Research Article:

An Electroencephalography (EEG) Study of Cognitive Load and Neural Efficiency During Higher-Order Thinking in Secondary Science Learning

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ABSTRACT

Higher-order thinking skills (HOTS) are vital for scientific reasoning and problem-solving, yet many students—particularly in Malaysian secondary schools—struggle to master them. Despite curriculum reforms emphasising HOTS, traditional instruction and assessment practices often fail to stimulate the cognitive processes required for deep learning. This study investigates the neural correlates of HOTS engagement using electroencephalography (EEG) among 45 Form Two students, categorised into high-, moderate-, and low-ability groups based on prior science performance. Students completed two 15-minute HOTS-based tasks: a learning activity and an assessment. EEG data were collected following the international 10–20 system, and spectral analyses focused on theta (4 Hz–8 Hz), alpha (8 Hz–12 Hz), and beta (12 Hz–30 Hz) bands to assess cognitive load and neural efficiency. Results revealed that high-ability students demonstrated elevated alpha and beta power, suggesting efficient processing and sustained engagement. In contrast, low-ability students exhibited increased theta activity, indicating cognitive overload. Assessment tasks elicited stronger beta responses than learning tasks across all groups, reflecting higher cognitive demands. Correlation analyses confirmed a positive relationship between alpha/beta activity and HOTS performance. This study provides empirical support for using EEG to explore learning engagement and cognitive effort in science education. The findings highlight the need for neuroscience-informed teaching strategies that reduce cognitive overload and promote deeper engagement with HOTS content.

Keywords: Higher-order thinking skills, EEG, cognitive load, neural efficiency, science assessment, secondary education

INTRODUCTION

Science education is a cornerstone of 21st-century learning, equipping students not only with content knowledge but also with the critical and creative thinking skills needed to navigate a rapidly evolving world. As global economies shift toward innovation, sustainability, and digital transformation, educational systems are expected to prepare learners who can analyse complex problems, think independently, and apply knowledge in novel contexts. International frameworks such as the OECD's *Future of Education and Skills 2030* and UNESCO's *Education for Sustainable Development* underscore the importance of higher-order cognitive skills—especially in science education, where inquiry, reasoning, and problem-solving are foundational (OECD, 2020; Zhang et al., 2022). However, while these global frameworks provide an important backdrop, the key challenge lies in how such aspirations are translated into classroom practices that genuinely enhance students' higher-order thinking skills (HOTS).

In response to these imperatives, Malaysia has prioritised science education as a strategic driver of human capital development. Curriculum reforms under the Standard Curriculum for Secondary Schools (KSSM) reflect this ambition, emphasising the integration of HOTS to foster analytical reasoning, creativity, and conceptual understanding. Yet, student outcomes suggest that these goals remain largely aspirational. Malaysian students continue to underperform in science on both national assessments and international benchmarks such as the Programme for International Student Assessment (PISA) and the Trends in International Mathematics and Science Study (TIMSS) (Ministry of Education Malaysia, 2020). This underperformance raises critical questions about whether current assessment and instructional approaches are adequately capturing and cultivating the cognitive processes needed for HOTS mastery.

Despite policy reforms, many students still struggle with HOTS-related tasks, highlighting a persistent gap between curricular intentions and students' actual cognitive readiness. Studies report that Malaysian students show limited development in critical and creative thinking skills—key competencies outlined in the national education blueprint. These deficiencies are often attributed to underdeveloped metacognitive awareness, working memory overload, and a lack of strategic problem-solving approaches (Zohar & Dori, 2022; Shah & Zakaria, 2024). Teachers, too, face challenges in designing instruction and assessments that authentically engage students in higher-order reasoning, particularly for learners with varying academic abilities. While traditional assessments (e.g., written tests, performance tasks, or surveys) provide insights into outcomes, they are limited in capturing the real-time cognitive effort and mental processes that underlie learning difficulties (Howard-Jones, 2014).

To address this challenge, there is growing interest in understanding the cognitive processes that underlie students' engagement with complex science tasks. Educational

neuroscience has emerged as a promising field that bridges psychology, pedagogy, and cognitive science to explore how learning occurs in the brain. Tools such as electroencephalography (EEG) offer real-time, non-invasive insights into students' mental effort, attention, and reasoning during learning. Unlike conventional assessments that measure only the end product of learning, EEG makes it possible to observe the neural dynamics of cognitive load and efficiency as they unfold, offering a more direct window into students' capacity to manage and process higher-order demands (Dikker et al., 2017).

