Effects of Increasing Working Memory Load on EEG Signal Amplitude and Variability in the Prefrontal Cortex During an n-Back Task

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Abstract:

Working memory is essential for cognitive processes such as reasoning, attention, and decision making, and can be assessed using tests such as the n-back task, a cognitive test that systematically increases memory load. The prefrontal cortex (PFC) plays a critical role in working memory because it is responsible for executive functions such as maintaining information, updating memories, regulating attention, and managing cognitive effort. Understanding how the PFC responds to increasing memory demands can provide insight into how the brain supports complex thinking and information processing. Previous research has shown that the prefrontal cortex becomes more active as the difficulty in the n-back task increases. In this study, electroencephalogram (EEG) data from an open access dataset were analyzed, focusing on activity recorded at the Fp1 (frontal) electrode across rest, 0-back, 2-back, and 3-back conditions. The n-back task was used to systematically vary working memory load, with higher levels requiring greater active remembering and continuous updating of information. EEG time-series plots, event-related potentials (ERPs), and frequency-based measures were examined to identify differences in signal amplitude and variability across the conditions. The results indicate that higher working memory load is associated with increased signal variability and larger amplitude fluctuations, suggesting greater neural engagement in the prefrontal cortex. These findings support previous research showing that neural activity increases as cognitive load rises, while also demonstrating how publicly available EEG datasets can be used to examine changes in working memory processing. Understanding these neural patterns may contribute to future research on attention, cognitive performance, and disorders that involve working memory impairments, including ADHD, age-related cognitive decline, and other neurological conditions.

Introduction:

Working memory is a fundamental cognitive process that enables individuals to temporarily store, manipulate, and use information necessary for learning, reasoning, decision making, and attentional control (Huang et al., 2025). Because working memory is involved in many higher-order cognitive functions, researchers are interested in understanding how the brain responds as memory demands increase. Prior research indicates that the hippocampus, and frontal and temporal cortices are responsive to memory demands (Huang et al., 2025). However, the exact role of working memory when managing tasks at varying levels of cognitive effort, and its neural activity patterns during mentally demanding tasks, remains unclear.

One of the primary brain regions involved in working memory is the prefrontal cortex, which is responsible for executive functions such as attention regulation, information updating, and cognitive control. Previous neuroscience research has consistently shown that activity within the prefrontal cortex increases as working memory tasks become more difficult. Because of this relationship, frontal brain regions are commonly examined in studies investigating cognitive load and active remembering. Here, I aimed to investigate how varying working memory load influences neural activity in the prefrontal cortex. Tasks that require active remembering engage the brain so that it continuously updates, maintains, and processes information in dynamic contexts, making working memory an effective model for studying cognitive load and neural engagement as demands change in the environment.

While working memory relies heavily on the prefrontal cortex, it also depends on communication between several other brain regions. The parietal cortex contributes to attention and the maintenance of information, while the hippocampus is involved in memory formation and retrieval (Shin et al. 2018). These regions work together as a network that supports the temporary storage, manipulation, and updating of information needed to perform cognitive tasks. Understanding how these brain areas interact provides insight into the neural mechanisms underlying learning, reasoning, and attention, as well as how these processes may be affected in neurological and psychiatric disorders. Although working memory involves several interconnected brain regions, this study focuses primarily on the prefrontal cortex because it is consistently identified as a central hub for executive control and active remembering.

Electroencephalogram (EEG) is a widely used neuroimaging tool in cognitive neuroscience because it records electrical brain activity with high temporal resolution, allowing researchers to observe rapid neural changes in real time. EEG is particularly useful for studying working memory because processes such as information updating and active recall occur very quickly within the brain. Researchers examine many aspects of EEG signatures to infer how the brain is responding to an experiment. In addition to continuous EEG activity,event-related potentials (ERPs) are frequently analyzed to represent brain responses that occur in relation to specific stimuli. In working memory research, the P300 component has been strongly associated with attention allocation, stimulus evaluation, and working memory processing (Shalchy et al., 2020). Variations in P300 amplitude are often interpreted as indicators of differences in cognitive effort and attentional demand (Shalchy et al., 2020; Dong et al., 2015). In addition, oscillatory signals during the n-back task, specifically in the theta (4 to 8 Hz) and alpha (8 to 13 Hz) bands, are known to be involved in encoding during working memory load (Huang et al., 2025).

