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Exploring Cognitive Load and Relative Neural Efficiency in Aging:

Preliminary Insights from fNIRS and the SLUMS Assessment

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Abstract

Objective. To examine whether prefrontal cortex activation measured by functional near-infrared spectroscopy (fNIRS) during the St. Louis University Mental Status (SLUMS) exam differs by cognitive status and whether relative neural efficiency (RNE) can serve as a physiological marker of cognitive impairment. **Methods.** This exploratory study was conducted in 2024 at a senior center in a small Mid-Atlantic U.S. city. Thirteen community-dwelling adults aged 65–85 years completed the SLUMS while wearing an fNIRS sensor positioned over the prefrontal cortex. Participants were classified as having normal cognition (NOR), mild cognitive disorder (MCD), or dementia (DEM) based on SLUMS scores. ΔHbO served as the indicator of cognitive effort, and RNE was calculated by combining normalized SLUMS performance and oxygenation values. Group differences were tested using ANOVA with confirmatory nonparametric analyses. **Results.** RNE differed significantly among groups ($F_{2,10} = 5.26$, $p = 0.0275$). Post-hoc comparisons showed lower RNE in the DEM group compared with the NOR group ($p = 0.0224$). Confirmatory Kruskal-Wallis testing supported these findings ($p = 0.0287$), with a significant DEM–NOR difference on Dunn's test ($p = 0.0311$). Descriptive hemodynamic patterns indicated higher ΔHbO and ΔHbR variability in the DEM group across SLUMS question blocks. **Conclusions.** Older adults with dementia demonstrated reduced neural efficiency during SLUMS administration, suggesting greater cognitive effort relative to performance. These preliminary findings indicate that SLUMS items impose different cognitive workloads depending on impairment level. **Policy Implications.** Integrating physiological markers such as neural efficiency into cognitive screening may enhance early identification of impairment, support more targeted referral pathways, and inform public health planning for Delaware's aging population.

Introduction

Age-related cognitive decline—including impairments in memory, attention, and executive functioning—can undermine daily independence, increase safety risks, and elevate healthcare needs.[1,2] These challenges are becoming more consequential as adults aged 65 and older now represent 17.3% of the U.S. population (57.8 million people), a proportion projected to reach 22% by 2040.[3] Given the growing prevalence and impact of cognitive decline, effective and sensitive screening tools are essential for detecting early changes and enabling timely intervention.

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Cognitive assessments are valuable instruments for evaluating cognitive function in aging populations. Common options include the Montreal Cognitive Assessment (MoCA), Mini-Mental State Examination (MMSE), and the St. Louis University Mental Status (SLUMS) exam. The MoCA assesses memory recall, attention, executive function, visuospatial skills, language, and orientation, though debate exists regarding appropriate cutoff scores due to high sensitivity and lower specificity.[4] The MMSE includes questions on attention, orientation, memory recall, language, and registration, but scores may be influenced by education and cultural background.[5] The SLUMS exam assesses attention, immediate and delayed recall, memory, orientation, numeric calculations, spatial and executive function, and extrapolation, and demonstrates good internal consistency reliability.[6] While MoCA and SLUMS are more sensitive to mild cognitive impairment, the MMSE is more sensitive to probable dementia.[5]

The SLUMS has been suggested as a possible tool for cognitive assessment instead of the MoCA due to the similar scoring, reliability, and availability in many languages.[7] Developed in 2006 at Veterans Affairs facilities, SLUMS is widely recognized for its sensitivity in detecting mild neurocognitive disorder and has demonstrated strong reliability across various demographic groups. The SLUMS is free to use and administer, compared to the MoCA exam which has required a paid training program since 2020, and the MMSE exam which is available for purchase. The SLUMS shares many features with the MoCA, may be implemented in a shorter time period compared to the MoCA, and provides cutoff scores for normal, mild cognitive impairment, and dementia-related impairment, and it adjusts scores based on education level, enhancing its precision across populations with varying educational backgrounds.[7,8] Research comparing these tools has highlighted significant correlations between SLUMS and MMSE scores, further cementing SLUMS as a reliable option for cognitive screening. [9,10]

