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Validation of a mobile fNIRS device for measuring working memory load in the prefrontal cortex

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ABSTRACT

Functional near-infrared spectroscopy (fNIRS) is a neuroimaging technique that measures cortical blood flow to infer neural activation. Traditionally limited to laboratory settings due to high costs and complex operation, recent advancements have introduced mobile fNIRS devices, significantly broadening the scope of potential research participants. This study validates the use of the Mendi, a two-channel mobile fNIRS system, for measuring prefrontal oxyhemoglobin concentration changes during an n-back task. We manipulated task difficulty through different n-back levels (one-back versus three-back), revealing increased oxyhemoglobin concentrations in the prefrontal cortex during the more demanding three-back task compared to the one-back task. This finding demonstrates the Mendi's ability to distinguish between low and high cognitive task loads. Behavioural data, showing a decrease in accuracy under high load conditions, further corroborates these neuroimaging findings. Our study validates the Mendi mobile fNIRS system as an effective tool for assessing working memory load and underscores its potential in enhancing neuroscientific research accessibility. The user-friendly and cost-effective nature of mobile fNIRS systems like the Mendi opens up neuroscientific research to a diverse set of participants, enabling the investigation of neural processes in real-world environments across a variety of demographic groups.

1. Introduction

Functional near-infrared spectroscopy (fNIRS), first introduced by Jöbsis (1977), uses light in the near-infrared range (700–900 nm) to penetrate biological tissues, such as the scalp and skull and reach the cerebral cortex. Near-infrared light can detect changes in oxygenated (HbO) and deoxygenated (HbR) hemoglobin concentrations due to their differential absorption properties in this wavelength range (Delpy and Cope, 1997). As neurons increase firing rates, their higher metabolic needs demand more oxygen. Consequently, the surrounding blood vessels show a rise in oxygen-rich blood and a decrease in oxygen-depleted blood. Near-infrared spectroscopy can indirectly measure neural activity by measuring these changes (Delpy and Cope, 1997). Wearable fNIRS devices typically consist of light-emitting diodes (LEDs) and photodetectors placed on the scalp in a predefined arrangement (Pinti et al., 2018). The LEDs emit near-infrared light that penetrates the scalp and skull and is partially absorbed by the underlying brain tissue. The remaining light is scattered back to the surface and detected by the photodetectors. Researchers can infer neural activity resulting from task engagement by analyzing the detected light and determining changes in oxygenation levels (Jöbsis, 1977). fNIRS is a promising technology adept at effectively investigating regions of the human brain, including the motor, sensory, visual, and prefrontal cortices (Ferrari and Quaresima, 2012; Leff et al., 2011; Pinti et al., 2020).

Mobile functional near-infrared spectroscopy (fNIRS) systems have gained popularity in recent years due to their portability, flexibility, and non-invasiveness (Ferrari and Quaresima, 2012; Kopton and Kenning, 2014; Quaresima and Ferrari, 2019; Pinti et al., 2020). As a non-invasive method with a relatively high temporal resolution that is also cost-effective, mobile fNIRS presents a versatile alternative to traditional neuroimaging techniques, such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET), electroencephalography (EEG) and conventional cap-mounted fNIRS systems (Scholkmann et al., 2014). These advantages enable researchers to examine brain function in more naturalistic and real-world settings and with a broader range of participants, including infants and individuals who may be unable to use larger systems due to physical constraints or claustrophobia (Quaresima et al., 2012). This capacity significantly advances

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neuroscience by offering a more accessible, flexible, and efficient approach to studying brain processes. However, ensuring rigorous validation of such devices is essential for confirming that the systems measure what they are supposed to, increasing the accuracy of data interpretation and generating reliable results. By validating mobile fNIRS technology, researchers can strengthen the credibility of their findings and enhance the overall understanding of cognitive processes across diverse populations and settings.

