Brain Activity During Repetitive Cognitive Load in Young Adults: a Pilot Study

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***Abstract*— Understanding how brain activity evolves with repetitive cognitive load is critical for assessing neural adaptations related to learning, fatigue, and efficiency. This pilot study investigates electroencephalographic (EEG) changes over five days of cognitive training in young adults performing a memory task. The study included eight healthy participants, who completed EEG recordings during a cognitive load task. To assess brain activity, we computed absolute spectral power across theta, alpha, sub-alpha (lower, upper), beta, sub-beta (lower, mid, upper), and gamma frequency bands. Non-parametric statistical methods, including a cluster-based permutation test, were applied to assess differences between the first and fifth day. Results indicate a significant power increase in theta, particularly in the midline and parietal regions, suggesting enhanced cognitive control and memory retrieval. Alpha power also increased, reflecting improved processing efficiency with reduced cognitive effort. Furthermore, lower and mid-beta activity showed an increase over time, indicating sustained attentional engagement and optimized cognitive processing. A reduction in the beta/alpha ratio suggests a transition from effortful processing to more automatic retrieval. No significant changes were observed in gamma power, implying that cognitive load did not induce excessive strain. These findings highlight neuroplastic adaptations to cognitive training, supporting the role of EEG in tracking learning-related changes in brain activity.**

Keywords*— *Cognitive load, working memory, repetitive learning, mental fatigue, EEG.

I. Introduction

Cognitive load and working memory processes play a crucial role in daily activities, influencing decision-making, problem-solving, and learning efficiency. Understanding how repeated exposure to cognitive tasks influences brain activity over time is important for assessing neural adaptations associated with cognitive training, fatigue, and performance optimization. Electroencephalography (EEG) is a valuable tool for investigating neural dynamics underlying cognitive effort, as it allows for the study of spectral content across different rhythms.

Prior studies have demonstrated that increasing task difficulty modulates EEG activity, particularly in theta (4–7 Hz) and alpha (8–12 Hz) bands, which are strongly linked and are sensitive to working-memory load and attentional control [1]. Frontal theta power has been consistently associated with cognitive effort and executive control, while parietal alpha power decreases with increased task demands, reflecting the suppression of irrelevant information [2]. Additionally, studies also reported that beta (13–30 Hz) power plays a crucial role in cognitive load processing as it is strongly linked with attentional control, motor response preparation, and task execution [3], Moreover, previous studies also linked the gamma rhythm (>30 Hz) to cognitive workload, memory consolidation, and neural synchronization, increasing during complex problem-solving and demanding working memory tasks [4]. Research has also shown that increased task familiarity can modulate EEG spectral power, indicating a reduction in cognitive demand as skills become more automatic [5]. Despite existing literature on EEG sensitivity to task complexity and acute mental effort, most existing studies focus on single-session assessments, leaving a gap in our understanding of how brain activity evolves after multiple sessions of cognitive load.

Moreover, prolonged engagement in cognitive tasks frequently leads to mental fatigue, which can be identified through shifts in EEG patterns—specifically higher theta power and lower alpha power [6]. These changes may indicate a transition from active engagement to a state of disengagement, potentially affecting executive function and attention [6]. Interestingly, while gamma power is often linked to heightened cognitive performance, fatigue-related declines in neural efficiency may dampen gamma activity, reflecting diminished cognitive processing capacity. The relationship

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between fatigue-related EEG patterns and adaptations due to task familiarity raises important questions about their coexistence during repetitive cognitive tasks. While the effects of acute fatigue have been well-documented [7], there is a notable lack of longitudinal studies examining how fatigue accumulates over consecutive days of task performance.

This pilot study aims to address these gaps by examining whether repeated exposure to cognitive tasks over five days induces specific modulations in EEG frequency bands, reflecting increased neural efficiency in young adults. Additionally, the study will examine whether sustained engagement with the same cognitive task induces signs of cognitive fatigue or disengagement.

II. Material and Methods

A. Dataset

This study was approved by the Research Committee for Scientific Ethical Questions (RCSEQ) at UMIT TIROL (approval no. 3431/24). A total of ten healthy participants were recruited for this study and informed written consent was obtained prior to participation. One participant withdrew before completing the experiment, and another one was excluded due to a technical issue during recording, which resulted in the memory task being performed twice. Consequently, the final analysis included data from eight participants (32 ± 4 years, mean ± standard deviation; gender distribution: 62.5% men). For each participant, five recordings were collected, corresponding to five training days.

Participants were eligible if they were proficient in German, aged between 18 and 40 years, and had no self-reported neurological or psychiatric disorders. No specific exclusion criteria were applied beyond the removal of data due to technical recording issues.