EEG signals can be analysed across frequency bands linked to specific cognitive functions: Alpha waves indicate attentional control and neural efficiency, theta waves reflect cognitive load and working memory demand, and beta waves are associated with sustained reasoning and task engagement (Batista-García-Ramó & Fernández-Verdecia, 2018). Capturing these patterns during science tasks that require HOTS can reveal how students of differing ability levels process complex information—insights that are invaluable for tailoring instruction to meet diverse learner needs. Unlike behavioural observations, EEG provides objective markers of when a student is cognitively overloaded or operating efficiently, thereby offering evidence that complements and extends traditional pedagogical evaluations (D'Mello et al., 2017).

Despite its potential, EEG research is rarely applied in Malaysian classrooms. Very few studies have explored how students' brain activity differs during HOTS-oriented learning or assessments, particularly across academic performance levels. This lack of neuroscientific data limits educators' ability to design cognitively appropriate instruction and may contribute to the continued mismatch between intended educational outcomes and student performance. Importantly, there remains little evidence showing how EEG can highlight neural efficiency and overload in relation to HOTS, and how these neural signatures might inform more equitable, evidence-based teaching practices (Shah & Zakaria, 2024).

To address this research gap, the present study investigates the neural correlates of HOTS engagement using EEG among Malaysian secondary school students. Specifically, the objectives are:

1. To analyse differences in alpha, beta, and theta EEG activity during HOTS learning tasks, to assess variations in cognitive load and neural processing efficiency across students with high, moderate, and low cognitive abilities.

2. To examine differences in alpha, beta, and theta EEG activity during HOTS assessment tasks to evaluate cognitive engagement and performance-related cognitive load among students with high, moderate, and low cognitive abilities.

3. To identify EEG-based neural markers of effective engagement in HOTS by analysing the relationship between alpha, beta, and theta activity and students' performance outcomes.

LITERATURE REVIEW

In today's rapidly evolving scientific and technological landscape, the ability to engage in higher-order thinking—analysing, evaluating, and synthesising information—has become a cornerstone of 21st-century education. In science learning, higher-order thinking skills (HOTS) empower students to construct new knowledge, solve real-world problems, and transfer learning across diverse contexts. These skills transcend rote learning, requiring deep engagement with scientific concepts through inquiry, reasoning, and evidence-based argumentation (Zohar & Ben-Ari, 2022).

However, a growing body of research highlights persistent difficulties in cultivating HOTS, despite widespread curricular reforms. International assessments such as PISA and TIMSS reveal that students continue to underperform on science tasks requiring abstract reasoning and conceptual integration (OECD, 2019; Mullis et al., 2020). Zohar and Alboher-Agmon (2018) argue that systemic emphasis on standardised testing often leads teachers to prioritise procedural content and exam preparation over deeper conceptual engagement. Consequently, students tend to reproduce factual information without activating the metacognitive and analytical processes that HOTS demand (Zohar & Dori, 2022).

Malaysian research mirrors global findings regarding the challenges of cultivating HOTS in science education. Although HOTS are formally embedded within the national science curriculum, many students continue to face difficulties when engaging in tasks that require reasoning, synthesis, or conceptual flexibility (Mat et al., 2025). Studies have identified several contributing factors, including cognitive overload, limited scaffolding, and the absence of instructional strategies that promote metacognitive awareness and strategic thinking (Hamzah et al., 2022; Shah & Zakaria, 2024). Teachers often emphasise procedural content over deep conceptual engagement due to curriculum pressures and exam-focused teaching (Shah & Zakaria, 2024). These challenges suggest that improving HOTS instruction in Malaysia requires not only pedagogical innovation but also a deeper understanding of how learners process complex cognitive tasks—especially through approaches that integrate metacognition, differentiated instruction, and context-sensitive support (Hamzah et al., 2022).

Cognitive Load Theory (CLT) provides a theoretical lens to explain these challenges. CLT posits that when instructional tasks exceed a learner's working memory capacity, learning efficiency diminishes (Sweller et al., 2019). HOTS tasks, by nature, impose high cognitive demands, making learners—particularly those with limited prior knowledge—vulnerable to overload. Therefore, effective HOTS instruction must strike a balance between task complexity and cognitive support, ensuring that learners are challenged without being overwhelmed (Choi et al., 2014; Paas & Ayres, 2014).