As with adopting any new research technology, thorough validation and validity evidence are needed to ensure reliable and accurate measurements while demonstrating its ability to fulfill its intended function effectively. For example, the n-back task, one of the most widely used working memory tasks in research (Owen et al., 2005), is a standard paradigm for mearing high and low cognitive workloads. During this task, participants are presented with a sequence of letters and instructed to identify repeating letters with either low load (one-back) or higher loads (two or three-back). The sensitivity of fNIRS devices in detecting differences in HbO changes in the prefrontal cortex has been previously evaluated using the n-back task (Ayaz et al., 2012; Fishburn et al., 2014; Herff et al., 2014; Hoshi et al., 2003; Li et al., 2010; Mandrick et al., 2016; Meidenbauer et al., 2021; Pinti et al., 2018; Saikia et al., 2021). For example, Ayaz et al. (2012) utilized fNIRS to measure HbO changes in the dorsolateral prefrontal cortex, an essential region involved in working memory, during the n-back task performance. They found consistent differences in oxygenation related to task load. Saikia et al. (2021) further supported this finding, showing that portable fNIRS accurately detected significant differences in HbO levels between low and high n-back conditions in the prefrontal cortex. In turn, the research conducted by Saikia et al. (2021) and others (Ayaz et al., 2012; Herff et al., 2014; Hoshi et al., 2003; Li et al., 2010; Mandrick et al., 2016; Meidenbauer et al., 2021; Pinti et al., 2018) demonstrates that the n-back task is an effective and reliable paradigm for validating fNIRS devices' ability to measure and discern prefrontal cortical activity during varying task loads.

Our research introduces a novel dimension to this established domain by employing the Mendi mobile fNIRS device, a leap from the previously used multi-channel WearLight system (Saikia et al., 2021). The Mendi's design is a sleek, two-channel headband, offering a stark contrast to the more elaborate full-cap setup of the WearLight, which necessitates four sources, eight detectors, and additional equipment like a control box and battery, often requiring a backpack or similar apparatus for the participant. In contrast, the Mendi simplifies the setup to just the headband. These innovations are not just a matter of improved aesthetics; they crucially expand accessibility, particularly benefiting populations that may find the full-cap system restrictive, such as children, the elderly, or individuals with sensory processing sensitivities. By reducing barriers to participation, the Mendi device opens the door to broader inclusivity in research populations, thereby enhancing the ecological validity of cognitive load studies.

The primary goal of our research was to substantiate the Mendi as a reliable tool for differentiating prefrontal cortical activity under varying cognitive loads. Participants engaged in the n-back task, a well-established paradigm for assessing working memory (Owen et al., 2005), while we recorded fNIRS data using the Mendi system. Previous studies have demonstrated the efficacy of fNIRS in detecting changes in HbO concentrations in the prefrontal cortex during such tasks (Ayaz et al., 2012; Fishburn et al., 2014; Herff et al., 2014; Saikia et al., 2021). Our hypothesis posited that the Mendi would reliably detect greater HbO concentration changes in the higher load (three-back) condition compared to the lower load (one-back), alongside a corresponding decrease in task accuracy due to increased cognitive demands. If these hypotheses are confirmed, it will validate Mendi's utility in lab-based cognitive research, with implications for its use in more varied and naturalistic settings, potentially transforming cognitive neuroscience research beyond traditional laboratory confines.

2. Methods

2.1. Participants

Thirty-five students from the University of Victoria participated in this study (M_{age} = 22 [21, 23]; 27 female, eight left-handed). We computed a sample size power analysis assuming an effect size of 1.14 for a dependent sample *t*-test between prefrontal HbO concentrations (Ayaz et al., 2012), a significance level of 0.05, and a power of 0.99, revealing a prospective sample size of 18 participants. To avoid conducting underpowered research, our lab follows a protocol where we continue to collect data until we have 30 participants. As such, five of the 35 participants were removed from the analysis because one device had a battery defect and stopped collecting data midway through the experiment. Our final sample demographics are as follows (M_{age} = 22 [21, 23]; 23 female, seven left-handed). All participants had a normal or corrected-to-normal vision and volunteered for extra course credit in a psychology course. Participants provided written and informed consent approved by the Human Research Ethics Board at the University of Victoria (Protocol Number 16-428).

