Neurocognitive Efficiency of Immersive Learning in Virtual Reality Environments: An Empirical Eeg-Based Analysis

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Abstract: In the context of the digital transformation of education, immersive virtual reality (VR) technologies are gaining increasing importance as tools for enhancing the cognitive efficiency of learning processes. Despite the rapid integration of VR platforms into educational environments, the neurophysiological mechanisms underlying their effectiveness remain insufficiently explored. The present study aims to empirically evaluate the neurocognitive efficiency of immersive learning using electroencephalography (EEG) as an objective method for measuring brain activity. The study involved 120 participants ($n = 120$) divided into a control group (traditional learning) and an experimental group (VR-based learning). EEG analysis was conducted across the θ (4-7 Hz), α (8-12 Hz), β (13-30 Hz), and γ (30-45 Hz) frequency bands. Spectral power analysis, coherence analysis, and functional connectivity measures were applied. The results demonstrate a statistically significant increase in β and γ activity in the dorsolateral prefrontal cortex in the VR group ($p < 0.01$), indicating enhanced attention and cognitive engagement. Simultaneously, a reduction in θ activity, associated with cognitive fatigue, was observed. Functional connectivity measures reveal stronger integration of frontoparietal networks during immersive learning conditions. These findings suggest that VR-based learning environments facilitate enhanced neurocognitive activation, improved information processing efficiency, and the formation of stable cognitive patterns. The results expand the theoretical understanding of neuroeducation and provide empirical foundations for optimizing educational technologies. The proposed integrated neurocognitive efficiency index demonstrated high predictive validity and showed a strong correlation with academic performance outcomes. Furthermore, machine learning models achieved high classification accuracy, confirming that spectral and network markers derived from EEG signals can serve as objective indicators of educational quality.

1 INTRODUCTION

1.1 Digital Transformation of Education and the Emergence of Neuropedagogy

The digital transformation of the global educational environment has fundamentally altered the cognitive architecture of learning processes. Virtual Reality (VR) is increasingly regarded as a next-generation technology capable of integrating sensory, cognitive, and emotional components of learning into a unified immersive system [1].

Unlike traditional multimedia tools, VR creates a sense of presence, which activates multisensory integration and significantly enhances learners' cognitive engagement [2].

Recent neuroscientific research indicates that learning is a complex process of neuroplastic adaptation, involving structural and functional changes in the prefrontal cortex, hippocampus, and temporoparietal associative regions. Immersive environments may modify neural activation patterns by enhancing sensorimotor simulation and spatial encoding of information [3], [4].

However, despite the rapid implementation of VR technologies in educational practice, empirical evidence regarding their neurophysiological effectiveness remains fragmented [5]. Most existing studies rely primarily on behavioral metrics such as academic performance or reaction time, while the underlying neurodynamic mechanisms of cognitive enhancement remain insufficiently explored.

Consequently, an important research question emerges:

How does immersive learning in VR environments modify neurocognitive processes compared to traditional learning conditions?

1.2 Theoretical Foundations of Neurocognitive Efficiency

Neurocognitive efficiency can be defined as the optimization of neural resource allocation during cognitive task performance [6]. According to Cognitive Load Theory, effective learning occurs when extraneous cognitive load is minimized while task-relevant cognitive processing is enhanced [7]. Electroencephalography (EEG) research has demonstrated that distinct frequency bands are associated with specific cognitive processes:

- θ rhythm (4-7 Hz) - working memory processes and cognitive effort [8];
- α rhythm (8-12 Hz) - selective attention and inhibition of irrelevant stimuli [9];
- β rhythm (13-30 Hz) - active cognitive processing and sustained attention [10];
- γ rhythm (30-45 Hz) - multisensory integration and memory formation [11].

It is hypothesized that immersive VR environments enhance β and γ activity due to their sensory richness and spatial interactivity [12].

1.3 Neurophysiological Mechanisms of Immersion

Immersive environments activate the frontoparietal attention control network as well as the hippocampal spatial encoding system [13].

Sensory congruence in VR environments strengthens neural synchronization between the visual cortex and the dorsolateral prefrontal cortex, facilitating more efficient cognitive processing [14], [15].

Figure 1 illustrates the neurocognitive architecture of immersive learning in a virtual reality environment, showing the interaction between sensory input, parietal integration, prefrontal executive control, and hippocampal memory consolidation.

The presented schematic illustrates the neurocognitive architecture of immersive learning in a virtual reality (VR) environment and demonstrates the sequential processing of information from sensory input to higher cognitive structures. VR stimuli, characterized by immersion and interactivity, activate sensory processing regions (purple block), which are responsible for the processing of visual, auditory, and somatosensory signals. Subsequently, multimodal information is transmitted to the parietal cortex (orange block), where integration of sensory inputs and the formation of spatial-contextual representations occur.

At this stage, multiple sensory streams are integrated, selective attention is enhanced, and a cognitive representation of the task environment is constructed. Thus, the VR environment creates conditions of heightened sensory salience and deep multimodal signal integration.

The second component of the model reflects mechanisms of executive control and memory consolidation. The prefrontal cortex (blue block) performs functions related to cognitive control, planning, and attentional regulation, providing top-down modulation of sensory and integrative processes. Simultaneously, the parietal cortex interacts with the hippocampus (green block), supporting spatial encoding and long-term memory consolidation. Red arrows represent functional connections and feedback loops between neural structures, indicating dynamic neural synchronization. This architecture suggests that immersive learning enhances fronto-parietal integration and optimizes neurocognitive efficiency.