One of the most widely established paradigms for investigating working memory load is the n-back task (Huang et al., 2025). The task allows researchers to systematically manipulate cognitive demand by changing the amount of information participants must actively maintain and recall. In lower-load conditions such as 0-back, participants primarily rely on attention and recognition processes. In higher-load conditions such as 2-back and 3-back, participants must continuously update and maintain information in working memory, placing substantially greater demand on the prefrontal cortex. This makes the n-back task especially effective for examining how neural activity changes across different levels of cognitive difficulty.

Although previous studies have established that working memory load influences neural activity, many have focused primarily on either continuous EEG signals or event-related potentials rather than examining multiple EEG measures together within the same dataset. Additionally, relatively few studies compare continuous EEG activity, ERP responses, and frequency-band activity across multiple levels of working memory demand. This study addresses that gap by investigating how these neural measures change as cognitive load increases. Specifically, this study asks: *How does increasing working memory load affect neural activity in the prefrontal cortex, as measured by continuous EEG signals and P300 event-related potentials during an n-back task?*

Methods:
Participants

Data were drawn from the n-back portion of a publicly available simultaneous EEG (Shin et al., 2018). The full dataset comprises 25 healthy right-handed adults (9 male, 16 female; mean age 26.1 years, range 17 to 33).

Experimental Task

The n-back task consisted of three sessions, each containing three blocks of 0-back, 2-back, and 3-back in counterbalanced order. Within a 40 second task block, a random single-digit number was presented every 2 seconds, with each digit shown for 0.5s followed by a 1.5s fixation cross. Targets occurred on 30 percent of trials, and participants responded to every digit by pressing a target button (when the current digit matched the one presented two or three positions earlier) or a non-target button. Each block was preceded by a 2s instruction and followed by a 20s rest period, and each block start and end were signaled by a 250 ms tone. A total of 180 trials were collected per n-back level per participant. The present analysis was restricted to the 2-back and 3-back conditions, giving a 2 (load: 2-back, 3-back) by 2 (trial type: target, non-target) design.

EEG acquisition and preprocessing

EEG was originally acquired with a BrainAmp amplifier (Brain Products, Gilching, Germany) at 1000 Hz from 30 active electrodes placed according to the international 10-5 system, referenced to TP9 with TP10 as ground, together with horizontal and vertical EOG. The version of the data analyzed here was the preprocessed release distributed with the dataset, which had been downsampled to 200 Hz, band-pass filtered between 1 and 40 Hz with a sixth-order zero-phase Butterworth filter, and corrected for ocular artifacts using the improved weight-adjusted second-order blind identification (iWASOBI) algorithm. Each continuous file therefore contained 28 scalp channels plus the two EOG channels at 200 Hz.

EEG postprocessing

Stimulus-locked epochs were extracted from the continuous data over a window of -200 to 800 ms relative to stimulus onset. Each epoch was baseline-corrected by subtracting the mean amplitude of the -200 to 0 ms pre-stimulus interval, computed per channel and per trial.

Two electrode clusters were defined a priori. A parietal region of interest (P3, Pz, P4, POz) was used to capture the P300 (P3b), and a frontal-midline region of interest (AFz, F1, F2, FC1, FC2) was used for frontal theta. Within each region, signals were averaged across the constituent channels to produce a single waveform per epoch. Mean P300 amplitude was computed as the average parietal amplitude in the 300 to 500 ms post-stimulus window. P300 peak latency and peak amplitude were defined as the time and value of the maximum parietal amplitude within the same window. Stimulus-locked spectral changes were estimated from a wider epoch (-500 to 1000 ms). Power spectral density was computed with Welch's method separately for a pre-stimulus window (-500 to 0 ms) and a post-stimulus window (200 to 1000 ms). Band power was averaged within the theta band (4 to 8 Hz) at the frontal region of interest and within the alpha band (8 to 13 Hz) at the parietal region of interest. Task-related change was expressed as a decibel ratio of post- to pre-stimulus power, averaged across trials within each condition to yield one value per participant per condition.

