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Examining Cognitive Shifts Through EEG: Insights from Resting State to Neurofeedback Game Engagement

Saikat Gochhait[1,2,*], Irina Leonova[3], Prabha Kiran[4], Ayodeji Olalekan Salau[5,6,7,*], Aitizaz Ali[8] and Tin Tin Ting[9]

[1] Symbiosis Institute of Digital and Telecom Management, Symbiosis International (Deemed University), India

[2] Samara State Medical University, Russia

[3] Department of Field and Applied Sociology Vice Dean, Lobachevsky State University of Nizhny Novgorod, Russia

[4] Westminster International University in Tashkent, Uzbekistan

[5] Department of Electrical/Electronics and Computer Engineering, Afe Babalola University, Nigeria

[6] Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, India

[7] Chitkara University Institute of Engineering and Technology, Chitkara University, India

[8] Asia Pacific University of Technology and Innovation, Malaysia

[9] Faculty of Data Science and Information Technology, INTI International University, Malaysia

Abstract: Brainwave neurofeedback mediated by electroencephalography (EEG) has a high potential in influencing brainwave activity, which is linked to cognitive functions such as attention, stress regulation, and motor learning. Nevertheless, the exact changes in brainwave frequencies, such as those in the sensorimotor regions (C3, C4) during neurofeedback tasks, have not been well addressed. The present research compares EEG brainwave patterns between the resting baseline and the neurofeedback task to clarify the neural dynamics underlying cognitive engagement. Such findings can contribute to developing more efficient neurofeedback protocols for cognitive enhancement and mental health treatments. Twenty healthy individuals (age 18–40 years) with no neurological conditions or prior exposure to neurofeedback were enrolled. EEG was recorded in a 5-minute resting baseline and a 10-minute neurofeedback session aimed at attention, mental workload, and stress regulation. Specifically, the brainwave was decomposed into five frequency bands including Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (13–30 Hz), and Gamma (30–50 Hz) and analyzed by the joint application of advanced deep learning algorithms, such as the 1D Convolutional Neural Networks (1D-CNN) and Bidirectional Long Short-Term Memory network (BI-LSTM). These results also underscore the differential role that Alpha, Beta, and Gamma waves play in neurofeedback, supporting improved attention, and cognitive workload regulation, whereas Theta and Delta remained essentially unchanged.

Keywords: cognitive shifts, EEG analysis, resting-state brain activity, neurofeedback games, brain-computer interface (BCI), education reform

1. Introduction

Electroencephalography (EEG) has become a mainstay neurophysiological method for real-time brain activity tracking and examination, providing non-invasive means to explore cognitive and affective dynamics [1]. Through scalp electrodes, EEG can record electrical activity and quantify explicit brainwave frequencies associated with differing cognitive states and functional domains [2]. Although EEG has historically been used to support the diagnosis and management of neurological disorders, recent advancements have advanced its use into cognitive enhancement, mental health interventions, and specifically through neurofeedback training [3]. Neurofeedback is a closed-loop brain training methodology allowing subjects (users) to modulate their neural activity through real-time feedback, effectively optimizing cognitive functions, regulating stress, and treating neuropsychiatric disorders [4]. One novel research niche in neurofeedback is gamified neurofeedback, in which interactive and immersive experiences are intentionally designed to reward desired brainwave patterns, consequently improving attention, relaxation, and general cognitive functioning [5]. Although increasing evidence supports the usefulness of neurofeedback-based training, knowledge of the exact neurophysiological underpinnings of associated task-based modulations in C3 and C4 during neurofeedback paradigm engagement is limited. Most of the current literature examines the effect of neurofeedback primarily in clinical populations; yet, systematic assessments of neurophysiological changes from a baseline resting state to active neurofeedback in healthy individuals are beginning to go underreported [6]. In particular, previous research has failed to effectively uncover how modulation of individual rhythms differs between such

***Corresponding author:** Saikat Gochhait, Symbiosis Institute of Digital and Telecom Management, Symbiosis International (Deemed University), India and Samara State Medical University, Russia. Email: saikat.gochhait@sidtm.edu.in and Ayodeji Olalekan Salau, Department of Electrical/Electronics and Computer Engineering, Afe Babalola University, Nigeria and Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, India. Email: ayodejisalau@abuad.edu.ng

