

Neural Correlates of Cognitive Load Variation In Elementary School Students During Mental Arithmetic Tasks

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Abstract: Cognitive load theory emphasizes the limited capacity of working memory in processing new information, with excessive cognitive load potentially inhibiting learning outcomes. This study investigated the use of electroencephalography (EEG) signals to interpret cognitive load variation in elementary school students during arithmetic operations in an authentic school environment, addressing gaps in existing research that has primarily focused on adults in laboratory settings. We manipulated the task complexity of mental addition to induce a low and a high complexity level of cognitive load amongst a sample of 82 fourth graders. Self-report cognitive load, task performance, and oscillation-band powers were collected. Our results show that increased cognitive load induced by arithmetic task complexity was associated with increased theta power and theta/alpha ratio, as well as decreased alpha power and low beta power. These findings demonstrate the potential of EEG signals to provide non-disruptive, objective insights into the temporal dynamics of cognitive load in educational settings.

Introduction

Cognitive load has long been recognized as a focus in understanding learners' cognitive states (Mayer, 2005). According to cognitive load theory by Sweller et al. (1998), novel information must be processed by working memory before it can be stored in long-term memory in the information-processing model of human cognitive architecture (Paas et al., 2004). Cognitive load refers to the amount of cognitive resources required for the person's cognitive system when performing any task (Paas & Van Merriënboer, 1994). People have limited working memory capacity, therefore managing cognitive load states during learning processes is imperative, as it directly impacts an individual's ability to process information and achieve meaningful learning outcomes. For instance, learners are more likely to make mistakes when they are under a high cognitive load (Boring et al., 2020). Exceeding working memory capacity could result in inhibited learning due to cognitive overload (Anmarkrud et al., 2019).

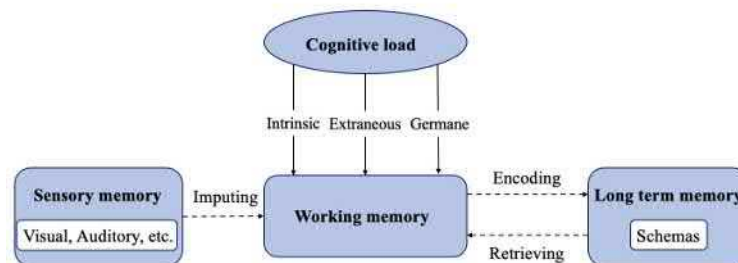
The advent of advanced non-invasive physiological sensors and analytics has made it possible to capture and interpret subtle changes in physiological signals that are indicative of students' mental states (e.g., attention, engagement, cognitive load, and emotional arousal). Most of the approaches to assessing these states rely on self-report measures or offline behavior data analysis, which can be subjective or interruptive. However, physiological measures, such as electroencephalography (EEG) patterns, eye tracking, and heart rate variability, can make it feasible to gain a more direct, uninterrupted, and objective window into learner's learning experiences. Among the physiological signals, EEG signals have proven useful for detecting changes in cognitive load (Boring et al., 2020). However, few studies explain the physiological significance of the EEG features in educational contexts. Moreover, existing research predominantly focuses on adult participants, with limited investigation into whether these findings can be generalized to child populations. Furthermore, most studies were conducted in controlled laboratory settings. Therefore, the purpose of this study is to explore whether EEG can provide information about interpreting cognitive load experienced by children as they complete arithmetic operations. This study was conducted in an authentic school environment, aiming to provide more ecologically valid insights.

Cognitive load theory

Cognitive load theory (CLT) assumes a cognitive architecture that includes several structures and processes showing how the mind works during a learning episode (Figure 1). Human memory can be divided into two basic forms: working and long-term memory. Learning begins with sensory organs inputting sensory information to the cognitive system. The inputs are processed by a working memory (WM) that is limited in capacity and duration when dealing with novel information (Paas & Sweller, 2012). Working memory then communicates with limitless long-term memory (LTM), both in retrieving information from memory and in encoding new information to memory (Norman, 2013). Any learning and problem-solving activity, including information processing,

consumes working memory resources, which results in cognitive load imposed on the system (Sweller, 1988). The concept of cognitive load (CL) refers to the amount of cognitive resources required to perform a task (Kirschner et al., 2018).

