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USING FNIRS TO IDENTIFY AGE-RELATED NEUROCOGNITIVE CHANGES IN WORKING MEMORY

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USING FNIRS TO IDENTIFY AGE-RELATED NEUROCOGNITIVE CHANGES IN WORKING MEMORY

by

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ABSTRACT

Previous research has found distinct brain activity differences between older and younger adults that correlate with cognitive performance. Older adults tend to show an increase in brain activity and demonstrate over-recruitment of bilateral brain regions compared to younger adults, which allows them to perform at a comparable level to younger adults at low task loads (Compensation-Related Utilization of Neural Circuits Hypothesis or CRUNCH model). This additional brain activity may be a form of neural compensation. However, others have observed compensatory brain activity during more difficult tasks, highlighting discrepancies in the literature. The main objective of the present study is to examine age-related differences in bilateral prefrontal (PFC) and right parietal lobe activity using functional near-infrared spectroscopy (fNIRS) (21 channels, 25 Hz, Brite, Artinis) while participants completed visuospatial working memory N-back tasks of increasing cognitive load (1-back, 2-back, and 3-back), thus testing the CRUNCH model. Twenty-four healthy younger (18-25 years) and 25 older (65-91 years) adults took part in the study. The results show older adults had higher error rates to target and were slower during the N-back tasks ($p < .05$). Age-related brain activity differences were observed between older and younger adults. Older adults demonstrated increased bilateral brain activation compared to younger adults, especially during the 2-back task. Behavioural differences were also observed between age groups, with older adults showing lower accuracy (*Pr*) at higher loads (i.e., 2-back, and 3-back) but performed similar to younger adults at low loads (i.e., 1-back). The results of our study do not support the CRUNCH model nor the compensation view, but rather align with the Neural Inefficiency model, where older adults exhibit increased bilateral brain activity but show reduced task-related performance.

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1. INTRODUCTION

1.1. Background

The proportion of older adults within the population is increasing worldwide, and while factors such as improved education and living standards, as well as advances in medicine and public health measures have improved, cognitive decline is considered an inevitable consequence of ageing (Cabeza et al., 2018). Even in the healthy ageing population, a decrease in most aspects of cognition exist, particularly in processes that involve attention (Commodari and Guarnera, 2008), processing speed, executive function abilities, and memory (Harada et al., 2013). There is variation in the trajectory of cognitive function as people age: some individuals show very little decline or preservation, which can be considered healthy or optimal. Conversely, others exhibit a more rapid trajectory of cognitive decline (Jamadar, 2020). Age-related decline is often associated with structural changes in the brain, like white matter degredation or brain atrophy (Peters, 2006), and functional changes (Grady, 2012). Therefore, investigating the underlying neural mechanisms of age-related decline will help our understanding of why some individuals experience a faster decline in their cognition compared to others (McDonough et al., 2022). Investigating age-related differences in brain activity has become much more feasible with the recent use of non-invasive neuroimaging methods, such as functional magnetic resonance imaging (fMRI) and functional near-infrared spectroscopy (fNIRS) (McDonough et al., 2022). Researchers using neuroimaging have reported distinct brain activity differences between older and younger adults that relate to differences in cognitive performance and could explain this decline (McDonough et al., 2022; Cabeza et al., 2018). However, there are discrepancies in the recent literature related to whether brain activity differences are positively (Nyberg et al., 2009; Mattay et al., 2006; Cabeza et al.,

2002) or negatively associated with cognitive performance (Park et al., 2010; Li et al., 2001). Therefore, further research using neuroimaging is needed to better understand how theses age-related brain activity differences affect cognitive performance to better understand age-related decline.

1.2. Theories of Brain Ageing

Neuroimaging researchers have identified at least four distinct age-related patterns that characterize the structural and functional changes across various cognitive domains (McDonough et al., 2022). These patterns include: maintenance, neural inefficiency, de-differentiation, and neural compensation.

The Brain Maintenance theory states that some older adults display preserved brain structure and function similar to younger adults (Reuter-Lorenz and Park, 2014; Nyberg et al., 2012). There are numerous studies whose findings align with the Brain Maintenance theory and show preserved cognition in older adults, which is demonstrated as similarities in brain activation patterns relative to younger adult groups (Geerligs et al., 2014; Chanraud et al., 2013; Davis et al., 2011; Vallesi et al., 2011). Alternatively, the De-differentiation model is based on the process of de-differentiation or desegregation, which refers to brain activity becoming less distinct or selective with age (Koen and Rugg, 2019). Researchers have found this de-differentiation pattern of brain activity is associated with lower levels of cognition and poorer task-related performance (Park et al., 2010; Li et al., 2001). Similarly, the Neural Inefficiency Theory proposes that an increase in brain activity

correlates to reduced task performance in older adults and is negatively associated with cognitive performance (Logan et al., 2002; Reuter-Lorenz et al., 2001; Morcom and Henson, 2018).

On the other hand, the Neural Compensation theory, which has the most empirical support, suggests that age-related increases in neural activity, particularly in the PFC, are positively associated with cognitive performance and therefore benefit cognition (Spreng and Turner, 2019; Cabeza et al., 2018; Reuter-Lorenz and Park, 2014; Davis et al., 2007; Greenwood, 2007). Researchers have observed that older adults typically demonstrate recruitment of bilateral brain areas when performing cognitive tasks, where both hemispheres are active; in contrast, younger adults show lateralization for the same tasks, which is when one hemisphere is active (Cabeza, 2002). The Hemispheric Asymmetry Reduction in Old adults (HAROLD) model proposes that this bilateral activation is used as a compensatory mechanism to counteract age-related cognitive decline, particularly in tasks requiring PFC activation (Cabeza, 2002). Compensation can then be defined as the enhancement of cognitive performance by the recruitment of additional brain networks (Cabeza et al., 2018). In terms of behaviour, these compensatory mechanisms allow older adults to perform at a similar level to younger adults during cognitive tasks. For example, Cabeza et al. (2002) found that low-performing older adults recruit similar networks to younger adults but do not perform as well, whereas high-performing older adults recruit additional bilateral areas. This supports the idea that bilateral activation allows older adults to perform comparatively to their younger counterparts.

Compensation found in older adults has been characterized in several different ways. Researchers have reported compensation is characterized by bilateral PFC activation during cognitively demanding tasks (Reuter-Lorenz and Cappell, 2008; Cabeza, 2002) paired with lower

brain activity in the sensory cortex, which is referred to as the Posterior-to-Anterior Shift in Ageing (PASA) (Davis et al., 2007). Essentially, PASA suggests there is a shift in neural activity from the posterior to the anterior regions of the brain with age, which can be exhibited during a cognitive task. Researchers using neuroimaging have observed these distinct brain patterns, with older adults showing increased PFC (anterior) activity and less parietal (posterior) activity while demonstrating compensation during a cognitive task (Ansado et al., 2012; McCarthy et al., 2014; Zhang et al., 2017).

Major challenges remain in how to best characterize the structural and functional changes that occur as we age due to mixed results within the literature. The question remains whether increases in brain activity shown in older adults is, in fact, compensatory, or if these increases are potentially unrelated or even detrimental to task performance. An overlooked concept is that multiple patterns of brain ageing could co-exist in an individual (Logan et al., 2002), which suggests the potential need for a more integrative theory that connects these distinct models of brain ageing.

1.3. Cognitive Performance and its Relationship to Task Load

Since age-related differences in brain activity have often been dependent on the difficulty of a task, particularly in the PFC, manipulating the complexity of a task (i.e., task load) is essential in understanding age-related neurocognitive changes (Cabeza et al., 2018; Grady, 2012). The most commonly used empirical model to test the predictions of neural compensation is the Compensation-Related Utilization of Neural Circuits Hypothesis (CRUNCH) model, which proposes that, as task load increases, more brain regions will be activated (Mattay, 2006; Reuter-

Lorenz et al., 2000). As the Neural Compensation theory suggests, increases in task load lead to additional recruitment of neural resources in older adults in order to meet increasing cognitive demands while maintaining performance. However, the CRUNCH model suggests there might be a threshold of task complexity. CRUNCH predicts this compensatory over-recruitment cannot be maintained during highly demanding tasks once this threshold has been reached, which leads to reduced brain activity as well as task performance (Nyberg et al., 2009; Mattay et al., 2006). Furthermore, the CRUNCH model proposes that older adults reach this threshold sooner than younger adults. Therefore, during an easy or intermediate task, older adults will recruit more neural resources compared to younger adults to compensate and maintain performance. However, during a difficult task with a high task load, this threshold will be reached, and the over-recruitment mechanisms being employed will not be able to be sustained, leading to reduced brain activity and poorer performance in older adults (Reuter-Lorenz and Cappell, 2008).

