INVESTIGATIONS INTO WIDESPREAD BRAIN ACTIVITY IN OLDER ADULTS: A FNIRS STUDY

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INVESTIGATIONS INTO WIDESPREAD BRAIN ACTIVITY IN OLDER ADULTS: A

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ABSTRACT

Researchers have observed that older adults show widespread activity in the brain (in both hemispheres) when completing a working memory task, while younger adults show lateralized brain activity (to one hemisphere) for the same task. They suggest that this widespread activity may be compensatory and is used to counteract age-related cognitive decline; however, others have not found this widespread activity to be compensatory and instead suggest that it reflects neural inefficiency. The aim of this study is to examine age-related changes in brain function and its links with cognitive performance to provide further insight into whether widespread brain activity is compensatory. Bilateral frontal lobe brain activity was measured using functional near infrared spectroscopy (fNIRS, 24 channels) while 29 young (18-25 yrs), 14 middle-aged (30-55 yrs), and 30 older adult (> 65 yrs) participants performed a N-back task with increasing working memory loads. Accuracy and reaction times (RT) were compared between age-groups and between task complexity conditions. Significantly active channels reflecting more brain activity in both hemispheres were obtained using a general linear model (GLM) and contrasts between groups and across task complexity were performed. We found that as cognitive load increases, accuracy decreases, and longer RT are observed. Older adults in particular show longer RTs compared with younger adults; however, we did not observe any significant differences in overall accuracy between these two age groups. Furthermore, we confirm that older adults show more bilateral brain activity and recruit more neural resources compared with younger adults, and this can be seen across task loads. We, therefore, showed age-related differences in brain activity that were linked with cognitive performance, and thus provide support for the compensation view. In the end, this study provides valuable insight into the changes that occur in brain activity and in our cognition as we age.

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INTRODUCTION

With the increasing advancements in technology, healthcare, and medicine it is no surprise that individuals are living longer, leading to a greater proportion of the population living beyond the age of 65 years old (Blum et al., 2021; Cabeza et al., 2018). A growing older adult population is also predicted to increase the prevalence of neurodegenerative diseases (e.g., Alzheimer's disease; statcan.gc.ca). As a result, it is imperative to understand the cognitive and neural changes that occur during healthy aging (Blum et al., 2021; Cabeza et al., 2018) and potentially be able to identify changes that correspond to healthy versus disease aging trajectories.

It is well reported that older adults demonstrate some decline in specific cognitive abilities, mainly in executive attention and working memory (see Grady, 2012 for review). Alongside these age-related cognitive changes, researchers have identified differences in brain activity, with older adults exhibiting lower activity in regions also active in young adults but also show more activity and reduced hemispheric asymmetry in comparison to younger adults (Cabeza, 2002; Grady, 2008; Piefke et al., 2012). That is, younger adults demonstrate lateralization in brain activity (appearing in only one hemisphere or the other) whilst older adults, show bilateral activity (in both hemispheres) while performing the same task, particularly in the prefrontal cortex (PFC; Cabeza, 2002). For example, Piefke et al. (2012) demonstrated that during a visual-spatial working memory task, younger participants showed activation in the left PFC, while older individuals showed PFC activity across both hemispheres (bilateral). This indicates age-related changes in brain activity; however, this increase in activity and reduction in lateralization as aging occurs is not yet fully understood (Blum et al., 2021; Cabeza et al., 2018).

Potential explanations of changes in brain activity

Researchers have made links between the observed reduction in lateralization in older adults and cognitive decline (Cabeza et al., 2018). Currently, there are two dominant theories that attempt to explain this phenomenon, 1) the dedifferentiation hypothesis, and 2) the compensation view. The dedifferentiation hypothesis proposes that brain structures exhibit decreased processing specificity (Carp et al., 2010; Piefke et al., 2012), thus reflecting difficulty in recruiting specialized brain areas (Cabeza, 2002). One way to test dedifferentiation would be to examine brain activity across tasks and determine whether there is less specialized, similar activity across those tasks. For example, Rieck et al. (2021) used cov-STATIS (a multivariate technique) to examine functional connectivity in the brains of older adults and found that domains of working memory (WM), inhibition, and shifting attention (all prefrontal cortex functions) were more similar and less dissociable in older adults compared to younger adults, in accordance with dedifferentiation.

The compensation view suggests that widespread activity in older adults compensates for age-related cognitive decline (Cabeza, 2002; Piefke et al., 2012). This theory is based on observations that older adults exhibit more activity compared with young adults, particularly in the bilateral prefrontal cortex (PFC), and that this additional activity is linked with benefits in older adults' cognitive performance (i.e., similar performance between older and younger adults; Grady, 2012). Cabeza et al. (2018) thus outlined two requirements for greater brain activity to be attributed to compensation: 1) increased activity should be associated directly or indirectly with some deficiency in neural resources in relation to task demands, and 2) increased activation should have a beneficial effect on cognitive performance.

There is indeed evidence to support this compensatory view with researchers showing increases in brain activity that correlate with better cognitive performance across many tasks (e.g., Cappell et al., 2010; Schneider-Garces et al., 2010; also see Cabeza et al., 2002, and Grady et al., 2012 for review). However, others have found that additional activity does not always lead to better task performance, and instead, may represent less efficient use of neural resources (Grady, 2008). Such discrepancies highlight the need to further characterize cognitive aging and examine the role of widespread activity to fully understand this phenomenon and how it impacts cognitive performance.

