

Selection and Validation of Spectral EEG Markers for Real-Time Monitoring of Attention and Cognitive Engagement in Learning Contexts

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ABSTRACT: Electroencephalography (EEG) provides precise neural measures for brain-computer interface (BCI) applications monitoring cognitive states. This empirical study evaluates the sensitivity of established EEG spectral markers to distinguish sustained attention from cognitive engagement. Fifteen participants completed a sustained attention task (D2-R), a N-Back working memory task (2-Back), and an ecological video learning task. Results indicate that the sustained attention task induced significant modulations in the $\beta/(\alpha + \theta)$ ratio, posterior theta, and occipital beta power. Conversely, the cognitive engagement task yielded no significant spectral deviations, highlighting potential overlaps in cognitive networks and the critical impact of task-order effects on post-effort baselines. Furthermore, linear mixed models revealed distinct, non-linear temporal dynamics during the ecological task, demonstrating that aggregating EEG metrics over the entire task duration obscures critical real-time state fluctuations. This study provides a rigorous framework for selecting appropriate EEG markers, emphasizing the necessity of continuous monitoring and controlled experimental designs in educational BCI applications.

INTRODUCTION

The capacity to maintain attention over extended periods and to actively engage cognitive resources constitutes fundamental aspects of human performance across educational, professional, and clinical contexts. Brain-computer interfaces (BCIs) increasingly require robust, real-time estimation of these cognitive states to enable adaptive systems that respond dynamically to user mental states [1].

Electroencephalography (EEG) offers unique advantages for monitoring cognitive states: high temporal resolution, non-invasiveness, portability, and relative cost-effectiveness compared to neuroimaging techniques. However, the multiplicity of available EEG markers and their overlapping sensitivities necessitate a clear conceptual framework distinguishing sustained attention from cognitive engagement.

Sustained attention refers to the ability to maintain vigilance and receptivity to stimuli over time, characterized by resistance to fatigue and mind-wandering. Its decline

manifests as increased response times, errors, and subjective reports of mental fatigue [2].

Cognitive engagement, conversely, reflects the active investment of mental resources in task processing, modulated by task difficulty, motivation, and strategic control. It encompasses the depth of information processing rather than mere wakefulness [3].

This study examines EEG markers across two principal analytical domains: (1) spectral power measures and (2) brain connectivity metrics.

Spectral Power Signatures: Specific frequency bands across cortical regions provide distinct signatures for sustained attention and cognitive engagement (Tab. 1).

- **Sustained Attention Markers:** Maintaining vigilance modulates multiple bands. Prolonged tasks induce progressive δ and θ power increases over occipital regions, reflecting mental fatigue and decreased alertness [2], whereas frontal θ increases indicate compensatory effort [4]. Parieto-occipital α acts as an attentional filter: external focus induces desynchronization [5, 6], while synchronization signals disengagement [7, 8]. Posterior β exhibits duality: occipito-temporal decreases precede lapses [2], while occipital increases predict active processing [9]. The centro-parietal $\beta/(\alpha + \theta)$ ratio aggregates these dynamics into a continuous vigilance index [1, 10].
- **Cognitive Engagement Markers:** Active mental investment relies on distinct spectral modulations. Frontal Midline Theta (FMT) transiently increases with strategic mental investment and cognitive load [3, 11]. Engagement intensity is indexed by strong parietal α suppression (11–13 Hz), correlating with motivation and learning efficacy [12]. Fronto-central β modulations reflect efficient top-down control [11, 13], and left-temporal γ (>30 Hz) marks high-quality information integration [14].