B. Data Recoding

All participants underwent EEG recording using an eego rt amplifier and a waveguard 64-channel EEG cap (ANT Neuro, Netherlands), along with simultaneous single-channel EOG, with a sampling frequency of 512 Hz. Simultanously, single-channel ECG was recorded with a sampling rate of 1000 Hz. All recordings were performed under three conditions: resting state with eyes closed before cognitive training, during cognitive training, and resting state with eyes closed after the cognitive task.

C. Cognitive Training/Memory Task

All participants completed a comprehensive baseline neurocognitive assessment followed by an intensive memory training lasting approximately 25 minutes per session across five days, with a two-day break between the third and fourth days. The neurocognitive assessment included standardised tests of episodic memory, executive functions, attention, and numerical competence, to confirm participants' cognitive intactness. During the memory training, participants were repeatedly presentedsix equations in the form of "a # b = c", in randomized order where # held no mathematical significance. Participants were required to memorise the operand–solution association and to type in the correct response when prompted with "a # b =?". In the first three days of training, participants received a cue in the form of the full equation, including the answer (a # b = c). The proportion of cued trials diminished from day 1 to day 3and on the last two training days, the cue was not presented at all, to promote memory based retrieval. The six equations were repeated at least 90 times over the five sessions.

D. Behavioral Measures:

To assess behavioral performance during the task, we calculated three key metrics for each participant on day 1 and day 5. First, Accuracy Rate (ACC) was computed as the proportion of correct responses. Second, Reaction Time (RT) was measured in milliseconds, reflecting the average time taken to respond to each equation. Third, we derived an Inverse Efficiency Index (IEI) by dividing reaction time by accuracy rate, providing a combined measure of speed and accuracy; lower IEI values indicate higher performance efficiency. To evaluate learning effects over the training period, we computed the gain in efficiency, defined as the difference in IEI between day 1 and day 5. These behavioral metrics enabled us to quantify cognitive improvement over time and were later used in conjunction with EEG spectral features to explore the relationship between behavioral performance and neural adaptation.

E. Pre-Processing of EEG data:

All analyses were performed using MATLAB 2022a (MathWorks, Natick, MA, USA), the EEGLAB 2024 toolbox, and FieldTrip 2023 toolbox [8, 9]. To assess the impact of training, EEG data from day 1 and day 5 of the memory task were analyzed. The EEG recordings during the task were segmented into epochs, excluding periods when participants were waiting for a cue, ensuring that only EEG data corresponding to task performance was included.

EEG preprocessing involved re-referencing to both the common average and the M1/M2 electrodes (applied on the earlobes). A high-pass filter at 0.5 Hz was applied to remove slow drifts, a low-pass filter at 80 Hz eliminated high-frequency noise, and a notch filter between 49 and 51 Hz was introduced to remove powerline interference. Additionally, Independent Component Analysis (ICA) with the Infomax algorithm was performed to identify and reject components affected by ECG and EOG artifacts [10]. Components were classified using the automated ICLabel classifier [11]. Labels with an artifact-related activity contribution exceeding 90% (e.g., eye blinks and muscle noise) were automatically removed.

F. Brain Activity Analysis

Brain activity was analyzed by estimating the power spectral density (PSD) of each EEG channel using the EEGLAB's *spectopo* function, which applies the Welch's method for PSD estimation. Absolute power was extracted for the spectrum in the following frequency bands: theta (4–8 Hz), lower alpha (8–10 Hz), alpha (8–12 Hz), upper alpha (10–12 Hz), lower beta (12–18 Hz), beta (12–30 Hz), mid-beta (18–21 Hz), upper beta (21–30 Hz), gamma (30–50 Hz), Additionally, beta/alpha ratio was computed.

Absolute power was averaged across epochs for each participant and frequency band, followed by a grand average across all participants. This analysis was conducted on EEG recordings collected during the memory task on both day 1 and day 5.

G. Stastistical Analysis

To determine statistical differences in the EEG data, we first performed a normality test using the Lilliefors Test. Given that the output indicated non-normal distributions, we opted for a non-parametric test, i.e., a cluster-based non-parametric paired permutation test with 500 iterations and 4 neighboring channels, over the entire frequency spectrum.

This allowed us to identify the frequency bands and brain regions that potentially exhibit significant differences between training sessions. We chose this approach because it is particularly well-suited for EEG data, where spatial and temporal dependencies are common[12]. Additionally, it effectively corrects for multiple comparisons, reducing the risk of false positives, and provides a more reliable assessment of significant effects in the high-dimensional EEG data. To identify differences between day 1 and day 5, we computed non-parametric paired permutation test across all frequency bands (e.g., theta day 1 vs. theta day 5). All results with *p-value* < 0.05 were considered statistically significant.