Compensation and task complexity

In contrast with the dedifferentiation theory, which suggests reduced lateralization regardless of load, the compensation theory, and specifically the Compensation-Related Utilization of Neural Circuits Hypothesis or CRUNCH model, suggest that a decrease in lateralization may aid performance, but only in lower task demands (Reuter-Lorenz & Cappell, 2008). Carp et al. (2010) examined brain activity patterns during WM tasks with varying cognitive demands in older adults. Although Carp et al. (2010) found evidence for dedifferentiation across loads in verbal and visuospatial memory conditions, they also found that during memory maintenance, older adults recruit more areas of the brain compared to younger adults in low cognitive load conditions, providing support for the compensatory theory. They suggested that at high cognitive loads, older adults no longer have those compensatory resources, and an under-activation is observed (Carp et al., 2010). In contrast, Crowell et al. (2020), who also had young and older adults complete a WM task with increasing loads (reordering letters alphabetically), found that older adults showed increased bilateral network connectivity with increased task difficulty, particularly those older adults with higher WM capacity. Crowell et al. (2020) then

proposed that to compensate for higher cognitive loads, the brain increases the number of areas used and that these additional recruited areas aid each other as part of an integrated network, in older adults. Thus, there are discrepancies as to if and when additional activity is compensatory, which require further investigation using distinct cognitive loads.

Using fNIRS to measure age-related differences in brain activity

Brain imaging studies have contributed greatly to our understanding of age-related changes in brain activity. For example, Hinault et al. (2019) used fMRI to observe the brain activity of young and old adults during an arithmetic verification task and found age-related changes in performance due to both structural and functional changes in cognitive control networks of the brain. There are, however, limitations within these techniques (e.g., fMRI and PET) such as cost, accessibility, and typically, a participant needs to lie down and not move for a long period of time, making it taxing for a participant and reducing the ecological validity of these findings (Blum et al., 2021; Llana et al., 2022).

Functional near-infrared spectroscopy (fNIRS) is a novel tool to measure brain activity and is becoming a widely used technique as it is cost effective, non-invasive, more accessible (portable), and can be used to link behaviour with cortical processes on a neurophysiological level (Blum et al., 2021; Llana et al., 2022). Additionally, fNIRS has greater spatial resolution compared with EEG (Llana et al., 2022). The fNIRS technique uses the same principle as fMRI, that is, metabolic requirements as a proxy of brain activity. Specifically, when a particular brain area is activated, oxygen is consumed which then increases oxygen requirements to that area and thus a surge of blood containing oxygenated hemoglobin is supplied to that particular brain region. This signal is called the hemodynamic response function (HRF; Llana et al., 2022). fNIRS then

measures the changes in the concentration of oxygenated (HbO) and deoxygenated (HbR) hemoglobin in the cortex via differences in the absorption of near- infrared light (NIR) passing through the cortical layers of the brain (Llana et al., 2022).

Blum et al. (2021) used fNIRS's ability to detect hemodynamic changes to measure cognitive abilities of younger and older adults when completing a Trail Making Test (TMT), which assesses mental flexibility, WM, and visuomotor processing speed. They found that older individuals had fewer completed items during the task compared with younger adults, which initially seemed to support the dedifferentiation theory; however, they also found that older adults had lower error-rates compared with younger adults and increased cortical activity during the task for the items that they did complete (Blum et al., 2021), providing some evidence for the compensation view. Similarly, Meidenbauer et al. (2021), used fNIRS in conjunction with an Nback task to examine WM in only young adults. They observed that at higher cognitive demands, there was increased frontoparietal activation compared to lower cognitive loads (Meidenbauer et al., 2021). Additionally, greater brain activity was positively correlated with performance in the more cognitively demanding task in young adults, thus also providing some evidence for the compensation view (Meidenbauer et al., 2021). Essentially, even young adults may benefit from more brain activity, thus leading to better performance on a task. As a result, this suggests that widespread activity is related to cognitive demands and that fNIRS can be a feasible technique to identify these changes seen in older adults. In addition, fNIRS may be an ideal way to examine age related differences and determine whether reduced lateralization and thus, more bilateral brain activity is simply a symptom of neurological decline due to dedifferentiation, or a means to compensate for this age-related cognitive decline.

Given the inconsistencies in the literature as to whether this widespread activity in older adults is advantageous or simply a symptom of age-related neurological decline (or both), further research is required to truly understand the significance of this phenomenon. More specifically, in the case of the compensation view, understanding the age-related changes (plasticity) in brain function and how these impact cognitive functions, like memory, could help identify neurological decline associated with aging early, before behavioural symptoms appear, at which point the neural degradation has become more severe. This early detection could also aid prevention and facilitate interventions that promote healthy aging.

Objective

The objective of the study is to examine bilateral brain activation in older adults compared with younger adults. More specifically, to determine whether additional brain activity measured using fNIRS compensates for age-related cognitive decline during working memory tasks with increasing cognitive loads. We predict that older adults will show reduced lateralization in comparison to younger adults in accordance with previous reports describing cognitive aging. Whilst young adults are expected to rely on more specialized mechanisms as load increases (Carp et al., 2010), the compensation theory and CRUNCH model would predict that older adults will show reduced lateralization in low cognitive loads and better or comparable performance to young adults. Thus, we would also expect more specialized brain activity in young adults vs. older adults in the high load. The differentiation hypothesis would predict that older adults would show similar widespread activity across all tasks that would demonstrate neural inefficiency. However, how dedifferentiation changes with task complexity is less understood. We also aimed to examine how middle-aged adults differ from young adults since this is a largely ignored population and changes in brain activity may already be occurring at this age range.