Brain Connectivity Measures: While spectral power analysis examines activity within isolated brain regions, functional connectivity approaches assess statistical dependencies between regional activities, thereby capturing

Table 1: Synthesis of Spectral EEG Estimators and Corresponding Experimental Variables

Domain	Estimator (Feature Name)	Modulation Interpretation	Target Regions
Sustained Attention	Occipital Theta & Delta Power (Attention_Theta)	Increase: Reflects mental fatigue installation and alertness decline [2, 4].	Occipital (O1, O2, Oz)
	Posterior Alpha Power (Attention_Alpha)	Increase: Disengagement, internal attention, mind-wandering [7, 8]. Decrease: External stimulus focus [5, 15].	Parieto-occipital (Pz, O1, O2)
	Occipital Beta Power (Attention_Beta)	Decrease: Associated with vigilance decline. High baseline required for alertness maintenance [2, 9].	Occipital (O1, O2, Oz)
	Ratio $\beta/(\alpha + \theta)$ (Attention_Ratio)	Increase: High vigilance index [1]. Decrease: Fatigue/drowsiness index [10].	Centro-parietal (Cz, Pz, P3, P4)
Cognitive Engagement	Frontal Midline Theta (Engagement_Theta)	Increase: Strategic mental investment, controlled motivated effort or compensatory effort [3, 4, 11].	Frontal midline (Fz, FC1, FC2)
	Parietal Alpha Suppr. (Engagement_Alpha)	Stronger decrease: Intense, efficient attentional allocation. Sensitive to motivation, predicts learning [3, 11, 12].	Parietal α_2 (11–13 Hz) (Pz, PO3, PO4)
	Beta Power	Increase: Reflects efficient top-down control, especially in experts [11, 13].	Fronto-central

the inherently interconnected nature of brain functioning [16].

- **Sustained Attention:** In the context of sustained attention, graph-theoretical approaches have revealed that attention decline is associated with network disorganization, characterized by decreased local segregation and reduced global integration. Multiple studies demonstrate reduced clustering coefficient (CC) and increased characteristic path length (CPL) during fatigue, particularly in the theta band [17]. Similarly, dyslexic children performing attention tasks exhibit lower CC, reduced global efficiency, and longer CPL compared to controls, predominantly in θ and α bands [18]. However, the heterogeneity across studies and occasional inverse findings suggest the potential involvement of compensatory mechanisms [19].

Beyond local network topology, large-scale network interactions, particularly between internally-oriented networks (e.g., the Default Mode Network, DMN) and task-oriented networks, provide robust markers of attentional state. Sustained attention is characterized by stronger anti-correlations between these networks, which are significantly enhanced during high-performance periods [20]. The fronto-parietal control network (FPCN) functions as a dynamic switch: it couples with the dorsal attention network (DAN) during attentive states and shifts toward the DMN during attention lapses, with connection strength predicting individual attentional performance even at rest [21]. Complementing these functional connectivity findings, effective connectivity analyses reveal that voluntary attentional control manifests as top-down information flow from prefrontal to parietal cortex, particularly dominant in the θ band, which is considered a neural signature of the cognitive effort required to maintain at-

tentional focus [22, 23].

- **Cognitive Engagement:** Turning to cognitive engagement, similar connectivity patterns emerge but with distinct characteristics. Increased engagement promotes a more integrated and efficient network architecture, with graph theoretical analyses demonstrating increased mean node degree [24] and enhanced betweenness centrality of central-frontal regions [25]. Notably, dynamic functional connectivity (dFC) patterns have proven particularly valuable as neural signatures for predictive modeling of engagement. fMRI-based dFC models successfully predict momentary fluctuations in engagement [25, 26], revealing that high engagement is associated with increased within-DMN connectivity and enhanced DMN-FPCN connectivity, while within-FPCN connectivity decreases [26]. These findings are corroborated by EEG-based dFC models, which emphasize the importance of central region connections [25], while leading eigenvector dynamics analysis (LEiDA) identifies recurrent connectivity states with remarkable discriminative power, achieving nearly 99% accuracy in classifying social engagement contexts [24].

