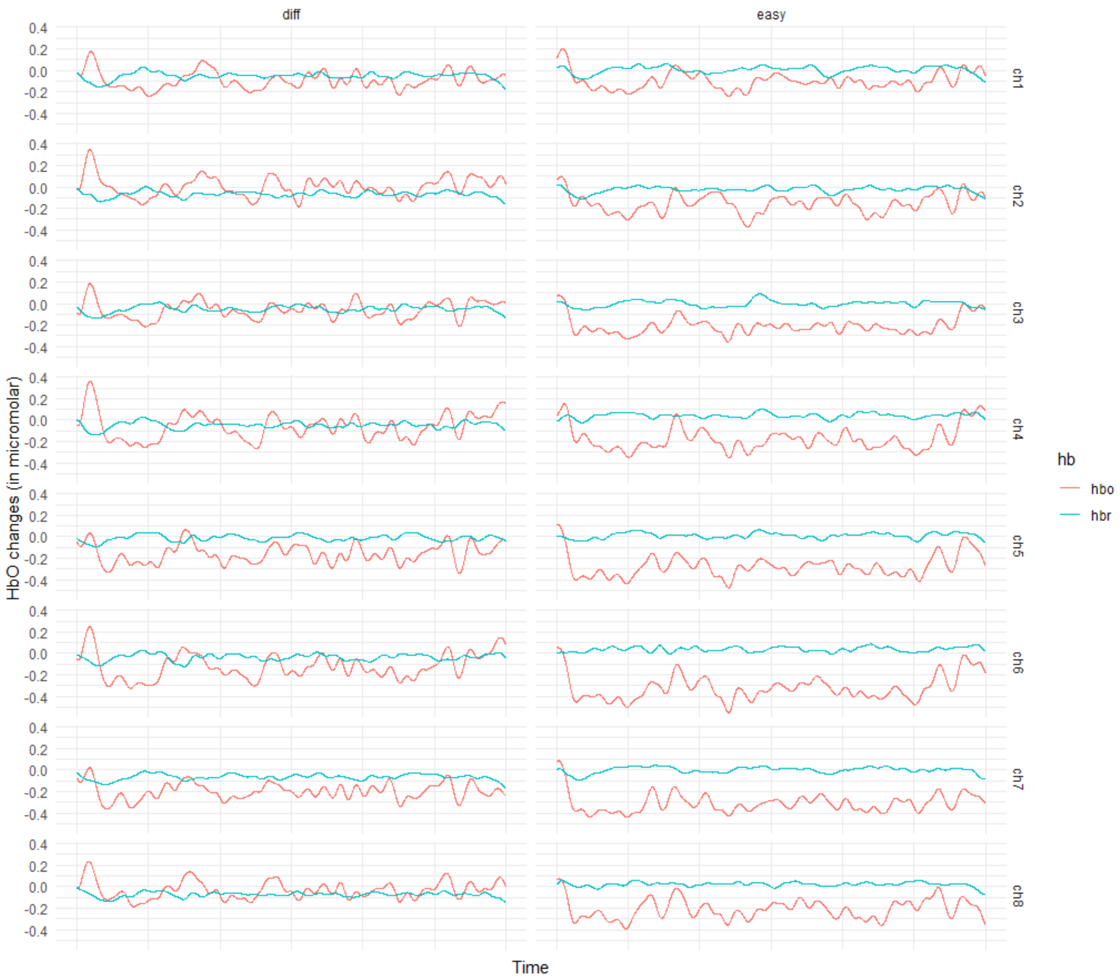
Taken together, the significant differences observed in both performance scores and subjective workload measures indicate that the manipulation of task demand was successful, demonstrating that the easy and difficult conditions elicited meaningfully different levels of cognitive load as experienced and performed by the participants.

Haemoglobin Changes

We focused our analysis on HbO changes due to its sensitivity to task-related brain activation. In fNIRS research, it is more common to use HbO as a reliable signal of neurovascular response since it is typically found in cerebral blood flow during increased cognitive load [39], [57]. Previous studies have demonstrated that, compared to HbR, HbO is more activated during task-evoked cortical activation [58].