Advances in cognitive neuroscience offer promising avenues for addressing these instructional barriers. Electroencephalography (EEG), in particular, enables researchers to observe neural responses to learning tasks with high temporal resolution. Unlike behavioural assessments, EEG allows real-time tracking of mental workload, attention, and reasoning processes (Howard-Jones & Jay, 2016), making it well-suited for investigating how students engage with HOTS-based science learning. Still, most prior studies applying EEG in education have focused on controlled laboratory tasks rather than authentic classroom settings (Barry et al., 2020), raising concerns about ecological validity.

EEG studies commonly examine three key frequency bands: theta (4 Hz–8 Hz), alpha (8 Hz–12 Hz), and beta (12 Hz–30 Hz). These bands correspond with distinct cognitive functions relevant to educational performance and engagement. However, much of the existing discussion of these bands remains descriptive. For instance, theta is often linked to working memory demand (Kober et al., 2020), yet studies rarely address whether elevated theta reflects overload, novelty of task, or situational anxiety. Similarly, while alpha activity has been positioned as a marker of attentional regulation (Lim et al., 2020), fewer studies critically examine why alpha sometimes fails to predict performance in heterogeneous learning groups. Beta, associated with executive functioning and reasoning (Batista-García-Ramó & Fernández-Verdecia, 2018), is often celebrated as a sign of deep engagement, but its potential confounding with stress responses is less acknowledged.

Recent research supports these associations. He et al. (2025) integrated EEG data with machine learning to classify learner engagement during HOTS tasks, finding that increased coherence in alpha and beta bands predicted higher reasoning efficiency. Their study was limited to a small, homogeneous sample, and the machine learning models were tested in laboratory settings rather than classrooms—raising questions about scalability. Similarly, Sanabria-Z et al. (2025) highlighted the rapid growth of EEG applications in science education, particularly in monitoring complex cognitive engagement in inquiry-based learning environments. Yet, their review did not fully consider methodological challenges such as small sample sizes, short intervention periods, and the difficulty of applying EEG meaningfully in authentic school settings.

Beyond diagnosing individual learner profiles, EEG data can also inform instructional design. Recent studies have shown that students who perform well on science tasks often exhibit elevated alpha and beta activity during both learning and assessment, suggesting more efficient neural processing and attentional control (Batista-García-Ramó & Fernández-Verdecia, 2018; He et al., 2025). These findings support pedagogical approaches such as problem-based learning and authentic assessment, which are designed to promote cognitive flexibility and deeper engagement. However, many of these studies (e.g. Dikker et al., 2017) emphasise positive associations between EEG patterns and academic performance without adequately testing competing

explanations, such as whether high-performing students simply had greater prior knowledge, task familiarity, or motivational advantages. This methodological gap limits the generalisability of findings and underscores the need for more rigorous, ecologically valid designs that integrate neurophysiological data with contextual classroom factors.

Despite its promise, EEG remains underutilised in domain-specific research on HOTS in science education. Masson et al. (2014) highlighted that much of the work in educational neuroscience focuses on foundational cognitive functions, leaving a gap in the study of complex reasoning. Zohar and Ben-Ari (2022) call for neuroscience-informed pedagogy that aligns instructional strategies with students' cognitive profiles—an approach particularly relevant in science, where abstract reasoning is integral.

EEG's sensitivity to rapid cognitive fluctuations makes it a valuable tool not only for research but also for responsive teaching. Batista-García-Ramó and Fernández-Verdecia (2018) argue that EEG can serve as both a diagnostic and feedback mechanism in adaptive learning environments, helping educators adjust instruction in real time to maintain optimal cognitive engagement. Yet, the practicality of this application in schools is constrained by cost, technical requirements, and training demands (Howard-Jones & Jay, 2016; Dikker et al., 2017), underscoring the need for feasibility studies alongside experimental research to explore how EEG can be implemented effectively and ethically in authentic educational settings.

In summary, the integration of EEG into science education research offers a powerful framework for understanding and improving students' engagement with HOTS. By analysing brainwave patterns across learners and tasks, researchers can generate insights that go beyond test scores, helping to refine pedagogy, reduce cognitive strain, and support more equitable learning outcomes. However, much of the existing EEG-based research in education has been limited by methodological constraints. Studies such as Barry et al. (2020) relied on small, homogeneous samples in controlled settings, raising concerns about ecological validity. Moreover, Dikker et al. (2017) highlighted the technical and logistical barriers of using EEG in real classrooms, underscoring the need for studies that integrate cognitive neuroscience with authentic educational practice. The present study addresses these limitations by employing EEG within a HOTS-oriented science learning environment that emphasises ecological validity, contextual sensitivity, and inclusivity in cognitive analysis.