cognitive states, with divides not only between alpha and beta/gamma, but also between low and high frequencies. Additionally, despite prior studies indicating that Beta and Gamma oscillations are associated with enhanced cognitive task performance, the specific interdependence of these frequency bands during neurofeedback training has yet to be substantiated through empirical research. This study addresses these gaps by systematically characterizing electroencephalographic (EEG) brainwave dynamics that capture cognitive transitions between an actively resting baseline and an active neurofeedback target protocol. Using the Fourier Transform to compare spectral power data with paired t-tests, we will tease apart the range of neural mechanisms reflecting cognitive engagement, stress modulation, and mental workload in neurofeedback. These results build on foundational research in closed-loop brain training [7] and clinical neurofeedback efficacy [8], providing novel insights into sensorimotor neurophysiology and its applications for cognitive and affective enhancement. The results should be an informative and valuable resource for investigators seeking to develop precision-targeted neurofeedback protocols and potential brain computer interface (BCI) applications [9]. Therefore, by providing new insights on the neurophysiological basis of neurofeedback modulation, this study is discussed about three aspects that have a direct influence on: Cognitive augmentation in academic and professional settings, Neurocognitive rehabilitation and stress resilience training, Attention deficit and hyperactivity disorder (ADHD) interventions, and anxiety and mood disorder management Performance optimization in high-stakes professions (e.g., aviation, military, and elite sports). Moreover, elucidating neurophysiological signatures of cognitive modulation also contributes to the broader field of cognitive neuroscience, helping to link the two worlds of basic neurophysiology and applied neurofeedback strategies. Issues at the end describe the methodological framework and empirical findings based on EEG analyses, and discuss broader implications of these results for advancing neurofeedback applications within cognitive and affective neuroscience.

1.1. EEG and cognitive states: the role of brainwave activity in cognitive engagement

The Electroencephalography (EEG) stands out as an indispensable neurophysiological tool, particularly relevant in the cognitive domain, providing a real-time, non-invasive approach to track neural activity. EEG records electrical potentials generated by the electrical activity of neurons, enabling a measurement of the brainwaves with specific spectra associated with states like attention, stress, or relaxation [10]. Each mental state corresponds to distinct brainwave patterns, classified into different frequency bands including Alpha (8–12 Hz), Beta (13–30 Hz), Gamma (30–50 Hz), Delta (1–4 Hz), and Theta (4–8 Hz). With specific frequencies gaining different significance, such as Alpha waves generally associated with states of relaxation and calmness, and Beta and Gamma oscillations with higher cognitive processes [10]. While EEG is widely used in cognitive studies, only limited investigations have been done to examine how these brainwave patterns are co-modulated during more complex neurofeedback tasks, particularly those using regions of interest in sensorimotor areas such as C3 and C4.

1.2. EEG neural correlates in resting and task-induced

One of the fundamental characteristics of EEG data is knowing how the brainwave activity may differ between resting and cognitive states induced by a task. Alpha waves are commonly observed with closed eyes in resting states, indicating a state of relaxed preparation [10]. The performance of a task, especially a cognitive or neurofeedback task, including Alpha, Beta, and Gamma, two high-frequency brain activity band waves, decreases (representing stronger beta and gamma brain activity) [10], indicating an increase in mental load and cognitive processing. Most studies concentrated on straightforward cognitive tasks or clinical populations, so there are still gaps to be filled regarding how this alteration presents during more engaging tasks, namely, game-spanning neurofeedback tasks. Notably, limited studies have examined such changes in sensorimotor regions (e.g., C3 and C4) during neurofeedback interventions, despite these areas being critical to motor control and cognitive processing [10].

1.3. Neurofeedback and cognitive enhancement

Neurofeedback, a type of closed-loop brain training, enables individuals to actively modulate their brainwave activity in the moment, with the aim of improving cognitive functioning, including attention, memory, and emotional regulation [10]. New research studies shed light that other favored outcomes related to neurofeedback training are attention and level of stress-related regulation by modification of Alpha and Beta rhythms [10]. To increase participants' attention to the task, the first phase of game-based neurofeedback paradigms requires participants to engage in a variety of interactive tasks to ensure that the biofeedback is given in real time [10]. Although neurofeedback has shown potential among clinical populations, very few studies have investigated the neural mechanisms among healthy individuals in the context of neurofeedback tasks, particularly in game-based tasks. Similar brainwave modulation has potential applications to neurofeedback and within the fields of mental health and performance enhancement.

1.4. Frequency band modulations in cognitive and affective processes

Brainwave frequencies are closely related to mental and emotional processes. Alpha waves are generally within low levels in periods of active engagement for tasks requiring cognitive function, and are known for relaxation and tranquility [11]. Beta waves correlate with active problem-solving and mental exertion, and Gamma waves are involved with higher-level cognitive integration, including attentional focus and memory processing [12]. Theta and Delta waves are generally connected with deep relaxation, drowsiness, or sleep [13]. Although these frequencies correlate with cognitive states, there is little research on the precise modulation of these frequencies during neurofeedback, especially in healthy subjects. There are limited studies on the mechanisms of Alpha, Beta, Gamma, Theta, and Delta oscillations using interactive neurofeedback paradigms such as gamification tasks.