MATERIALS AND METHODS

Participants

We recruited a total of 83 participants for the study. However, 10 participants were excluded from the study due to having saturated/noisy fNIRS data (7 participants), technical issues (1 participant), or the participant was unwilling to complete all procedural tasks (2 participants). As a result, our final sample consisted of 73 participants: 29 young adult (YA) participants (18-27 years (yrs) old, M = 20.55, SD = 2.43, 10 males, 19 females), 14 middle- aged adult (MA) participants (33-58 yrs, M = 48.5, SD = 8.05, 7 males, 7 females), and 30 older adult (OA) participants (64 – 84 yrs, M = 71.5, SD = 5.39, 10 males, 20 females). Participants were recruited through posters placed on bulletin boards of establishments (with permission), such as the YMCA, TRU, TCC, retirement communities, and local coffee shops. Recruitment was also advertised on online sites, such as on social media (e.g., Facebook), with permission of site administrators, and on the local news media (i.e., Castanet). The inclusion criteria consisted of age (within the abovementioned ranges), normal or corrected-to-normal vision, fluency in English, at least 6 years of formal education (including elementary and high school), no known neurological or psychological disorders (e.g., stroke, brain injury, Parkinson's disease, mild cognitive impairment, bipolar disorder, depression), non-smokers, not taking Aricept (attention enhancing medication) or psychoactive drugs, and being right handed (self-reported). Participants were further screened for these criteria by email prior to coming to TRU to take part in the study. Participants were compensated for their participation with a 2% bonus credit or a \$10 gift certificate. Participants gave informed consent prior to any experimental procedure. This study was approved by the TRU's research ethics committee and in accordance with the declaration of Helsinki.

Procedure

All participants completed an anxiety questionnaire, the State-Trait Anxiety Inventory (STAI-6) short version (Spielberg et al., 1983), since it is known that anxiety can interfere with working memory and may explain some of the widespread activity (not analysed here). Middle-aged and older participants completed the Montreal Cognitive Assessment (MoCA, Nasreddine et al., 2005) test to determine their overall cognitive function, such as working memory, verbal fluency, and visual spatial attention (M = 26.93, SD = 1.80; normal range is a score > 26). Also, the Memory Complaint Scale (MCS) version A (Vale et al., 2012) was used to determine how participants assess their own memory (not analyzed here). Both the MCS and the STAI-6 were completed on SurveyMonkey (SurveyMonkey Inc., CA, USA), while the MoCA was completed on paper.

Participants were then asked to complete two N-back tasks with increasing cognitive loads, a simple 2-back task and a dual 2-back task, presented on a computer laptop (Dell Latitude 3410, 14" HD, 1920 x 1200 resolution) positioned in front of the seated participant. The tasks were designed in E-prime 3.0 (Psychology Software tools, PA, USA) and required the participants to respond to visuospatial stimuli only (simple 2-back), and visuospatial and auditory stimuli (dual 2-back) using a keyboard. While they completed these tasks, their brain activity was measured using fNIRS (Brite, Artinis Medical Systems, The Netherlands). fNIRS data was collected using Oxysoft (Artinis, Medical Systems, The Netherlands, version 3.2.51.4). Task events were inserted from E-prime into Oxysoft via DCOM methods. Participants were given a demonstration video, which explained the N-back tasks and had some practice prior to each N-back task. Additional practice was given when necessary. The entire session took approximately 90 minutes to complete, and participants were given a rest break in between the simple and dual tasks, and when requested.

fNIRS Set Up

Participants were fitted with the fNIRS Brite head cap (Artinis, Medical Systems, The Netherlands). Each participant's head was measured to find Cz (according to the 10-20 system) and the Cz location on the cap was then aligned with this mark to ensure that the cap was in a similar location for every participant. The cap was equipped with 10 light-emitting optodes (sources) that transmitted near-infrared light between 650-950 nm and 8 detectors that detected changes in light absorption, sampling at 25 Hz. All optodes were placed at an optimal 3 cm apart from each other, except for 2 short separation channels which were 1.5 cm apart, used to eliminate unwanted physiological noise (e.g., heart rate), which then corresponded to a 2 x 12 array and a total of 24 recording channels (Figure 1). Brain activity from both right and left prefrontal lobes (12 channels per hemisphere) was measured, continuously monitoring relative changes in the concentration of HbO and HbR from each channel.



Figure 1. Topographic arrangement of fNIRS optodes over bilateral prefrontal cortex. Lower-left image shows a frontal view of the placement, where D (blue) represents the detectors and S (yellow) represents the sources. The source-detector pairings make up the 24 channels across the right and left hemispheres (RH and LH, respectively). Short separation channels are also indicated in analogous locations in both hemispheres. Right and left side views of the optode array are also provided in the top right-hand corner (optode sizes are not to scale).