Unlike MoCA and MMSE, SLUMS, while widely implemented as a cognitive assessment, has limited research exploring the underlying physiological mechanisms associated with its administration, particularly in older adults. Previous studies have investigated cerebral artery blood flow and functional connectivity in relation to MoCA and MMSE scores, revealing significant associations between these assessments and neurovascular function.[11 - 13] Emerging evidence underscores the link between neurovascular function and cognitive performance as measured by MoCA and MMSE scores. Nakaoku et al. demonstrated that reduced cerebral artery blood flow, particularly in regions associated with executive function and memory, correlated with lower cognitive assessment scores, suggesting vascular contributions to cognitive decline.[11] Wang et al. expanded on this by examining resting-state functional connectivity, revealing that disruptions in key neural networks were significantly associated with diminished MoCA and MMSE performance.[12] Similarly, Zou et al. identified that alterations in cerebrovascular reactivity and connectivity patterns were predictive of early cognitive impairment, reinforcing the role of neurovascular integrity in maintaining cognitive health.[13] Collectively, these studies highlight the utility of MoCA and MMSE as sensitive indicators of underlying neurovascular changes, whereas lower MoCA and MMSE scores are consistently associated with reduced cerebral perfusion, disrupted functional connectivity, and impaired neurovascular coupling—neural signatures that reflect diminished executive and memory function.

These findings suggest that similar relationships may exist for SLUMS; however, research examining neural activity during SLUMS administration remains scarce. To address this gap, our study uses functional near-infrared spectroscopy (fNIRS) to investigate prefrontal cortex (PFC) activity in older adults during SLUMS administration. fNIRS measures brain oxygenation and hemodynamic changes and is well-suited for real-time cognitive assessment due to its motion tolerance, portability, and ecological validity.[14–18] fNIRS can detect changes in cognitive load, working memory, neural efficiency, and engagement.[19–20] Executive function correlates strongly with oxygenation changes measured via fNIRS.[21-23]

Recent work shows that fNIRS-derived biomarkers may outperform traditional screening tools in detecting mild cognitive impairment.[24] fNIRS has been used across diverse populations—including young adults, individuals with mental illness, older adults, and Alzheimer's patients—and consistently reveals associations between oxygenation patterns and cognitive status.[25-30]

Aging is associated with increased reliance on PFC resources, with compensatory activation reaching a ceiling around age 70.[31] As tasks become more demanding, older adults may recruit additional neural resources despite declining performance. Relative neural efficiency (RNE) quantifies the balance between cognitive effort and performance.[32-37] Higher RNE reflects optimized processing; lower RNE reflects inefficiency or compensatory over-recruitment.

This exploratory study integrates SLUMS performance with fNIRS-derived neural efficiency measures to examine cognitive workload in older adults classified as having normal cognition (NOR), mild cognitive disorder (MCD), or dementia (DEM). By assessing prefrontal oxygenation across SLUMS question blocks, this work aims to clarify how cognitive screening tasks influence neural activation and resource allocation. Understanding the neurophysiological demands of SLUMS may refine screening accuracy and support improved diagnostic approaches for early detection of cognitive decline. Since this was an exploratory study, we did not have predefined hypotheses; however, based on prior findings linking MoCA and MMSE scores to reduced prefrontal activation and altered neurovascular coupling in aging and cognitive impairment, we explored whether SLUMS performance might show similar relationships with fNIRS-measured PFC activation. Rather than assuming a specific pattern, we examined whether group differences (NOR, MCI, DEM) would emerge in relative neural efficiency of the hemodynamic response. This exploratory approach allowed us to investigate whether SLUMS-related neural patterns align with those observed in other cognitive screening measures and may set the stage for a better understanding into how neural efficiency varies among individuals with different levels of cognitive impairment. This research is particularly relevant given the need for early detection of cognitive decline in aging populations. Understanding how cognitive screening tools elicit neural responses can refine diagnostic criteria and enhance screening accuracy. SLUMS is widely recognized for its utility in detecting mild cognitive impairment (which is described as mild neurocognitive disorder or MCD in the assessment), yet its neurophysiological basis has remained largely unexplored. By combining behavioral measures (SLUMS) with fNIRS-based neural efficiency analysis, our study aims to bridge this gap, offering valuable data on the cognitive workload associated with executive function tasks in older adults.

Methodology

Participants

13 community dwelling older adults between the ages of 65-85 years (9F/4M, 75.46 $\pm$ 3.77 years) participated in this study. Participants were recruited from a senior center in a small city in the Mid-Atlantic region of the United States. Participants were included if they had no diagnosis of

mental/psychiatric disorders. Exclusion criteria were a history of gait disorders, mild to severe osteoarthritis, heart conditions, pulmonary or renal dysfunction, and other neurological disorders. All study procedures were reviewed and approved by the University of Delaware Institutional Review Board prior to participant recruitment and data collection. The research was conducted under approved IRB protocols (e.g., Protocol #1477774-13), and all activities adhered to federal regulations governing human subjects research, including the Common Rule (45 CFR 46) and relevant institutional policies. Participants were informed of the study purpose, procedures, risks, and benefits, and provided written informed consent before participation. All data were collected, stored, and analyzed in accordance with IRB requirements to ensure confidentiality, minimize risk, and uphold the highest ethical standards for human subjects research.