METHODOLOGY

This study used a within-subject experimental design to examine the neural correlates of HOTS during science learning and assessment. Real-time EEG data were recorded as participants completed cognitively demanding tasks, allowing fine-grained analysis

of intra-individual variations in cognitive engagement while minimising inter-subject variability.

Forty-five 14-year-old students (15 high ability, 15 moderate ability, 15 low ability) from five schools in a state in Malaysia were selected via stratified purposive sampling based on prior science achievement. High (n = 15), Moderate (n = 15), and Low (n = 15). Although the sample size is relatively small, this is consistent with prior EEG studies in education and cognitive neuroscience, where samples often range between 20 to 50 participants due to the intensive nature of EEG data collection and analysis (Masson et al., 2014; He et al., 2025). Thus, while statistical power is limited, the sample remains adequate for exploratory EEG research in education.

Inclusion criteria: Right-handed, normal vision, no neurological disorders. Exclusion criteria: Neurological conditions, cognition-altering medications, or non-compliance with pre-test instructions (e.g., caffeine, strenuous activity).

Research Design and Tasks

Participants completed two 15-minute EEG tasks within a 60-minute session:

1. HOTS Learning Task (HOTSLT): Three scaffolded science problems targeting analytical reasoning, data interpretation, and conceptual synthesis.

2. HOTS Assessment Task (HOTSAT): Four structured test items assessing problem-solving, critical evaluation, and evidence-based reasoning.

Each task was broken into 3-minute to 5-minute modules to capture distinct cognitive stages while minimising fatigue. EEG resting-state data were recorded pre-task, mid-task, and post-task to compare active vs. baseline neural activity.

HOTSLT sample tasks:

1. Data prediction from temperature–evaporation tables.

2. Biodiversity reasoning using food webs.

3. Designing simple plant growth experiments.

HOTSAT sample items:

1. Evaluating flawed scientific claims.

2. Predicting motion outcomes using Newtonian mechanics.

3. Analysing chemical vs. physical changes.

4. Identifying errors in experimental procedures.

Task prompts were synchronised on-screen to allow precise EEG epoching for each item.

Experimental Procedure

Sessions were conducted in a controlled EEG lab following a standardised protocol:

1. Baseline EEG (5 min) – Eyes-open and closed.

2. HOTSLT (15 min) – 3 sequential tasks.

3. Mid-task Rest EEG (5 min).

4. HOTSAT (15 min) – 4 structured questions.

5. Post-task Rest EEG (5 min).

EEG Acquisition and Analysis

EEG was recorded using a 32-channel system (10–20 electrode placement) targeting frontal, parietal, temporal, and occipital lobes. Frequency bands analysed:

1. Theta (4 Hz–8 Hz) – Cognitive load.

2. Alpha (8 Hz–12 Hz) – Attention and processing.

3. Beta (12 Hz–30 Hz) – Problem-solving engagement.

Preprocessing included a 0.5 Hz–40 Hz band-pass filter, a 50 Hz notch filter to remove powerline noise, and Independent Component Analysis (ICA) to eliminate artifacts such as eye blinks and muscle activity. EEG data were segmented into 2-second epochs with 50% overlap and baseline-corrected using pre-task resting EEG. Trials exceeding ± 100 µV were rejected to ensure signal quality. These preprocessing steps align with established protocols in EEG research using EEGLAB (Delorme & Makeig, 2004). To support replication and transparency, all acquisition parameters—such as sampling rate, electrode placement, impedance thresholds, and artifact rejection criteria—were documented in full detail.

Statistical Analysis

1. Repeated-measures ANOVA for EEG power differences across tasks and ability groups.

2. Bonferroni-corrected post hoc tests (HOTSLT vs. HOTSAT).

3. Pearson correlation for EEG-performance links.

4. Significance threshold: $p < 0.05$.

Ethics and Validity

Ethical approval was granted by the University Ethics Board. Parental consent and student assent were obtained, with full anonymity and withdrawal rights assured. While sample size and lab-based tasks limit broad generaliatsion, the combination of EEG precision, structured HOTS tasks, and transparent preprocessing parameters strengthens replicability and ecological interpretation. This provides insights to inform brain-based science instruction and curriculum design**.**

RESULTS

The findings are presented according to students' EEG responses during the HOTS learning and assessment tasks.