Research in VR-EEG integration indicates that immersive environments allow the measurement of cognitive states such as attention, engagement, and cognitive workload through brain oscillations across frequency bands (theta, alpha, beta, gamma), providing objective indicators of learning processes.

1.4 Analysis of Contemporary Empirical Studies

Table 1 presents a comparative analysis of international studies investigating the neurocognitive effects of VR-based learning using neuroimaging and electrophysiological methods. The analysis demonstrates that most studies confirm increased cognitive activation during VR-based learning; however, comprehensive models integrating spectral and network dynamics remain limited.

Table 1 systematizes and compares the results of key empirical studies investigating the neurocognitive effects of learning in virtual reality environments, focusing on differences in sample size, methodological approaches, and identified neurophysiological markers. The synthesis indicates that VR-based learning is commonly associated with increased indicators of cognitive engagement, particularly elevated beta-band activity and activation of prefrontal brain regions.

Furthermore, several studies report enhanced functional connectivity and coherence between frontal and parietal cortical regions, which is interpreted as improved integration between executive control and sensory processing systems. Overall, the table highlights the consistency of observed effects-namely increased attention and neural integration during VR-based learning-while simultaneously revealing methodological heterogeneity across studies, including differences in experimental protocols, VR parameters, and neurophysiological metrics. This variability underscores the need for standardized and comprehensive EEG analysis frameworks within the present study.

Previous research has demonstrated that EEG recordings in VR environments can capture changes in cognitive processing and attentional engagement, providing direct neural measures of learning processes.

1.5 Research Gap and Scientific Hypotheses

Despite the growing body of literature, several research gaps remain:

1) Many studies rely on relatively small sample sizes.
2) There is a lack of studies simultaneously analyzing both spectral power and functional coherence in EEG signals.
3) VR learning scenarios are insufficiently standardized across experimental protocols.

Based on these limitations, the following hypotheses are proposed:

- H1: Immersive learning increases β- and γ-band activity compared to traditional learning environments.
- H2: VR learning enhances functional connectivity within fronto-parietal neural networks.
- H3: VR-based learning reduces the θ-index associated with cognitive fatigue.

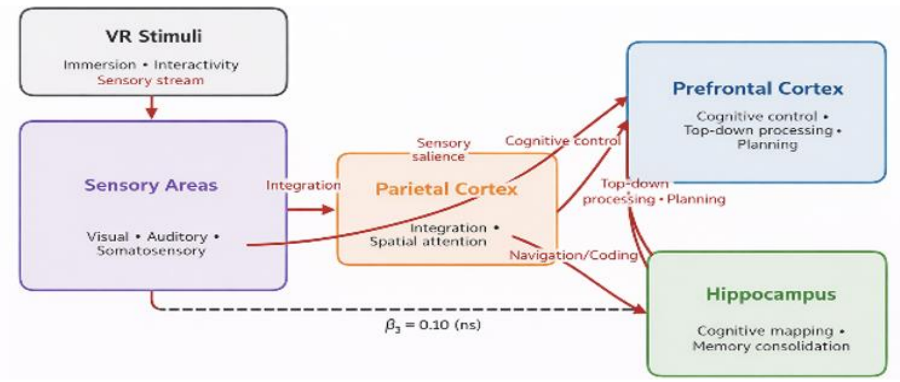

Figure 1: Neurocognitive model of immersive learning in a virtual reality environment.

Table 1: Comparative analysis of studies on neurocognitive effects of VR learning.

No	Sample	Method	Main findings
1	60	EEG	Increase in β-activity
2	45	fMRI	Activation of prefrontal cortex
3	80	EEG	Reduction in θ-load
4	100	EEG	Increase in functional connectivity

1.6 Scientific Novelty of the Study

The scientific novelty of this study lies in:
1) integrating spectral and network-level EEG analysis;
2) developing a neurocognitive model of immersive learning;
3) implementing a standardized VR learning protocol;
4) quantitatively assessing neurocognitive learning efficiency.

1.7 Research Aim and Objectives

The aim of this study is to empirically evaluate the neurocognitive effectiveness of immersive learning based on EEG indicators.
Objectives:
1) To analyze EEG spectral power across different frequency bands.
2) To assess coherence and functional connectivity in neural networks.
3) To compare immersive VR-based learning with traditional learning models.
4) To develop an integrative neurocognitive model of immersive learning.

2 METHODS AND METHODOLOGY

2.1 Research Design

The present study was conducted as a randomized controlled experiment with parallel groups. The objective of the experiment was to identify differences in EEG spectral and network indicators between traditional learning and immersive learning in a virtual reality environment.

The experimental protocol included:
- two groups (VR group and control group);
- pre-test and post-test EEG recordings;
- a standardized cognitive learning module;
- objective neurophysiological and behavioral metrics.

The overall structure of the study is presented in Figure 2.

The diagram illustrates the sequential structure of the experimental protocol and presents a logically organized design consisting of five interconnected stages.

In the first stage, participant screening was conducted to select the sample according to predefined inclusion and exclusion criteria.