Task Procedure

Data collection took place within the senior center described above. Participants were provided with a brief introduction to the SLUMS exam and to fNIRS before they began the study. Next, one researcher placed the fNIRS sensor pad on their forehead and sensor data was checked on Cobi Studio software (fNIR Devices LLC, Potomac, MD, USA). If optical density data fell outside the recommended collection range (40-40,000), the signal gain was adjusted accordingly until it was within that range. Participants were then instructed to minimize head and body movements and empty their mind for a 30-second baseline of fNIRs data collection. This was followed by the administration of the SLUMS by a second researcher. The researcher sat across from the participant and asked 11 questions regarding thinking and memory skills. The SLUMS test includes questions assessing the following topics: attention, immediate and delayed recall, memory, orientation, numeric calculations, spatial and executive function, and extrapolation. Responses to the questions are scored on a scale of 1 – 30, with higher scores indicating lower levels of cognitive deficit. Once the participant completed the final question, the sensor pad was removed. The entire session took between 15 – 20 minutes, with no session lasting longer than 25 minutes.

Imaging Procedure

Optical signals were recorded on a fNIR Devices System 2000s, a continuous wave functional near-infrared spectroscopy device (fNIR Devices LLC, Potomac, MD USA). An 18 optode (4 light sources/10 detectors creating 16 measurement channels, with two near short-separation channels to help isolate scalp and superficial signals from cortical hemodynamics) sensor pad was applied to the participants forehead using the sensor's vertical axis and situated in the Fp1 and Fp2 locations defined in the international 10 – 20 system of cerebral electrode placement (Figure 1).[38-40]

Figure 1. fNIR Devices Sensor Pad

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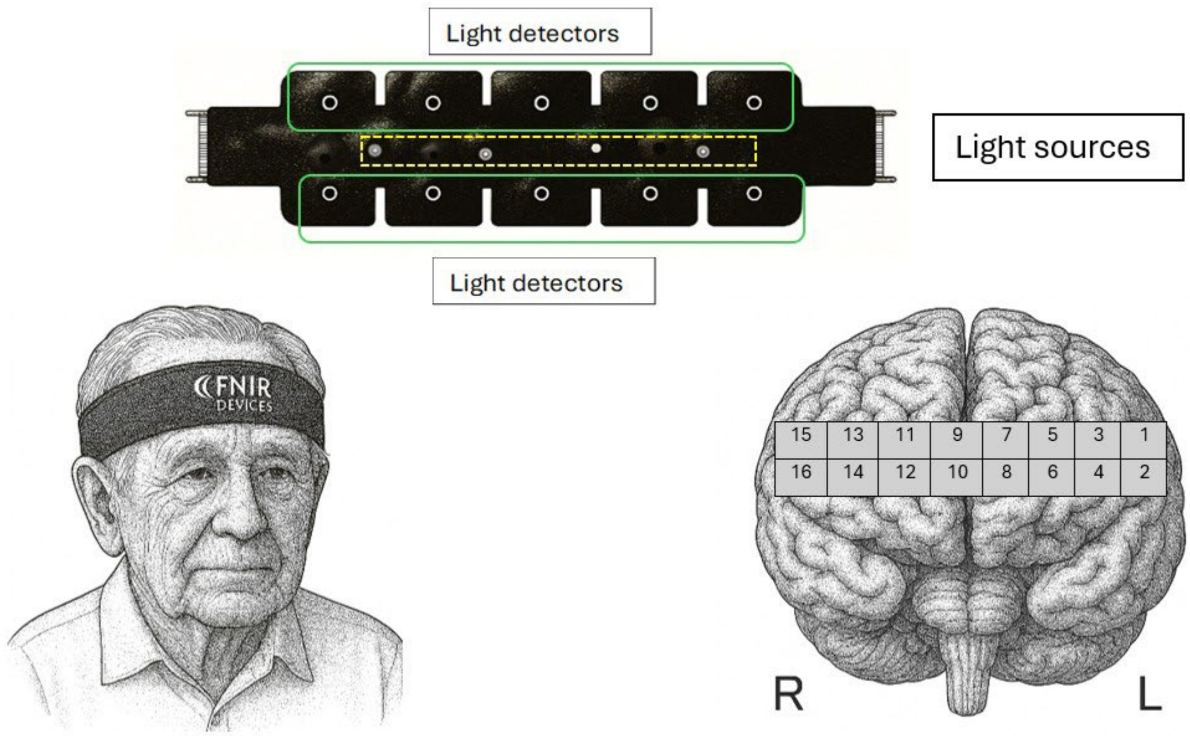

fNIR Devices sensor pad with four light sources and ten detectors identified (top), illustration of sensor pad placement on participant (bottom, left) and approximate optode position superimposed on prefrontal cortex (bottom, right).