Statistical analysis

The primary analysis focused on the Fp1 electrode, representing activity in the prefrontal cortex. Additional ERP analyses used parietal electrodes (p3, Pz, P4, POz), where P300 responses are typically stronger. Each dependent measure (P300 mean amplitude, P300 peak latency, frontal theta change, and parietal alpha change) was analyzed with a 2 (load) by 2 (trial type) repeated-measures ANOVA, with partial eta-squared reported as an effect size. Target versus non-target differences were further examined at each load level with paired t-tests, accompanied by Cohen's dz. To test whether the four measures responded differently to load and trial type, values were z-scored within measure and entered into a three-way repeated-measures ANOVA with load, trial type, and measure as within-subject factors; the measure-by-trial-type and measure-by-load interactions index whether the experimental effects differed across measures, while the main effect of measure is uninformative by construction.

Results:

To investigate how increasing working memory load affects neural activity, continuous EEG recordings from the Fp1 electrode were examined during the n-back task. A visual inspection of the EEG signal revealed noticeable differences between low-load and high-load working memory conditions.

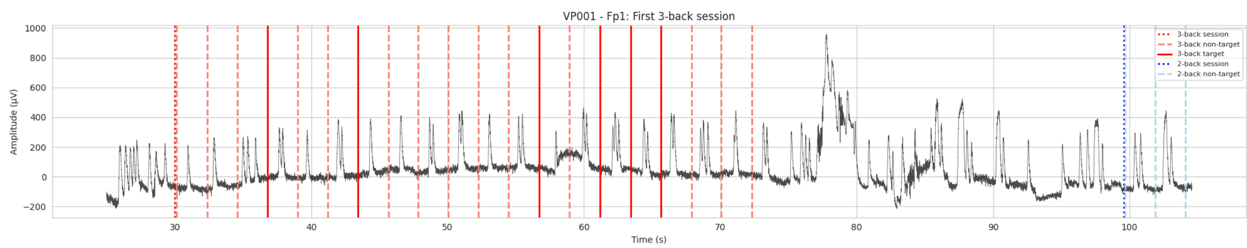

Figure 1. Continuous EEG signal during task suggested trial and condition differences. Zoomed-in EEG signal during the 3-back condition showing increased amplitude fluctuations and waveform variability associated with higher working memory demand.

As shown in Figure 1, the EEG signal recorded during the 3-back condition exhibited larger amplitude fluctuations and greater waveform variability compared to lower-demand conditions. Throughout the task period, the signal displayed more frequent peaks and rapid changes in amplitude, suggesting increased neural engagement while participants actively maintained and updated information in working memory. Because the 3-back condition requires participants to continuously compare the current stimulus to one presented three trials earlier, this increased variability likely reflects the additional cognitive resources needed to perform the task successfully.

The observed pattern is consistent with previous research showing that the prefrontal cortex becomes increasingly engaged as cognitive load increases. While the present analysis is qualitative, the larger amplitude changes observed during the 3-back task suggest that the higher working memory demands are associated with stronger neural activity with frontal brain regions.