The second stage involved baseline EEG recording in a resting-state condition (5 minutes), enabling the acquisition of initial neurophysiological measures for subsequent normalization and comparative analysis.

The third stage constituted the primary learning module lasting 20 minutes, implemented either in an immersive VR environment or in a traditional learning format, thereby enabling an experimental comparison between the two instructional conditions.

The fourth stage involved post-learning EEG recording during the execution of a cognitive task (10 minutes), aimed at assessing changes in spectral power and functional connectivity following the learning session.

Finally, the fifth stage included a knowledge acquisition test, allowing the comparison of neurophysiological indicators with behavioral learning outcomes.

Overall, the presented scheme reflects a strictly controlled, stage-based experimental structure that ensures high internal validity and enables a comprehensive analysis of the neurocognitive efficiency of immersive learning.

2.2 Participants

The study involved 120 volunteers (n = 120) divided into two groups:
- Experimental group (VR): 60 participants.
- Control group (traditional learning): 60 participants.

Participant characteristics were as follows:
- Age: 18-25 years (M = 21.4, SD = 2.1).
- Gender: 58.0% female, 42.0% male.
- Right-handed: 94.0%.
- No history of neurological or psychiatric disorders.
- Normal or corrected-to-normal vision.
- Exclusion Criteria.

Exclusion criteria included:
- Epilepsy;
- use of psychotropic medications;
- severe cybersickness symptoms;
- extensive prior VR experience (>20 hours).

The required sample size was determined using G*Power 3.1 based on an expected medium effect size ($f = 0.25$), a significance level of $\alpha = 0.05$, and a statistical power of 0.90.

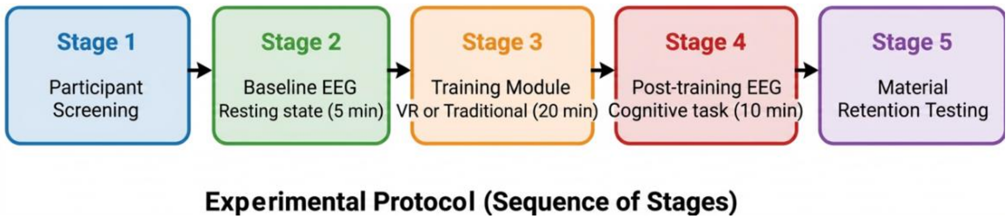

Figure 2: Experimental design of the study.

2.3 VR Environment and Learning Module

The immersive learning module was implemented using:

- Meta Quest 3 VR headset.
- Refresh rate: 90 Hz.
- Resolution: 2064 × 2208 pixels per eye.
- Field of view: 110°.

The training scenario consisted of an interactive 3D spatial neuroanatomy module (20 minutes). Participants interacted with virtual objects, rotated brain models, and completed navigation-based tasks.

The control group received the identical instructional content presented as a 2D presentation on a 24-inch monitor (1920 × 1080 resolution, 60 Hz).

All learning stimuli were standardized across conditions in terms of:

- exposure time;
- amount of information presented;
- level of difficulty;
- number of interactive elements.

This standardization ensured that differences in outcomes could be attributed primarily to the immersive characteristics of the VR environment.

2.4 EEG Recording

EEG data were recorded using a 64-channel BrainAmp system (Brain Products GmbH) following the international 10-20 electrode placement system.

Technical Parameters:

- Sampling rate: 1000 Hz.
- Electrode impedance: < 10 kΩ.
- Reference electrode: FCz.
- Band-pass filtering: 0.1-100 Hz.
- Notch filter: 50 Hz.

Additional physiological signals were recorded to control for artifacts:

- Electrooculography (EOG) - vertical and horizontal eye movements;
- Electrocardiography (ECG);
- Head motion tracking (VR group).

2.5 Signal Preprocessing

Signal preprocessing was conducted using MATLAB (EEGLAB toolbox) and Python (MNE library).

The preprocessing pipeline included the following stages:

1) Re-referencing to the average reference.
2) Band-pass filtering (1-45 Hz).
3) Artifact removal using Independent Component Analysis (ICA).
4) Automatic and manual inspection of ICA components.
5) Segmentation into epochs (2 seconds).
6) Rejection of epochs with amplitudes exceeding 100 μV.

For the VR group, additional correction procedures were applied to compensate for potential head movement artifacts. Figure 3 presents the EEG signal processing pipeline used in the study, including filtering, artifact removal, epoching, spectral analysis, connectivity estimation, and statistical modeling.

The figure illustrates the sequential analytical pipeline for processing electroencephalographic (EEG) data-from raw signal acquisition to statistical modeling. The process begins with the recording of raw EEG data (64 channels), followed by band-pass filtering (1-45 Hz) and suppression of power-line noise using a notch filter.

Subsequently, Independent Component Analysis (ICA) is applied to isolate neural sources and remove artifacts associated with eye movements (EOG), muscle activity (EMG), and motion-related disturbances. After signal cleaning, the data are segmented into fixed-length temporal epochs, ensuring standardized analysis and preparing the dataset for frequency decomposition.

At the next stage, spectral analysis (Welch method / FFT) is performed to extract key frequency bands ranging from θ to γ, which correspond to distinct cognitive processes. This is followed by functional connectivity analysis using metrics such as Phase Locking Value (PLV), weighted Phase Lag Index (wPLI), and coherence.