To test the predictions of the CRUNCH model, it is necessary to manipulate three or more levels of cognitive load to determine whether there is a task load threshold present, and whether this threshold is being reached sooner in older adults (Jamadar 2020; Mattay et al., 2006). While a very limited number of studies have tested the predictions of the CRUNCH model, recent research has found supporting evidence (Bauer et al., 2015; Toepper et al., 2014; Mattay et al., 2006). For example, Schneider-Garces et al. (2010) used a verbal working memory task and found that older adults showed increased brain activity at low task loads and reduced brain activity at high task loads in the frontoparietal network, whereas younger adults demonstrated a linear trend of increasing brain activity with increasing task load. Furthermore, older adults performed worse on the working memory task relative to younger adults (Schneider-Garces et al., 2010).

While there has been some recent support to validate the predictions of the CRUNCH model, other recent studies have found contradicting results (Blum et al., 2021; Van Ruitenbeek et al., 2023; Ranchod et al., 2023). For example, Jamadar (2020) used fMRI technology to examine brain activity in older and younger adults while manipulating task load to test the CRUNCH model. They found a linear increase in brain activity in both older and younger adults at both low and high task loads, which contradicts the predictions of CRUNCH (Jamadar, 2020). Additionally, research by Blum et al. (2021) reported that older adults were able to maintain compensatory over-recruitment of neural resources during high task loads. These inconsistencies make it difficult to characterize age-related brain activity differences and the role of compensation in relation to task load. This highlights the need for future research which manipulates cognitive load to determine whether the increases in brain activity seen in older adults are limited to a certain level of task difficulty, or whether these over-recruitment strategies are maintained regardless of task load.

1.4. Use of fNIRS to Study Age-Related Neurocognitive Changes

fNIRS technology is a non-invasive neuroimaging method used for studying brain activity in individuals across different age groups. Compared to other imaging techniques like fMRI, fNIRS offers better temporal resolution and lower sensitivity to body movements (Pinti et al., 2020). Additionally, fNIRS is a portable technology, increasing its versatility and potential for experimental testing. It operates by emitting near-infrared (NIR) light at varying wavelengths (between 650-950nm) from a transmitter, which penetrates the layers of the head (skin, skull, cerebrospinal fluid) and reaches the cortical brain tissue. The light is then attenuated, absorbed, and scattered, and these changes are detected by corresponding receivers (Pinti et al., 2020). By

measuring the concentrations of oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR), fNIRS allows researchers to examine brain activity in specific areas of interest (Pinti et al., 2020). When neural activity increases, this leads to increased blood flow and a subsequent increase in HbO concentrations to support the increasing metabolic demands of that brain area (Meidenbauer et al., 2021). Ultimately, the availability of neuroimaging methods such as fNIRS has significantly advanced research in the area of cognitive neuroscience and has allowed researchers to better understand how the brain changes with age.

1.5. Study Objectives

The purpose of this study is to examine brain activity in younger (18-25 years) and older adults (65-91 years) using fNIRS on bilateral prefrontal (PFC) and right parietal cortices. The main objective of this project is to determine if an increase in bilateral brain activity is occurring in older adults relative to younger adults, and if this activation correlates with better task performance and is thus, compensatory. Measuring the frontal and parietal areas will allow us to determine if a posterior-to-anterior shift in aging (PASA) is occurring, and if these brain activation patterns are benefiting task performance (compensation). To test for compensation and in accordance with CRUNCH, we will be using three different N-back tasks, each with increasing complexity, while the participant is wearing the fNIRS cap.

2. MATERIALS AND METHODS

2.1. Participants

A total of 49 participants were recruited for this study, consisting of 24 younger adults (18-25 years (yrs), *M* = 22.1 yrs, *SD* = 1.2 yrs; 10 females and 14 males) and 25 older adults (65-91 yrs, *M* = 74.9 yrs, *SD* = 7.0 yrs; 17 females and 8 males). This was the final sample after excluding 3 participants who had poor fNIRS data quality (see Analysis section of Results, pg. 14). For recruitment, posters were placed at TRU and in local community spaces (e.g., Golds Gym, 5Bean, Tournament Capital Centre). The study was also advertised on online recruitment sites such as social media (e.g., Facebook), with permission of site administrators, and on the local Castanet news media. Additionally, 5 older adult participants were recruited from the Riverbend Mayfair Old Age Community Centre in Kamloops, BC. Participants were screened prior to testing to ensure they met the inclusion criteria. Inclusion criteria included age, as well as having normal or corrected vision, fluency in English (90-100%), having at least 6 years of formal education, having no known neurological or psychological disorders (e.g., stroke, brain injury, Parkinson's disease, bipolar disorder, depression), being right-handed (self-reported), and not taking Aricept (attention-enhancing medication) or psychoactive drugs. Furthermore, two cognitive assessments were performed on older adults (i.e., the Montreal Cognitive Assessment (MoCA), and the Repeatable Battery for the Assessment of Neuropsychological Status (RBANS)) to ensure participants were within the normal range of cognitive functioning. All participants gave written consent prior to testing. This study was approved by the Thompson Rivers University research ethics board.

2.2. Procedure

The testing sessions were 45-60 minutes long for younger adults, and 90 minutes long for older adults. Thirty minutes of cognitive assessments (MoCA, RBANS) as well as a cognitive reserve index questionnaire (CRIq) were administered to older adult participants prior to the N-back task. All participants were fitted with the fNIRS Brite head cap (Artinis Medical Systems, The Netherlands) to measure brain activity whilst they performed working memory tasks with 3 levels of difficulty. To ensure consistent placement of the optode array, each participant's Cz were measured and marked on the scalp. Subsequently, the pre-marked Cz point of the fNIRS cap was aligned with the participant's Cz according to the 10-20 international system (Klem et al., 1999). The cap is equipped with 10 light-emitting optodes or sources (S) that transmit NIR light (650-950 nm) as well as 8 detectors (D) that detect changes in light absorption (25 Hz). The optodes were placed on the cap an ideal 3 cm apart, and the pairing of source-detector optodes corresponded to a recording channel (CH). Our array covered the bilateral prefrontal cortex (PFC) as well as the right parietal lobe with a total of 21 channels: 7 channels on the right PFC, 12 channels on the left PFC, and 2 channels on the right parietal lobe. Brain activity is found to be lateralized on the right hemisphere for visuospatial processes, which is why the right-side parietal lobe was examined for the present study (Corballis, 2003).

The fNIRS device continuously recorded changes in oxygenated (HbO) and deoxygenated (HbR) hemoglobin concentrations from each channel over the cortex. A greater level of HbO indicated a higher level of hemoglobin delivery to a particular brain area, which then specifies, indirectly, increased brain activity in that area. One short separation channel was placed on the fNIRS cap (SSCH, source-detector distance of 1.5cm), located on the left hemisphere (channel 15,

Figure 1), which was used as a regressor to eliminate physiological "noise" (e.g., heartbeat, blood flow) or activity not relevant to the task (Funane et al., 2015). Prefrontal and parietal regions were chosen based on previous research using fNIRS which examined similar areas during a visuospatial N-back task (Meidenbauer et al., 2021). The locations of the source and detector optodes were digitized using a Polhemus optode digitization system in reference to vertex, inion, naison, and preauricular landmarks. The estimated source-detector pairings were registered to a 3D brain template (Colin 27, atlas) using the Brain AnalyzIR toolbox (Figure 1).

All fNIRS data was collected using Oxysoft (Artinis, Medical Systems, The Netherlands, version 3.2.51.4) and a sampling frequency of 25 Hz was used. Prior to data collection, each individual optode was removed and participant's hair was pushed to the sides to optimize channel data quality. Additionally, an age-dependent differential path-length factor (DPF) was applied, which uses participant age to estimate the ratio of mean optical pathlength and light travelling within the cortical tissue to the source-detector separation distance. The DPF for age 50 was used for all older adult participants, as the DPF for those who are older than 50 years of age has not yet been determined (Schroeter et al., 2003).

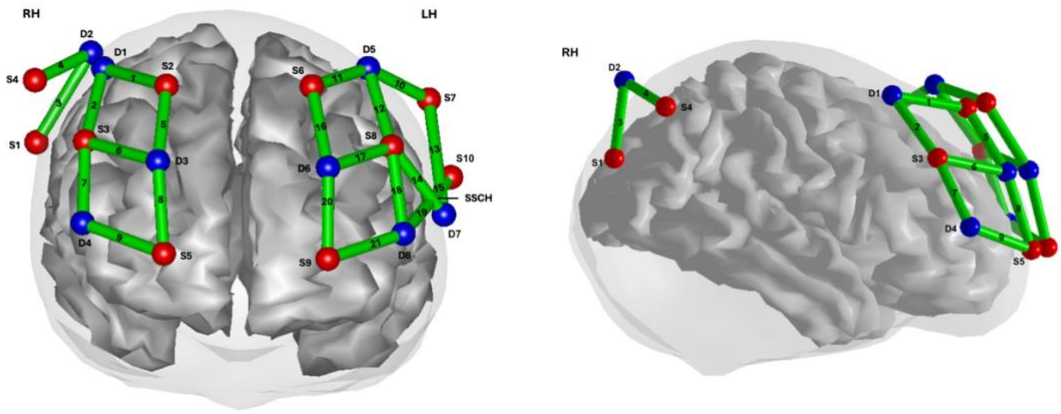

Figure 1

3D Visualization of the 21-channel fNIRS optode array from frontal (left) and lateral (right) views. Ten sources (S, in red) and 8 detectors (D, in blue) over bilateral prefrontal cortex (PFC) and right parietal lobe areas were digitized using a Polhemus system and registered to a 3D brain template (Colin27, atlas). The source-detector pairings make up 21 channels (in green); 12 on the left hemisphere (LH) and 9 on the right hemisphere (RH). One SSCH (short-separate channel) was placed on the left hemisphere (CH 15). Optode placements were identified using the 10-20 international system.