N-Back Task

Following practice trials (which were identical to the actual tasks except they had 10 trials per block instead of 20) and once a good fNIRS signal was obtained, participants then completed two task load conditions consisting of a simple and a dual 2-back tasks. A rest or baseline block was presented prior to a 2-back block. The rest blocks consisted of 20 second (s) periods in which participants rested by simply observing a blank screen with the word "rest" displayed in the middle of the screen. Following each rest block, there was a 40 s simple or dual 2-back block (Figure 3). For the simple 2-back task, a blue box appeared at one of six possible positions for 0.5 s and would change its position throughout the 40 s block (Figure 3). After each blue box disappeared, the

participant would have an additional 1.5 s (so a total of 2 s overall) to indicate whether the stimulus was in the same location as two trials previous, by pressing the "S" key, or different compared to two trials previous, by pressing the "D" key using their right hand (Figure 2 and 3). Similarly, for the dual 2-back task, in addition to the blue box changing positions, an audible letter (i.e., G, H, K, L, P, Q, T, V) was played for 0.5 s simultaneously with each box through the speakers of the laptop and the participant needed to indicate whether the visual, auditory, or both stimuli occurred 2 trials ago using the same keys as before (S and D). Thus, each trial required a response. The volume for the letters was tested in the practice trials to make sure that the participant could hear the stimulus. There was a total of twenty 2-back trials over the 40 second blocks. Out of the twenty trials, 20% were targets (a stimulus that was the same as 2 trials ago, requiring a "S" response) and 80% were non-targets (stimulus was different from 2 trials ago, requiring a "D" response). The 20 s rest period plus the 40 s simple or dual task period was repeated 5 times in total, leading to approximately 5 minutes for each task load condition, followed by a 5-minute rest period between conditions. All participants performed the simple task prior to the dual task.



Figure 2. Example of targets and non-targets in a simple 2-back task. Upper panel a) is demonstrating a sequence of 3 trials of non-targets which required a "D" response. Since the third trial is in a "different" location as 2 trials back, all require a "D" response. The lower panel b) demonstrates a sequence of 3 trials in which the third trial corresponds to a target and required a "S" response as it is in the "same" location as 2 trials back. In a dual task, participants would hear a letter in addition to see the box at the same time.



Figure 3. Representation of the simple 2-back task with visuospatial stimuli and the respective times for stimulus presentation and response. Following a rest period (20 s), participants performed 40 s of the 2-back task. The box was presented for 0.5 s and participants were allowed 2 s (0.5 s during stimulus presentation and an additional 1.5 s after stimulus presentation) to respond by pressing "S" or "D", then the box would change locations. Participants performed 40 s of 2-back block consisted in which 20% of the trials were targets ("S" response) and 80% were non-targets ("D" response). The 20 s rest blocks and 40 s 2-back blocks were repeated 5 times in total for both task-load conditions.

Analysis

Behavioural data

The results from the 2-back tasks (simple and dual) for each participant were extracted from E-prime and exported to an Excel database (Microsoft Corporation, 2023). Trials in which no responses were observed and those in which reaction times were < 80 milliseconds (ms) were extracted from further analyses. We then calculated overall accuracy of the responses as error rates, that is the number of incorrect responses for targets (misses) and non-targets (false alarms) divided by the number of target and non-target trials, and RTs obtained from correct responses for each participant in both the simple and dual tasks as well as for target type (target and non-target). Additionally, for the dual task, the number of correct visual and auditory targets (respectively) were compared to observe if any specific strategy was implemented. Finally, all measures were averaged across age-group to identify behavioral differences in accuracy and RTs between groups. JASP (JASP, 2022) was used to conduct repeated measures analysis of variances (ANOVAs) and post-hoc tests with Bonferroni corrections were used to determine significant interactions (p < .05).

fNIRS data

An age-dependent differential path-length factor (DPF) was applied to determine the distance traveled by the light emitted from the optodes, which changes depending on the age of the participant. Due to a lack of research to determine the DPF in adults older than 50, the DPF for 50 years old was used for all participants who were 50 and older (Schroeter et al., 2003). All data was visually inspected and exported from Oxysoft, then formatted and converted to *.snirf* for further analyses using the AnalyzIR toolbox (MATLAB, 2021). The modified Beer-Lambert Law (Sassaroli & Fantini, 2004) was applied to convert changes in optical density to changes in HbO

and HbR concentration (µM). Only HbO values from this conversion were used for further analyses (Blum et al. 2021). After extensive testing of best methods to extract movement artifact and physiological noise from the data, we identified autoregressive pre-whitening methods combined with short-channel regression as the most robust preprocessing technique (Huppert, 2016). This model uses short-channel regression combined with autoregressive filters that correct for serially correlated (common) features caused by systemic physiological noise and large outliers caused by movement artifacts. A subject-level general linear model (GLM) was also applied to identify channels that were significantly active during the 2-back epochs in each task load condition. For this, the onsets and durations of task events were used as model parameters. The GLM is a well-established method for the analyses of event-related activity and minimizes the probability of finding false positive events that are more likely when using peak values or areas under the curve methods. The GLM assumes a canonical HRF response and calculates beta coefficients as indicators of the changes in intensity (amplitude) and direction (positive or negative) of the HbO signal across all channels, during task epochs. To assess group specific differences in brain activity across task loads, a subsequent linear mixed effect model was used with group and task loads as fixed effects and participant as a random effect. Corrected for multiple comparison t-test contrasts were then used to identify significant differences in brain activity across all channels (24 in total), between task load conditions within each group and between groups. Significant effects were set at p < .05.