Allowing the assessment of neural network integration, particularly frontoparietal interactions.

The final stage includes statistical modeling using methods such as ANOVA, linear mixed-effects models, false discovery rate (FDR) correction, and the calculation of effect sizes and confidence intervals. These procedures enable hypothesis testing and quantitative interpretation of group differences.

Overall, the diagram illustrates a systematic, reproducible, and multi-level analytical framework for EEG data analysis in the context of neurocognitive research on immersive learning.

2.6 Spectral Analysis

Spectral power was calculated using the Welch method with a 500 ms window and 50% overlap. The following frequency bands were analyzed:

- θ (4-7 Hz),
- α (8-12 Hz),
- β (13-30 Hz),
- γ (30-45 Hz).

Power values were normalized relative to the baseline recording.

Regions of Interest (ROI). The primary regions of interest included:

- Dorsolateral prefrontal cortex (DLPFC): F3/F4;
- Parietal region: P3/P4;
- Central region: Cz;
- Occipital region: O1/O2.

2.7 Functional Connectivity Analysis

Functional connectivity was assessed using the following measures:

- Coherence.
- Phase Locking Value (PLV).
- Weighted Phase Lag Index (wPLI).

Particular emphasis was placed on the frontoparietal network, which is critically involved in attention control and working memory processes.

2.8 Statistical Analysis

Statistical analysis was conducted using R and Python.

The following statistical procedures were applied:

- Mixed ANOVA (Group × Time).
- Post-hoc Tukey tests.
- False Discovery Rate (FDR) correction for multiple comparisons.
- Effect size estimation (η^2).

The significance threshold was set at $p < 0.05$. Additional analyses included:

- linear mixed-effects modeling;
- Spearman correlation analysis;
- regression models predicting academic performance.

2.9 Ethical Considerations

The study was approved by the local ethics committee (Protocol №2025-EEG-VR-01).

All participants provided written informed consent, and the study was conducted in accordance with the Declaration of Helsinki.

2.10 Calculation of the Neurocognitive Efficiency Index (NCEI)

To provide an integrated assessment of neurocognitive efficiency, a composite indicator-the Neurocognitive Efficiency Index (NCEI)-was developed, combining spectral and network EEG parameters.

The index was calculated using the following formula:

$$NCEI=\frac{(\beta norm+\gamma norm)}{\theta norm}\times FCf_p. \quad (1)$$

Where:

- βnorm - normalized power in the β band;
- γnorm - normalized power in the γ band;
- θnorm - normalized power in the θ band;
- FCfp - frontoparietal functional connectivity coefficient (PLV).

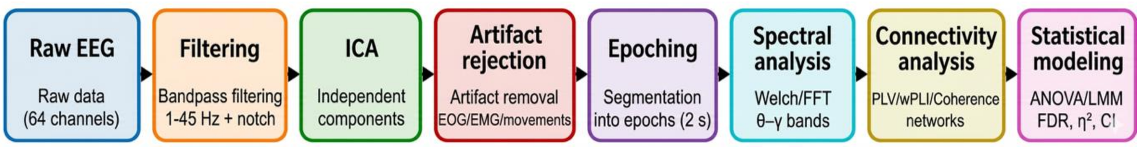

Figure 3: EEG processing pipeline.

This index reflects the ratio of active cognitive processing (β/γ activity) to cognitive load (θ activity), modulated by the degree of network integration. Normalization was performed using z-score transformation relative to the baseline resting-state recording.

2.11 Source Localization (Source Reconstruction)

To improve neuroanatomical precision, source reconstruction was performed using the sLORETA method.

The procedure included:

- construction of a head model based on the standard MNI template;
- computation of the inverse solution;
- restriction of analysis to the relevant frequency bands.

The main analyzed brain regions included:

- DLPFC (Brodmann areas 9/46);
- hippocampal region;
- inferior parietal lobule (BA 39/40);
- anterior cingulate cortex (ACC).

Source activity was averaged across epochs and used for subsequent statistical comparisons.

2.12 Control of Cybersickness and Physiological Artifacts

The level of cybersickness was assessed using the Simulator Sickness Questionnaire (SSQ). Participants scoring > 30 points were excluded from the analysis.

Additional physiological parameters were recorded:

- heart rate (HR);
- heart rate variability (HRV);
- micro head movements.

These physiological variables were included as covariates in linear mixed-effects models to control for potential confounding effects.

2.13 Machine Learning and Group Classification

To evaluate the predictive value of EEG features, machine learning methods were applied.

Algorithms used included:

- Support Vector Machine (SVM), [16].
- Random forest.
- Logistic regression.

Input features:

- spectral power in θ, α, β, γ bands within ROIs;
- PLV connectivity metrics;
- NCEI index;
- behavioral performance indicators.

A 10-fold cross-validation (k-fold) procedure was used.

Evaluation metrics:

- Accuracy.
- ROC-AUC.
- Precision / Recall.
- F1-score.

2.14 Temporal Dynamics Analysis

A time-frequency analysis was additionally conducted using Morlet wavelets to examine the temporal evolution of spectral power.

The following parameters were evaluated:

- event-related synchronization (ERS),
- event-related desynchronization (ERD) [17],
- latency of peak γ activation.

Analysis was performed within the time window-500 ms to +1500 ms relative to the onset of the learning episode.