In addition, to evaluate changes in behavioral performance over time, we used the Wilcoxon signed-rank test to compare ACC and RTs between day 1 and day 5. Statistical significance was determined using a $p < 0.05$.

III. Results and Discussion

As illustrated in Fig. 1, we observed significant differences in brain activity between day 1 and day 5 for each frequency band. Specifically, theta power was significantly higher on day 5 compared to day 1. This increase was particularly pronounced in the midline cortical areas, including the medial-frontal, medial-central, and medial-centro-parietal regions, as well as in the parietal region. This is in line with evidence from prior research linking theta oscillations to key cognitive processes. Specifically, midline-frontal theta activity is widely recognized as a neural correlate of cognitive control, facilitating processes such as task engagement and error monitoring [13]. Additionally, theta oscillations in the parietal region are implicated in memory encoding and retrieval, supporting their role in integrating information during recall tasks [14].

To better understand the distinct roles of alpha in cognitive processing, we divided the alpha band into lower and upper alpha sub-bands. Our results show a similar pattern across all alpha and its sub-bands as illustrated in Fig. 1 and Fig. 2, with a power increase across the entire cortical region on day 5. This finding aligns with a recent study reporting that during memory encoding, alpha power decreases as cognitive load increases, whereas during retrieval, cognitive load reduces, leading to an increase in alpha power [15]. Similarly, we divided the beta band into lower, mid, and upper beta sub-bands. In Fig. 2, a notable increase in lower beta activity on day 5 is observed across the entire cortical region, reflecting a state of focused and controlled attention crucial for memory retrieval. Since lower beta frequencies are linked to quiet concentration and cognitive processing [3], this suggests that participants maintained a steady attentional state while recalling information. Additionally, mid-beta activity increased in the temporal, left parietal, and occipital regions on day 5, indicating enhanced memory processing, cognitive control, and visual recall.

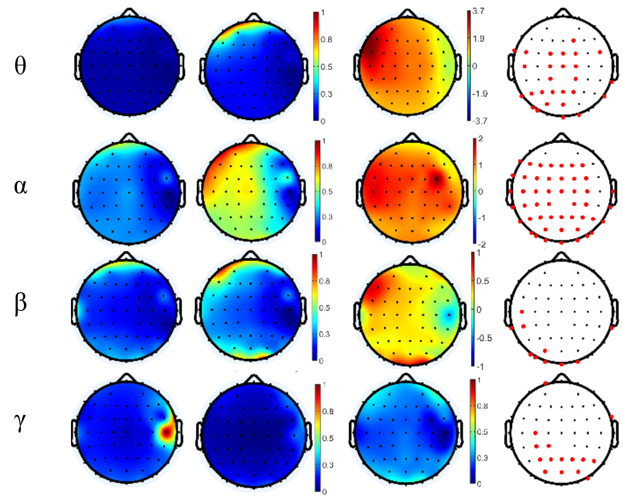

Fig 1: Comparison of absolute power (theta (θ), alpha (α), beta(β), gamma (γ)) between day 1 and day 5. Columns: (1) Topoplot for day 1, (2) Topoplot for day 5, (3) Difference in absolute power (day 5 - day 1), (4) p-values (red dots indicate significant channels). Column 1 and 2 Normalized for visualization.

The temporal region suggests stronger retrieval processes, and the occipital region supports visual processing during recall [3]. It should be noted that parietal regions are also found to play a critical role in attention processing as well as in number processing [16]. This aligns with the kind of memory training we used here, which entails learning and recalling numerical information from memory. In contrast, higher beta frequencies, associated with stress and high arousal, showed no significant changes over time, suggesting that retrieval on day 5 did not impose excessive cognitive load compared to day 1. The distinction between lower-beta and higher-beta activities aligns with their known roles, with lower and mid-beta supporting sustained focus and cognitive engagement, without overwhelming mental effort [3].

In addition, we calculated the beta/alpha ratio, which recent studies suggested as EEG-based engagement index for tracking attentional levels [17]. In our study, we observed a decrease in the beta/alpha ratio on day 5, primarily in the parietal region, which is strongly associated with higher cognitive functions such as mathematical reasoning, language processing, and attention [18]. Such a reduction suggests that participants no longer required increased cognitive effort or attentional resources to perform the task, indicating a transition from effortful processing to more automatic and efficient retrieval.