HbO values are expressed in relation to a pre-stimulus baseline, which is important to consider when interpreting our data. As a result, in both scenarios, values might seem negative. As a result, a less negative value denotes a relative increase in brain activation since it shows a smaller drop in HbO values compared to its baseline. According to this explanation, there would be more activation in the high-demand multitasking condition than in the low-demand condition. Eight channels of hemodynamic response data are displayed in Figure 2 under both multitasking scenarios. HbO signals during the high-demand multitasking condition exhibit noticeable fluctuations in the left panel of Figure 2, especially in the early stages of task performance. Conversely, there are comparatively fewer channel fluctuations in HbR signals. In high-demand situations, when more cognitive resources must be allocated, these patterns show increased brain activation [14], [15]. On the other hand, during low cognitive load, HbO signals tend to decrease in the right panel of Figure 2, indicating a lower hemodynamic response and brain activation.

Table 1 shows a summary statistical analysis of mean HbO changes across all channels for both multitasking conditions, further supporting the initial observations. HbO values in all channels were consistently more negative



HbO and HbR activity across fNIRS channels during high- and low-demand multitasking.

Table 1. Summary of statistical analysis of mean HbO data across all channels for low- and high-demand multitasking conditions

Channel	**Level**	**Mean (µM)**	**SD**	***p-value***
ch1	difficult	-0.092	0.08	$p < .001$
	easy	-0.1	0.08	
ch2	difficult	0.003	0.092	$p < .001$
	easy	-0.154	0.087	
ch3	difficult	-0.058	0.08	$p < .001$
	easy	-0.209	0.079	
ch4	difficult	-0.059	0.122	$p < .001$
	easy	-0.174	0.112	
ch5	difficult	-0.159	0.087	$p < .001$
	easy	-0.275	0.101	
ch6	difficult	-0.121	0.119	$p < .001$
	easy	-0.321	0.116	
ch7	difficult	-0.199	0.075	$p < .001$
	easy	-0.311	0.086	
ch8	difficult	-0.033	0.081	$p < .001$
	easy	-0.21	0.091	

 DOI: 10.25077/josi.v24.n2.p305-323.2025

in the low-demand condition ($p < .001$). For instance, in Channel 1 (ch1), Hb shows a decrease from −0.092 μM in the high-demand condition to −0.100 μM in the low-demand condition. This pattern was also visible in Channel 6 (ch6), from −0.121 μM to −0.321 μM. The most visible patterns of HbO decline were observed in Channels 6 and 7, where HbO decrease in the low-demand condition exceeded the high-demand condition by more than 0.15–0.20 μM.

Our results show that the PFC region is activated by multitasking performance, with variations based on demand levels. Higher executive resources are needed for high-demand multitasking performance, which raises the hemodynamic response [59], [60]. A comparatively slight drop in HbO when compared to the low-demand condition was indicative of this increase in our data. This pattern should be interpreted as an attenuated decline rather than an absolute increase over the baseline. Through the neurovascular coupling mechanism, increased cerebral activity raises the HbO concentration in the standard hemodynamic response functions [61]. On the other hand, higher negative HbO values under low-demand multitasking circumstances may indicate a lower hemodynamic response due to a decreased neurovascular response [62].

Overall, our results are in line with earlier fNIRS research, which found that increased cognitive load during multitasking performance led to an increased HbO response [63]. According to earlier studies, an increase in demand during a cognitive task also causes an increase in HbO responses. For instance, PFC activation is more pronounced during dual-task walking than during single-task walking, suggesting that higher cognitive demands are needed during dual-task walking [57]. Another study on dual-task walking revealed a similar pattern, with participants exhibiting higher HbO in PFC regions during higher cognitive load (2-back task) compared to lower cognitive load (1-back task). The idea that increased cognitive load causes an elevated HbO response, which indicates higher cortical activation, is further supported by this data [64].

Multitasking increases cognitive load, which raises cerebral oxygen consumption. In order to meet the increased demands during multitasking, oxygen is redistributed among different parts of the brain [65]. Significant oxygen consumption during high cognitive load is apparent in a study involving multiple tasks carried out under varying oxygen levels, further supporting the link between oxygen intake and cognitive load [66]. In order to manage increased load during multitasking performance, this redistribution strategy was also demonstrated by a decrease in the number of active brain voxels in specific brain regions, such as the visual cortex [67]. This pattern, which reflects the functional specialization of brain regions, may account for the uneven increases in brain activation seen in our study. Certain brain regions may exhibit decreased activation as a result of resource reallocation, while other regions may exhibit increased activation under conditions of increased demand.