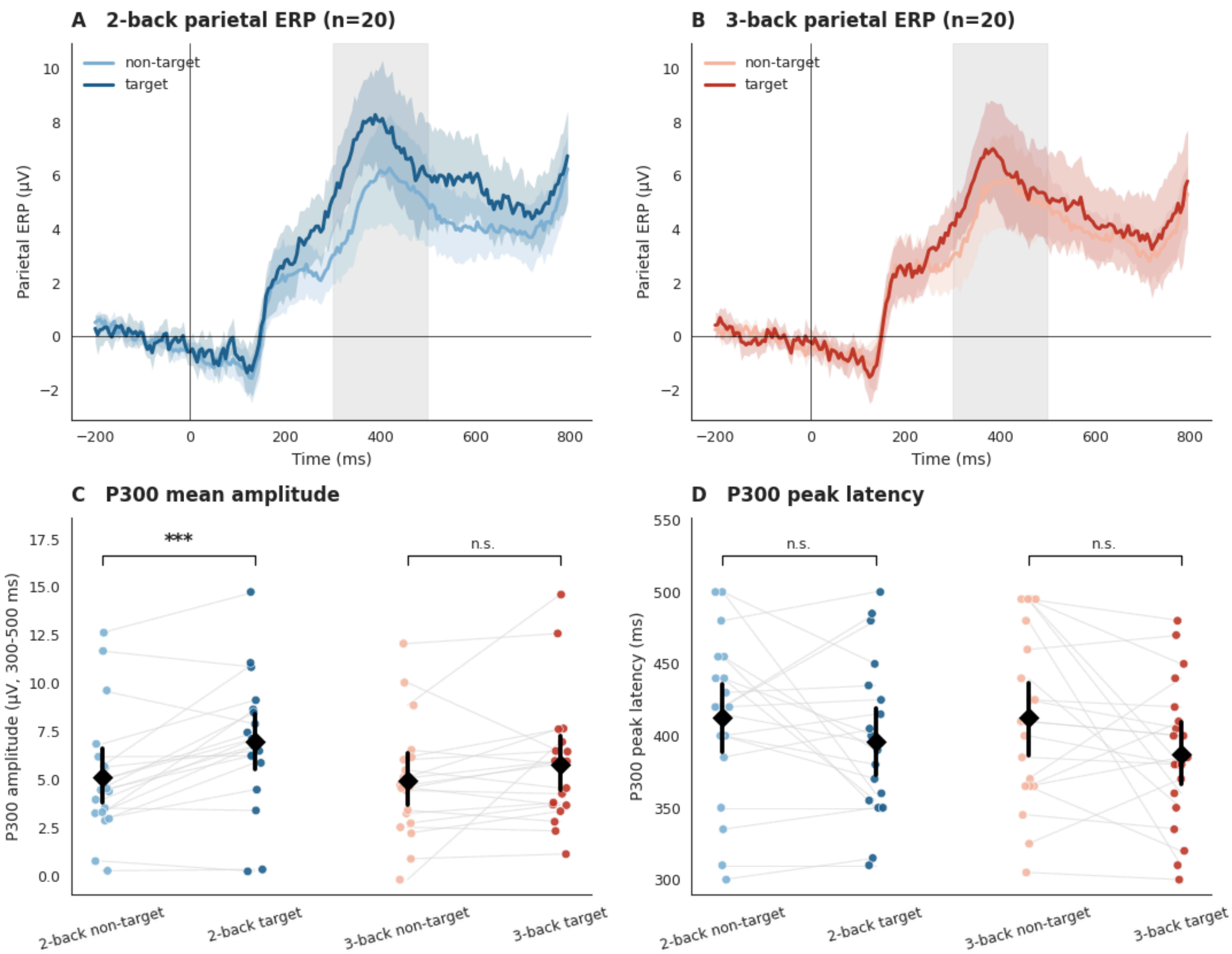

Figure 2. Parietal P3b discriminates targets from non-targets at both 2-back and 3-back working memory loads. (A, B) Grand-average ERP at the parietal ROI (P3, Pz, P4, POz) for 2-back and 3-back trials respectively, with target trials (dark) overlaid on non-target trials (light). Shaded ribbons are 95% confidence intervals across subjects. The gray box marks the 300 to 500 ms P300 measurement window. **(C)** Mean P300 amplitude per condition, computed as the average parietal-ROI voltage in the 300 to 500 ms window. Trial type $F(1, 19) = 14.92$, $p = 0.001$, $\eta^2p = 0.44$; load $F(1, 19) = 2.90$, $p = 0.10$, $\eta^2p = 0.13$; load × trial type $F(1, 19) = 2.25$, $p = 0.15$, $\eta^2p = 0.11$. **(D)** P300 peak latency per condition, computed as the time of maximum amplitude in the same window, plotted as in C. Trial type $F(1, 19) = 4.78$, $p = 0.04$, $\eta^2p = 0.20$; load $F(1, 19) = 0.48$, $p = 0.50$, $\eta^2p = 0.03$; load × trial type $F(1, 19) = 0.29$, $p = 0.60$, $\eta^2p = 0.02$. Each P300 metric was tested with a 2 × 2 within-subjects ANOVA with factors load (2-back, 3-back) and trial type (target, non-target). ***$p < 0.001$,, n.s. = not significant.