fNIRS Processing and Analysis

fNIRS data processing was completed in fNIRSoft Pro; although the sensor pad includes two short-separation channels, fNIRSoft Pro does not implement short-separation regression. Because this was an exploratory pilot study, we did not perform external regression of superficial signals. As a result, ΔHbO values may include mixed cortical and extracerebral contributions. Physiological noise (heartbeat and respiration) was attenuated using a 20th-order FIR band-pass filter (0.1–0.5 Hz) as implemented in fNIRSoft Pro, and ambient light contamination was removed using the software's default ambient light filter.[41] Motion artifacts were removed using the default SMAR filter in fNIRSoft Pro, which identifies spikes exceeding ±3 standard deviations within a 1-second sliding window and replaces them using cubic spline interpolation.[42] Monte Carlo simulations indicate this algorithm is suitable for different kinds of noise.[42] The light was converted to oxygenation data using the Modified Beer-Lambert Law, and further signal processing steps were used as described below.

In oxygenation data, linear detrending was applied to remove global drift. This filter removes the influence of systemic variables and improves the sensitivity of HbO to independent variables.[43] It also leverages the principle that HbO and HbR should be negatively correlated during functional activity, but become more positively correlated during motion artifacts, enabling correction for head movement.[44,45] Finally, an area-windowed nonlinear median filter was applied to remove sharp spikes.[37,41]

Oxygenation data were divided into 9 question blocks based on the SLUMS (Table 1). Questions 1–3 were combined into one block because of the type and simplicity of the questions and the speed with which they could be answered (less than 1–2 seconds). The hemodynamic response in the prefrontal cortex requires several seconds to detect changes in oxyhemoglobin and deoxyhemoglobin concentrations; onset typically occurs 1–2 seconds after neural activity begins, with a peak between 4–8 seconds.[47-49] Each of the remaining questions (4–11) was analyzed individually as a question block for a total of nine blocks.

Table 1. SLUMS Questions with Corresponding fNIR Question Blocks

SLUMS Question	fNIRS Question Block	Measured by Question
1 - 3	1	Attention, immediate recall, and orientation
4	2	Delayed recall with interference
5	3	Numeric calculation and registration
6	4	Memory: immediate recall with interference (time constraint)
7	5	Delayed recall with interference
8	6	Registration and digit span
9	7	Visual spatial
10	8	Visual spatial and executive function
11	9	Executive function plus extrapolation

Outcome Measures

The fNIRS system provided measures of hemodynamic change in concentration, oxygenated (ΔHbO) and deoxygenated hemoglobin (ΔHbR) were calculated for each participant, and the 16 channels of data were averaged within each of the 9 question blocks. Block-level averaging was used to obtain coarse descriptive trends appropriate for this pilot study. For our analysis of relative neural efficiency (RNE), we used ΔHbO as our measure of cognitive effort,[29,50] calculating an average across the entire SLUMS test for each individual, then normalizing these values across the 13 participants. SLUMS scores were also normalized across participants, and RNE was calculated using established formulas.[29, 32,35]

1. $P_z = ((1/MD_i) - (1/MD_{GM})) / (1/MD_{SD})$
2. $CE_z = ((1/\Delta HbO_i) - (1/\Delta HbO_{GM})) / (1/\Delta HbO_{SD})$
3. $RNE = (P_Z - CE_Z) / \sqrt{2}$

Pz is the normalized SLUMS performance score, CEz is the normalized ΔHbO measures from fNIRS, and RNE is the resultant relative neural efficiency. The resultant relative neural efficiency (RNE) is an index of SLUMS performance relative to standardized cognitive effort. [17,32,33]
RNE represents the perpendicular distance of the normalized performance score relative to the

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normalized cognitive effort scores (see equations 1 and 2). In addition, we tracked ΔHbO and ΔHbR over individual SLUMS questions to descriptively examine their changes over the course of the SLUMS exam.