Brain Activation

Visualization of brain activation was produced using AtlasViewer [68], by projecting fNIRS data onto an anatomical cortical surface. The process started by positioning optodes according to Montreal Neurological Institute (MNI) atlas space using cranial markings. Light propagation is simulated via cranial tissues utilizing Monte Carlo-derived sensitivity profiles, resulting in a forward model that determines the contribution of each cortical site to the observed signals. These sensitivity maps are used in an inverse reconstruction procedure, whereby the observed HbO signals are mathematically redistributed across the cortical surface. The resulting activation maps therefore represent anatomically guided estimates of cortical activity, rather than direct channel measurements alone.

Optode placement and anatomical registration followed the procedures described by Aasted et al. [68]. First, we used the 2D optode layout defined in the *.sd* file generated in Homer3, which specifies the manufacturer-provided source–detector positions in two-dimensional scalp coordinates. The inter-optode distance was set to

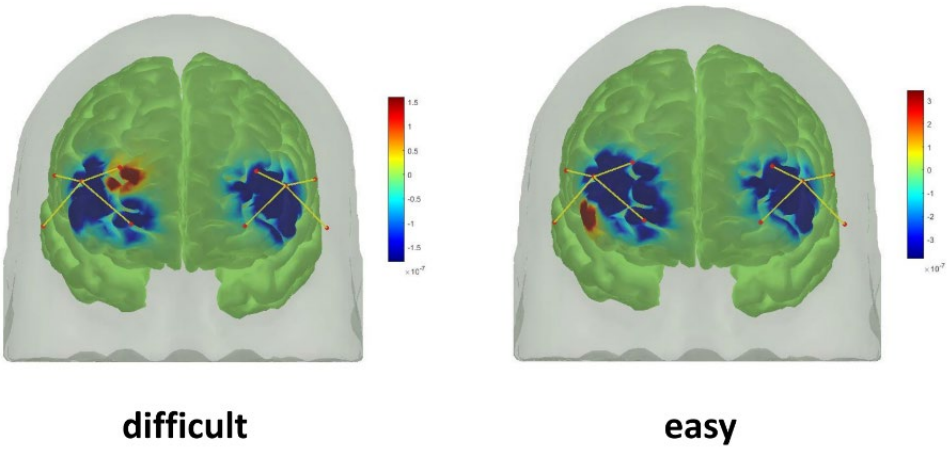


Figure 3. Cortical activation reconstructed from HbO data under high- (left) and low-demand (right) multitasking conditions.

35 mm to match the real sensors, which use a 35-mm separation. The optode positions were subsequently registered to the international 10–5 system using the Colin27 template atlas within AtlasViewer (default anatomical model). Each optode was aligned to its corresponding 10–5 landmark as follows: Optode 1 at F6, Optode 2 at F8, Optode 3 at AF4, Optode 4 at Fp2, Optode 5 at AF3, Optode 6 at Fp1, Optode 7 at F5, and Optode 8 at F7. Using this mapping, AtlasViewer performed the forward-model–based alignment of the optode array to the scalp surface of the Colin27 head model.

After the registration procedure, we mapped each channel onto the cortical surface using the AtlasViewer projection method, producing MNI coordinates for every channel. To aid in functional interpretation, Brodmann area (BA) labels matching the projected cortical areas were subsequently retrieved. The projection results indicated that Channels 1 and 2 were associated with BA 45 in the right hemisphere, while Channels 7 and 8 were associated with BA 45 in the left hemisphere. In addition, Channels 3 and 4 corresponded to BA 10 in the right hemisphere, while Channels 5 and 6 corresponded to BA 10 in the left hemisphere.