Collectively, these findings highlight the potential of functional connectivity measures as biomarkers of both sustained attention and engagement. A promising avenue for future research would be to systematically evaluate various connectivity estimators using independent datasets, establishing their reliability and generalizability across different experimental paradigms and populations.

However, while connectivity measures offer rich insights into network dynamics, spectral power features remain the most established and computationally efficient candidates for real-time BCI implementation in educational settings. Therefore, to test

the replicability and relevance of these spectral findings, we developed an experimental protocol combining standardized cognitive tasks with an ecological learning task (viewing a scientific lecture). The empirical contribution of this study focuses on evaluating the sensitivity of selected spectral EEG markers to distinguish sustained attention from cognitive engagement in a cohort of university students.

MATERIALS AND METHODS

Participants: Fifteen healthy, native French-speaking university students (2 females; age 23.1 ± 2.2) with no neurological history participated. To ensure the validity of the learning task, all were non-experts in immunology. The protocol was approved by the INRIA ethics committee (COERLE).

Experimental protocol: The session lasted approximately 90 minutes in a controlled environment. The protocol consisted of four sequential blocks:

1. Sustained Attention Task (D2-R): A paper-based cancelation task assessing attention speed and precision under time pressure [27]. Behavioral performance was measured using the Concentration Performance (CP) score.
2. Cognitive Engagement Proxy (N-Back): A computerized 2-back working memory task (PsyToolkit [28]) soliciting executive functions and working memory updates. Performance was evaluated using the discriminability index (d').
3. Baseline Recording: Two 30-second resting-state EEG baselines (eyes open and closed).
4. Ecological Learning Task (Video): A 27-minute scientific video lecture on immunology (Collège de France). Following the video, participants completed a 20-item comprehension questionnaire and 10-point Likert scales evaluating subjective fatigue and engagement.

Data Acquisition and Feature Extraction: EEG was recorded using a 32-channel BioSemi ActiveTwo system (10-20 montage, 2048 Hz sampling, impedances < 20 k Ω). Preprocessing in MNE-Python included band-pass (1-100 Hz) and notch (50 Hz) filtering, followed by Infomax ICA for artifact removal. Power spectral density (PSD) was estimated via Welch's method on 4-second epochs with a 50% overlap [29, 30]. Median power across epochs was calculated to mitigate transient noise. Targeted spectral biomarkers (Delta: 1-4 Hz, Theta: 4-8 Hz, Alpha: 8-13 Hz, Beta: 13-30 Hz) were computed by aggregating standard frequency bands over predefined electrode clusters, strictly corresponding to the theoretical markers synthesized in Tab. 1 (e.g., Attention_Theta).

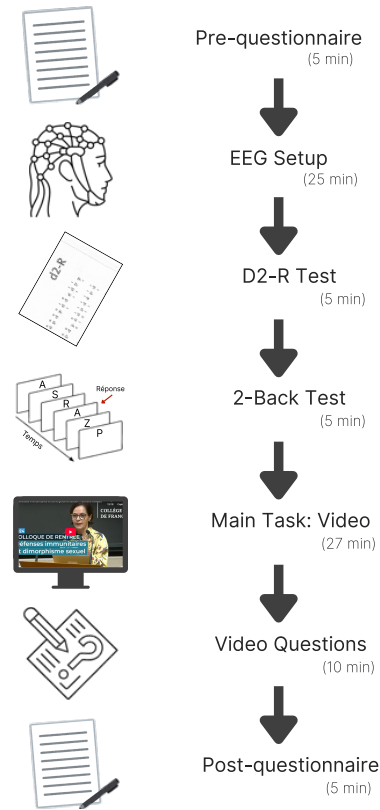


Figure 1: Timeline of the experimental protocol.