Figure 1
Cognitive Architecture in Cognitive Load Theory



Cognitive load measurement

The measurement techniques of cognitive load can be classified into three categories: (1) self-assessment measures, usually including self-report questionnaires and subjective rating scales; (2) task performance measures, which consider both primary and secondary task measures; (3) physiological measures which are derived from the physiology of the individual (Longo, 2018).

Physiological measures are based on the principle that changes in cognitive functioning are reflected in physiological responses controlled by the autonomic nervous system (Hirachan et al., 2022). The techniques include heart rate and variability, blood pressure, brain activity signals measured by EEG, eye activity (e.g., pupil diameter, blink rate), and muscle signals measured by electromyograms (EMG) (Longo, 2018). Physiological measures collect objective physiological signals from sensors that can reflect fluctuations of cognitive states while performing the intended task without interfering with it (Nourbakhsh et al., 2012). They have demonstrated high levels of sensitivity and diagnosticity (Rubio et al., 2004).

Cognitive load variation and EEG indicators

Researchers have correlated EEG signal variations with changes in cognitive load, task difficulty, and engagement (Negi & Mitra, 2022). The oscillations in different EEG frequency bands (i.e., delta (0–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz)) are the most popular features for recognizing variations in cognitive load, especially the alpha and theta ranges, which appear to involve higher brain functions, reflecting task difficulty or cognitive load among diverse task demands (Wu et al., 2022). The alpha band has shown sensitivity to cognitive load that a decrease in or a progressive suppression of alpha waves has been linked to increasing levels of task complexity, reflecting increased attentional engagement and allocation of cognitive resources toward internal processing (Alnajashi, 2021; Grabner & De Smedt, 2012). Previous studies show that alpha power decreases with the increase of working memory load in several brain regions, including the prefrontal, frontocentral, posterior parietal, and occipital regions (Borghini et al., 2014; Micheloyannis et al., 2005).

Moreover, the increase in theta spectral power has been associated with higher task complexity, sustained cognitive concentration, memory encoding, and retrieval (So et al., 2017). For instance, increases in theta power following target onset were interpreted to reflect the encoding of the stimulus information in visuo-spatial tasks (Wang et al., 2018). Specifically, the fronto-parietal theta network has been proven to be modulated by the demands on information manipulation in the working memory system (Wang et al., 2018). Additionally, the theta/alpha ratio has been used as an indicator of cognitive load based on the assumption that an increase in cognitive load is associated with a decrease in alpha power and an increase in theta power (Fernandez Rojas et al., 2020; Negi & Mitra, 2022).

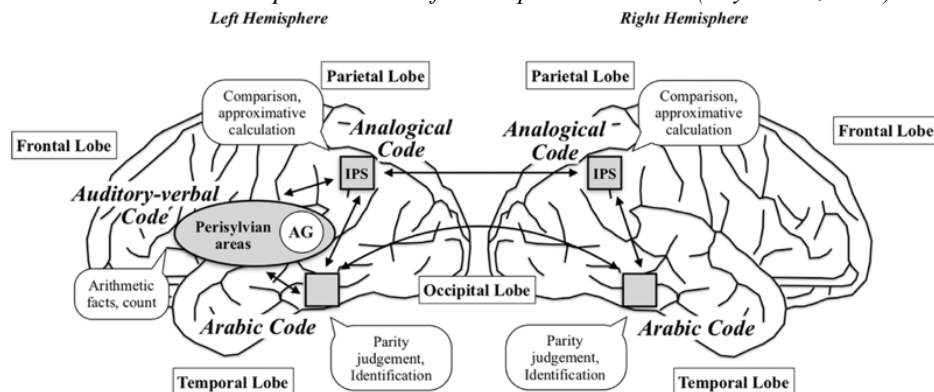
Mental arithmetic and brain network

In the triple code model (TCM) of numerical cognition (Dehaene, 1992), three types of interconnected representations deal with the different numerical activities, namely, the analogical magnitude representation, the verbal word frame, and the visual Arabic form (Faye et al., 2019). Dehaene et al. (2005) distinguished three parietal circuits that correspond to the representational systems: (1) the bilateral intraparietal sulcus (IPS) engages in nonverbal semantic representations of number size or distance relations (quantity system); (2) the left angular