In our HbO projections, the two multitasking conditions show different response patterns. As shown in Figure 3, in difficult multitasking conditions, increased HbO concentration is visible in the right areas of the PFC (red/yellow), with higher increases concentrated over the superior and middle frontal gyri. The activation tends to concentrate within the superior frontal gyrus, with limited extension toward the adjacent dorsolateral cortical areas. Similarly, during easy, low-demand multitasking conditions, the concentration of increased HbO is also visible in the right PFC. However, the location of concentration is in lower areas of the PFC, particularly around the middle and inferior frontal gyrus. Relative to the difficult conditions, the HbO increase is both more spatially restricted and less intense.

Our findings indicate that the right PFC was recruited during multitasking performance, consistent with previous studies suggesting that this region is associated with the management of higher-order goals and sub-goals [69], [70], [71]. As part of the dorsolateral prefrontal network, both the middle and superior frontal gyri have been linked to sustained attention under complex conditions and the allocation of resources across concurrent tasks [72], [73]. Therefore, under the challenging multitasking condition, the HbO increase seen in our study indicates a stronger neurovascular response linked to higher oxygen consumption. Asymmetric prefrontal involvement is further highlighted by the lateralization of activation, suggesting that the right hemisphere may play a major role in supporting executive functions during periods of increased cognitive load. These results support the idea that the

 DOI: 10.25077/josi.v24.n2.p305-323.2025

right PFC is a crucial area for multitasking performance and are in line with resource theories of attention, which contend that more difficult tasks necessitate greater cortical resource allocation [69], [70].

Prior research employing the tDCS paradigm has demonstrated that multitasking performance is also significantly influenced by the left PFC [70]. However, variations in task characteristics, temporal focus, and the neuroimaging modality used are probably responsible for the right-lateralized activation found in our study. Symbolic or rule-based tasks that depend on the verbal-analytic control processes of the left dlPFC are commonly used in tDCS paradigms. However, the MATB in this study required rapid coordination across multiple information streams, attentional switching, and visuospatial monitoring. The right dlPFC is more strongly linked to these functions, particularly those pertaining to interference resolution and sustained attention. Furthermore, our fNIRS approach captured neurovascular responses in real time while the task was being performed. However, research employing tDCS, such as that conducted by Hsu et al. [70] focused on behavioral alterations seen about an hour after stimulation, which are more indicative of learning or strategy consolidation than of immediate cognitive control.

Numerous factors pertaining to the various functional roles and underlying neural mechanisms of these regions are likely responsible for the observed right-lateralization of PFC activation during multitasking performance in this study. The right PFC regions, especially the dlPFC, play important roles in concurrent task management and cognitive control. This region is essential for storing and modifying data while multitasking [74]. Additionally, improved task performance has been associated with increased fronto-visual network connectivity, and the right dlPFC facilitates visual selective attention [75]. The right PFC is crucial for managing attention and task-switching during multitasking because it encodes task contexts, makes task preparation easier, regulates attention, and increases efficiency. The observed right-lateralized activation in the context of MATB is consistent with established evidence that the right dlPFC supports cognitive control and the coordination of multiple concurrent subtasks [24], [25], even though the current experimental design prevents us from identifying the precise mechanism underlying this activation. We speculate that this pattern may represent tasks that are typically associated with the right dlPFC, such as maintaining task-relevant context across subtasks and supporting attentional and preparatory control processes that allow for efficient transitions between competing task demands. This theory suggests that the observed stronger right PFC activation during MATB performance may be due to a greater need for flexible attention regulation and goal management when participants participate in multiple simultaneous task components.

Research Implications

The findings of our study have consequences for both theory and practice. From a cognitive perspective, the resource models of attention are further reinforced by the notion that complex multitasking requires a greater distribution of limited cognitive resources [76], [77]. Changes in HbO across channels show that cortical activation patterns reflect this resource allocation. Specifically, the activation patterns of the right dlPFC under difficult and easy multitasking scenarios are consistent with executive control theories, emphasizing its role in preserving working memory representations, managing interference, and maintaining effortful attention during multitasking performance.