RESULTS

Predefined EEG markers during tasks (D2-R and 2-Back): To evaluate whether the biomarkers identified in previous literature reliably reflect sustained attention and cognitive engagement within our specific experimental paradigm, we conducted direct evaluations and comparisons between the two tasks (D2-R and 2-Back). Predefined EEG marker (Tab. 1) differences between the cognitive tests were assessed using Wilcoxon signed-rank tests. As detailed in Tab. 2, significant differences were observed for the Attention_Ratio, Attention_Theta, and Attention_Beta markers ($p < 0.01$). Conversely, no significant differences were found for the predefined engagement markers (Engagement_Theta and Engagement_Alpha) between the two tasks.

Table 2: FDR-corrected statistical comparison of predefined EEG markers between Sustained Attention (D2-R) and Cognitive Engagement (2-Back) tasks.

Marker	Stat (W)	p_{FDR}	η^2
Attention_Alpha	54.00	0.7615	0.00
Attention_Ratio	15.00	0.0167	0.54
Attention_Theta	9.00	0.0060	0.75
Attention_Beta	6.00	0.0051	0.54
Engagement_Theta	33.00	0.2031	0.00
Engagement_Alpha2	44.00	0.4673	0.00

Predefined EEG Marker Contrast between tasks and Baseline: To contextualize these task-specific differ-

ences, absolute spectral deviations were evaluated against the resting baseline (eyes open) using Wilcoxon signed-rank tests. A striking asymmetry was observed between the two experimental tasks. The D2-R task induced massive and highly significant spectral modulations compared to the baseline. Notably, the Attention_Beta marker exhibited a 206% median power increase ($p < 0.001$), alongside significant increases in the Attention_Ratio (+46.1%, $p < 0.001$) and Attention_Theta (+34.0%, $p < 0.001$).

Conversely, the 2-Back working memory task did not elicit significant spectral differences relative to the baseline across any of the predefined markers (all $p > 0.05$). The Engagement_Theta and Engagement_Alpha markers, for instance, exhibited negligible median variations (+0.76% and +6.72% respectively, n.s.).

Predefined EEG Marker Correlation with Behavioral Performance: To investigate the relationship between neural markers and task performance, we computed Spearman's rank correlations (ρ) between the EEG features and the behavioral metrics: the CP score for the D2-R and the d' index for the 2-Back. Following False Discovery Rate (FDR) correction, no significant correlations were found across any task (all $p_{FDR} > 0.5$). For instance, the expected correlation between the Attention_Ratio and the D2-R CP score was not observed ($\rho = -0.26$, $p_{FDR} = 0.53$). Similarly, frontal theta modulations did not significantly correlate with the 2-Back d' score ($\rho = 0.25$, $p_{FDR} = 0.53$).

Regional Band Power during tasks (D2-R and 2-Back): To expand our contrast between sustained attention and cognitive engagement to a whole-brain approach, regional band power comparisons were conducted. Given the experimental design involving three tasks, differences were first assessed using a global non-parametric Friedman test, followed by Wilcoxon signed-rank post-hoc comparisons. To control for the false discovery rate across multiple regional and spectral comparisons, all p -values were adjusted using the Benjamini-Hochberg FDR correction.

Tab. 3 presents the FDR-corrected post-hoc p -values specifically isolating the contrast between the D2-R sustained attention task and the 2-Back cognitive engagement task.

Table 3: FDR-corrected p -values for regional EEG band power comparisons (D2-R vs. 2-Back post-hocs).

	Frontal	Central	Parietal	Occipital	Temporal	Global
δ	0.638	0.978	0.001	0.020	0.421	0.160
θ	0.934	0.488	0.012	0.007	0.025	0.106
α	0.302	0.207	0.761	0.978	0.890	0.524
α_1	0.599	0.276	1.000	0.846	1.000	0.846
α_2	0.311	0.359	0.421	0.846	0.678	0.584
β	0.561	0.180	0.095	0.003	0.207	0.032