Once a good signal was established, the participant was asked to complete three visuospatial working memory (N-back) tasks of increasing cognitive load (1-back, 2-back, and 3-back, respectively). The task was designed using E-prime 3.0 (Psychology Software Tools Inc., PA, USA) and positioned in front of the seated participants on a computer laptop (Dell Latitude 3410, 14" HD, 1920 x 1200 resolution). Each N-back began with a 20-second (s) rest period to collect a baseline measurement, where a white screen with the word "rest" on the center of the screen was displayed, and participants were asked to simply sit still while keeping their fingers on the keyboard. This was followed by 40s of the N-back task (either 1, 2, or 3-back). This sequence

was repeated 4 times in total for each N-back condition. For the N-back tasks, a blue box appeared at one of six possible locations (i.e., upper left, middle, and right, and lower left, middle, and right) (Figure 2). The box would appear on the screen for 0.5s before disappearing. After the box disappeared, participants were given 1.5s to respond by pressing a keyboard button on the computer. A new box would then appear after the 1.5s. The participants were required to indicate whether the current presented stimulus (i.e., the blue box) was in the same (S) location (by pressing the "S" key) or different (D) location (by pressing the "D" key) as either 1 box ago (1-back), 2 boxes ago (2-back) or 3 boxes ago (3-back) for each cognitive load. Each N-back task had a total of 80 trials, with 20% of trials being targets (which required an "S" response), and 80% being non-targets (which required a "D" response). This ratio of targets to non-targets was implemented as it reflects executive function engagement rather than being more perceptual or predictive in nature (Posner, 1980). Participants were given verbal step-by-step set of instructions from the researcher on how to perform the N-back task, as well as given practice trials with feedback in each trial and a total score prior to each N-back task. Additionally, the order in which participants completed the task load conditions was counterbalanced, with half of participants completing the 1-back, followed by the 2-back then the 3-back, and the other half completing the 1-back, followed by the 3-back and then the 2-back.

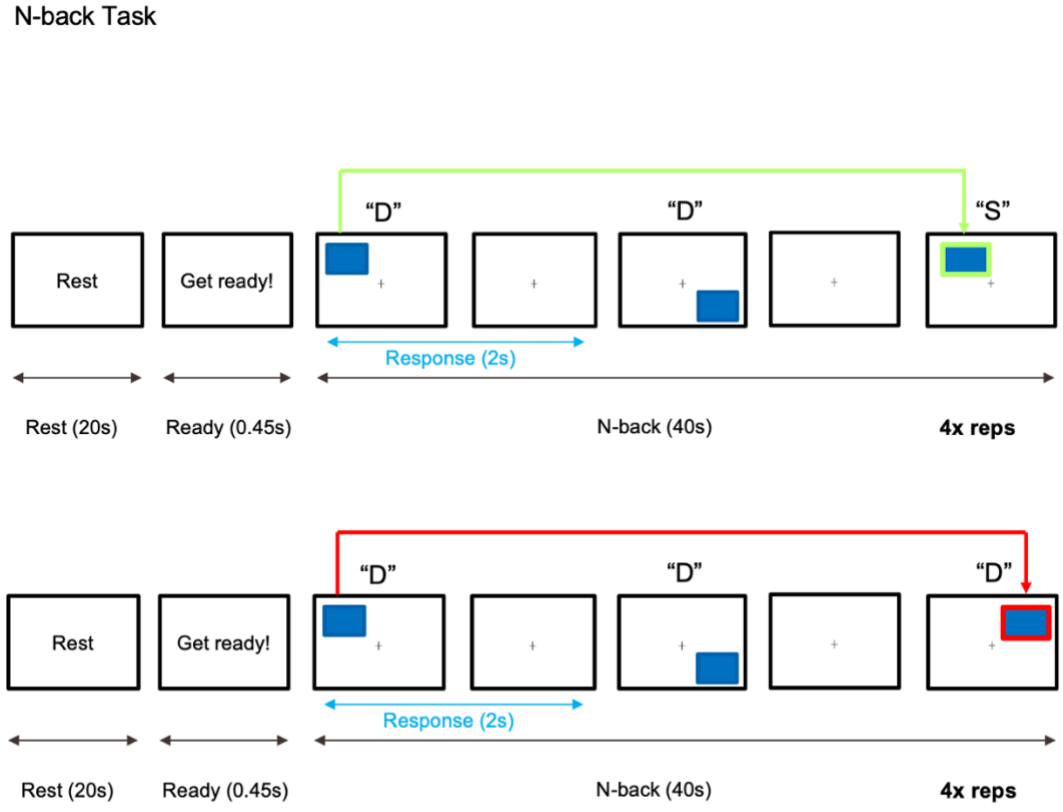

Figure 2

Example of a 2-back visuospatial working memory task. Participants had to determine whether the current box was in the same or different location as two trials back by pressing the "S" key for same or "D" key for different. The top panel shows a sequence where the box is in the same location as two trials back, and an "S" response is required, while the bottom panel shows a sequence where the box is in a different location than two trials back, and a "D" response is required.

2.3. Analysis

Behavioural data from each of the three N-back tasks for each participant was extracted from E-prime and compiled into an Excel database. Trials with no observed responses and those with reaction times less than 80 milliseconds (which was indicative of a guess) were excluded from further analysis. On average, OA had 4.92% of trials removed (*SD* = 7.05%) while YA had 2.04% of trials removed (*SD* = 3.56%). Behavioural measures included error rate percentages (i.e., the total number of incorrect responses divided by the total number of possible responses) for targets, where the stimulus was in the same location and an "S" response was required, and for non-targets, where the stimulus was in a different location and a "D" response was required. *Pr* values were calculated as another measure of accuracy by subtracting the number of incorrect non-target responses or "false alarms" from the number of correct target responses or "hits", reflecting true positives (Jaeggi et al., 2008) and combining all trial types (target and non-target) for better statistical power. Reaction times (in milliseconds) were also recorded for each participant across the three N-back tasks and for target and non-target categories only for correct trials. The statistical software JASP (version 0.17.2.1, 2023, MacOS) was used to conduct repeated-measures analysis of variance (ANOVAs) for error rates (%), *Pr* values, and reaction times within task load conditions and target types to identify behavioral differences between older and younger adults. Statistical significance was set to $p < .05$, and Bonferroni corrections were applied for post hoc tests.

fNIRS data was exported from Oxysoft and converted to SNIRF files (MATLAB 2022b, version 9.13.0, MathWorks Inc., Massachusetts) using the Brain AnalyzIR toolbox (Santosa et al., 2019). The data was down sampled (10 Hz) and pre-processed using the modified Beer-Lambert

Law, which converted changes in optical density to changes in HbO concentration (μM). Only HbO values from this conversion were considered for subsequent analysis. A Structured Noise Index (SNI) was used to identify "bad" channels; however, given our sampling differences vs. Zhuang et al. (2022) (i.e., ours 10 Hz vs 4 Hz), an SNI < 4 was chosen instead of an SNI < 2. At this stage, three participants were removed due to a high number of bad channels, indicating poor fNIRS signal quality.

A subject-level general linear model (GLM) was then applied to the fNIRS data using the Brain AnalyzIR toolbox (Santosa et al., 2019) to identify significantly active channels during the N-back trial blocks for each task load condition. The short-separate channel (SSCH), as well as an autoregressive iteratively reweighted least-squares model (AR-IRLS) was used in the GLM to eliminate motion artifacts and physiological noise from our fNIRS signals. The AR-IRLS uses robust regression and pre-whitening techniques and has been shown to control for false positive rates caused by high amounts of noise (Barker et al., 2013; Huppert et al., 2016). The GLM is a well-established method for analyzing event-related or time series data, and essentially fits the raw data to a modeled response with set parameters; in this case, it assumes a canonical hemodynamic response function (HRF). The output of the GLM is a series of calculated beta (β) coefficients for each participant and task load, which indicate changes in HbO signal intensity and direction (Santosa et al., 2019). These beta values are a measure of how well our data fits the ideal HRF response. By using the GLM, we are controlling for type I errors or false positive rates while also reducing noise and activity that was not a response of an event.