Lastly, we did not observe any significant differences in the gamma band. This lack of change in gamma activity during training suggests that the cognitive tasks were performed efficiently, without requiring increased neural synchronization typically associated with more demanding or

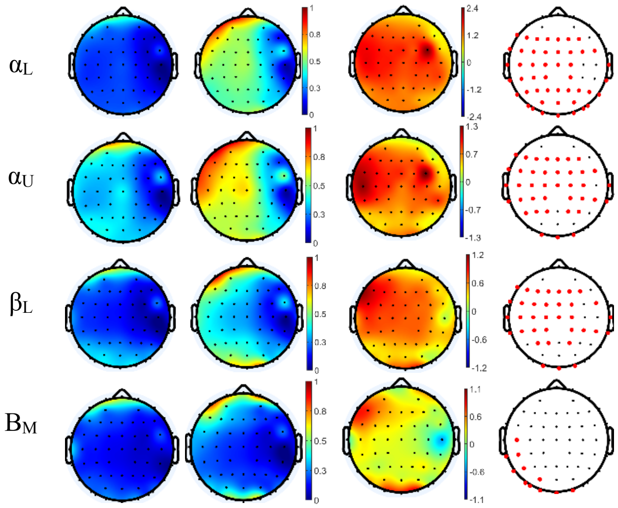

Fig 2: Comparison of absolute power (lower (α_L) and upper (α_U) alpha, lower (β_L) and mid (β_M) beta between day 1 and day 5. Columns: (1) Topoplot for day 1, (2) Topoplot for day 5, (3) Difference in absolute power (day 5 - day 1), (4) p-values (red dots indicate significant channels). Column 1 and 2 Normalized for visualization.

effortful cognitive processes. This indicates that the information being retrieved was well-integrated and easily accessible. Furthermore, as participants became more familiar with the task over the days, their brains likely required less arousal or synchronization, which is often necessary for novel or challenging tasks. Consequently, the stable gamma activity observed reflects a lower cognitive load and efficient processing during retrieval, aligning our findings with those from previous research [4, 5].

TABLE I. SCORES ON THE COGNITIVE TASK FOR DAY 1 AND DAY 5

	Day 1		Day 5		Day 1 vs Day 5
Participant.	***ACC (%)***	***RTs (ms)***	***ACC (%)***	***RTs (ms)***	***Gain in Efficiency***
P01	96	1553	98	949	655
P02	52	2717	96	1187	3972
P03	44	2531	97	1461	4315
P04	87	2950	99	1734	1641
P05	35	3322	98	1185	8338
P06	91	2850	97	1306	1778
P07	48	2906	94	1822	4149
P08	91	3532	1.00	1809	2060
Mean ±SD	68 ±26	2795 ±595	98 ±2	1432 ±329	3364 ±2425

a. ACC = accuracy rate, RTs = reaction time, ms = milliseconds, SD = standard deviation

In parallel with the observed changes in EEG activity, behavioral performance also significantly improved over the five training sessions as illustrated in Table 1. ACC increased and RT decreased from day 1 to day 5 *($p < 0.05$),* reflecting enhanced task proficiency as well as faster information retrieval and task execution following training. Moreover, the average gain in efficiency was 3364 (SD = 2425), with individual values ranging from 655 to 8338, indicating heterogeneity in learning effects. These results suggest a transition from controlled to more automatic task execution with repeated exposure.

IV. CONCLUSION

Our findings indicate that repetitive cognitive training leads to significant changes in both neural activity and behavioral performance. In terms of neural dynamics, we particularly observed changes in theta, alpha, and beta bands. Increased theta power in midline and parietal regions suggests improved cognitive control and memory retrieval, while the rise in alpha power reflects more efficient processing with reduced cognitive effort. The increase in lower and mid-beta activity supports sustained attention and enhanced memory processing of numerical information. The decrease in the beta/alpha ratio suggests that participants required less cognitive effort over time, indicating greater task familiarity and a shift toward more automatic retrieval. These neural adaptations were paralleled by behavioral improvements, including increased accuracy, faster response times, and higher task efficiency across training days. The convergence of EEG and behavioral evidence suggests a shift from effortful to more automatic cognitive processing. Additionally, the absence of significant changes in high-beta and gamma activity also suggests that training did not induce mental fatigue or excessive cognitive load. Collectively, these results highlight the neuroplastic effects of cognitive training, promoting efficient and sustained cognitive performance.

There are some limitations to note. For example, the sample size was small, which limits the generalizability of the findings from this pilot study. Additionally, we did not analyze the brain activity for all five days which could likely enhance our understanding of the changes in brain activity associated with training-related cognitive improvements. Future studies should also examine the impact of increased cognitive load on gamma band.

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