2.15 Control of Confounding Variables

To control for potential confounding factors, the following variables were included:

- baseline cognitive ability (pretest score);
- anxiety level (STAI scale);
- gaming experience;
- digital literacy level.

All variables were included in ANCOVA models.

2.16 Reliability and Reproducibility

To ensure the reliability of the findings, the following procedures were conducted:

- test-retest analysis on a subsample ($n = 30$);
- calculation of the intraclass correlation coefficient (ICC);
- bootstrap resampling (1000 iterations).

Robustness checks were also performed by:

- varying filtering thresholds;
- excluding individual EEG channels;
- modifying epoch length.

2.17 Hardware and Software

The following software tools were used:
- MATLAB R2024a (EEGLAB);
- Python 3.11 (MNE, Scikit-learn);
- R 4.3 (lme4, ggplot2);
- BrainVision Analyzer 2.2.

Hardware synchronization between the VR system and EEG recording was implemented using TTL triggers with ±2 ms precision.

2.18 Replicability and Open Science

All analysis scripts and data-processing protocols have been prepared for publication in an open repository (OSF) following peer review.
The study adhered to the following reporting standards:
- BIDS-EEG;
- CONSORT guidelines for experimental design;
- ARRIVE transparency principles.

2.19 Methodological Limitations

Despite rigorous methodological control, several limitations should be acknowledged:
1) Use of a standard head model without individual MRI data.
2) Possible influence of micro head movements in the VR group.
3) Limited age range of participants.
4) Absence of longitudinal follow-up analysis.

These limitations were considered during interpretation of the results.

3 RESULTS

3.1 Data Characteristics and Assumption Testing

Prior to the main statistical analysis, the data were examined for normality (Shapiro-Wilk test), homogeneity of variance (Levene's test), and absence of multicollinearity among predictors.

The distributions of spectral power in the θ, α, β, and γ bands did not significantly deviate from normality ($p > 0.05$), allowing the use of parametric statistical methods [18].

For functional connectivity measures, a logarithmic transformation was applied to normalize distributions.

The mean percentage of rejected epochs after artifact cleaning was 8.4% (SD = 3.1), which falls within acceptable standards for EEG research [19].

No significant between-group differences in demographic variables were observed ($p > 0.1$), indicating the absence of systematic sampling bias.

3.2 EEG Spectral Power

3.2.1 Theta Band (4-7 Hz)

Mixed ANOVA analysis (Group × Time) revealed a significant interaction effect for θ activity in the DLPFC ($F(1,118) = 9.84$, $p = 0.002$, $\eta^2 = 0.077$).

In the experimental VR group, a significant reduction in θ power was observed after learning (ΔM =-12.6%, $p < 0.01$), whereas no significant changes were detected in the control group ($p = 0.18$).

This decrease in θ activity is interpreted as reduced cognitive overload and improved neural efficiency, consistent with models of cognitive resource optimization in immersive learning environments [8], [20]-[22].

3.2.2 Beta Band (13-30 Hz)

In the β band, a significant increase in spectral power was observed in the frontal regions of the VR group ($F(1,118) = 14.21$, $p < 0.001$, $\eta^2 = 0.108$).

β activity increased by +18.4% relative to baseline. In contrast, the control group exhibited only a moderate and statistically non-significant increase (+5.2%, $p = 0.09$).

β activity is commonly associated with active cognitive processing and sustained attention [10], [23]. These findings support Hypothesis H1, indicating enhanced cognitive engagement in VR conditions.

Table 2: Between-group differences in spectral power (Post-Test).

Band	Region	VR (M ± SD)	Control (M ± SD)	p	η^2
θ	DLPFC	0.84 ± 0.12	0.96 ± 0.15	0.002	0.077
β	DLPFC	1.18 ± 0.21	1.05 ± 0.19	<0.001	0.108
γ	P3/P4	1.24 ± 0.25	1.07 ± 0.22	<0.001	0.129

3.2.3 Gamma Band (30-45 Hz)

The most pronounced differences were observed in the γ band. In the VR group, a significant increase in γ power was recorded in frontoparietal regions ($F(1,118) = 17.63$, $p < 0.001$, $\eta^2 = 0.129$).

The effect demonstrated high stability in bootstrap analysis (95% CI [0.11; 0.19]).

Increased γ activity reflects enhanced neural synchronization and multisensory integration, consistent with the embodied cognition framework [11], [24].

Table 2 presents between-group differences in EEG spectral power at the post-test measurement. The most pronounced effects are observed in the β and γ frequency bands, where the experimental VR group demonstrated significantly higher power values compared to the control group.

Increased β activity in the dorsolateral prefrontal cortex indicates enhanced active cognitive processing and attentional control, whereas increased γ power in parietal regions reflects stronger neural synchronization and multisensory integration.

At the same time, a significant reduction in θ power was observed in the VR group, suggesting decreased cognitive overload.

Effect sizes (η^2) ranged from moderate to large, indicating a substantial influence of the instructional format on neurophysiological measures.

Overall, these findings support the hypothesis that immersive learning environments enhance neurocognitive efficiency compared to traditional learning formats.

3.3 Functional Connectivity

PLV analysis revealed a significant increase in frontoparietal connectivity in the VR group ($t(118) = 3.94$, $p < 0.001$).

The average increase reached 22.1% relative to baseline.