A group-level analysis was then conducted based on the subject-level results, which used a mixed effects regression model to obtain significantly active channels relative to baseline across

groups for each cognitive load (1, 2, and 3-back) with significance set to $p < .05$. T-test contrasts, corrected for multiple comparisons, were then conducted to identify significant differences in brain activity across all 21 channels between task conditions and groups, with significance set at $p < .05$. Contrast directions were pre-determined based on previous research and the CRUNCH model, that is, older adults would have increased brain activity relative to younger adults (YA > OA in the 1-back, 2-back, and 3-back), and participants would have increased brain activity with increasing task load (3-back > 2-back, 2-back > 1-back, and 3-back > 1-back). This resulted in 9 contrasts, in addition to the group analyses.

3. RESULTS

3.1. Cognitive Assessment Results

Participant MoCA scores were found to be within the normal range of 26-30 ($M = 26.7$, $SD = 3.8$). Additionally, participant's RBANS total scale scores were also within normal range ($M = 108$, $SD = 15.7$), as the average RBANS total scale score for healthy older adults is 100, with a standard deviation of 15 (Phillips et al., 2015). On average, our older adult participants scored in the upper 63rd percentile (%) relative to their age group, which further confirms our sample of older adults is within a healthy range of cognitive functioning. Furthermore, a cognitive reserve index (CRIq) questionnaire was implemented, which scores individuals based on factors such as age, education, work activity, and social or leisure activities ($M = 133.3$, $SD = 16.9$). According to Nucci et al. (2012), a score of $\geq$130 is considered in the "high" cognitive reserve category, with the "medium" or average range between 85-114. This means that, on average, our OA participants

may be considered to have high cognitive reserve, which suggests that they have an increased ability to cope with the effects of cognitive decline (Nucci et al., 2012). Individual participant scores for these assessments can be seen in Table 3 of the Appendix, pg. 48.

3.2. Behavioural Results

Both accuracy, measured by error rates (%) and *Pr* values (hits – false alarms), as well as reaction times (in milliseconds) for target (trials requiring "S" responses for same as N-back trials) and non-target stimuli (trials requiring "D" responses for different as N-back trials) were compared between older (OA) and younger (YA) adults, as well as between 1-back (1B), 2-back (2B), and 3-back (3B) task load conditions.

Two separate repeated measures ANOVAs were performed on participant error rates (%) which revealed an effect for task load on both non-target, $F(2,94) = 56.785$, $p < .001$, $\eta 2 = .215$, and target error rates, $F(2,94) = 20.561$, $p < .001$, $\eta 2 = .151$. For non-target stimuli, error rates were higher in the 3B vs. 1B ($p < .001$), as well as in the 3B vs. 2B ($p = .005$), and higher in the 2B vs. 1B ($p < .001$). Target error rates exhibited a similar trend across tasks, with error rates being higher in the 3B vs. 1B ($p < .001$), as well as in the 3B vs. 2B ($p < .001$), and higher in the 2B vs. 1B ($p = .019$).

Similarly, results revealed an effect for age group on non-target, $F(1,47) = 7.198$, $p = .010$, $\eta 2 = .080$, and target error rates, $F(1,47) = 12.745$, $p < .001$, $\eta 2 = .104$. For non-target stimuli, older adults ($M = 14.103$, $SD = 9.055$) had higher error rates than younger adults ($M = 8.178$, $SD = 7.344$). For target stimuli, older adults ($M = 33.148$, $SD = 6.470$) also had higher error rates than

younger adults (M = 18.775, SD = 4.902). No group by task load interactions were observed for either non-target, p = .159, nor target error rates, p = .151.

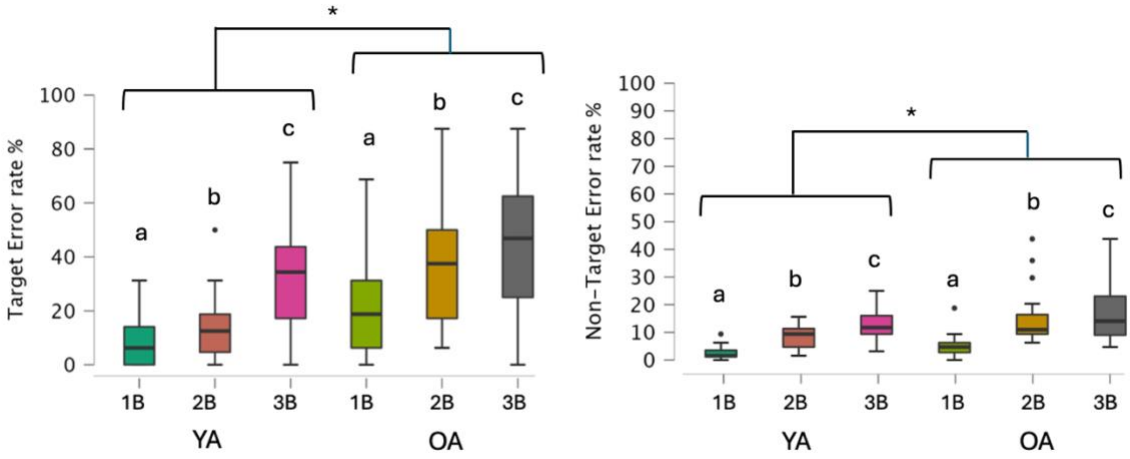

Figure 3

Boxplots for target and non-target error rates (%). Differences in error rates (%) between older (OA) and younger (YA) adults and between task load conditions and can be observed for both target (left) and non-target stimuli (right). OA were less accurate than YA for both target, (*) p < .001, and non-target types, (*) p = .010. Additionally, an effect for task load was found for target and non-target types, both p < .001. Means with different letters are significantly different from each other, p < .05.

Additionally, an analysis was performed on participant *Pr* values (hits – false alarms) as a measure of task accuracy (Figure 4). The results revealed an effect for task load, F(2,94) = 78.195, p < .001, η2 = .264. Task accuracy was higher in the 1B vs. 2B as well as in the 1B vs. 3B, and

higher in the 2B vs. 3B (all $p < .001$). Similarly, our results revealed an effect for age group on *Pr*, $F(1,47) = 15.055$, $p < .001$, $\eta 2 = .138$. Younger adults ($M = 7.630$, $SD = 5.421$) had higher task accuracy than older adults ($M = 1.282$, $SD = 6.860$).

Whilst no significant interaction was found for *Pr*, a trend, $p = .078$ was observed, which prompted further investigation through post hoc tests (also see Mattay et al., 2006). Note that higher *Pr* values correspond to better performance (more hits) and lower *Pr* values correspond to worse performance (more false alarms). The post hoc tests further revealed that, for older adults, *Pr* values were significantly higher in the 1B vs. 2B ($p < .001$), as well as in the 1B vs. 3B ($p < .001$) but were not significantly higher in the 2B vs. 3B ($p = .096$). For younger adults, *Pr* values were significantly higher in the 1B vs. 2B ($p = .014$) as well as the in 1B vs. 3B and in the 2B vs. 3B (both $p < .001$). Furthermore, younger adults had higher task accuracy than older adults in the 2B, $p < .001$, and 3B, $p = .033$, but not the 1B, $p = .302$.

An analysis was also performed on participant reaction times (in ms) for target and non-target stimuli (Figure 5). The results of the analysis revealed an effect for task load on both non-target, $F(2,94) = 31.511$, $p < .001$, $\eta 2 = .118$, and target reaction times, $F(2,94) = 36.525$, $p < .001$, $\eta 2 = .116$. For non-target stimuli, reaction times were slower in the 3B vs. 1B as well as in the 3B vs. 2B (both $p < .001$), and slower in the 2B vs. 1B ($p = .004$). Target reaction times exhibited a similar trend across tasks with reaction times being slower in the 3B vs. 1B well as in the 3B vs. 2B (both $p < .001$), and slower in the 2B vs. 1B ($p = .003$).

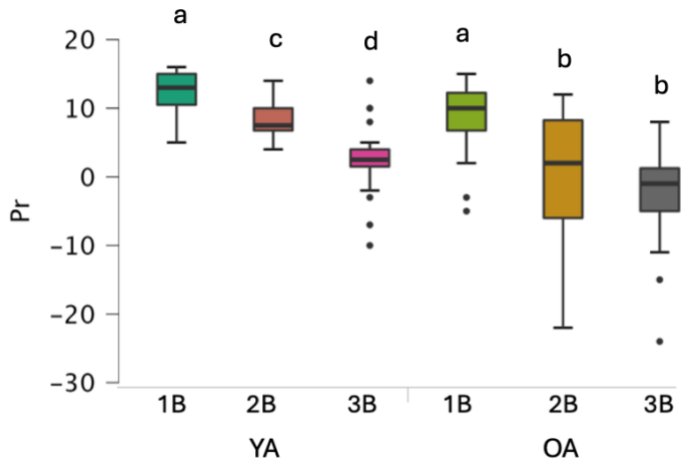

Figure 4

Boxplot for Pr values. Differences in *Pr* (hits – false alarms) can be observed between older (OA) and younger (YA) adults, as well as between task load conditions according to a trend, $p = 0.078$. YA had higher task accuracy than OA in the 2B, $p < .001$, and 3B, $p = .033$. For OA, task accuracy was higher in the 1B vs. 2B as well as in the 1B vs. 3B, both $p < .001$. For YA, task accuracy was higher in the 1B vs. 2B, $p = .014$, as well as in the 1B vs. 3B and in the 2B vs. 3B, (*) both $p < .001$. Means with different letters are significantly different from each other, $p < .05$.