RESULTS

Behavioural Results: N-Back Performance

With regards to the overall accuracy (i.e., error rates for targets and non-targets) on both the simple and dual 2-back tasks, there was a significant effect for age group (F(2, 72) = 3.25, p =

.045, $\eta^2 = .03$, Figure 4). More specifically, OA overall showed greater error rates compared to MA (p = .045). There were no significant differences in overall error rates between MA and YA (p = .584) nor between OA and YA (p = .443). There was a significant interaction of task complexity by target type (F(1, 72) = 4.24, p = .043, $\eta^2 = .01$, Figure 5). The post hoc test revealed an increase in the overall error rates for targets in the dual task compared with targets in the simple task (p < .001), but no significant differences in non-targets between the tasks (p > .05). Furthermore, there were more errors when identifying targets ("S" responses) compared with non-targets ("D" responses) during the simple task (p = .003). Similarly, participants made more errors when identifying targets compared with non-targets during the dual task (p < .001, Figure 4). No significant interactions were found between complexity and age-group, target type and age-group, nor between complexity, target type, and age-group (all p > .05).

To examine potential differences in visual vs. auditory targets in the dual task, we performed a repeated measures ANOVA that showed no significant differences in error rates between visuospatial and auditory targets in the dual task (p = .116), nor group interactions (p = .918). A group effect revealed that OA had more errors than MA, with a difference of -18.54% (F(2, 72) = 4.46, p = .015, $\eta^2 = .07$).



Figure 4. Group effects for error rates (mean and standard deviations, as well as distribution of data points). *A small significant difference was observed between OA and MA (p = .045).



Figure 5. Mean error rates between task complexity and target type (standard deviations are shown as well as distribution of data points). *Error rates for targets ("S" responses) were higher compared with non-targets ("D" responses) overall. In addition, error rates to targets were higher in the Dual task vs. the Simple task.

With respect to RTs there a significant effect for complexity (F(1, 72) = 146.19, p = <.001, $\eta^2 = .18$). More specifically, participants had faster RTs during the simple compared with the dual task (p < .001, Figure 6). There was also a significant interaction of target type by age group (F(2, 72) = 8.483, p < .001, $\eta^2 = .01$, Figure 7). The post hoc test revealed that OA had slower RTs compared with YA when identifying targets (p = .005) and were also slower compared with YA's RTs to non-targets (p = .007). Furthermore, OA overall were slower when identifying targets compared with non-targets (p < .001). No significant interactions were found between complexity and age-group, complexity and target type, or between complexity, target type, and age-group (all p > .05).



Figure 6. Mean RTs (ms) and SDs for each age group in each task. Overall, age-groups showed an increase in RT in the dual vs. the simple task. No group differences were observed.



Figure 7. Mean RTs (ms) and SDs for each age group for targets and non-targets. *OAs had slower RTs when identifying targets vs. non targets and were overall slower vs. YAs.

fNIRS

For this thesis and to examine brain function differences in bilateral hemispheric activation, we report the significant channels from each hemisphere following a group-level analyses (i.e., a second level analysis). All reported results were significant at *p*-values of < .05 and their corresponding betas and *t*-values are described in Table 1.

Group analysis OA vs. YA in simple vs. dual tasks

fNIRS group analysis revealed that the OA group showed bilateral activity in the prefrontal cortex in both the simple and dual tasks (Figure 8, upper panel). Furthermore, contrasts between task complexity (Simple > Dual) revealed that OA showed overall, more active channels during the simple task compared with the dual task, specifically, Ch2 (D1-S2 pairing) in the RH, and Ch14 in the posterior-medial and Ch16 in the posterior-lateral of the LH (Figure 8). OA thus

showed more brain activity, particularly in the LH, in the simple vs. dual task. YA simple vs. dual contrast revealed 2 active channels only in the RH, that is Ch2 (D1-S2 pairing, similar to OA) and Ch3 in the posterior-lateral RH (Figure 8). There were no significantly active channels in the LH. These channels, Ch2 and Ch3 in RH, were not active in the dual task, thus, YA showed differential lateralization to the RH with more activity in the simple compared to the dual task.

Group analysis also revealed that for the simple task, OA showed more brain activity in comparison to YA in only 1 channel in the anterior RH (Ch9) and showed more activity in 4 channels in the LH (Ch13, Ch16, Ch19, Ch23), mostly in the medial and posterior-lateral regions of the LH (Figure 8, lower panel). Thus, OA showed more activity in RH in one channel but mostly, additional active channels in the LH compared with YA. For the dual task, OA showed more brain activity compared to YA, showing greater activity in 2 channels in the RH (Ch3, Ch5) and 5 in the LH (Ch13, Ch19, Ch20, Ch23, Ch24), which appeared mostly in the anterior-medial region of the LH (Figure 8). Thus, OA are showing additional active channels, particularly in LH, that were not active in YA across task loads.



Figure 8. Contrasts for OA and YA in the simple and dual tasks showing the beta values from significantly active source to detector pairings (p < .05). RH indicates the right hemisphere of the brain, while LH indicates the left hemisphere.

Comparisons with MA group

MA simple vs dual contrast revealed that MA had one active channel in the anterior RH (Ch9) and no active channels in the LH in the simple task compared to the dual (Figure 9). Since this channel was not active in the dual task, MA showed differential lateralization to the RH with more activity in the simple compared to the dual task.