EEG Responses During HOTS Learning Tasks

EEG recordings during the HOTS Learning Task (HOTSLT) revealed distinct neural activation patterns across cognitive ability groups. Descriptive statistics are presented in Table 1.

Table 1. EEG responses during HOTS learning tasks

Cognitive ability	Alpha power (μV^2)	Theta power (μV^2)	Beta power (μV^2)	Cognitive load	Processing efficiency
High	12.3	4.5	8.1	Low	High
Moderate	9.8	6.8	7.2	Moderate	Moderate
Low	7.5	10.2	6.0	High	Low

A repeated-measures ANOVA showed **statistically significant differences** across all EEG bands:

1. Alpha: $F(2, 42) = 6.21$, $p < 0.05$

2. Theta: $F(2, 42) = 9.84$, $p < 0.01$

3. Beta: $F(2, 42) = 4.19$, $p < 0.05$

Bonferroni-corrected post hoc tests revealed that differences were most pronounced between high- and low-ability students, with very large effect sizes for alpha ($d = 4.23$) and theta ($d = 4.78$), and a large effect for beta ($d = 1.22$), as summarised in Table 2.

Table 2. EEG learning task – ANOVA and effect size

EEG band	F(2,42)	p-value	Significant pair	Cohen's d	Effect size
Alpha	6.21	< 0.05	High vs. Low	4.23	Very large
Theta	9.84	< 0.01	Low vs. High	4.78	Very large
Beta	4.19	< 0.05	High vs. Low	1.22	Large

Neural efficiency in high-ability students

As presented in Table 1, high-ability students recorded the highest alpha power (12.3 μV²) and beta power (8.1 μV²), alongside the lowest theta power (4.5 μV²) during the HOTS Learning Task. These EEG patterns are statistically supported by the ANOVA and effect size results in Table 2, showing significant group differences ($p < 0.05$) and large effect sizes (alpha: $d = 4.23$, beta: $d = 1.22$).

These results indicate greater neural efficiency in high-ability students, consistent with Cognitive Load Theory, which explains that learners with well-developed schemas can process complex tasks with less cognitive strain (Wang et al., 2020).

Cognitive overload in low-ability students

In contrast, Table 1 shows that low-ability students exhibited the highest theta power (10.2 μV²) and the lowest alpha (7.5 μV²) and beta (6.0 μV²) activity. As confirmed in Table 2, the theta differences were statistically significant ($p < 0.01$) with a very large effect size ($d = 4.78$).

This pattern reflects cognitive overload and reduced processing efficiency, likely due to underdeveloped cognitive schemas (Hashemi et al., 2021). Instructionally, this highlights the need for scaffolded supports—such as guided questioning and chunked content delivery—to help manage mental load during HOTS tasks (Zohar & Dori, 2022).

EEG Responses During HOTS Assessment Tasks

During the HOTS Assessment Task (HOTSAT), EEG data revealed universally elevated beta activity across all groups and increased theta activity among low-ability students. Mean values are shown in Table 3.

Table 3. EEG responses during HOTS assessment tasks

Cognitive ability	Alpha power (μV^2)	Theta power (μV^2)	Beta power (μV^2)	Cognitive load	Task engagement
High	10.8	5.2	9.3	Moderate	High
Moderate	8.5	7.6	7.8	High	Moderate
Low	6.3	11.8	5.5	Very High	Low

Repeated-measures ANOVA indicated significant differences across all bands:

1. Alpha: $F(2, 42) = 6.45$, $p < 0.05$.

2. Theta: $F(2, 42) = 10.32$, $p < 0.01$.

3. Beta: $F(2, 42) = 8.87$, $p < 0.001$.

Post hoc tests identified high- vs. low-ability as the most significant comparison across all bands, with very large effect sizes, as shown in Table 4.