Furthermore, our results revealed an effect for age group on target reaction times, $F(1,47) = 11.172$, $p = .002$, $\eta 2 = .139$, but no effect for non-target reaction times ($p = .070$). For target stimuli, younger adults ($M = 577.435$, $SD = 449.783$) had faster reaction times compared to older adults ($M = 748.464$, $SD = 384.120$).

Our RT results revealed a significant interaction between task load and age group for non-targets, $F(2,94) = 4.569$, $p = .013$, $\eta 2 = .017$. Post-hoc tests further revealed that, for older adults, non-target reaction times were significantly faster in 1B vs. 3B and in the 2B vs. 3B tasks (both *p*

< .001), but not different between the 1B and the 2B (p = 1.00). Similarly, for younger adults, non-target reaction times were faster in the 1B vs. 2B and in the 1B vs. 3B tasks (both p < .001), but not in the 2B vs. 3B (p = 1.00). No significant differences were found for non-target reaction times when comparing younger adults to older adults for the 1B (p = .172), 2B (p = 1.00), or 3B (p = .643).

A significant interaction between task load and age group was also found for target reaction times, $F(2,94) = 3.729$, p = .028, $\eta 2$ = .012. Post-hoc tests further revealed that, for older adults, target reaction times were significantly faster in the 1B vs. 3B and in the 2B vs. 3B tasks (both p < .001), but not the 1B vs. 2B (p = 1.00). For younger adults, target reaction times were faster in the 1B vs. 2B (p = .004) as well as in the 1B vs. 3B (p < .001), but not the 2B vs. 3B (p = 1.00). Furthermore, older adults had slower reaction times compared to younger adults in the 1B (p = .019,) and 3B tasks (p = .004), but not the 2B (p = 1.000).

In summary, behavioural results showed that participants had higher error rates (%), lower *Pr* values, and slower reaction times in the higher task loads compared with the lower task loads. Specifically, older adult participants had higher task accuracy (*Pr*) in the 1B compared to the 2B and 3B tasks, albeit no accuracy (*Pr*) differences were observed between 2B and 3B. Younger adults showed accuracy differences between 1B vs. 2B, 1B vs. 3B, and 2B vs. 3B, with better accuracy in the 1B and worse accuracy in the 3B. Furthermore, younger adults had higher task accuracy (*Pr*) than older adults in the higher task loads (i.e., 2B and 3B) but both groups had similar accuracy (*Pr*) in the 1B. Additionally, younger adults had significantly faster reaction times in the 1B and 3B tasks (no differences in the 2B) compared to older adults for target stimuli and

no significant differences in reaction times between age groups were observed for non-target stimuli.

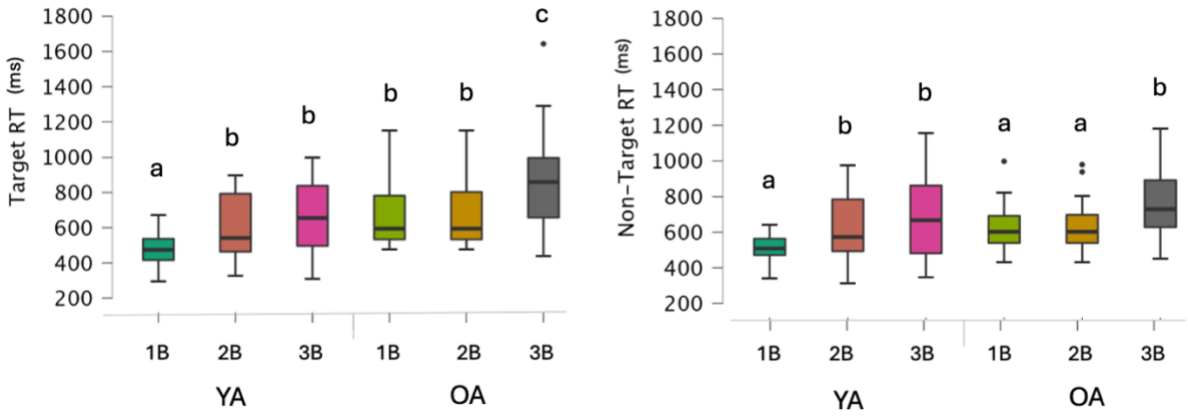

Figure 5

Boxplots for target and non-target reaction times (in milliseconds**)**. Differences in reaction time (RT) between older (OA) and younger (YA) adults and between task load conditions can be observed for both target (left) and non-target stimuli (right). For targets, YA were faster than OA in the 1B, $p = .019$, and 3B, $p = .004$. For non-targets, OA were faster in the 1B vs. 3B and in the 2B vs. 3B, both $p < .001$; YA were faster in the 1B vs. 2B and in the 1B vs. 3B, both $p < .001$. For targets, OA were faster in the 1B vs. 3B and in the 2B vs. 3B, both $p < .001$; YA were faster in the 1B vs. 2B, $p = .004$, and in the 1B vs. 3B, $p < .001$. Means with different letters are significantly different from each other, $p < .05$.

3.3. fNIRS Results

fNIRS analysis was conducted to investigate brain activity differences between older (OA) and younger (YA) adults in the PFC and parietal lobe areas during 1-back (1B), 2-back (2B), and

3-back (3B) tasks. The results from the group-level and contrast analysis are channels with significant increases or decreases in HbO concentrations (calculated as beta (β), $p < .05$) and superimposed over the brain template as T-stat values in the below figures. Channels with significant HbO increases are demonstrated in red, whilst HbO decreases are in blue. All significant channels, betas, T-stat, and p values are shown in Table 2.

Results from the group-level analysis compared brain activity for both OA and YA in each task load condition relative to baseline, which are reported in Table 1 and Figure 6. These results showed that YA had significant HbO increases in CHs 3, 4, 5, 8, and 9 on the RH and CHs 12, 13, and 14 on the LH for the 1B task (Figure 6, upper left panel). YA also showed significant increases relative to baseline in CHs 1, 4, and 5 on the RH and one channel, CH 16, on the LH for the 2B task (Figure 6, upper middle panel). For the 3B task, YA showed increased activity in CHs 3, 4, and 8 on the RH and one channel, CH 14, on the LH (Figure 6, upper right panel). OA showed significant brain activity increases in CHs 2, 4, 7, 8, and 9 on the RH and CHs 16, 18, and 21 on the LH for the 1B task (Figure 6, lower left panel). For the 2B task, OA showed increases in CHs 3, 4, 5, 7, 8, and 9 on the RH and CHs 16, 19 and 20 on the LH (Figure 6, lower middle panel). For the 3B task, OA showed increases in CHs 1, 3, 4, 5, 6, 7, 8, and 9 on the RH and CHs 14, 16, 19, 20, and 21 on the LH (Figure 6, lower right panel).

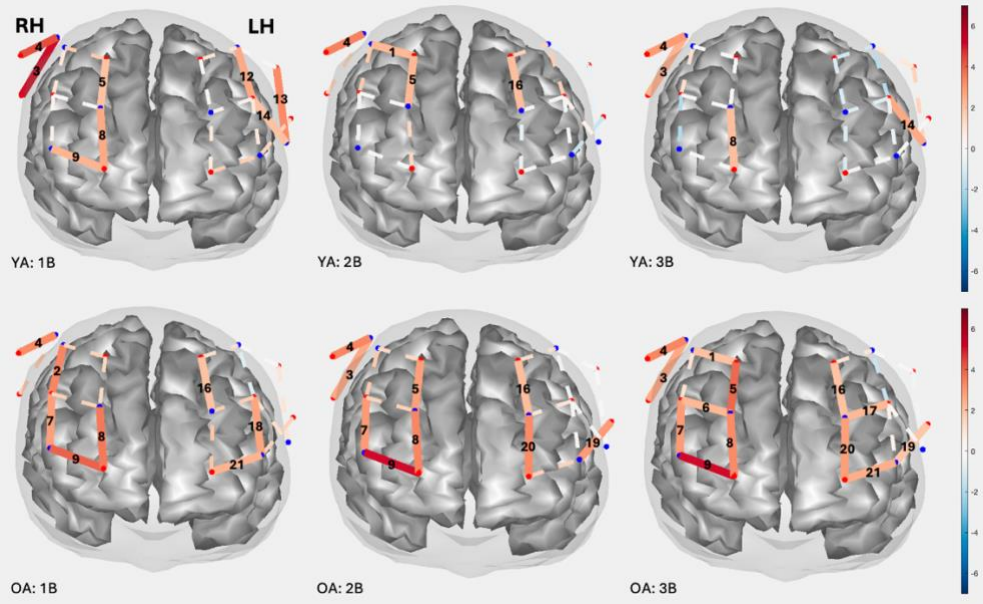

Figure 6

Active HbO channels relative to baseline (Table 2) for older (OA) and younger (YA) adults. Significant channels ($p < .05$) are based on T-stat values from the group-level analysis for YA (top panel) and OA (bottom panel) for each task load condition. The solid red lines correspond to significant activity or increases in HbO within a channel.