To further investigate neural responses associated with active remembering, event-related potentials (ERPs) were examined during both the 2-back and 3-back conditions. Particular attention was given to the P300 component, a positive ERP waveform that typically occurs between 300 and 500 milliseconds after stimuli presentation and has been linked to attention allocation, stimulus evaluation, and working memory processing.

As shown in Figure 2A and Figure 2B, both the 2-back and 3-back conditions produced clear positive ERP responses following stimulus presentation. In both task conditions, target stimuli generated larger positive deflections than non-target stimuli within the P300 measurement window. This finding suggests that participants allocated greater attentional resources when identifying relevant target stimuli compared to non-target stimuli.

The largest positive responses occurred approximately 300-500 ms after stimulus onset, which corresponds to the expected timing of the P300 component. In the 2-back condition, target trials produced noticeably larger amplitudes than non-target trials, indicating stronger cognitive processing during successful target detection . A similar pattern was observed in the 3-back condition, although the differences between target and non-target trials appeared somewhat smaller.

The mean P300 amplitude analysis shown in FIgure 2C further supports these observations. Target stimuli generally produced larger average amplitude than non-target stimuli, particularly in the 2-back condition. This suggests that identifying task-relevant information requires greater neural processing than responding to non-target stimuli. The increased amplitude is consistent with previous studies showing that larger P300 responses are associated with increased attentional allocation and working memory engagement.

In contrast, the P300 peak latency measurements shown in Figure 2D revealed relatively small differences between conditions. Peak latency reflects the timing of cognitive processing, and the similar latency values observed across task conditions suggest that participants processed stimuli within approximately the same time window regardless of task difficulty. Therefore, while working memory load appears to influence the strength of neural responses, it may have less impact on the timing of those responses.

Overall, the ERP findings indicate that target detection during working memory tasks is associated with stronger neural activation, particularly within the P300 time window. These results support the idea that increasing cognitive demand requires greater attentional and memory-related processing.