Table 4. EEG assessment task – ANOVA and effect size

EEG band	$F(2, 42)$	p-value	Significant pair	Cohen's d	Effect size
Alpha	6.45	< 0.05	High vs. Low	3.01	Very large
Theta	10.32	< 0.01	Low vs. High	4.89	Very large
Beta	8.87	< 0.001	High vs. Low	2.54	Very large

Increased cognitive demand in assessment tasks

As shown in Table 3, all ability groups displayed higher beta power during the HOTS Assessment Task compared to learning tasks, with high-ability students reaching 9.3 μV^2. This increase was statistically significant ($F(2, 42) = 8.87$, $p < 0.001$; see Table 3), with a very large effect size ($d = 2.54$) between high- and low-ability groups.

Elevated beta activity, particularly in high-ability students, indicates greater cognitive engagement and executive control, consistent with the complex reasoning demands of assessment tasks (Batista-García-Ramó & Fernández-Verdecia, 2018; He et al., 2025). These findings suggest that HOTS assessments activate more sustained mental effort

than learning tasks, especially among students with stronger cognitive schemas and more automated reasoning strategies (Wang et al., 2020).

Performance strain in low-ability students

Table 3 also shows that low-ability students exhibited the highest theta power (11.8 μV^2) and the lowest beta (5.5 μV^2) and alpha (6.3 μV^2) power during assessments. These differences were significant, with theta showing the strongest effect ($F(2, 42)$ = 10.32, $p < 0.01$; d = 4.89, see Table 4).

High theta activity in low-ability students likely reflects cognitive overload caused by the combined demands of complex tasks and evaluative pressure during assessments. This pattern aligns with prior EEG studies linking increased theta power to excessive working memory load and reduced executive function (Mohamed & Saleh, 2025; Schapkin et al., 2020). Such findings underscore the need for scaffolded assessment designs, especially for learners more vulnerable to performance stress (Wei et al., 2025; Puma et al., 2018).

Neural Markers of Effective HOTS Engagement

To identify EEG-based neural markers associated with successful engagement in HOTS, a Pearson correlation analysis was conducted between EEG band power and HOTS performance scores across all participants. The findings are presented in Table 5.

Table 5. Correlation between EEG markers and HOTS performance

EEG band	r-value	p-value	Direction	Strength	Interpretation
Alpha	0.62	0.001	Positive	Strong	High alpha = better cognitive control and attention regulation
Theta	−0.55	0.003	Negative	Moderate	High theta = working memory overload and inefficiency
Beta	0.48	0.021	Positive	Moderate	High beta = sustained cognitive engagement and task monitoring

Identified neural markers of HOTS engagement

The results from Table 5 indicate the following EEG frequency bands as reliable neural markers of HOTS engagement:

1. Alpha power emerged as the strongest neural marker of effective HOTS performance ($r = 0.62$, $p = 0.001$). This suggests that efficient attentional modulation and cognitive control—reflected in higher alpha activity—are critical for reasoning and problem-solving during HOTS tasks.

2. Beta power showed a moderate positive correlation with HOTS performance ($r = 0.48$, $p = 0.021$), indicating that sustained executive engagement and monitoring contribute to task success.

3. In contrast, theta power had a moderate negative correlation ($r = –0.55$, $p = 0.003$), identifying it as a neural marker of cognitive overload and reduced performance efficiency.

These findings validate alpha and beta power as positive neural markers of effective HOTS engagement, while elevated theta power serves as a negative marker, reflecting cognitive strain. Increased alpha activity is associated with attentional control and reduced cognitive effort (Wang et al., 2020), and beta activity reflects sustained cognitive engagement and executive functioning (Batista-García-Ramó & Fernández-Verdecia, 2018; He et al., 2025). In contrast, high theta power has been linked to working memory overload and inefficient processing, especially during complex reasoning tasks (Hashemi et al., 2021). These neural indicators provide empirical grounding for designing neuroscience-informed instructional strategies—for example, promoting attentional focus and managing cognitive load in science learning and assessment (Zohar & Dori, 2022).

DISCUSSION

This study investigated how students' cognitive ability levels relate to neurophysiological responses during HOTS learning and assessment in science education. EEG data revealed differentiated brainwave patterns linked to cognitive load, task engagement, and processing efficiency—affirming EEG's potential in educational diagnostics. As shown in Tables 1– 5, alpha and beta power were positively associated with higher performance and ability, while theta power reflected overload, particularly in lower-ability students.

However, while EEG provides valuable insights, its interpretation must move beyond descriptive reporting of Cognitive Load Theory (CLT) and consider contextual, affective, and cultural factors—such as classroom practices, assessment pressure, and the novelty of EEG procedures. These confounding influences suggest that neural markers should be treated as context-dependent signals, not universal biomarkers of learning.