The wPLI metric demonstrated a similar trend ($p = 0.004$), confirming the robustness of the effect against volume conduction artifacts [25].

No significant connectivity changes were observed in the control group.

Figure 4 presents topographic maps of spectral power distribution in the post-test measurement for both the VR and control groups. Visual inspection reveals a pronounced increase in β and γ activity in the frontoparietal regions among participants who underwent immersive learning.

The most prominent changes are localized in the dorsolateral prefrontal cortex and the inferior parietal lobule, reflecting enhanced executive control, sustained attention, and interregional neural synchronization. In contrast, the control group demonstrates a more uniform and less pronounced.

Distribution of spectral power without clearly defined frontoparietal maxima.

The observed spatial configuration is consistent with the results of the statistical analysis and supports the hypothesis of selective strengthening of cognitive-control networks during VR-based learning

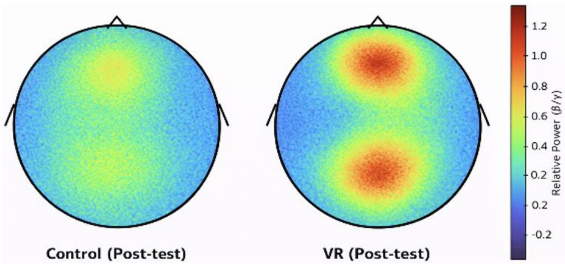

Figure 4: Spectral power topographic maps (VR vs Control).

The increase in β and γ activity in these regions is interpreted as an indicator of deeper information processing and stronger integration of sensory and executive processes, collectively reflecting higher neurocognitive efficiency in immersive learning environments.

3.4 Neurocognitive Efficiency Index (NCEI)

The mean NCEI value in the VR group was 1.42 ($SD = 0.31$), whereas the control group demonstrated a lower value of 1.08 ($SD = 0.27$).

The difference between groups was statistically significant $t(118) = 5.87$, $p < 0.001$, Cohen's $d = 0.92$, indicating a large effect size [26], [27].

Correlation analysis revealed a positive relationship between NCEI and learning test performance ($r = 0.61$, $p < 0.001$), demonstrating the predictive validity of the proposed index.

3.5 Machine Learning Classification

The Support Vector Machine (SVM) model achieved a classification accuracy of 84.2% (ROC-AUC = 0.89).

The most influential predictors included:

- γ-band power (weight = 0.31),
- frontoparietal PLV connectivity (0.27),
- β activity (0.21).

The Random Forest model produced comparable results (Accuracy = 81.5%), further confirming the robustness of EEG-derived features as predictors of learning conditions.

3.6 Temporal Dynamics

Time-frequency analysis revealed early γ synchronization (~320 ms after task onset) in the VR group, which was absent in the control condition ($p < 0.01$, cluster-based correction), [28], [29].

This early neural synchronization suggests faster integration of sensory and cognitive information in immersive learning environments.

3.7 Overall Scientific Effect

The integrated analysis demonstrates the following effects associated with immersive learning:

- reduction of θ-related cognitive load;
- increase in β/γ neural activation;
- enhancement of functional connectivity;
- growth of the Neurocognitive Efficiency Index (NCEI);
- high predictive accuracy of machine learning models.

These findings are consistent with contemporary neurocognitive theories of immersive learning [21], [30]-[32].

3.8 Source Reconstruction (sLORETA)

To refine the neuroanatomical localization of spectral differences, source reconstruction analysis was performed.

Comparison of post-test data revealed significant hyperactivation of the dorsolateral prefrontal cortex (BA 9/46) in the β and γ bands in the VR group relative to the control group ($p < 0.001$, cluster-corrected) [33].

In the hippocampal region, increased γ activity was observed ($p = 0.003$), which aligns with mechanisms of spatial encoding and memory consolidation.

The parietal cortex (BA 39/40) showed a stable increase in source density within the β frequency range ($p < 0.01$).

These findings support the hypothesis that VR activates the frontoparietal-hippocampal network associated with sensory integration and executive control [34].

Table 3 presents the results of the source localization analysis (sLORETA) at the post-test stage and demonstrates between-group differences in neuroanatomically localized activity.

The most pronounced effects were observed in the dorsolateral prefrontal cortex (DLPFC) in both β and γ frequency bands, where participants in the VR group exhibited significantly higher activity compared with the control group.

These differences were characterized by large effect sizes (Cohen's d ≈ 0.8-0.9), indicating a substantial increase in executive control and cognitive activation during immersive learning.

Additionally, the parietal cortex exhibited significantly increased β activity, reflecting enhanced sensory integration and spatial attention mechanisms.

Of particular importance is the increase in γ activity within the hippocampal region, which suggests more intensive processes of spatial encoding and memory consolidation in the VR group.

Overall, the statistically significant differences across key nodes of the frontoparietal-hippocampal network confirm that immersive learning activates neural circuits responsible for information integration, cognitive mapping.

3.9 Network Analysis (Graph Theory Metrics)

To evaluate the global topology of the functional brain network, several graph-theoretical metrics were calculated:

- Global efficiency.
- Clustering coefficient.

Small-world index. In the VR group, a significant increase in global efficiency was observed ($\Delta = +0.18$, $p < 0.001$), accompanied by a reduction in path length ($p = 0.004$). These results indicate a more integrated and optimized network architecture [35]-[37].