Statistical Analysis

Several different statistical analyses were performed on measures. For the RNE data, we first checked that parametric assumptions were not violated for a one-way analysis of variance (ANOVA). We checked the residuals for outliers, and the largest standardized residual is "2" with no outliers. Further, there were no patterns in the residuals suggesting structure unaccounted for in the model. We examined the normality of residuals using the Shapiro-Wilk test ($p=0.2090$) and the Anderson-Darling test ($p=0.2040$), and both failed to reject normality. To test the homogeneity of variance across groups the Brown-Forsythe ($p=0.8240$) test failed to reject homogeneity. Therefore, we moved forward using parametric statistical tests. We used a one-way ANOVA to compare mean values of RNE among the different groups, then followed these with a Tukey-HSD post-hoc test for paired comparisons. We also calculated confidence bounds for the RNE mean within each group. Given the small sample size, we ran confirmatory nonparametric tests corresponding to the ANOVA (Kruskal-Wallis) and the Tukey-HSD (Dunn) test.

Results

Participants

Thirteen community-dwelling older adults between the ages of 70 and 83 years participated in the study. Based on SLUMS classifications, three participants were categorized as having normal cognition (NOR), six as having mild cognitive disorder (MCD), and four as having dementia-range scores (DEM). The NOR group had a mean age of 72.33 ± 2.08 years and a mean SLUMS score of 27.33 ± 0.71. The MCD group had a mean age of 77.67 ± 4.03 years and a mean SLUMS score of 24.17 ± 1.33. The DEM group had a mean age of 74.50 ± 3.32 years and a mean SLUMS score of 17.50 ± 3.11. All participants completed the full protocol, and no data were missing.

Cognitive Workload and Relative Neural Efficiency Analysis

First, we plotted pairs of normalized SLUMS scores (performance) vs. normalized change in oxyhemoglobin for each participant, coded for classification to develop an RNE graph (see Figure 2). On this graph, the X-axis indicates normalized cognitive effort based on ΔHbO and the Y-axis represents normalized cognitive performance based on SLUMS scores. The dotted zero line that extends from the lower left to upper right side represents a neutral efficiency condition, E = 0, which is the e point at which performance and activation are balanced; that is, cognitive effort matches behavioral performance.

Figure 2. Graph of Relative Neural Efficiency of Participants

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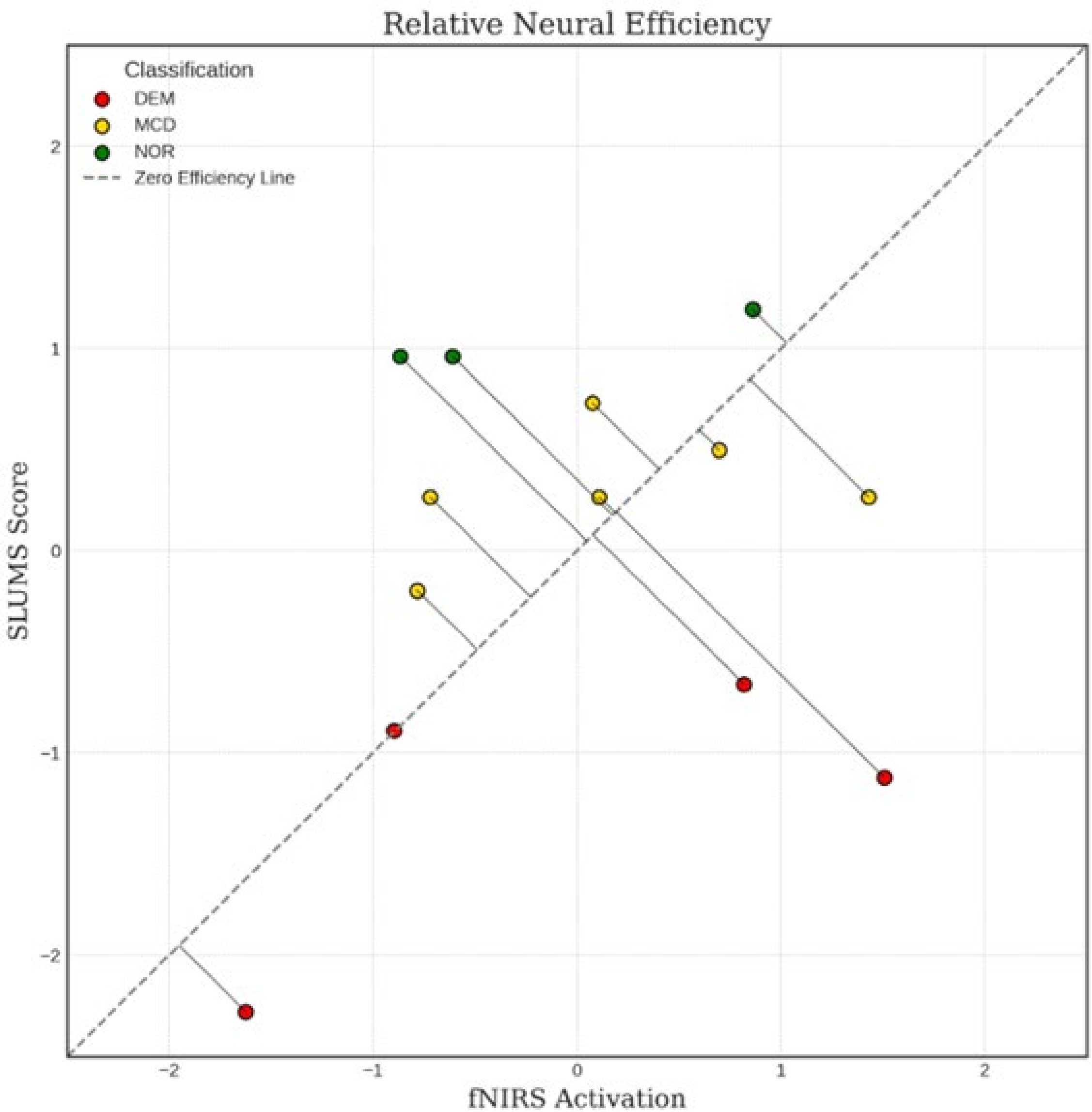