2.2. Experimental design

Participants were seated in a sound-dampened room, viewed stimuli on a 12' iPad Pro, and responded using the touch screen of this device. The experimental task was the n-back (Kirchner, 1958) with varying low and high difficulty levels, precisely the one- and three-back versions of this task. Participants were instructed to monitor a series of stimuli (letters) and respond whenever a letter that was the same as the one in previous trials was presented. Accuracy was calculated by the number of times the participant correctly tapped the screen in response to these target letters divided by the total targets presented in the condition. Performance feedback was given after each screen tap in the form of a square surrounding the letter (red – incorrect, green – correct). Each block began with a 20-second baseline recording while participants sat quietly with their eyes open. Next, participants completed four three-minute blocks of the task, with two blocks of each condition in random order. Finally, participants were given a one-minute break between blocks to allow HbO and HbR concentration changes to return to a baseline.

2.3. Data acquisition

We used Mendi's portable headband fNIRS device to measure the change from baseline in HbO concentrations during each three-minute task block (Mendi®, Sweden, 2020). Each block began with a 20-s baseline recording to establish each participant's base-level HbO concentrations. The system uses 765 and 856 nm wavelengths and outputs HbO and HbR concentration changes. The sampling rate of the device is 31.23 Hz. There is a hardware low-pass filter before sampling at 2.5 kHz. The optodes of the Mendi equipment measure activity in the prefrontal Brodmann area 10, one each for the left and right hemispheres. All data is recorded via Bluetooth directly to the Mendi custom IOS application.

2.4. Data processing & analysis

Data analysis was performed after the raw data were converted into optical density and concentration changes using the modified Beer-Lambert law (Jöbsis, 1977). All data processing was completed in MATLAB 2022a (Version 9.12, MathWorks, Natick, MA, USA). Data were then filtered through a dual-pass Butterworth filter with a Hamming taper (0.05 Hz to 2 Hz) to remove physiological noises (cardiac, respiratory, and Mayer waves) and signal drift (Pinti et al., 2020). Next, each participant's left and right HbO concentration measures were averaged. Then, blocks one and two of each n-back condition were averaged. Finally, the overall mean was taken for each condition (one-back, three-back). Similarly, participants' accuracy scores for each block were averaged separately (blocks one and two), and then the mean was taken for each condition (one-back, three-back).

All statistics were conducted in R (Version 4.0.0, the R Foundation, Vienna, Austria; R Team, 2016) using RStudio (Version 1.1.463, RStudio Inc., Boston, U.S.A.). All figures were created in GraphPad Prism (Version 9.2.1). We used dependent sample *t*-tests to compare the changes in prefrontal oxyhemoglobin concentration and the accuracy scores between one-back and three-back task loads. Furthermore, to ensure the quality of our data, we also determined the signal-to-noise ratio (SNR) values for each condition (one-back, three-back). We used the MATLAB function '*snr*' from the signal processing toolbox to calculate these values (MathWorks, 2022). By evaluating the SNR, we could assess the strength of the relevant signal compared to background noise, giving us a better understanding of the reliability and accuracy of our measurements. Finally, to examine any difference in signal quality between task conditions, we ran a dependent samples t-test between SNR values for the one- and three-back condition signals.

3. Results

Comparing participants' accuracy scores found a difference between one-back (M = 98 %, SD = 2) and three-back (M = 76 %, SD = 15) conditions, $t(29) = 8.429$, $p < .001$. The effect size, Cohen's D, was calculated as 1.54. In comparing participants' mean oxyhemoglobin concentration changes between conditions, a significant difference was found between one-back ($M = -0.0078$, SD = 0.021) and three-back ($M = 0.025$, SD = 0.054) conditions, $t(29) = 2.743$, $p = .002$. Cohen's D was calculated as 0.50. Descriptive statistics are presented in Fig. 1 with 95 % confidence intervals.