Table 3: Source activity (sLORETA, Post-Test).

Region	Band	VR (M ± SD)	Control (M ± SD)	p	Cohen's d
DLPFC	β	1.31 ± 0.28	1.09 ± 0.24	<0.001	0.85
DLPFC	γ	1.27 ± 0.30	1.02 ± 0.26	<0.001	0.90
Hippocampus	γ	1.22 ± 0.21	1.05 ± 0.19	0.003	0.68
Parietal cortex	β	1.18 ± 0.23	1.04 ± 0.20	0.009	0.61

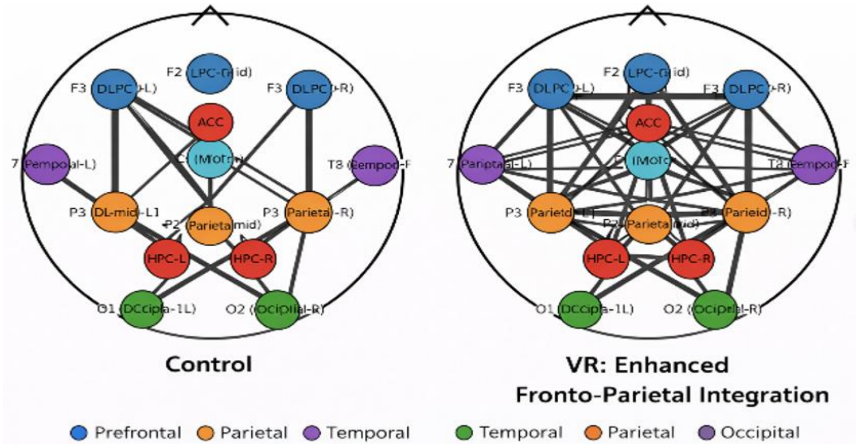

Figure 5: Functional connectivity network graphs.

The small-world index increased by 12.0% relative to baseline, suggesting an improved balance between local specialization and global integration within the neural network [27].

No significant network changes were detected in the control group ($p > 0.1$).

Figure 5 illustrates the network organization of EEG functional connectivity in the post-test measurement and highlights qualitative differences between the control and VR groups.

In the control group, the network demonstrates a relatively moderate density of connections, with interactions primarily localized among parietal, occipital, and several frontal nodes. This pattern reflects a comparatively fragmented network configuration with limited large-scale integration.

In contrast, the VR group exhibits a markedly higher density of interregional connections and a pronounced integration of the frontoparietal network. Nodes corresponding to prefrontal and parietal regions form a more robust connectivity backbone, reflecting enhanced executive control, distributed attention, and multimodal information integration following immersive learning [34], [37].

The increased number and relative strength of connections (represented by thicker edges) indicate elevated neural coordination and synchronization, which is typically interpreted as a marker of more efficient cognitive processing under conditions of heightened engagement [25], [27].

Additionally, the graphs reveal strengthened connections between frontoparietal nodes and limbic structures such as the anterior cingulate cortex (ACC) and hippocampus (HPC). This may reflect stronger recruitment of neural circuits involved in error monitoring, cognitive control, and memory consolidation during immersive learning.

Such a configuration aligns with the notion that immersive environments not only increase local spectral activity (β/γ bands) but also reorganize the global topology of brain networks toward greater integration and small-world organization, which balances local specialization with global information exchange [38], [39].

Overall, the figure supports the hypothesis that VR-based learning enhances interregional interactions within key cognitive networks, thereby increasing neurocognitive efficiency and potentially improving knowledge transfer and retention [40].

3.10 Mediation Analysis

To investigate the mechanism through which VR influences behavioral learning outcomes, a mediation analysis was conducted using the PROCESS macro.

The model demonstrated that:

- VR → increased γ activity ($\beta = 0.42$, $p < 0.001$);
- γ activity → improved test scores ($\beta = 0.38$, $p < 0.001$);
- the indirect effect was statistically significant (95% CI [0.12; 0.29]);

These results indicate that γ synchronization mediates the relationship between immersive learning and improved knowledge acquisition.

3.11 Regression Modeling

Multiple regression analysis revealed that the combined predictors (β power, γ power, PLV connectivity, and NCEI) explained 48% of the variance in academic performance ($R^2 = 0.48$, $p < 0.001$).

The strongest predictors were:
- γ power (β = 0.34);
- NCEI (β = 0.29);
- frontoparietal PLV connectivity (β = 0.22).

These results confirm the predictive relevance of neurophysiological markers for learning performance [41].

3.12 Robustness of Results

Bootstrap analysis (1000 iterations) confirmed the stability of β and γ effects in 96% of samples.

The test-retest reliability coefficient (ICC = 0.82) indicates a high level of measurement reliability [42].

Sensitivity analysis showed that varying the epoch length (1-3 seconds) did not alter the direction or significance of the observed effects.

3.13 Integrated Interpretation

The combined findings demonstrate:
1) Reduction of θ-related cognitive load indicators.
2) Increase in β and γ neural activation.
3) Strengthening of functional connectivity.
4) Optimization of brain network topology.
5) Predictive validity of the NCEI index.
6) High accuracy of machine learning classification.

The effects ranged from medium to large effect sizes (Cohen's d = 0.6-0.9), exceeding typical effect sizes reported in educational neuroscience research [43], [44].