gyrus (AG) and perisylvian areas engage in verbal representations of numerals (verbal system); and (3) the bilateral occipito-temporal regions (i.e., the ventral visual stream) engage in the encoding of numbers as Arabic strings (visual system) (Dix, 2015). To examine the predictions derived from the TCM, Faye et al. (2019) conducted a meta-analysis based on 28 neuroimaging, 12 Transcranial Magnetic Stimulation (TMS), and 12 brain-damaged patient studies, including arithmetic and magnitude tasks in symbolic and non-symbolic formats. The findings added the role of the left AG in matching quantities to Arabic digits, the preference for the right IPS involving specific non-symbolic magnitude representations, and the preference for the left IPS involving general symbolic magnitude representations.

Figure 2

The Neuroanatomical Implementation of the Triple Code Model (Faye et al., 2019)



Generally, numerical tasks are associated with a fronto-parietal brain network implementing domain-specific numerical processes (Spüler et al., 2016). Neuroimaging studies have found increased activation in the left prefrontal, frontal, and parietal regions when performing arithmetic tasks (Alnajashi, 2021). For instance, Earle et al. (1996) reported higher left-hemispheric theta power when participants solved arithmetic problems compared to inserting an arithmetic sign into an equation. Moreover, Micheloyannis et al. (2005) found frontal theta power increases and parietal alpha power decreases during multiplication relative to viewing numbers.

Based on Baddeley's working memory model, three components can be distinguished in working memory: the central executive, the articulatory loop, and the visuospatial scratch pad (Harmony et al., 1999). During mental calculation, the central executive carries out several processes, such as sustaining attention to information processing and continuously maintaining numerical information by rehearsal in working memory (Hitch, 1978). Regarding the brain structure participating in the process, the frontal cortex is reported to be activated (Sammer et al., 2007). Besides, the prefrontal region within the frontal area has been found to be largely responsible for activities related to planning, imagination, strategy selection and organization, which involve working memory (Taillan et al., 2015). In addition, the articulatory loop has been reported to be involved and comprises two processes: the active subvocal rehearsal process and the passive phonologically based store. Therefore, the left parietal cortex has been related to the storage of verbal information during mental calculation (Jonides & Smith, 2013). The parietal area also includes general domain abilities, including retrieving arithmetic facts in the left angular region, attention in the posterior superior parietal region, and perceiving mental number representations in the intraparietal region, which also involves working memory (Dehaene et al., 2005). Therefore, lesions over the two areas (i.e., frontal – general cognitive abilities; parietal – general domain abilities) produce acalculia (McCarthy & Warrington, 1990).

Previous studies have shown that EEG power in the theta band increases with greater levels of cognitive effort in mental arithmetic tasks, while alpha- and beta-power decreases (Lin et al., 2012). For example, Spüler et al. (2016) found a difficulty-related effect in the theta, alpha, and low beta frequency bands located at the parieto-occipital electrodes during mental addition tasks, whereas the upper beta band (25-40 Hz) did not show this effect. Moreover, Micheloyannis et al. (2005) recorded EEG activity from 18 right-handed participants with a mean age of 23 years during the performance of three mental arithmetic tasks (number comparison, single-digit multiplication, and two-digit multiplication) and two control tasks that did not require arithmetic operations. The results show that, with increasing task complexity/difficulty, the power of the alpha 2 band (10-13 Hz) decreased in the central right hemisphere and parietal areas, while the power of the theta band (4-8 Hz) increased in frontal areas.

The current study

The research question of this study is *How do brain activity measured by EEG respond to changes in cognitive load induced by task complexity?* According to cognitive load theory, higher task complexity should increase cognitive load. An increase in task complexity demands additional cognitive processing resources that might be provided by domain-general brain structures (e.g., frontal cortex) and by domain-specific structures (e.g., parietal cortex). Therefore, this study expects that an increase in cognitive load in the task should result in an increase in theta power and theta/alpha ratio, and a decrease in the alpha power and low beta power.