Compared to MA, OA showed more bilateral brain activity during the simple task and mostly recruited additional active channels not seen in MA: 2 active channels in the RH (Ch11, Ch12) and 4 channels in the LH (Ch16, Ch19, Ch23, Ch24), appearing mostly in the anteriormedial region of the optode array in the PFC (Figure 9). During the dual task OA showed greater activity than MA in 1 channel in the RH (Ch11) and 7 channels in the LH (Ch13, Ch16, Ch19 – Ch21, Ch 23, Ch24), which appeared mostly in the posterior and the anterior-medial regions of the LH (Figure 9). Thus, OA also showed more bilateral brain activity compared to MA during the dual task and again, recruited additional active channels that were not recruited by MA, particularly in the LH. Furthermore, MA showed more activity in Ch2 in the posterior RH compared to OA, which was not recruited by OA during the dual task (Figure 8 and 9).

For the comparison between MA and YA during the simple task, MA had more activity in Ch9 in the anterior-medial RH compared to YA (an additional channel not recruited by YA), and YA had more activity in Ch11 in the anterior-medial RH compared to MA (was recruited by MA but to a lesser extent, Figure 9). There were no significantly more active channels in either YA or MA in the LH. Finally, during the dual task, YA showed more activity in Ch11 in the anterior-medial RH compared to MA, and MA showed more activity in Ch2 in the posterior RH compared to YA (not recruited by YA in the dual task), while neither showed significantly more active channels in the LH (Figure 9). Thus, MA and YA show relatively minimal differences in brain activity in the two tasks.



Figure 9. Contrasts for MA in the simple and dual tasks as well as contrasts to OA and YA showing the beta values for significantly active source to detector pairings (p < .05). RH indicates the right hemisphere of the brain, while LH indicates the left hemisphere.

Contrast	Source	Detector	Channel	Hemisphere	beta	<i>t</i> -stat	<i>p</i> -value
YA: S > D	2	1	2	R	2.59	3.77	0.034
	3	1	3	R	1.26	2.13	0.030
MA: $S > D$	3	4	9	R	1.98	2.19	<.001
OA: S > D	2	1	2	R	2.06	3.51	0.008
	6	5	14	L	1.75	2.65	<.001
	7	7	16	L	2.21	3.33	0.037
S: OA > YA	3	4	9	R	1.69	2.09	<.001
	6	6	19	L	2.97	3.90	0.037
	7	5	13	L	1.68	2.10	<.001
	7	7	16	L	3.15	4.20	<.001
	9	6	23	L	3.04	3.49	<.001
S: OA > MA	5	3	11	R	3.69	3.45	0.042
	5	4	12	R	2.41	2.04	0.004
	6	6	19	L	2.71	2.86	<.001
	7	7	16	L	3.68	4.07	<.001
	9	6	23	L	4.51	4.68	0.005
	9	8	24	L	3.15	2.84	0.007
S: MA > YA	3	4	9	R	2.66	2.72	0.013
	5	3	11	R	-2.72	-2.51	0.004
D: OA > YA	3	1	3	R	2.03	2.90	0.018
	3	2	5	R	1.89	2.38	<.001
	6	6	19	L	2.86	3.53	0.002
	7	5	13	L	2.71	3.17	0.028
	8	6	20	L	1.91	2.21	<.001
	9	6	23	L	4.01	4.42	0.022
	9	8	24	L	2.33	2.30	0.014
D: OA > MA	2	1	2	R	-2.31	-2.48	<.001
	5	3	11	R	3.41	3.39	<.001
	6	6	19	L	3.45	3.45	<.001
	7	5	13	L	3.45	3.81	0.037
	7	7	16	L	1.74	2.09	0.023
	8	6	20	L	1.92	2.29	0.032
	8	8	21	L	1.88	2.16	<.001
	9	6	23	L	5.35	5.37	<.001
	9	8	24	L	4.05	3.82	0.027
D: $MA > YA$	2	1	2	R	2.09	2.22	0.021
	5	3	11	R	-2.38	-2.32	<.001

Table 1. Group-level contrasts showing significantly active channels (p < .05) for simple task (S), and dual task (D). Directionality, hemisphere of each channel, beta, t-stat, and p-values are all reported.

DISCUSSION

Our behavioural results confirm that the dual task was more complex than the simple task, given that the dual task had longer RTs and decreased accuracy overall. Participants took longer to respond during the dual task compared to the simple task, indicating that the dual task is more cognitively demanding and required more time to process the information being presented. Furthermore, the overall accuracy also decreased in the dual task compared to the simple task, particularly participants showed more errors to targets compared with non-targets. This is likely due to our use of the typical 20/80 trial ratio of targets to non-targets. As a result, there is a greater chance of correctly identifying non-targets compared to targets simply because there are more opportunities to respond to non-targets. Our findings are in accordance with several previous studies (Crowell et al., 2020; Jaeggi et al., 2003; Lamichhane et al., 2020; Meidenbauer et al., 2021). For example, Jaeggi et al. (2003) investigated the performance of YA during single (visual only or auditory only) and dual (visual and auditory, simultaneously) N-back tasks with 3 load conditions each (N = 1-3) and a 0-back as a control. They found that increasing loads made the task more difficult as reflected by longer RTs and a decrease in accuracy with increasing loads (Jaeggi et al., 2003). Additionally, they observed longer RTs and more errors during the dual tasks compared to the single tasks suggesting the task demands were excessive (Jaeggi et al., 2003) and, thus, reported similar results to our own study. Finally, they found that there were no differences in performance across auditory-verbal and visual-nonverbal stimuli in terms of accuracy and RT (Jaeggi et al., 2003). Our results are in accordance with Jaeggi et al. (2003) in that we see a difference in error rates to targets between simple and dual tasks and no differences in auditory and visual stimuli in the dual task. This means that the dual task has costs associated with the additional component compared to the simple task, thus supporting a greater cognitive load.