Mean signal-to-noise ratios were calculated as 10.19 [8.54, 11.84] and 11.39 [7.30, 15.28] for the one- and three-back conditions. No difference was found in comparing these values, $t(29) = 0.5591$, $p > .05$. Finally, no significant correlations were found between either measure (HbO or accuracy) and gender or age.

4. Discussion

The present work used a mobile fNIRS device to measure prefrontal HbO concentration during an n-back task to assess changes in working memory load. In support of our hypothesis, we found significantly higher prefrontal HbO concentration changes in the three-back (high load) condition than in the one-back (low load) condition. In addition, behavioural results illustrated that participants had reduced accuracy in the three-back (high load) than in the one-back (low load) condition. These outcomes align with previous research using fNIRS and the n-back task to measure prefrontal HbO changes in varying task loads task (Ayaz et al., 2012; Fishburn et al., 2014; Herff et al., 2014; Hoshi et al., 2003; Li et al., 2010; Mandrick et al., 2016; Meidenbauer et al., 2021; Owen et al., 2005; Pinti et al., 2018; Saikia et al., 2021).

In comparing our results with existing research, we noted that the effect size for the difference in oxyhemoglobin concentration between the one-back and three-back tasks was more modest in our study (Cohen's D = 0.50) than what has been reported in the literature. This discrepancy could be partly due to the lower signal-to-noise ratio (SNR) we encountered, a common challenge with mobile fNIRS devices. While these devices offer the advantage of quick and more comfortable data collection, they may also be more prone to measurement error. This potential trade-off underscores the need for methodological adaptations in future research. To mitigate the impact of a lower SNR, strategies such as prolonging data collection sessions or increasing the number of participants could be considered to enhance the robustness of the findings obtained from mobile fNIRS devices. These adjustments would help reconcile the ease of use provided by mobile fNIRS with the requirement for data precision in cognitive load assessment.

These results provide validity evidence for and emphasize the potential of the Mendi two-channel mobile fNIRS headband for assessing prefrontal cortex function in working memory tasks and expanding access to cognitive assessment tools (Ferrari and Quaresima, 2012; Pinti et al., 2020). The prefrontal cortex, particularly its dorsolateral and ventrolateral subregions, is responsible for maintaining, manipulating, and selecting relevant information from our environment (Goldman-Rakic, 1995; Petrides, 2000; Curtis and D'Esposito, 2003). As such, the observed changes in HbO correspond to an increased working memory load, underscoring the prefrontal cortex's involvement in working memory modulation (Owen et al., 2005; Sato et al., 2013). These findings also have implications for creating targeting interventions to address specific working memory deficits in individuals with cognitive