Methods

Participants

Ninety-one fourth graders were recruited from one elementary school, one of whom withdrew due to experiencing screen-induced vertigo symptoms during the experiment (50 female, 40 male; mean age 9.71 years, range [8-11]). Participants and their guardians provided informed assent and consent. Participants reported normal or corrected to normal vision with glasses and normal hearing without the assistance of hearing aids; they report no history or concurrent diagnoses neurodevelopmental disorders, such as Autism Spectrum Disorders (ASD) or Attention-deficit/hyperactivity disorder (ADHD), neurological condition, or a history of brain injury. The study was approved by the Institutional Review Board at Teachers College, Columbia University (TCIRB24-393).

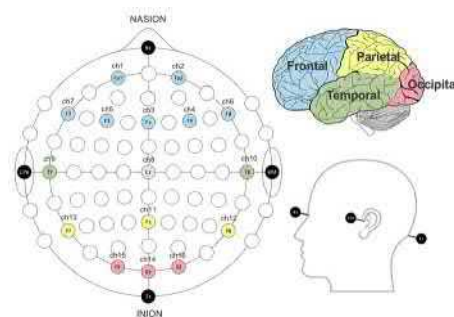
Mental arithmetic task

The mental arithmetic task was adopted and revised from Boring et al. (2020). Specifically, the mental addition task requires participants to maintain and manipulate the numbers and the rules of the arithmetical operation, and to update intermediate results dynamically. The current study used task complexity level (i.e., complexity of manipulations on items in working memory) as an independent variable to induce two different cognitive load levels (i.e., high and low). For the high-complexity condition, participants were sequentially presented with three 2-digit numbers in black, which they were instructed to memorize and sum. They were then shown a fourth number in blue (Pei et al., 2023) and asked to indicate whether it equals to the sum of the three 2-digit numbers. For the low-complexity condition, participants were instructed to only sum the leftmost digit of each black number. The proposed sums were correct 50% of the time. Participants responded by pressing either the 'Z' or the 'M' key; the corresponding key for equal/unequal were counterbalanced across participants. After finishing a block, participants were asked to rate their perceived task difficulty ("How easy or difficult were the tasks?") and amount of mental effort required ("How hard did you have to think to complete the tasks?"; Sweller et al., 1998) between 1 to 5 using a slider.

Data collection procedure

Before the experiment began, the researcher presented the experiment in its entirety to the participants and their parents. Participants were seated 60-centimeters in front of the computer screen, and completes a practice session consisting of two trials of the high-complexity condition and two trials of the low-complexity condition. EEG data were recorded using the Mentalab portable EEG system (mentalab.com/mobile-eeeg) with 16 dry electrodes at 250 Hz sample rate and right mastoid reference. Figure 3 shows the electrode placements according to the 10-20 international standard. Participants completed sessions in a quiet office room at the elementary school. Impedances were kept below 50k Ω and were re-checked twice during the session.

Figure 3
Electrode Placement According to the 10-20 System



A total of six minutes resting-state were collected at the start of each session (three minutes eyes-open and three minutes eyes-closed, counterbalanced across participants). During the resting phase, participants were asked to relax and let their mind wander while fixating on a central fixation square or closing their eyes. The mental arithmetic task had five high-complexity and five low-complexity blocks containing six trials each (sixty trials total). A two-second fixation square was displayed before each trial. The order of the blocks and trials in each block was randomized. Blocks were separated by self-paced breaks, and participants were informed of the complexity of upcoming trials via visual instructions at the start of each block. Black numbers were presented for one second each with four seconds in between. Blue numbers were presented for five seconds most each, during which participants responded by pressing either the 'Z' key or the 'M' key. At the end of each block, participants rated their perceived task difficulty and the perceived amount of invested mental effort on a scale from 1 to 5.

Data processing and analysis

Participants were excluded from analysis by performance on the arithmetic task: participants who are outliers on the number of non-valid responses are removed. Participants with accuracy lower than three standard deviations from the mean on the low-complexity task were removed for potential neurodevelopmental differences.