The analysis reveals distinct spatial modulation patterns characterizing the two cognitive states. No significant

differences were observed in the frontal and central areas, nor across any of the α sub-bands (all $p_{FDR} > 0.05$). Conversely, modulations in the lower frequencies were highly significant and posterior-dominant. The θ frequency band exhibited the most spatially distributed differences, significantly discriminating the two tasks across the parietal ($p_{FDR} = 0.0128$), occipital ($p_{FDR} = 0.0079$), and temporal lobes ($p_{FDR} = 0.0251$). The δ band showed highly significant localized differences in the parietal ($p_{FDR} = 0.0013$) and occipital lobes ($p_{FDR} = 0.0201$). Finally, the β band power was significantly modulated in the occipital lobe ($p_{FDR} = 0.0030$) as well as globally across all regions combined ($p_{FDR} = 0.0323$).

Temporal Dynamics across Tasks: To assess the continuous temporal evolution of the neural markers, Linear Mixed Models (LMM) were fitted to the time-series data of each experimental task. For each marker and task, three LMM were evaluated leading to five possible temporal trajectories: Null (flat), Linear (increasing/decreasing), and Quadratic (U-shape or inverted U-shape). P -values were corrected for multiple comparisons using the False Discovery Rate (FDR) method (Tab 4).

The analysis revealed that temporal dynamics were highly task-dependent. During the ecological Video task, the Attention_Ratio demonstrated a significant inverted U-shape trajectory ($p_{FDR} = 0.0197$), whereas it followed a U-shape dynamic during the D2-R task ($p_{FDR} = 0.0283$) and showed no significant temporal variation during the 2-Back task. A similar task-specific divergence was observed for the Attention_Theta marker, exhibiting a U-shape temporal dynamic during the Video task ($p_{FDR} = 0.0211$) but an inverted U-shape during the D2-R task ($p_{FDR} = 0.0006$).

Significant linear trends were also identified. The power of the Engagement_Alpha marker increased linearly over time exclusively during the Video task ($p_{FDR} = 0.0217$). Conversely, a significant linear increase in Attention_Beta power was strictly isolated to the 2-Back task ($p_{FDR} = 0.0053$).

DISCUSSION

Spectral Differences Between Tasks: Direct comparison between the D2-R and 2-Back tasks confirms the sensitivity of specific spectral markers to sustained attention. Significant modulations in the Attention_Ratio, Attention_Theta, and Attention_Beta markers align with literature linking sustained vigilance to posterior low-frequency dynamics and occipital beta power [2, 9].

Conversely, the predefined engagement markers (Engagement_Theta and Engagement_Alpha) failed to discriminate the tasks. Two hypotheses explain this: the 2-Back task may not have elicited a significantly higher cognitive load than the speed-constrained D2-R for university students, and median PSD aggregation

Table 4: LMM selection for temporal dynamics across tasks (PFDR).

Marker	Task	Best Model	PFDR
Attention_Alpha	Video	Quad. (U)	0.1125
	D2-R	Quad. (Inv-U)	0.0651
	2-Back	Quad. (Inv-U)	0.0196
Attention_Ratio	Video	Quad. (Inv-U)	0.0197
	D2-R	Quad. (U)	0.0283
	2-Back	Null (Flat)	1.0000
Attention_Theta	Video	Quad. (U)	0.0211
	D2-R	Quad. (Inv-U)	0.0006
	2-Back	Null (Flat)	1.0000
Attention_Beta	Video	Quad. (Inv-U)	0.0584
	D2-R	Quad. (Inv-U)	0.0393
	2-Back	Linear (Inc.)	0.0053
Engagement_Theta	Video	Quad. (U)	0.0594
	D2-R	Quad. (Inv-U)	0.0138
	2-Back	Quad. (Inv-U)	0.0263
Engagement_Alpha	Video	Linear (Inc.)	0.0217
	D2-R	Quad. (Inv-U)	0.1125
	2-Back	Quad. (Inv-U)	0.0263

likely smoothed out the transient, phase-locked bursts characteristic of Frontal Midline Theta (FMT) [3].