Neural Efficiency and Schema Activation

As indicated in Table 1, high-ability students exhibited the highest alpha (12.3 μV^2) and beta (8.1 μV^2) power, with significantly lower theta (4.5 μV^2) than other groups. These differences were statistically supported by the ANOVA and effect sizes in Table 2 ($p < 0.05$–0.01, $d = 4.23$–1.22). This neural profile, particularly in the frontal and parietal regions, suggests efficient attentional control and schema-driven processing, consistent with CLT (Sweller, 2011).

While these results affirm CLT's core propositions about working memory and schema automation, they also expose its limitations. CLT does not fully account for socio-emotional influences such as test anxiety, task novelty, or motivational state—all of which may modulate neural activation even in cognitively efficient students.

Pedagogically, this implies that instruction for high-ability learners should go beyond routine problem-solving and incorporate open-ended inquiry and creative challenges. This aligns with Vygotsky's Zone of Proximal Development (ZPD), which emphasises scaffolding tasks just beyond a learner's current competence to promote growth.

This approach is supported by recent research:

1. Peters and Bjork (2022) found that differentiated, inquiry-based instruction significantly enhances engagement and learning outcomes among high-ability students.

2. Maker et al. (2015) recommend the REAPS model, emphasising interdisciplinary, non-routine tasks for deep thinking.

3. Badolo et al. (2025) warn that repetitive or overly structured instruction can suppress higher-order thinking development in advanced learners.

Cognitive Overload in Low-Ability Students

In contrast, low-ability students exhibited the highest theta power (10.2 μV^2) and lowest alpha (7.5 μV^2) and beta (6.0 μV^2) during learning tasks (Table 1). As detailed in Table 2, these differences were statistically significant ($p < 0.01$) with very large effect sizes (e.g., theta: $d = 4.78$).

This pattern reflects cognitive overload and reduced processing efficiency, likely due to underdeveloped cognitive schemas (Sweller et al., 2019; van Merriënboer & Sweller, 2021). Without automated schemas to manage HOTS demands, these students experience increased working memory strain.

Instructionally, this highlights the importance of scaffolded learning experiences for lower-ability learners. Evidence-based strategies—such as chunked content, guided questioning, and peer collaboration—can help regulate cognitive load and support schema development (Kirschner et al., 2018).

Task Complexity and Executive Demand

As shown in Table 3, beta power increased across all groups during assessments, particularly in high-ability students (beta = 9.3 μV^2), indicating heightened executive engagement. This was statistically confirmed in Table 4 ($F(2, 42)$ = 8.87, $p < 0.001$; d = 2.54). For high-ability learners, this reflects goal-directed problem-solving and cognitive control.

However, low-ability students also showed a theta surge (11.8 μV^2), with a significant effect size (d = 4.89, Table 4), suggesting executive strain under task pressure. This co-occurrence of elevated beta and theta activity signals effortful processing without efficiency.

These results underscore the need to redesign assessment practices—not by reducing rigor, but by embedding responsive scaffolding. ZPD theory and Bruner's spiral curriculum suggest tasks should stretch learners without overwhelming them. Similarly, scaffolding frameworks advocate for calibrated support withdrawal as students gain independence. Meta-analyses confirm that formative feedback and differentiated questioning reduce anxiety and promote deeper learning across abilities (Hattie, 2023). In this light, beta activation should not be misinterpreted as stress alone, but rather as a sign of sustained cognitive effort (Immordino-Yang et al., 2024).

Neurocognitive Predictors of HOTS Success

As shown in Table 5, alpha power showed the strongest correlation with HOTS performance (r = 0.62, p = 0.001), indicating its role as a marker of cognitive efficiency. Beta power also correlated moderately (r = 0.48), while theta power was negatively associated with performance (r = −0.55, p = 0.003). These findings align with established interpretations: alpha reflects attentional modulation, beta engagement and control, and theta cognitive overload (Kober et al., 2020).

However, EEG frequency bands should not be treated as universal indicators of learning. Contemporary neuroscience shows that EEG signals are context-dependent, shaped by task type, emotional states, learner motivation, and prior experience (Immordino-Yang et al., 2024). EEG should thus be viewed as a multi-factorial signal, not a fixed proxy for academic success.