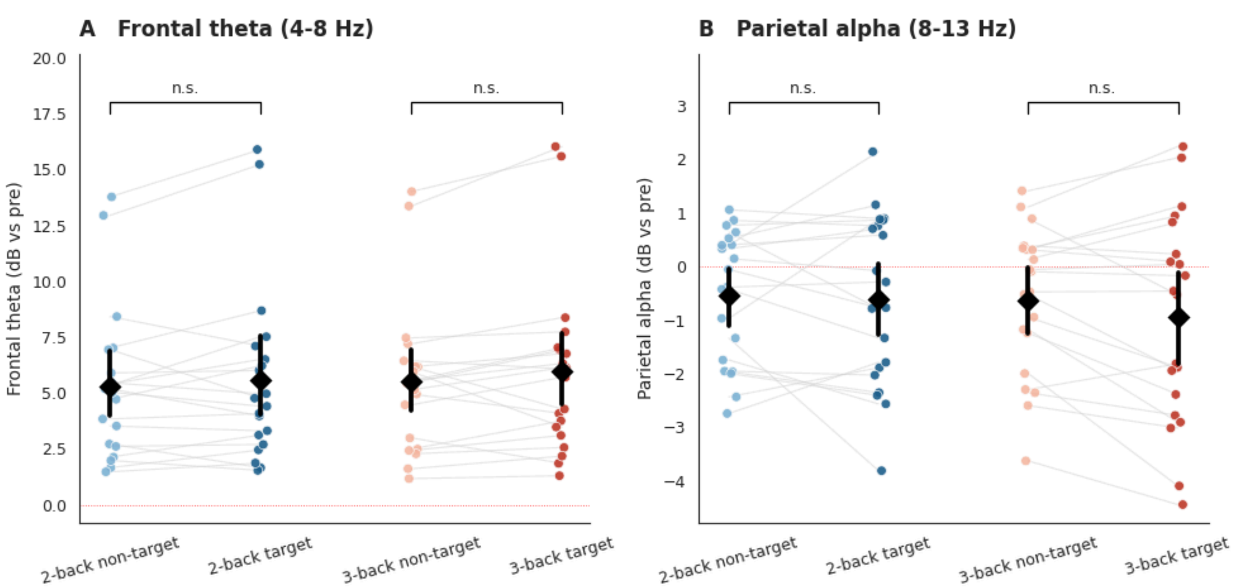

Figure 3. Stimulus-locked frontal theta and parietal alpha responses across n-back conditions. (A) Frontal theta (4 to 8 Hz) at the frontal ROI (AFz, F1, F2, FC1, FC2), expressed as the decibel change in post-stimulus power (200 to 1000 ms) relative to a pre-stimulus baseline (-500 to 0 ms). **(B)** Parietal alpha (8 to 13 Hz) at the parietal ROI (P3, Pz, P4, POz), plotted as in A. n.s. = not significant.

In addition to ERP responses, stimulus-locked oscillatory activity was examined to determine whether working memory load influenced frontal theta and parietal alpha activity. These frequency bands are commonly studied in working memory research because they are believed to reflect different aspects of cognitive processing.

Frontal theta activity (4-8 Hz) has been associated with executive control, attention, and working memory maintenance. As shown in **Figure 3A**, frontal theta power increased following stimulus presentation in both the 2-back and 3-back conditions. Although there was considerable variability among participants, the overall pattern suggests that theta activity remained elevated during active task performance. This observation is consistent with previous research demonstrating a relationship between frontal theta oscillations and working memory demands.

Parietal alpha activity (8-13 Hz), shown in **Figure 3B**, displayed greater variability across participants and conditions. Alpha oscillations are often associated with attentional allocation and information processing efficiency. While some participants exhibited increased alpha responses during target trials, the overall differences between target and non-target conditions were relatively small. The figure indicates that these changes were not statistically significant, suggesting that alpha activity may not have been strongly influenced by working memory load in this dataset.

Although neither frontal theta nor parietal alpha showed strong condition-dependent effects, these findings remain relevant because they provide additional context regarding the neural mechanisms involved in working memory. Together with the ERP results, they suggest that changes in attentional processing may be more clearly reflected in the P300 response than in broader oscillatory activity measures.

Discussion:

My secondary analyses aimed to investigate how increasing working memory load affects neural activity during an n-back task. Based on previous research, it was expected that more demanding working memory conditions would require greater neural engagement, as indexed by greater magnitude of the ERP and oscillatory power in scalp EEG, specifically in brain regions involved in attention, information updating, and cognitive control (Huang et al., 2025). Overall, I find partial evidence supporting this expectation, such that as working memory load increased, scalp EEG recordings in frontal and parietal regions showed greater signal variability and larger amplitude fluctuations as evoked by trials, but not oscillatory power in the theta and alpha bands in frontal and parietal regions, suggesting that the brain becomes more responsive as cognitive demands increase.

The continuous EEG analysis **(Figure 1)** suggested noticeable differences between lower-load and higher-load conditions. The 3-back task produced larger fluctuations in EEG amplitude and greater waveform variability than lower-demand conditions. Because the 3-back condition requires participants to continuously update and compare information held in working memory, these findings suggest that additional neural resources are recruited as task difficulty increases. This observation is consistent with previous studies, showing that the prefrontal cortex becomes increasingly active as working memory demands rise (Huang et al., 2025; Shalchy et al., 2020). Since the prefrontal cortex is responsible for executive functions such as attention regulation, information maintenance, and cognitive control (Huang et al., 2025), the increased activity observed during the 3-back condition suggests an important role in managing working memory load.