We also found a small group effect where OA had lower accuracy compared with MA, but there were no differences in accuracy between OA and YA. However, OA RTs were slower than YA when identifying both targets and non-targets. These age-group differences may be due to speed-accuracy trade-offs also shown in previous studies (Endrass et al., 2012; Salthouse, 1979; Starns & Ratcliff, 2010). For example, Starns and Ratcliff (2010) found that OA prioritize accuracy at the expense of a longer RT when completing a series of decision-making tasks compared with YA, who seem to balance accuracy and RT to achieve the most correct responses (Starns & Ratcliff, 2010). This may be a strategy used by OA to make up for age-related slowing and is also suggested to reflect changes in brain function, likely due to structural limitations in brain connectivity and not necessarily a strategic choice (see Forstmann et al., 2011). Furthermore, Sala-Llonch et al. (2012) examined high and low cognitively performing OA compared with YA during N-back tasks and found differences in accuracy between high versus low performing OA but no differences in performance between YA and high performing OA during the 3-back task (Sala-Llonch et al., 2012). This means that even during high task loads, such as a 3-back task, highperforming OA may exhibit similar performance as YA. Additionally, they found that the mean RT for high performing OA was longer compared to YA (Sala-Llonch et al., 2012). Our study included healthy, relatively high performing OA (as indicated by MoCA scores within the normal range), thus this may provide another explanation for why we observed longer RT in OA compared with YA but no differences in accuracy between the two groups. Although similar performance allows us to better compare brain activity between age-groups, we offer another explanation of similar performance in the next section.

In terms of our fNIRS results, we observed that OA showed more bilateral brain activity across both task loads as well as compared with YA and MA across both hemispheres, but mostly in the LH. That is, OA showed more activity and additional active channels compared to the other age groups and most of this additional activation occurred in the LH. In contrast, differential brain activity was more lateralized to the RH between YA and MA. Overall, OA showed more bilateral brain activity (more activity and additional active channels) compared with YA and MA (both within and between hemispheres), mostly in medial regions of the PFC, while YA and MA showed relatively similar levels of brain activity to each other, and differential activity was only observed in the RH.

Within group comparisons in the simple and dual tasks revealed that within all age groups, more brain activity, that is additional active channels and some channels with higher activity between task loads, was required when completing the simple compared to the dual task. Whilst differences between task load conditions were mainly observed in the RH in YA and MA, OA exhibited significant bilateral brain activity.

More activity during the simple task compared with the dual task within each group was contrary to our initial prediction and against the CRUNCH model. There are a few reasons for why this might be. Firstly, this could be due to a task-related effect. Specifically, the dual task engages executive processes such as inhibition, ongoing performance monitoring, managing two tasks simultaneously, and memory updating (Jaeggi et al., 2008). Since the simple task lacks some of these additional cognitive components (e.g., divided attention components, Salminen et al., 2020) it is possible that different brain areas may be activated when completing the different tasks. Furthermore, Salminen et al. (2020) investigated the effects of training with simple and dual Nback tasks on functional connectivity of the brain. They found that WM training with the more demanding dual task altered task related neural activity by increasing functional connectivity in the ventral DMN (default mode network) and rIFG (right inferior frontal gyrus), which was not seen in the single N-back training group (Salminen et al., 2020). Additionally, our study used a simple 2-back task as our low-cognitive load condition unlike previous studies who have started at a 0-back or 1-back task, then increase to a 2-back and 3-back task (Jaeggi et al., 2003; Lamichhane et al., 2020; Meidenbauer et al., 2021; Sala-Llonch et al., 2012). As a result, we may have already started with a relatively highly demanding task and thus have increased the cognitive workload for participants. However, it is in the 2-back task that we see the most age-related differences in WM in terms of brain activity, which is most affected at loads of n > 1 (Aghajani et al., 2017; Meidenbauer et al., 2021; Zhuang et al., 2022). At lower loads, as in a 1-back, there does not seem to be as high a demand in cognitive resources as there is in a 2-back but as we continue to add demands, such as in a 3-back, participants may experience a cognitive overload, leading to a loss of concentration, poorer performance, and a decrease in brain activity (Aghajani et al., 2017; Meidenbauer et al., 2021; Zhuang et al., 2022). Thus, it may be that in our dual task, YA are exhibiting saturation or disengagement from the task as it becomes too difficult such that it exceeds WM capacity and leads to poorer performance (Meidenbauer et al., 2021; Zhuang et al., 2022). This also explains the decreased accuracy in all age groups during the dual task. Thus, this may suggest that we observed the highest brain activity during the simple task compared to the dual task.