Triangulation is critical: combining EEG with behavioural data, academic outcomes, and teacher feedback offers a more valid interpretation. As Luck and Gaspelin (2017) argue, EEG alone cannot explain the social-affective processes central to learning. Education is neurocognitive and social, requiring interpretation beyond neural spikes.

Application and Practical Constraints

EEG-informed adaptive learning systems hold promise for personalising instruction based on real-time cognitive and affective states. By tracking rhythms like alpha and beta, teachers or intelligent systems could adjust task complexity, pacing, or feedback dynamically.

However, real-world applications remain limited. EEG setups are costly, time-consuming, and technically complex, making classroom integration impractical in most schools. Additionally, lab-based findings—such as those in this study—may not fully generalise to dynamic classroom environments with noise, peer interactions, and environmental variability (Immordino-Yang et al., 2024). Future research must address these limitations by prioritising:

1. School-based feasibility studies

2. AI-powered EEG analysis tools

3. User-friendly teacher interfaces

Recent innovations, such as real-time neural dashboards (Pinti et al., 2022), offer promise in translating EEG findings into pedagogical action. However, teacher training and ethical literacy must evolve alongside these tools to ensure EEG data supports learning rather than stigmatising students.

LIMITATIONS AND FUTURE DIRECTIONS

While this study offers novel insights into EEG markers of HOTS engagement, several limitations must be considered.

Sample Size and Generalisability

The sample size (n = 45) aligns with typical EEG studies but limits statistical power and generalisability. Small samples increase the risk of inflated or unstable effects, especially in neural data (Tzovara et al., 2012). Future research should replicate these findings with larger, more diverse cohorts to account for individual differences in cognitive and neural profiles (Keil et al., 2014).

Methodological Consistency and Replicability

EEG results are sensitive to analytic choices—such as artifact rejection, referencing, and preprocessing—which can affect outcomes and reproducibility (Luck & Gaspelin, 2017). To enhance transparency, future studies should adopt standardised frameworks like EEG-BIDS (Pernet et al., 2020) and promote open data practices, especially in educational settings.

Ecological Validity

Although HOTS tasks were pedagogically grounded, data were collected in a lab, limiting real-world applicability. The absence of classroom variables—like peer interaction and live teacher feedback—reduces ecological validity (Matusz et al., 2018). Emerging mobile EEG tools (Dikker et al., 2017) offer potential for capturing neural engagement in authentic learning environments, supporting future school-based applications.

CONCLUSION

This study demonstrates that students' performance in HOTS tasks is linked to distinct EEG patterns. High-ability students showed elevated alpha and beta activity, indicating greater neural efficiency, while low-ability students exhibited increased theta, reflecting cognitive overload. These neural profiles support Cognitive Load Theory (CLT) and highlight how schema development influences cognitive performance.

Beyond cognitive load, the findings emphasise that EEG markers are shaped by emotional and contextual factors, including test anxiety, task novelty, and motivation. This supports a more comprehensive view of CLT that integrates socio-emotional influences on learning.

While EEG offers valuable insights, its classroom use remains limited due to cost, complexity, and ecological validity concerns. Advances in mobile EEG show promise, but real-world learning involves dynamic interactions that lab settings cannot fully replicate.

Pedagogically, the results suggest that:

1. High-ability students benefit from open-ended, inquiry-based tasks that challenge and extend thinking.

2. Low-ability students need structured scaffolding and emotional support to manage load and build reasoning skills.

Importantly, EEG data should be interpreted alongside behavioural and academic evidence, not in isolation. When applied responsibly, neuroscience can inform teaching—not replace it—and contribute to more personalised, cognitively aware instruction.

CONFLICT OF INTEREST

DATA AVAILABILITY

The datasets generated and analysed during the current study are not publicly available due to participant confidentiality and ethical restrictions. However, anonymised data may be made available from the corresponding author on reasonable request.

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CONTRIBUTIONS OF AUTHORS

Salmiza Saleh and Nor Azila: Conceptualisation, Methodology, Investigation, Resources, Data curation, Writing – Original Draft Preparation, Writing – Review & Editing, Visualisation, Supervision, Project administration, Funding acquisition.

Fazrin Fazil and Liu Yufei: Formal analysis, Investigation, Data curation.

USE OF ARTIFICIAL INTELLIGENCE (AI)

This manuscript employed OpenAI's ChatGPT (GPT-4) for language refinement, citation updating, and integrating updated references into existing paragraphs, without altering their original structure or academic tone.

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