The ERP analysis **(Figure 2)** provided further evidence that working memory load influences neural processing in parietal regions. The P300 component, which is associated with attention allocation and stimulus evaluation (Shalchy et al., 2020), showed larger response magnitude during target trials than non-target trials. This finding suggests that participants devoted more cognitive resources to identifying and processing relevant stimuli that they were instructed to engage with. Larger P300 amplitudes have been reported in previous working memory studies and are often interpreted as evidence of increased attentional engagement (Shalchy et al., 2020; Dong et al., 2015). My ERP results therefore support a framework for parietal brain regions where active remembering requires greater neural processing than passive stimulus viewing. The larger P300 responses observed during target trials could be indicating that participants were actively evaluating incoming information and updating working memory representations in order to respond correctly.

The frequency band analyses offered additional insight into the neural mechanisms involved in task performance. Although frontal theta and parietal alpha activity did not show strong statistically significant differences across conditions **(Figure 3)**, I observed a general increase in frontal theta, and a marginal decrease in parietal alpha, after trial onsets. These results suggest that ERP measures may have been more sensitive to differences in cognitive demand within this dataset, while oscillatory activity reflected broader aspects of ongoing neural processing. Together, the ERP, and frequency-band findings provide a more complete picture of how the brain responds when memory demands increase.

Several limitations should be considered when interpreting these findings. My study used an existing open-access dataset, which limited control over participant recruitment, experimental procedures, and data collection methods. The participant sample consisted primarily of healthy young adults, which limits the ability to generalize the finding to other populations such as children, older adults, or individuals with neurological disorders. Additionally, scalp EEG has several inherent limitations for determining neurophysiological mechanisms behind cognitive processes. Although it provides fine temporal resolution by capturing neural activity on a millisecond timescale, its spatial resolution is relatively limited compared to imaging methods such as functional magnetic resonance imaging (fMRI), thus our claims regarding parietal and frontal localization are reflective of aggregated neural activity across not just local, but also long-range inputs to these regions from other brain areas. EEG recordings are also highly sensitive to noise from eye blinks, muscle activity, and movement artifacts, which while corrected using artifact detection algorithms, can nonetheless influence signal quality and interpretation.

Despite these limitations, this study contributes to the growing body of research investigating the neural basis of working memory. While the findings largely support previous research rather than identifying a completely new neural mechanism, they provide additional evidence that increasing working memory load produces measurable changes in brain activity.

Furthermore, my project demonstrates how publicly available neuroscience datasets can be used to explore meaningful research questions and replicate important findings in cognitive neuroscience.The broader significance of my findings extends to understanding the difficulties in working memory associated with conditions such as ADHD, age-related cognitive decline, traumatic brain injury, and other neurological disorders. Understanding how neural activity changes as cognitive demands increase in neurotypical individuals provides a reference point for researchers to compare to clinical populations.

Future research could build on these findings by incorporating larger and more diverse participant samples, applying more advanced statistical analyses, and examining additional EEG measures such as connectivity patterns or frequency-domain activity in greater detail. Researchers could also investigate how working memory load affects individuals with cognitive impairments or neurological conditions to better understand how memory-related brain processes differ across populations. These directions would help expand our understanding of the neural mechanisms that support working memory and cognitive performance.

Conclusion:

This study set out to answer the question: *How does increasing working memory load affect neural activity in the prefrontal cortex during an n-back task?* The findings showed that as working memory demands increased, EEG recordings displayed greater signal variability and stronger P300 responses, indicating that the brain recruits additional neural resources to support attention, information updating, and active remembering. While these findings are consistent with previous research, examining continuous EEG activity, ERP responses, and frequency-band activity together provided a broader picture of how the brain responds to increasing cognitive demands.

Understanding these neural changes has important implications beyond the laboratory. Because working memory is affected in conditions such as ADHD, traumatic brain injury, Alzheimer’s disease, and age-related cognitive decline, EEG may serve as a valuable, noninvasive tool for identifying changes in cognitive function and evaluating future interventions. As neuroscience continues to advance, combining multiple EEg measures may help researchers better understand how the brain adapts to challenging mental tasks and support the development of earlier detection methods and more personalized treatments.

The ability to understand how the brain adapts to increasing cognitive demands is an important step toward improving how we detect, monitor, and ultimately treat disorders that affect memory and cognition.

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