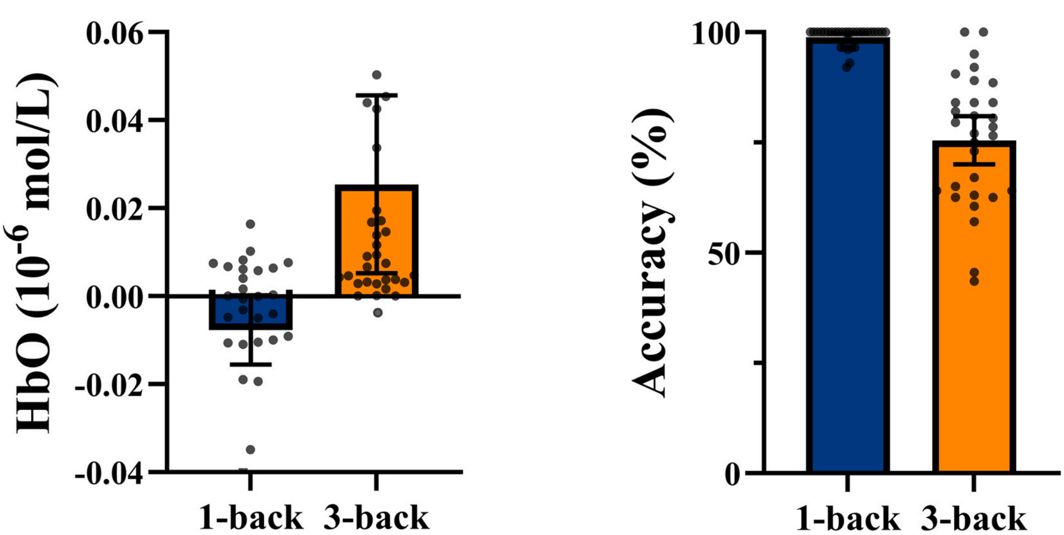

Fig. 1. Left panel – prefrontal HbO concentration changes recorded from the Mendi mobile fNIRS device between the task conditions (one- and three-back). Right panel – accuracy scores on the n-back task between task conditions (one- and three-back). Individual dots represent each sample. All error bars reflect 95 % confidence intervals.

impairments or neurological disorders, allowing for more personalized and effective treatment approaches that cater to the unique needs of each individual (Morrison and Chein, 2010).

Integrating mobile fNIRS devices into neuroscientific research, as demonstrated with the Mendi system in our study, offers an unprecedented opportunity to significantly expand access to cognitive neuroscience, opening up new avenues for diverse participant engagement. This technological leap is not merely about sleek, minimalistic designs; it significantly expands research accessibility. The headband design of the Mendi is particularly advantageous for including populations who might be uncomfortable with the more encumbering full-cap systems, such as children, older adults, or individuals with sensory processing sensitivities. This inclusivity extends the reach of neuroscience to previously underserved or inaccessible populations, such as those in remote or rural settings, making it possible to gather data from a wider sociodemographic array. Consequently, this advancement promises to enrich the dataset with a broader range of human experiences and conditions, significantly enhancing the ecological validity of research conducted with fNIRS technology.

Mobile fNIRS devices offer significant advantages, including ease of use, affordability, and portability. However, they also present limitations, such as extra-cerebral noise from motion artifacts and blood pressure changes, leading to inaccurate measurements and interpretations (Tachtsidis and Scholkmann, 2016). Traditional fNIRS devices often use short-separation channels to counter this issue (Brigadoi and Cooper, 2015), but this approach is less practical for mobile devices with limited channels. Alternative strategies like spatial filters, signal processing, and noise regression are promising in tackling this challenge (Cui et al., 2011; Huppert et al., 2009; Santosa et al., 2018). In our study, we applied a bandpass filter to mitigate high and very low-frequency noise and observed mean signal-to-noise ratios of 10.19 and 11.39 for the 1- and 3-back conditions, respectively. While no significant difference was noted between these values, they are comparatively lower than the reported SNR of 15.66 from a full fNIRS system using a single-step artifact rejection method (Hossain et al., 2022). It is important to note that while the data quality of mobile fNIRS might seem compromised compared to full fNIRS systems, these devices still offer considerable utility given their ease of use and adaptability to various environments. Hence, further research is needed to improve noise reduction techniques and find the optimal processing methods for mobile fNIRS systems, ensuring accurate and reliable data collection across various settings.

In addition, mobile fNIRS devices have a lower spatial resolution than fMRI or traditional large-array fNIRS systems, constraining measurements to superficial cortical layers and challenging the identification of specific underlying neural mechanisms. This issue can be particularly pronounced when studying populations with varying scalp and skull thickness, such as children or older adults (Pinti et al., 2018; Quaresima and Ferrari, 2016). Nevertheless, this limitation is not exclusive to mobile fNIRS and remains a significant obstacle for numerous neuroimaging techniques. Despite these challenges, the unique advantages of mobile fNIRS devices can be effectively harnessed through careful experiment planning and data analysis. Furthermore, adopting such an approach enables the investigation of cortical brain function in various contexts, such as the role of the prefrontal cortex in working memory. This foundation strengthens our understanding and allows us to explore future research avenues and potential applications.