A contrast analysis was performed to examine brain activity differences both within and between age groups, as well as between task load conditions (Table 2 and Figure 7). Based on the results, YA had significant HbO decreases in CH 3 on the RH and CH 12 on the LH when comparing 3B vs.1B tasks (Figure 7, top right panel). When comparing 3B vs. 2B tasks, YA showed decreased brain activity in CH 5 on the RH and CHs 11, 12, and 16 on the LH (Figure 7, top middle panel). When comparing 2B vs.1B tasks, YA showed decreased brain activity in CH 3 on the RH and CHs 13 and 19 on the LH (Figure 7, top left panel). In contrast, OA had no significantly active channels when comparing 3B vs. 1B tasks (Figure 7, middle right panel).

Table 1

Active HbO channels relative to baseline for each task load condition for both older (OA) and younger (YA) adults (significant channels ($p < .05$) for both left (LH) and right (RH) hemispheres are shown) (n = 49).

Relative to baseline	Source	Detector	CH	Hemisphere	beta	T-stat	p-value
	1	2	3	RH	0.868	5.138	<.001
	4	2	4	RH	0.944	4.401	<.001
YA: 1B	2	3	5	RH	0.241	2.085	.039
	5	3	8	RH	0.306	2.627	.010
	5	4	9	RH	0.328	2.361	.020
	8	5	12	LH	0.215	2.628	.010
	7	7	13	LH	0.339	3.266	<.001
	8	7	14	LH	0.206	2.089	.038
	2	1	1	RH	0.209	2.220	.028
YA: 2B	4	2	4	RH	0.615	3.459	<.001
	2	3	5	RH	0.265	2.301	.023
	6	6	16	LH	0.208	2.110	.037
	1	2	3	RH	0.379	2.360	.020
YA: 3B	4	2	4	RH	0.619	2.974	.003
	5	3	8	RH	0.246	2.145	.034
	8	7	14	LH	0.243	2.551	.012
	3	1	2	RH	0.265	3.384	<.001
	4	2	4	RH	0.212	3.303	<.001
OA: 1B	3	4	7	RH	0.175	2.769	.006
	5	3	8	RH	0.360	3.600	<.001
	5	4	9	RH	0.447	4.022	<.001
	6	6	16	LH	.116	2.036	.044
	8	8	18	LH	.221	2.647	.009
	9	8	21	LH	.302	2.340	.021
	1	2	3	RH	0.177	2.605	.010
	4	2	4	RH	0.213	3.329	<.001
OA: 2B	2	3	5	RH	0.242	2.860	.005
	3	4	7	RH	0.181	2.971	.003
	5	3	8	RH	0.350	3.401	<.001
	5	4	9	RH	0.410	5.133	<.001
	6	6	16	LH	0.120	2.108	.037
	10	8	19	LH	0.308	2.909	.004
	9	6	20	LH	0.235	3.268	<.001
	2	1	1	RH	0.172	2.025	.045
	1	2	3	RH	0.177	2.607	.010
	4	2	4	RH	0.214	3.341	<.001
	2	3	5	RH	0.355	3.882	<.001
	3	3	6	RH	0.193	2.288	.024
OA: 3B	3	4	7	RH	0.180	2.871	.005
	5	3	8	RH	0.33	3.226	<.001
	5	4	9	RH	0.409	5.129	<.001
	8	6	14	LH	0.152	2.234	.027
	6	6	16	LH	0.115	2.019	.045
	10	8	19	LH	0.221	1.980	.050
	9	6	20	LH	0.205	2.853	.005
	9	8	21	LH	0.324	2.519	.013

However, when comparing 3B vs. 2B tasks, OAs showed decreased brain activity in CH 20 on the LH (Figure 7, middle center panel). When comparing 2B vs. 1B tasks, OAs showed decreased brain activity in CH 18 on the LH (Figure 7, middle left panel).

Additionally, the contrasts revealed that during the 1B task, OA showed decreased HbO activity in CHs 3 and 4 on the RH and CH 12 on the LH (relative to YA) (Figure 7, bottom left panel). For the 2B task, OA showed increased HbO activity relative to YA in CHs 19 and 20 on the LH and CH 9 on the RH, but decreased brain activity in CH 4 on the RH (Figure 7, bottom middle panel). For the 3B, OA showed increased brain activity relative to YA in CHs 5, 7, and 9 on the RH and CHs 17 and 20 on the LH (Figure 7, bottom right panel).

In summary, YAs showed more brain activity in the 1B compared with the 2B and 3B, but also showed lower brain activity between the 2B vs. the 3B. In contrast, OA showed similar activity throughout the load conditions, with slight decreases in one channel in the RH. YA showed more activity than OA in the 1B, mostly in parietal lobe but overall, OAs had more brain activity in both RH and LH in the 2B and 3B.

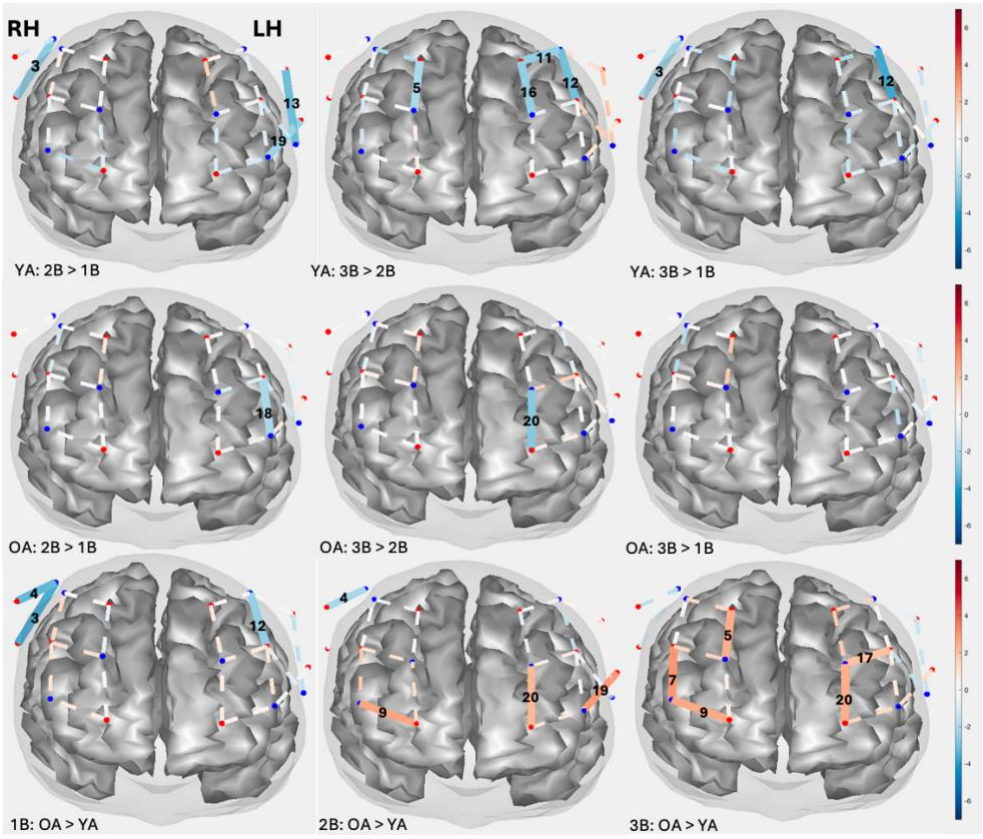

Figure 7

Active HbO channels for group-level contrasts (Table 3) between older (OA) and younger (YA) adults and between task load conditions. Significant channels ($p < .05$) are based on T-stat values for within-group contrasts for YA (top panel) and OA (middle panel) between task load conditions, as well as between-group contrasts for each task load condition (bottom panel). The solid red lines correspond to significant activity or increases in HbO, while the solid blue lines correspond to significant decreases in HbO activity.

Table 2

Active HbO channels based on group-level contrast results between older (OA) and younger (YA) adults and between task load conditions (significant channels ($p < .05$) for both left (LH) and right (RH) hemispheres are shown) (n = 49).