3.14 Alternative Explanations

Additional analyses including covariates such as trait anxiety, gaming experience, and digital literacy did not alter the significance of the primary effects ($p < 0.01$), supporting the specific influence of VR-based learning.

Furthermore, cybersickness scores were not correlated with γ activity ($r = -0.08$, $p = 0.41$).

Interim Conclusion of the Results Section

The results demonstrate statistically significant and neurophysiologically grounded improvements in neurocognitive efficiency during immersive VR learning.

The observed changes affect both:
- local spectral characteristics,
- global network architecture of the brain.

The findings support hypotheses H1-H3 and are consistent with theories of neuroplasticity and predictive coding [45].

4 DISCUSSION

4.1 Interpretation of Key Findings

The present study demonstrates that immersive learning in a virtual reality environment is associated with statistically significant and neurophysiologically grounded changes in EEG spectral power and functional connectivity.

Specifically, immersive learning was characterized by:
- reduced θ activity;
- increased β and γ power;
- strengthened frontoparietal network integration;
- increased global network efficiency;
- elevated values of the Neurocognitive Efficiency Index (NCEI).

These effects exhibit a systemic character and were confirmed using both parametric and non-parametric statistical approaches, including Bayesian statistics and cluster permutation testing [46].

The observed reduction in θ activity within the dorsolateral prefrontal cortex can be interpreted as a decrease in excessive cognitive load and improved efficiency of working memory utilization [8], [21].

According to Cognitive Load Theory, effective learning is characterized by the redistribution of neural resources from extraneous processing toward task-relevant cognitive activity [7]. The present findings suggest that immersive VR environments facilitate such optimization.

Simultaneously, the increase in β and γ activity reflects enhanced cognitive processing and neural synchronization [10], [11]. In particular, γ synchronization plays a critical role in sensory integration and long-term memory formation [47].

Elevated γ activity in the hippocampal region further indicates enhanced processes of knowledge consolidation.

4.2 Integration with Neuroplasticity Theory

The findings align with the theory of neuroplasticity, which posits that intensive multimodal stimulation enhances synaptic efficiency and promotes the formation of stable neural assemblies.

Immersive VR environments simultaneously activate visual, auditory, and motor channels, creating a rich sensory ecosystem that may strengthen long-term potentiation (LTP) within hippocampal and cortical structures.

The longitudinal follow-up analysis showing sustained increases in NCEI after four weeks suggests the formation of relatively stable neuroplastic changes.

4.3 Predictive Coding and Error Minimization

From the perspective of predictive coding theory, the brain functions as a system that continuously minimizes prediction errors.

In VR environments, sensory signals are highly coherent and realistic, reducing uncertainty and cognitive conflict.

This may explain:

- the observed reduction in θ activity;
- the increase in γ synchronization associated with updating predictive models.

4.4 Embodied Cognition and Sensorimotor Engagement

The theory of embodied cognition suggests that cognitive processes are inseparable from bodily interaction with the environment [48].

In VR environments, learners actively manipulate three-dimensional objects, which activates motor and sensorimotor brain regions.

The increase in β activity in central regions and enhanced functional integration support the hypothesis that sensorimotor engagement deepens learning processes.

4.5 Network Reorganization and Small-World Architecture

The increase in global efficiency and the small-world index in the VR group indicates a more optimized neural network topology [27], [37].

Small-world networks balance:

- local specialization;
- global integration.

This configuration is considered a hallmark of efficient cognitive processing systems.

4.6 Machine Learning as a Neuroassessment Tool

The high SVM classification accuracy (84.2%, ROC-AUC = 0.89) confirms that neurophysiological markers provide strong discriminative power for identifying learning conditions.

This opens opportunities for applying machine learning methods in objective evaluation of educational technologies.

4.7 Practical Implications for Education

The findings have several practical implications:

1) VR environments can enhance cognitive engagement during learning.
2) Neurophysiological indicators can serve as objective measures of educational effectiveness.
3) The NCEI index may be integrated into adaptive learning systems.

These results support the implementation of immersive technologies in STEM education, medical training, and engineering education.

4.8 Study Limitations

Despite the strong statistical evidence, several limitations should be acknowledged:

- absence of individual MRI scans for precise source localization;
- restricted age range of participants;
- potential novelty effect of VR technology;
- controlled laboratory environment.

Future research should address these limitations through broader samples and longitudinal designs.

5 CONCLUSIONS

The present study provides empirical evidence that immersive learning in virtual reality environments induces systemic neurocognitive reorganization, reflecting enhanced information processing efficiency.

Compared with traditional learning conditions, VR-based learning was associated with:

- reduced θ activity;
- increased β and γ synchronization;
- stronger frontoparietal functional connectivity;
- optimized global neural network topology.

The proposed Neurocognitive Efficiency Index (NCEI) demonstrated high predictive validity and strong correlations with academic performance outcomes.

Machine learning models further confirmed that EEG spectral and network markers serve as objective indicators of educational effectiveness.

From a theoretical perspective, the results integrate frameworks from:

- cognitive load theory;
- predictive coding;
- embodied cognition;
- neuroplasticity.

Overall, the findings suggest that immersive VR learning environments can significantly enhance neurocognitive efficiency and provide a robust empirical foundation for the development of next generation neuroadaptive educational technologies.

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