EEG recordings were preprocessed using the Harvard Automated Processing Pipeline for Electroencephalography 4.0 (HAPPE; Gabard-Durnam et al., 2018). Data was band-pass filtered to 1-45 Hz and epoched 0-15s relative to trial onset. Bad channels, defined as those that flat-lined for longer than 5 seconds during a recording, were manually detected and removed from the remainder of the pipeline, and was not interpolated. Artefacts were identified and removed via wavelet thresholding and Independent Component Analysis (ICA). Power spectral density (PSD) was estimated using Fast Fourier Transform (FFT) at a frequency resolution of 0.1 Hz. Spectral power for theta (4-8 Hz), alpha (8-13 Hz), and low beta (13-20 Hz) bands were calculated by taking the common logarithm of the sum power within a band; we also calculated the theta-alpha ratio at all electrodes.

All EEG metrics were computed at trial-level; condition-level data were derived by averaging the trial-level values within each condition. Comparisons between high and low complexity conditions were performed using paired-t tests. Without prior hypotheses regarding specific electrode sites, false discovery rate (FDR) correction was applied to all EEG analyses.

Results

After data processing, a total of 82 participants (46 females, 36 males) were kept in analysis. Across all recordings, an average of 15.73 (SD: 0.58, 98%) of channels were good, with a range of 13 (81%) to 16 (100%). One participant self-reported as left-handed, and one as ambidextrous. Sensitivity analyses showed no difference between including and excluding these participants; therefore, they were not excluded from the study.

Mental arithmetic task

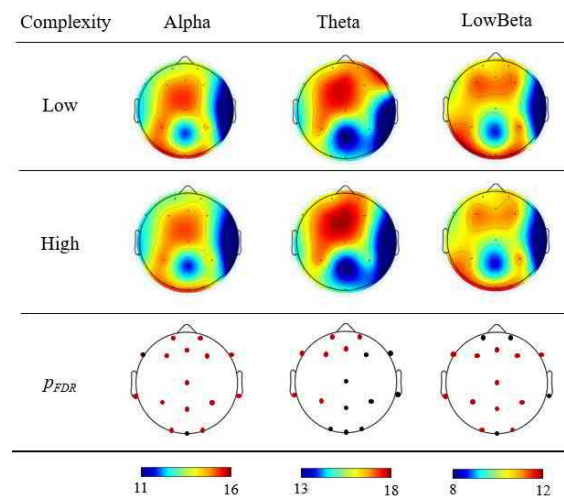
Accuracy significantly differed between conditions ($t[81] = 26.305, p < .001$) with a large effect size ($d = 2.905$). Participants showed significantly lower accuracy in high-complexity condition (High: Mean=0.554, SD=0.123; Low: Mean=0.898, SD=0.083). Self-report of cognitive load also significantly differed between conditions ($t[81]=11.966, p < .001$) with a large effect size ($d=1.321$). Participants reported significantly higher cognitive load in high-complexity condition (High: Mean=3.230, SD=0.840; Low: Mean=2.279, SD=0.721).

EEG spectral power

Spectral power within the theta band was significantly higher during the high-complexity condition compared to the low-complexity condition (Fp1, Fp2, Fz, F3, F7, T7, P7, p_{FDR} 's $< .05$; Figure 4). Spectral power within the alpha band was significantly lower during the high-complexity condition compared to the low-complexity condition across most the electrodes (All electrodes except F7 and Oz, p_{FDR} 's $< .05$; Figure 4). Spectral power within the low beta band was significantly lower during the high-complexity condition compared to the low-complexity condition across most electrodes (All electrodes except Fp1, Fp2, T8 and Oz p_{FDR} 's $< .05$; Figure 4). Similarly, theta-alpha ratios were significantly higher during the high-complexity compared to low-complexity condition across most the electrodes except T8, Pz, P8, and O1 (See Table 1).

Figure 4

Topoplot Differences Between the High Complexity and Task Average Band Power



Note: Electrodes marked in red show significant differences between conditions ($p_{FDR} < .05$)

Table 1

T-test Coefficients of Theta-alpha Ratios Between High-and Low-Complexity Conditions