Participants are classified as DEM (red), MCD (yellow) and NOR (green). The X-axis indicates cognitive effort based on normalized ΔHbO and the Y-axis represents cognitive performance based on normalized SLUMS scores.

RNE values that are above the zero line indicate that performance on the SLUMS exceeds neural activation, representing efficient cognitive resource allocation. RNE values below the zero line indicate that neural activation exceeds cognitive processing, representing inefficient cognitive resource allocation. Perpendicular lines run from the zero-efficiency line to each point. The length and direction of each line indicate how much and in what direction each participant deviates from balanced efficiency.[19,21,32-34] Short lines are close to balanced efficiency, where long lines above the diagonal indicate efficient processing and long lines below the diagonal indicate inefficiency processing. The distribution of points around the zero-efficiency line reflects different patterns of cognitive resource allocation. Higher performance with lower neural effort reflects more efficient processing, whereas higher effort with lower performance reflects reduced efficiency. Following the principles of neurovascular coupling, cases in which both performance and effort are low may indicate under-engagement or limited recruitment of prefrontal resources; according to cognitive load theory, this suggests individuals are not fully engaging the prefrontal cortex to support task demands.[32-34] Alternatively, cases with both high performance and high effort may reflect compensatory activation: individuals (particularly lder adults or individuals with cognitive impairment) may recruit additional neural resources in order to maintain performance.[32-34,37] These regions of the plot provide a qualitative framework for interpreting how individuals balance cognitive demand and neural activation.

Next, we compared RNE values across groups to see if group differences existed in relative neural efficiency values (Figure 3). Least squares means and standard errors were recorded for DEM (-0.628, 0.318), MCD (-0.054, 0.260), and NOR (0.942, 0.367) along with 95% confidence intervals for the mean; DEM (-1.34, 0.08), MCD (-0.63, 0.53), and NOR (0.12, 1.76). The ANOVA indicated significant differences existed among the groups ($F_{2,10}$=5.26, p = 0.0275) with R^2=0.51 proportion of the variation explained; the Tukey-HSD post-hoc test indicated that differences existed only between DEM and NOR groups (p=0.0224). A confirmatory Kruskal-Wallis test found a significant difference among groups (p=0.0287) with a difference only between DEM and NOR groups, post-hoc Dunn test (p=0.0311).