In our study, the predominance of female participants (27 out of 35) presents a limitation regarding gender representation. This skew may be significant as some studies suggest gender may affect brain activation during cognitive tasks, including those involving working memory. For example, Bell et al. (2006) and Goldstein et al. (2005) have shown very small gender differences in brain activation during cognitive and working memory tasks. These findings imply that our study's gender imbalance might influence the generalizability of our results. Achieving a more gender-balanced sample in future research is essential for a broader understanding of gender-specific brain activation, particularly in working memory tasks like the n-back. Such an approach would enhance our study's relevance in the broader context of neuroimaging research on gender differences in neural processing.

In addition, if our primary aim is to rigorously validate the Mendi device for assessing prefrontal cortex activation, utilizing a suite of diverse behavioural tasks is imperative. While our current findings offer valuable replication of previous research, genuine validation in cognitive neuroscience necessitates a broader investigative scope. Currently underway in our laboratory are a series of future studies that include various tasks, particularly those that evaluate working memory load in real-world environments that closely mimic everyday experiences. This methodological expansion would provide converging evidence of Mendi's effectiveness across different cognitive domains and task conditions, bolstering its applicability and reliability as a laboratory and field research tool. By exploring working memory and other cognitive functions through tasks set in naturalistic contexts, we can further affirm the utility of the Mendi system in capturing the true breadth of neural activity as it occurs in real-life scenarios.

Mobile fNIRS systems, like the one used in our study, enable data collection in real-world and more naturalistic environments. Prior research has effectively employed mobile fNIRS to investigate cognitive workload, for instance, in pilots (Mark et al., 2022; Hamann and Carstengerdes, 2022; Tang et al., 2022). Additionally, virtual environments that simulate authentic tasks requiring active manipulation of information within working memory provide an ecologically valid approach to studying the prefrontal cortex in a controlled laboratory setting (von Lühmann et al., 2021). Future research could enhance this validation process by incorporating more complex working memory tasks that closely represent daily real-world activities. By rigorously validating mobile fNIRS technology, researchers can strengthen their findings' credibility and gain deeper insights into the prefrontal cortex's function during intricate tasks across various populations and settings.

5. Conclusion

In conclusion, this study successfully utilized the Mendi two-channel mobile fNIRS headband to explore changes in prefrontal HbO concentration during an n-back task, providing insights into working memory load. Our findings, indicating a significant increase in HbO concentration under high cognitive load, align with previous neuroimaging research (Ayaz et al., 2012; Fishburn et al., 2014; Herff et al., 2014; Hoshi et al., 2003; Li et al., 2010; Mandrick et al., 2016; Meidenbauer et al., 2021). Crucially, these results validate the Mendi device's ability to differentiate between low and high cognitive loads. A notable aspect of this study is Mendi's design, which enhances participant accessibility, making it especially suitable for populations uncomfortable with more invasive full-cap systems, such as children, older adults, or those with sensory sensitivities. Its cost-effectiveness and user-friendliness position mobile fNIRS technology as a promising tool for advancing cognitive neuroscience research, particularly in naturalistic and real-world settings. Therefore, this study contributes to our understanding of working memory and paves the way for more inclusive and ecologically valid research methodologies.

CRediT authorship contribution statement

KB designed the study, collected the data, completed the analysis, and wrote the manuscript. OK oversaw the project and contributed to the manuscript. KH reviewed and edited the manuscript. All authors approved the submitted version.

Declaration of competing interest

No conflicts of interest to report.

Data availability

The data supporting this study's findings are available from https://rb.gy/2ilfmc.

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