From a practical perspective, our finding that the right dlPFC is sensitive to cognitive load presents a promising neural target for fNIRS-based monitoring. By focusing on this area, real-time overload detection may be made possible and training for occupations like pilots, air traffic controllers, and surgeons—where continuous multitasking is crucial for safety—may be supported. In real-world operational contexts such as driving, aviation, or other high-stakes decision-making environments, adaptive systems that detect cognitive overload and modify task demands in real-time could be informed by monitoring PFC activation [78], [79]. Beyond these specific applications, fNIRS's portability and ecological validity make it especially suitable for monitoring multitasking in real-world scenarios where traditional neuroimaging methods, such as fMRI, are impractical. When taken as a whole, our findings demonstrate that fNIRS is both theoretically useful for testing cognitive models of multitasking and practically valuable for the development of neuroadaptive technologies aimed at enhancing human performance and safety.

Limitations and Future Directions

This study also has several limitations. First, we only recorded fNIRS over the PFC, even though multitasking involves a wider network, including parietal, temporal, and subcortical areas [67]. Future studies could expand optode placement or combine fNIRS with fMRI or EEG to capture this broader interconnection. Second, we relied on atlas-based registration instead of individual MRI scans, which limit the precision of spatial localization. Incorporating participants' own anatomical data would allow more precise mapping of functional activity.

Third, the multitasking paradigm was limited to a specific experimental setting with a relatively homogeneous participant sample, reducing the generalizability of the findings to diverse populations or real-world contexts. Future research should therefore test a wider range of multitasking paradigms, including more ecologically valid or workplace-relevant tasks, and recruit samples with broader demographic and cognitive characteristics. Fourth, fNIRS data are inherently vulnerable to extracerebral confounds, such as scalp blood flow [80] and motion artifacts [81], which may partially influence measured hemodynamic responses. Advanced signal processing techniques, short-separation channels, or multimodal recordings could help to dissociate neural signals from systemic noise in subsequent investigations.

Third, the results are less applicable to larger populations or real-world situations because our multitasking paradigm was tested in a controlled laboratory environment with a homogeneous sample. More varied multitasking tasks—ideally ones that mimic actual work environments—as well as participants with a wider range of cognitive and demographic profiles should be included in future studies. Fourth, the recorded hemodynamic signal in fNIRS data can be impacted by confounds outside the cortex, such as movement-related artifacts and scalp blood flow. By employing more sophisticated preprocessing, adding short-separation channels, or combining fNIRS with other modalities to more effectively separate neural activity from systemic noise, future research could reduce these problems.

Another drawback is that fNIRS's capacity to resolve the quick temporal dynamics of the brain processes involved in multitasking is limited because it mainly records slow hemodynamic responses. By connecting vascular responses to fast neural oscillations, fNIRS combined with electrophysiological techniques like EEG may provide a more comprehensive picture. In general, broader cortical coverage, multimodal imaging, and a greater variety of task paradigms and participant samples would be beneficial for future research in order to confirm, improve, and expand the current findings.

CONCLUSION

This study used functional near-infrared spectroscopy (fNIRS) to investigate how multitasking demands affect prefrontal cortex (PFC) activation. Time-course analyses and reconstructed activation maps support our findings, which show that increasing multitasking difficulty selectively increases activation in the right dorsolateral prefrontal cortex (dlPFC). This pattern highlights the right PFC as a crucial area for handling complex cognitive demands and supports oxygenated hemoglobin (HbO) as a trustworthy indicator of neurovascular coupling. These results suggest that right-dlPFC activation increases with multitasking load, providing resource-based theories of attention with ecologically sound support. From an applied perspective, the study highlights fNIRS as a promising tool for monitoring cortical workload in real-world contexts like human-machine interaction, adaptive training, and performance evaluation. Future studies should expand cortical coverage to include parietal regions and integrate

 DOI: 10.25077/josi.v24.n2.p305-323.2025

fNIRS with complementary neuroimaging methods to gain a better understanding of the relationship between dlPFC hemodynamic responses and rapid neural processes involved in task switching and cognitive control.

ACKNOWLEDGMENTS

We thank the JOSI Editor and Reviewers for their time, expertise, and constructive feedback, which greatly improved the quality of this article.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest that could have influenced the work presented in this manuscript.

FUNDING

The author received no financial support for the research, authorship, and/or publication of this article.

DATA AVAILABILITY STATEMENT

Due to privacy restrictions, the data are not publicly available. De-identified data may be available from the corresponding author upon reasonable request.

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