Figure 3. RNE Score Averages for DEM, MCD, and NOR Groups

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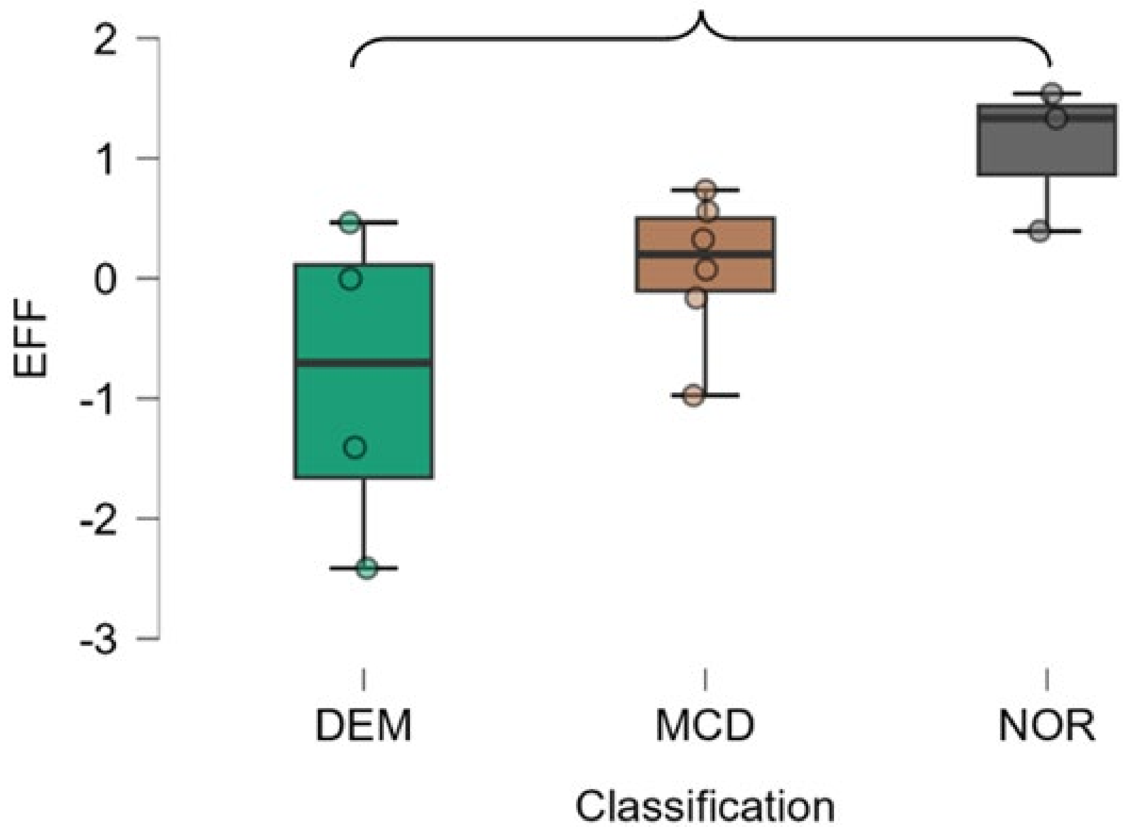

Significant differences existed between DEM and NOR (p = 0.0224)

Oxygenation Patterns Across SLUMS questions

Next, we examined the patterns of ΔHbO and ΔHbR over the question blocks in the SLUMS. These patterns are descriptive only and were not subjected to statistical testing. In the prefrontal cortex, when neural activity increases, there is typically an increase in oxyhemoglobin (HbO) and a corresponding decrease in deoxyhemoglobin (HbR), meaning that as HbO levels rise due to increased blood flow during brain activation, HbR levels tend to fall simultaneously or with a slight delay. All three groups appear to show a positive hemodynamic response across the blocks, demonstrating neurovascular coupling between the variables where increased HbO and decreased HbR concentrations indicate increased PFC activity. However, looking across the three categories, the DEM group shows far higher values of HbR during the first three blocks, followed by higher values of HbO in the five subsequent blocks.

Discussion

This exploratory study provides a novel perspective on cognitive screening by assessing prefrontal cortex (PFC) activation during SLUMS administration using functional near-infrared

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spectroscopy (fNIRS). Our preliminary findings indicate that, in this small sample, individuals with dementia exhibit significantly lower Relative Neural Efficiency (RNE) than those with mild cognitive impairment and normal cognition. This pattern suggests that executive function deterioration may be accompanied by heightened cognitive workload and inefficient neural resource allocation, consistent with the hypothesis that excessive cortical recruitment reflects a compensatory response to cognitive deficits. However, given the small and uneven group sample in this exploratory study, these interpretations should be viewed as preliminary and hypothesis-generating rather than conclusive. Because this study is preliminary and underpowered, interpretations of the RNE regions should be viewed as descriptive rather than diagnostic, and future work with larger samples will be needed to validate these patterns. At the same time, this is an important first step in understanding oxygenation patterns and cognitive efficiency during administration of the SLUMS.