Relative to baseline	Source	Detector	CH	Hemisphere	beta	T-stat	p-value
YA: 3B > 1B	1	2	3	RH	-0.489	-2.215	.028
	8	5	12	LH	-0.371	-3.726	<.001
	2	3	5	RH	-0.291	-1.993	.048
YA: 3B > 2B	6	5	11	LH	-0.262	-2.465	.015
	8	5	12	LH	-0.301	-3.072	.003
	6	6	16	LH	-0.320	-2.474	.015
	1	2	3	RH	-0.607	-2.640	<.001
YA: 2B > 1B	7	7	13	LH	-0.415	-3.167	<.001
	10	8	19	LH	-0.466	-2.246	.026
OA: 3B > 2B	9	6	20	LH	-0.029	-2.675	.008
OA: 3B > 1B	-	-	-	-	-	-	-
OA: 2B > 1B	8	8	18	LH	-0.196	-2.080	.039
	2	1	1	RH	-0.335	-2.425	<.001
	3	1	2	RH	-0.355	-2.88	0.005
	1	2	3	RH	-1.038	-5.389	<.001
1B: OA > YA	4	2	4	RH	-1.155	-5.163	<.001
	2	3	5	RH	-0.375	-2.482	<.001
	5	3	8	RH	-0.665	-4.336	<.001
	5	4	9	RH	-0.775	-4.357	<.001
	7	7	13	LH	-0.432	-3.083	0.002
	8	7	14	LH	-0.302	-2.317	0.022
	8	8	18	LH	-0.304	-2.39	0.018
	10	8	19	LH	-0.435	-2.206	0.029
	9	8	21	LH	-0.525	-2.873	0.005
	2	1	1	RH	0.337	2.582	0.011
	3	1	2	RH	0.313	2.531	0.012
2B: OA > YA	1	2	3	RH	0.439	2.355	0.02
	4	2	4	RH	0.828	4.382	<.001
	2	3	5	RH	0.506	3.547	<.001
	5	3	8	RH	0.511	3.282	<.001
	5	4	9	RH	0.374	2.307	0.023
	6	5	11	LH	0.242	2.067	0.041
	6	6	16	LH	0.328	2.883	0.005
	2	3	5	RH	0.381	2.508	.013
3B: OA > YA	3	4	7	RH	0.383	3.074	.003
	5	4	9	RH	0.426	2.614	.010
	8	6	17	LH	0.243	2.051	.042
	9	6	20	LH	0.324	2.433	.016

4. DISCUSSION

4.1. Behavioural results

We expected to observe slower reaction times, higher error rates (%) and lower task accuracy (*Pr*) for participants as a function of task load. Our results demonstrated that the N-back tasks were indeed increasing cognitive load in our participants who showed lower accuracy (*Pr*), higher error rates and longer reaction times in the 3B compared to lower task loads (1B and 2B) in both YA and OA. This indicates that, with increasing cognitive demands, our participants showed reduced performance and took longer to respond to stimuli.

Our results also demonstrated behavioural differences between age groups across task load conditions. OA showed higher error rates (%) than YA for both target and non-target stimuli. Also, OA were slower than YA to respond to targets in the 1B and 3B but not in the 2B. In addition, no RT differences were observed for non-target stimuli. Additionally, accuracy measured as *Pr* showed no significant interaction between task load and age group, however a trend can be observed within our results, which prompted post hoc tests for further exploration. Post hoc tests revealed OA were less accurate than YA in the 2B and 3B but had similar accuracy compared to YA in the 1B. These results could be attributed to speed-accuracy trade-offs, where OA presumably prioritize accuracy over speed to avoid making mistakes (Salthouse, 1979; Rabbitt, 1979; Starns and Ratcliff, 2010). While this speed-accuracy trade-off may have been beneficial in the 1B, it is not observed or not beneficial at higher task loads (2B and 3B respectively). Importantly, similarities in performance were mostly observed at lower task loads (1B) and not at higher task loads in accordance with previous research using N-back tasks (Mattay et al., 2006; Nyberg et al., 2009). Given the level of cognitive function (MoCA and RBANS) and high cognitive reserve

(Cabeza et al., 2018; Nucci et al., 2012) in our OA group, it was not a surprise to see some similarities in performance (accuracy and RT) between the age-groups. A question arises from these observations – would OAs then show more brain activity than YAs in the 1B and then attenuation at higher loads as per the predictions of CRUNCH (e.g., Mattay et al., 2006)?

4.2. fNIRS results

Our primary objective was to compare OA and YA across three task load conditions of increasing complexity. We predicted that OA would show compensation based on support from previous research. This compensation can be defined as an increase in bilateral brain activation with increasing cognitive load, allowing OA to perform at a comparable level to YA (Cabeza, 2002; Reuter-Lorenz and Cappell, 2008; Cabeza et al., 2018). If compensation was occurring, this would mean the additional recruitment of neural resources would be beneficial to OA and allow them to maintain performance and thus counteract the effects of age-related cognitive decline. Additionally, we implemented three task load conditions in order to test the predictions of the CRUNCH model (Reuter-Lorenz et al., 2000; Mattay et al., 2006; Nyberg et al., 2009). Specifically, the CRUNCH model predicts that OA will reach a threshold of task complexity sooner than YA and exceed their limit of cognitive capacity more rapidly, resulting in reduced brain activity as well as reduced task performance at high task loads. Thus, increased brain activity in OA relative to YA in the 1B, but decreased brain activity or attenuation in the higher task loads would support the CRUNCH model.

Relative to baseline, YA had 5 channels in RH and 3 in LH as active vs. 3 channels in RH and 1 channel active in LH both in the 2B and 3B. Contrast analysis results thus revealed that YA had slightly more activity in the 1B compared to the 2B, as well as in the 1B compared to the 3B, and exhibited more activity in the 2B compared to the 3B, including parietal lobe. Overall, YA seem to have similar activity throughout, with most differences observed in 2B vs 3B, i.e., decreases with more load which could be in line with CRUNCH. However, the fact that they did not increase brain activity between 1B and 2B is against the model. Furthermore, OA had similar activity levels in the 3B compared to the 2B as well as the 2B compared to the 1B; no differences were found in the 3B compared to the 1B. Therefore, OAs seem to be maintaining brain activity across task loads, which is not in line with CRUNCH.

These results indicate that YA may have exceeded their limits after the 1B and were not able to recruit additional brain areas at higher task loads. Some research has suggested that YA may disengage or "give up" during a task if deemed too difficult, which could be a potential explanation for this observed brain activity and decreased performance (Causse et al., 2017; Mandrick et al., 2013). Another explanation may be that both YA and OA are already activating more attention and working memory resources needed for the tasks early on in the 1B and although minimal decreases are seen in YA, for the most part, they use similar brain activity throughout the tasks. Additionally, factors such as fatigue or practice effects may be contributing factors. Practice effects typically lead to decreases in brain activity (Jolles et al., 2010). Alternatively, because of its simplicity, the 1B may potentially activate distinct areas that are more associated with visual memory and attention rather than working memory, since the working memory requirements at this load are almost null. Kane et al. (2007) examined the validity of the N-back task in measuring purely

working memory and stated the 1-back challenges attentional control more while engaging memory less in individuals. Therefore, more brain activity observed in the 1B compared to the 2B and 3B tasks may be due to the activation of other areas not associated with working memory per se. This can be supported based on group-level fNIRS results (Figure 6, pg. 23) which shows YA are activating channels 12, 13, and 14 in the 1B, but not in the 2B and 3B. A region of interest (ROI) analysis, which identifies the location of channels based on Brodmann areas (BA), indicated that these channels are located mainly in the dorsolateral PFC (BA 9 and 46) and frontal eye fields (BA 8). Research shows these BAs are responsible for visual attention (Yantis, 2008; Martinez-Trujillo, 2022), which could explain why these channels are activating in the 1B for YA.

Based on these results, our study does not show support for the CRUNCH model for either the YAs or OAs. The lack of increased brain activity at 1B and reduced brain activity at the 3B level therefore indicates that OA did not reach a threshold of task complexity according to CRUNCH model predictions. Mattay et al. (2006) found OA performed at a similar level compared to YA in the 1B but performed worse than YA in the 2B and 3B, similar to our results. However, Mattay and colleagues found reduced brain activity in OA at high task loads (3B), and more activity in the 1B in accordance with CRUNCH. In contrast, our results align with previous research that contradicts the CRUNCH model (Ranchod et al., 2023; Van Ruitenbeek et al., 2023; Jamadar, 2020; Blum et al., 2021). Jamadar (2020) implemented 4 load levels and measured brain activity in YA using fMRI and found many active areas had an inverted U (e.g., in the right middle frontal gyrus), maintenance (e.g., in the inferior frontal gyrus and supplementary motor area) or decreases (e.g., left middle frontal gyrus) in activity across increasing task loads, not in line with CRUNCH.

Additionally, Jamadar (2020) argued that although the CRUNCH model is the most used model for testing compensation, there are only a few studies that have tested its predictions. While it seems neither of our age groups exceeded their cognitive limits, it is worth noting that the 3B task may not be difficult enough to accurately identify this threshold. Although three task loads were implemented to test CRUNCH (as suggested by Jamadar, 2020), a fourth load may have been needed to identify this threshold in OA. Furthermore, our study only examined working memory using a single modality (visuospatial), whereas other studies (i.e., Ranchod et al., 2023) incorporating more than one modality (e.g., visuospatial and auditory) may be employing a more difficult task or activating more working memory related areas, and therefore observe different results in brain activity.