Spatio-Spectral Signatures of Cognitive States: Regional band power analysis (Tab. 3) provides a granular view of the networks distinguishing these tasks, revealing a strictly posterior distribution of low-frequency modulations. Significant differences in δ and θ bands across parietal and occipital lobes align with established neural signatures of visual vigilance decline [2]. Crucially, the absence of α band differences across all regions is informative. Literature reports parieto-occipital α increases during disengagement for both states [7, 11]. Our results corroborate this shared mechanism: α networks were likely equally suppressed by the external focus required in both tasks, rendering α ineffective for discriminating between them.

Baseline and Order Effects: The fixed sequential design (D2-R $\rightarrow$ 2-Back $\rightarrow$ Baseline $\rightarrow$ Video) introduced a critical confounding factor. The D2-R task was performed by “fresh” participants, yielding massive spectral deviations (e.g., +206% in Attention_Beta) compared to a post-effort baseline. Conversely, the 2-Back spectral signature was compared to an immediately subsequent baseline. This “resting” state was actually a post-effort recovery phase, likely saturated with residual fatigue and engagement markers, thereby masking statistical differences for the 2-Back task. Future protocols must employ true pre-task baselines or randomized orders to isolate state-specific deviations.

Temporal Dynamics in Ecological Settings: Despite baseline limitations, Linear Mixed Models (LMM) applied to continuous data revealed robust, task-dependent temporal dynamics (Tab. 4), highlighting the critical loss of information when temporal data is globally averaged. During the 27-minute Video task, Attention_Ratio followed an inverted U-shape trajectory, while Attention_Theta exhibited a U-shape.

This suggests a tri-phasic response: initial high-vigilance, mid-task decline (rising θ and dropping ratio), and a final attention regain. Although participants were aware of the 27-minute total duration, the absence of a visible progress bar suggests this late-stage rebound reflects an internal time estimation or spontaneous resource re-allocation, rather than a cue-driven anticipation. Interestingly, Engagement_Alpha2 showed a linear increase exclusively during the Video, indicating gradual disengagement of parietal attentional filters. These trajectories emphasize the necessity of continuous, non-linear tracking for educational BCIs.

Behavioral Correlations and Statistical Power: The lack of significant correlations between predefined EEG markers and behavioral performance underscores a common limitation in BCI studies. Following FDR correction, no robust brain-behavior links remained. This is primarily attributable to the limited sample size ($N = 15$), which drastically reduces statistical power for detecting medium-to-small effect sizes. Furthermore, due to the loss of temporal information, discrete behavioral scores may inadequately estimate online cognitive effort fluctuation (e.g., maintaining performance despite fatigue) during task execution in BCI learning contexts.

CONCLUSION

This study establishes a framework for distinguishing EEG markers of sustained attention from cognitive engagement for real-time BCI monitoring. Sustained attention decline manifested robustly through increased posterior θ and occipital β power, alongside modulations of the $\beta/(\alpha + \theta)$ ratio. Conversely, the absence of significant spectral divergence for the engagement task (2-Back) underscores overlapping neural networks and the susceptibility of markers like Frontal Midline Theta (FMT) to cumulative fatigue. Furthermore, linear mixed models revealed that cognitive states exhibit distinct, non-linear temporal trajectories during continuous ecological learning, demonstrating that aggregating EEG metrics over the entire task duration obscures critical real-time state fluctuations.

Methodologically, marker selection must align with both the task order and the baseline position. Future protocols must enforce strictly randomized task orders and true pre-task baselines to prevent post-effort confounds. As BCI technology transitions from laboratory to real-world applications, research should investigate subject-specific frequency calibration and explore functional connectivity measures (e.g., DMN-DAN anti-correlations) within hybrid machine-learning architectures to enhance adaptive systems. Differentiating these states provides a rigorous foundation for nuanced, theory-driven BCI design in attention-aware educational technologies.

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