We did, however, find that OA had more brain activity compared with YA in both hemispheres of the brain, with greater recruitment of LH channels that are mostly not significantly recruited by YA. Thus, OA demonstrated the predicted bilateral brain activity, while YA show more lateralized brain activity to the RH (see Cabeza, 2002). Unlike previous studies that use a 1-

back and then 2-back, we observed more brain activity in OA during the simple task (Mattay et al., 2006; Nyberg et al., 2009), and this activity was relatively maintained in the dual task (though to a lesser extent in a couple channels). As a result, OA may be working harder, thus showing more bilateral brain activity by recruiting more neural resources, and thus leading to comparable performance on the task to YA. Therefore, this may provide evidence for the compensation view. This is because OA and YA have similar performance, but OA show bilateral brain activity across the simple and dual tasks; though this would also suggest dedifferentiation, that is, a general overrecruitment of brain areas (Rieck et al., 2021). However, the fact that OA had more activity in the simple task compared with the dual task and performed better in the simple task while performing similarly to YA, suggests that this activity is mainly compensatory. Talamonti et al. (2020) investigated differences in brain activity between YA, high and low performing OA using fNIRS during a free recall task (temporal or spatial strategy). They found that all groups performed similarly, and that YA showed more right anterior PFC lateralization while OA showed no hemispheric lateralization (Talamonti et al., 2020). They thus suggested that OA may have recruited areas in both hemispheres of the brain to have equal performance to YA on the task (Talamonti et al., 2020).

Sala-Llonch et al. (2012) used fMRI and a verbal N-back task with increasing loads (0-3 back) to observe differences in brain activity between YA vs. high and low performing OA. They found that high-performing OA recruited areas of the brain that YA and low-performing OA did not while performing the tasks (Sala-Llonch et al., 2012). This, in addition to high-performing OA showing similar performance to YA on the 3-back task, suggested that high-performing OA were recruiting non-task related resources (those not typically active in WM tasks) to compensate for the aging brain (Sala-Llonch et al., 2012). Furthermore, high performing OA showed more

bilateral brain activity than YA in the frontoparietal networks (FNP), which was not seen in low performing OA (Sala-Llonch et al., 2012). As a result, this highlights a compensatory link between bilateral brain activity and performance in OA. However, to make more definitive conclusions, we need to include behaviour and fNIRS in the same model, thus further analysis is needed. The most common approach is to correlate brain activity with performance measures in a population in which compensation takes place (i.e., OA) (Cabeza et al., 2018). Additionally, brain stimulation may help establish causal effects of left hemisphere activation in OA (Cabeza et al., 2018).

We found that MA had relatively similar brain activity compared to YA with only differences in RH activation. However, we found that the MA performed relatively well on the task behaviourally such that they had fewer errors compared to OA (despite no differences in performance between OA and YA). As a result, the MA do not follow a linear pattern between the other two age groups. This could be because they are the middle group and thus might be applying strategies from both YA and OA leading to a greater efficiency overall. On the other hand, this might be due to some limitations within this study. Our sample size for MA is almost half that of YA and OA, thus exaggerations or outliers have a greater influence in our data. Furthermore, many of the MA tested had high formal education levels in comparison to YA and OA cohorts, which may have influenced the behavioural performance favourably. Jaeggi et al. (2003) briefly mentioned that motivation can influence behaviour, where lower motivation may lead to poorer performance on the task. The fact that this group includes many highly educated individuals, they may generally be more motivated to do well, and this thus reflected in their performance. Furthermore, the age range in middle aged adults could be too wide and some researchers divide them into young-middle aged vs. older-middle aged adults. Thus, middle aged differences in brain activity need to be studied further using these considerations.

Other limitations of this study include the fact that all participants were recruited on a volunteer basis and thus we may not be accurately representing the general population. We also gave participant substantial practice on both the simple and dual tasks to limit the potential confounding influence of practice effects. This may differ from other studies where learning effects may have influenced their findings as there are associative differences in performance and brain activity with practice (Jansma et al., 2001). Alternatively, our extensive practice may contribute to reduced brain activity in the dual task compared to the simple task (Jansma et al., 2001; Meidenbauer et al., 2021). We also did not counterbalance the simple and dual tasks; thus, it is possible that some practice effects may have occurred. Lastly, we assumed that the hemodynamic response function (HRF) was relatively the same in all age groups. However, West et al. (2019) investigated age-related changes in BOLD-HRF shape and timing as participants completed an audio-visual sensorimotor task in an fMRI machine. They found no differences in performance between OA and YA but did observe age-related HRF shape and timing differences in occipital, temporal, and precentral ROIs (regions of interest, West et al., 2019). They suggested that this may be due to age-related vascular changes in the brain, for example, a decrease in vasodilation or vascular reactivity with age (West et al., 2019; see also D'Esposito et al., 2003 for review). As a result, age-related HRF differences may also reflect alterations in neuro-vascular coupling rather than changes in only neural activity (West et al., 2019). As a result, future studies should take this into consideration when testing different age groups.

Future studies may want to investigate not only the PFC but the FPN as a whole as this has been shown to be involved in WM (Sala-Llonch et al., 2012). Furthermore, more research should investigate age-related changes in MA as this is typically an underrepresented group in the literature and often provides mixed results. Also, including behavioural and fNIRS data in the same model can aid in constructing more definitive conclusions. A better representation of specific brain areas that are being activated may be achieved through the digitization of the optodes on the fNIRS cap, and thus future studies should aim to incorporate this in their research. Lastly, investigations into the clinical applications of fNIRS and this apparent compensatory mechanism in OA in early detection of neurodegenerative diseases would be an interesting avenue to pursue.

In the end, we show robust support for the compensation view as we show that OA are recruiting more neural resources that allow for comparable task performance to YA, and this is especially the case in the PFC during the dual task. Finally, fNIRS has been an effective tool in improving our understanding of neurocognitive aging by identifying age-related differences in brain activity and thus allowing future work to examine the relationships between cognitive function and compensation.

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