Despite SLUMS being a widely used cognitive assessment, the physiological mechanisms underlying its administration remain largely unexplored. Compared to MoCA and MMSE, SLUMS has been validated as an effective tool for detecting mild cognitive impairment while maintaining accessibility and cost-effectiveness.[51] Unlike MoCA and MMSE, SLUMS incorporates education-adjusted scoring, which enhances its applicability across diverse populations.[8] The neurophysiological disparities identified in SLUMS administration parallel trends observed in MoCA studies, where altered cerebral blood flow patterns correlate with cognitive impairment severity.[12]

The present findings suggest that integrating behavioral performance with fNIRS-derived measures such as Relative Neural Efficiency (RNE) may offer a useful complementary perspective in cognitive screening. In this exploratory sample, individuals categorized as “with dementia” showed lower RNE than those with normal cognition, indicating a mismatch between neural activation and task performance. Although no physiological conclusions can be drawn from the descriptive oxygenation patterns, the RNE results highlight the potential value of assessing how efficiently cognitive resources are allocated during screening tasks. Incorporating fNIRS-based metrics alongside traditional assessments like the SLUMS may, with further validation, help refine approaches to identifying individuals who experience greater cognitive effort for a given level of performance. Future studies with larger samples are needed to determine whether such combined behavioral-neurophysiological markers can enhance early detection or inform tailored intervention strategies.

Additionally, integrating real-time neuroimaging into cognitive assessments could provide a more dynamic and individualized approach to cognitive screening. While traditional cognitive exams rely primarily on behavioral performance, neuroimaging can reveal underlying neurophysiological deficits that are not always apparent through scoring alone. Understanding how impaired neurovascular coupling influences SLUMS performance could lead to tailored cognitive therapies targeting vascular health and metabolic function in aging populations.

Given the exploratory nature of this study, future research should expand sample sizes to strengthen the reliability of findings and explore additional neurophysiological markers of cognitive decline. Direct comparisons between SLUMS and other cognitive assessments using fNIRS would clarify how different screening tools engage distinct neural networks. Additionally, longitudinal studies tracking neural efficiency across cognitive screening sessions could assess how dementia progression influences oxygenation dynamics over time. Further investigation

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into the relationship between executive function and neural efficiency is needed to determine whether compensatory cortical activation remains consistent across different cognitive domains. Understanding how neurovascular deficits manifest across distinct cognitive processes could lead to more refined interventions addressing specific impairments in aging individuals. By advancing neurophysiological research in cognitive screening, this study contributes to the growing body of evidence supporting the integration of neuroimaging into dementia diagnostics. The insights gained from fNIRS may ultimately help develop individualized cognitive assessment.

Limitations

While this exploratory study provides valuable insights into prefrontal cortex (PFC) activity during SLUMS administration, several limitations must be acknowledged. First, the small sample size (n = 13) limits the generalizability of our findings to broader populations. Future research should incorporate larger (>30), more diverse (at least 10/cognitive category group) samples to enhance statistical power and validate neurophysiological patterns across different demographic groups. In terms of the use of fNIRS, while it is a powerful tool for assessing cortical activation, it primarily measures hemodynamic responses and does not directly capture neuronal activity. Because of the design of our sensor pad, we were restricted to measuring oxygenation of the prefrontal cortex, which omitted other brain regions that may have been active when completing the SLUMS. Complementary neuroimaging techniques, such as EEG or fMRI, could provide a more comprehensive view of neural mechanisms underlying cognitive assessments. Another limitation is the absence of longitudinal data as the current study captures a single assessment session, but cognitive function and neural efficiency fluctuate over time. Longitudinal studies tracking changes in oxygenation patterns and Relative Neural Efficiency (RNE) across repeated SLUMS administrations could provide deeper insights into cognitive decline progression. Finally, because the nature of the study is exploratory without directly testing hypotheses, the strength of causal inference is limited, and the results should be interpreted primarily as hypothesis-generating rather than generalizable.

Public Health Implications

This exploratory study examined cognitive workload during SLUMS administration by integrating behavioral performance with fNIRS-derived measures of Relative Neural Efficiency (RNE). The only statistically significant finding was that participants classified in the dementia group demonstrated lower RNE than those with normal cognition, suggesting reduced efficiency in how cognitive resources were allocated during the task.

As the prevalence of cognitive impairment and dementia continues to rise among older adults, there is a critical need for accessible and objective methods to support early detection and monitoring. These findings suggest that combining cognitive screening with physiological measures of neural efficiency may improve the identification of cognitive decline beyond traditional performance-based assessments alone. Community-based settings, such as senior centers, may provide valuable opportunities for implementing innovative screening approaches that facilitate earlier intervention, support healthy aging, and ultimately reduce the public health burden associated with cognitive decline including dementia. Future research with larger samples, standardized timing, and longitudinal designs will be essential for determining whether RNE or related fNIRS-based metrics can enhance early detection or support more tailored intervention strategies in aging populations.

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