Additionally, OA showed more PFC activity and less parietal lobe activity relative to YA, which aligns with The Posterior-to-Anterior-Shift in Ageing model (Davis et al., 2007). This model suggests that there is a shift in neural activity from the posterior to anterior regions of the brain with age, specifically during cognitive tasks. However, PASA shows support for neural compensation, which is discussed below.

fNIRS results revealed that OA had increased brain activation in both left and right hemispheres (bilateral) relative to baseline (as per group-level analysis) and relative to YA in higher task load conditions (2B and 3B) but not in the 1B. Similarities between YA and OA in addition to comparable performance fits the maintenance theory rather than compensation. However, once again, it could be argued that the requirements in the 1B are not high enough to show many differences between the age-groups and it is in the higher task loads that age-related

effects are mostly observed. Indeed, OA showed more bilateral activation in the higher load tasks, however, this bilateral brain activation did not seem to benefit OA task performance at these higher task loads, therefore the compensation view is not supported. Our results suggest that an increase in brain activity is not positively associated with task performance, which aligns more with the Neural Inefficiency model (Reuter-Lorenz et al., 2001; Logan et al., 2002; Morcom and Henson, 2018). This theory suggests than increases in brain activity may be associated with lower cognition or reduced task performance or may not be related to performance at all (non-selective recruitment). For example, Morcom and Henson (2018) found that OA showed increased bilateral PFC activity but lower cognitive performance relative to YA, which supports the notion that this increased activation reflects reduced efficiency or specificity rather than compensation.

While our study does not show support for neural compensation defined as increased activity paired with benefits to task performance (Cabeza et al., 2018), it should be noted that other studies have speculated that different forms of compensation exist, such as unsuccessful or "failed" compensation. Chanraud and Sullivan (2014) defined changes in brain function as two distinct types: they may be adaptive and enable successful compensation or improved performance, or these changes in brain function may be poorly preserved, resulting in unsuccessful or attempted compensation. This proposes an alternate perspective – if OA show an increase in brain activity but perform worse on the task than YA, could compensation still be occurring? That is, they could perform worse on the task without this increased bilateral activation. With this in mind, it is important to note that the only way to measure if compensation is truly occurring is through alteration (inhibition/enhancement) of brain activity. For example, Rossi et al. (2004) used repetitive (rTMS) to examine brain activity during a visuospatial recognition memory task and

found OA had bilateral brain activation relative to YA, which demonstrated a compensatory effect. This study by Rossi and colleagues (2004) is the only study that has examined brain activity by inhibiting specific brain areas, which prompts the need for more research using these same strategies to establish causal relationships between additional brain activity and performance. For now, the CRUNCH remains as the main model to test for compensation and our study did not provide evidence supporting the model or that bilateral activity was compensatory in OAs.

4.2. Limitations and Future Considerations

We acknowledge some limitations in the present study. Firstly, factors such as fatigue, anxiety, practice effects, or motivation may have caused YA to disengage from the more difficult tasks. Because of this, it is difficult to identify if the lack of additional recruitment at higher task loads is attributed to YA exceeding their cognitive limits, or if other factors are responsible for these observed results. Therefore, future research should consider implementing measures of motivation as well as cognitive fatigue into the study design. Additionally, fatigue could have potentially played a role in the reduced performance at higher loads found in OA compared to YA. While our study counterbalanced the order of task load conditions presented to participants, it should be noted that OA performed thirty minutes of cognitive assessments (MoCA, RBANS) prior to these tasks, which could have affected their performance when completing the N-back later on in the study. Future research should consider conducting two separate sessions to minimize the effects of cognitive fatigue. For example, Jamadar (2020) held two separate sessions for OA participants (Session 1 for demographic questionnaires (CRIq) and cognitive assessments (MoCA), and

Session 2 for N-back tasks). If measures are taken to reduce the potential effects of fatigue on participants, this could reveal different performance results.

Our results did not show support for the CRUNCH model, as OA showed increased brain activity from the 2B to the 3B task rather than showing inhibition or reduced activity. While the present study implemented three different levels of cognitive load to test the predictions of CRUNCH, a reduction in brain activity may not have been observed in either group at the 3B level simply because the task was not difficult enough to accurate identify the existence of a threshold. Therefore, future research should consider using a fourth task load (as done by Jamadar, 2020) or a more difficult task that involves more than one modality (e.g. visuospatial and auditory N-back dual task, as done by Ranchod et al., 2023).

Additionally, OA showed bilateral brain activation relative to YA in all task loads, but poorer performance in the 2B and 3B tasks vs. YA. Although it seems compensation might be occurring in the 1B task as OA and YA showed similar task performance, the 1B task may not have been an adequate measure of working memory, but rather be targeting brain areas associated with visual memory and attention (Kane et al., 2007). Therefore, the 1B may not be a reliable measure of working memory and should perhaps be used as a baseline measurement of brain activity rather than a low task load condition.

The present study examined brain activity through the lens of cognitive ageing, however other studies have examined brain activity while using cognitive reserve (CR) as a predictor rather than age. CR is measured indirectly by experiences across the lifespan, including educational and occupational attainment, leisure activities, and IQ, which is thought to better equip individuals for counteracting the effects of cognitive decline (Stern, 2002; Nucci et al., 2012). For example, Ji et

al. (2018) explored connections between neural compensation and CR and found those with higher CR scores performed better during the memory task and activated fewer neural networks compared to those with lower CR scores. Therefore, future research should explore measures of CR and how they might correlate to brain activity and performance. Similarly, examining OA of varying cognitive abilities rather than comparing healthy OA to YA may allow us to better address the question of how brain activity differences correlate to behaviour in the ageing population. For example, Vermeij et al. (2014) examined brain activity in high and low performing OA groups and found low performing OA had larger bilateral increases in PFC activity compared to high performing OA, who mainly used the right PFC. While there is evidence that functional changes occur in the brain with age, it is important to consider other factors that may be contributing to both differences in brain activation and working memory performance.

Finally, there is an urgent need to use longitudinal approaches to examine age-related brain activity, as these studies are very limited in number compared to the abundance of cross-sectional neuroimaging research (Jäncke et al., 2022). Since fNIRS is able to examine individual differences in brain activity, measuring activity in the middle-aged or older population and comparing an individual's activity over multiple years may allow for a better understanding of the brain ageing process.

4.3. Conclusion

The goals of the present study were to determine if age-related differences in brain activity exist between healthy younger and older adults, and to examine how these differences correlate to

performance on a visuospatial working memory (N-back) task. Three task load conditions of increasing complexity were implemented to test the predictions of the CRUNCH model, which is the most empirical model used to test for neural compensation. Our results suggest that our older adult sample is exhibiting increased brain activity and over-recruitment of bilateral brain areas, however this cannot support neural compensation as characterized by Cabeza et al. (2018) because performance is not being maintained in older adults relative to younger adults at higher task loads. Compensation may be occurring in the low task load condition (1-back), however the validity of the 1-back task to purely measure working memory should be considered (Kane et al., 2007). Additionally, older adults did not demonstrate attenuation at higher task loads, which contradicts the CRUNCH model predictions (similar to Ranchod et al., 2023; Van Ruitenbeek et al., 2023; Blum et al., 2021; Jamadar, 2020). Our study cannot fully address whether compensation is truly occurring or not, therefore future research should aim to use inhibition of brain activity through technologies such as transcranial magnetic stimulation (TMS) to better characterize the role of bilateral, widespread activity in OAs. Furthermore, variables such as cognitive fatigue and practice effects should be considered during experimental design. Cognitive reserve measures could also be used as a predictor of brain activity changes rather than age. Better understanding of the changes that occur in the healthy aging brain may also allow us to identify and understand why some individual experience decline that progresses into neurodegenerative diseases.

5. LITERATURE CITED

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6. APPENDIX

Table A1

Old adult participant scores for the Montreal Cognitive Assessment (MoCA), the Repeatable Battery for the Assessment of Neuropsychological Status (RBANS), and the Cognitive Reserve Index questionnaire (CRIq) (n = 25).

Participant ID	MoCA score	RBANS total scale score	RBANS total percentile (%)	CRIq score
P321	27	106	66	143
P322	29	104	61	125
P323	28	118	88	119
P324	27	118	88	149
P325	28	90	25	138
P326	26	144	99.8	120
P327	29	106	66	142
P328	26	106	66	116
P329	28	103	58	145
P330	28	136	99	135
P331	29	113	81	156
P332	29	96	39	121
P333	27	97	42	159
P334	28	121	92	120
P335	29	106	66	150
P336	30	141	99.7	101
P337	29	109	73	145
P338	27	104	61	163
P339	24	113	81	132
P340	28	113	81	140
P351	22	89	23	130
P352	18	79	8	110
P353	25	98	45	122
P354	22	96	39	105
P355	24	94	34	147
AVERAGE	**26.7**	**108**	**63.3%**	**133.3**