Channel	<i>t</i>	<i>df</i>	95% CI	<i>p</i> _{FDR}	Cohen's <i>d</i>
Fp1	-4.714	80	[-0.027, -0.011]	<0.001***	-0.524
Fp2	-4.193	81	[-0.025, -0.009]	<0.001***	-0.463
Fz	-5.853	81	[-0.030, -0.015]	<0.001***	-0.646
F4	-5.158	80	[-0.026, -0.011]	<0.001***	-0.573
F3	-5.144	81	[-0.029, -0.013]	<0.001***	-0.568
F8	-3.839	79	[-0.030, -0.010]	<0.001***	-0.429
F7	-4.768	81	[-0.027, -0.011]	<0.001***	-0.527
Cz	-3.63	81	[-0.021, -0.006]	<0.001***	-0.401
T7	-5.207	80	[-0.032, -0.014]	<0.001***	-0.579
T8	1.226	81	[-0.948, 4.113]	0.256	0.135
Pz	-0.578	81	[-0.019, 0.011]	0.603	-0.064
P8	-1.809	77	[-0.021, 0.001]	0.092	-0.205
P7	-6.45	80	[-0.031, -0.017]	<0.001***	-0.717
Oz	-2.565	77	[-0.022, -0.003]	0.016*	-0.290
O1	-0.289	74	[-0.022, 0.016]	0.773	-0.033
O2	-3.291	80	[-0.024, -0.006]	0.002**	-0.366

Note: Significance codes: ≤ 0.001 *** ≤ 0.01 ** ≤ 0.05 *

Discussion

This study investigated electroencephalographic (EEG) responses to varying cognitive load in elementary school students during mathematical task problem-solving. The experimental manipulation of cognitive load successfully produced both decreased task accuracy and elevated subjective cognitive load reports.

During arithmetic problem-solving, students engaged in mental representation and manipulation of visually presented operands through numerical coding processes, operations that specifically recruited working memory resources. The results revealed significant increases in theta power across frontal and left temporoparietal regions during high-complexity tasks compared to low-complexity conditions. This enhanced theta activity has been consistently associated with increased working memory engagement and executive function processes (Castro-Meneses et al., 2020). These modulations may reflect multiple cognitive processes: stimulus information encoding, arithmetic fact retrieval, maintenance of numerical representations, allocation of cognitive resources, and selection of calculation strategies (Wang et al., 2018).

Task complexity was inversely related to alpha power across nearly all electrode sites (except F7 and Oz). High-complexity tasks necessitated both the retrieval of fundamental mathematical facts, typically stored as verbal representations, and higher-order mathematical thinking. These processes engaged neural networks associated with language functions, particularly verbal working memory, encompassing left frontal, temporal, and parietal regions (Spüler et al., 2016). Additionally, the processing of numerical magnitudes and arithmetic operations is supported by the analogical system, with critical components located bilaterally in the posterior parietal and parieto-occipital regions (Klados et al., 2013). The observed alpha power reduction may also indicate enhanced attentional concentration (Wang et al., 2024).

The observed relationship between increased cognitive load, enhanced theta power, and decreased alpha power supports the utility of the theta/alpha ratio as a cognitive load indicator. This ratio analysis enables a more comprehensive assessment of cognitive load, incorporating both general cognitive and domain-specific aspects. Furthermore, low beta power decreases were observed across most electrodes, excluding Fp1, Fp2, T8, and Oz, consistent with previous research on mental arithmetic problem-solving. These modulations may reflect the focusing of cognitive resources on relevant internal representations while approaching task completion or reaching a solution (Lin et al., 2012).

These findings substantiate the utility of modulations in theta, alpha, and low beta power as reliable indicators of working memory demands in elementary school students during mathematical problem-solving tasks. By contributing empirical evidence to the limited literature on children in educational contexts, our study indicates that physiological signals (e.g., EEG) can capture the temporal dynamics of cognitive load in a non-disruptive, objective, and fine-grained manner. Moreover, the results support the feasibility of using portable EEG systems with dry electrodes to extend laboratory-based findings to authentic classroom environments.

However, several limitations emphasize the need for further research on the approach. First, the cognitive load manipulation was specifically implemented through math arithmetic tasks, necessitating further research to evaluate the generalizability of these band indicators across different task domains. Moreover, neural oscillation patterns may vary based on developmental stage and individual mathematical proficiency. Future investigations should incorporate a broader age range and control for mathematical ability levels to better characterize the developmental trajectory of these neural markers. Overall, the proposed approach holds promise for enhancing our understanding of temporal dynamics of cognitive load in real-world settings and for informing the design of more effective educational interventions.

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