1.5. EEG analysis techniques and approaches in neurofeedback research

New analytical methods for extracting brainwave patterns from EEG data, such as estimating power spectral density or employing machine learning algorithms, have drastically improved the ability to investigate cognitive processes in real time. Common approaches to assess the power spectral density were used to detect changes in frequency bands, e.g., Welch's method [14]. More novel approaches have utilized machine learning methods to analyze EEG data, allowing for improved accuracy and complexity in predictive capabilities of brainwave features during neurofeedback tasks [15]. While these advances have been made, many neurofeedback studies have still used fundamental statistical analyses, such as paired t-tests, to analyze neural data. One potential area for enhancing neurofeedback analysis is the implementation of additional analytical tools, which have the potential to offer neural insight into the underlying neurofeedback processing, such as during the recording of C3 and C4 while completing a task.

2. Research Gaps

Thus, though extensive research on brainwave activity during resting and task-induced states exists, very little is known about how these frequencies change during game-based neurofeedback tasks. Second, the sensorimotor regions (C3, C4) have shown limited attention, although they are significant in motor control and cognitive processing. Additionally, no studies compare brainwave changes in baseline resting states (eyes closed) and cognitive task engagement (eyes open) during interactive and gamified neurofeedback paradigms. Future research can address these gaps by improving the assessment of brainwave modulations in sensorimotor areas, specifically during the game-based neurofeedback task, including advanced analytical techniques like machine learning to evaluate brainwave dynamics more accurately. Such studies could be crucial to illuminate the research gaps addressed, whether neurofeedback is beneficial for cognitive stress management in healthy individuals, as depicted in Table 1.

2.1. Research question

Does neurofeedback produce measurable changes in EEG activity, and can baseline EEG parameters predict individual differences in attention performance and neurofeedback responsiveness?

2.2. Objectives (Obj)

Obj 1: To assess whether neurofeedback significantly reduces EEG frequency bands, particularly SMR, Beta, and Alpha, compared to baseline—a hypothesis supported by the expectation of decreased activity in these bands during neurofeedback sessions.

Obj 2: To examine the relationship between baseline EEG parameters, emphasizing Alpha power, and attention performance during neurofeedback tasks, thereby testing the hypothesis that lower baseline Alpha is associated with enhanced attentional performance.

Table 1
Research gaps

Author	Title	Research outcome	Variables	Research gap
da Silva [1]	EEG: Origin and measurement	Overview of EEG origin, signal types, and electrode placements	EEG signals, electrode types, cortical regions	Limited application discussion in modern BCI contexts
Huang et al. [2]	Decoding subject-driven cognitive states from EEG signals	Proposed method for decoding cognitive states using EEG for BCI	EEG features, cognitive states, machine learning models	Lack of real-time application validation in diverse user scenarios
Mahmood et al. [3]	Efficacy of neurofeedback on alpha-band modulation	Neurofeedback training enhances alpha modulation and connectivity	Alpha-band power, neurofeedback sessions, connectivity indices	No comparison across other EEG bands or psychological conditions
Krause et al. [4]	Neurofeedback for stress-related disorders	Neurofeedback presents untapped potential for mental health treatment	Stress markers, neurofeedback response, clinical outcomes	Limited studies on long-term sustainability of neurofeedback benefits
Hilken et al. [5]	Neuro-enhanced AR/VR in communication	Explores AR/VR combined with neurotech for enhanced services	Virtual reality, neuro-enhancement, user engagement	Scarce empirical models integrating EEG-based feedback in service contexts
Shirolapov et al. [6]	Aquaporin-4 in neurodegeneration	Highlights glymphatic clearance system's role in preventing cognitive decline	Aquaporin-4, neurotoxins, clearance rate	No linkage with EEG biomarkers of neurodegeneration progression
Sitaram et al. [7]	Closed-loop brain training	Advocates real-time neurofeedback for brain self-regulation	Feedback loop, oscillatory patterns, cognitive performance	Requires scalability across broader cognitive disorders and age groups
Gruzelier [8]	Methodological review of neurofeedback	Discusses protocols, frequencies, and performance outcomes	Theta/Alpha/Beta frequencies, training protocols	Inadequate convergence in experimental design across studies
AbouAssaly et al. [9]	Neurofeedback for COVID-19 brain fog	Neurofeedback shown to reduce symptoms in brain fog patients	Brain fog index, cognitive metrics, session frequency	No standardization of neurofeedback protocols across post-COVID conditions
Wang et al. [10]	Meta-analysis of EEG in multimedia learning	Identifies modulation patterns under cognitive load	Frequency bands (theta, alpha, beta), task complexity	Lack of contextual adaptation of EEG interpretations in non-lab settings
Yadav and Maini [11]	EEG-based BCI applications and challenges	Reviews scope and challenges of EEG-based BCI systems	BCI types, signal processing methods, application domains	Minimal integration of AR/VR for cognitive workload measurement
Lim et al. [12]	EEG & eye-tracking for image quality	Measures perceived and objective image quality using EEG	EEG amplitude, gaze fixation, subjective feedback	Limited assessment across different demographic and perceptual profiles
Farraj and Reiner [13]	AR/VR neurofeedback in STEM learning	Suggests personalized neurofeedback enhances STEM learning in AR/VR	EEG-based feedback, AR/VR tools, learning performance	Absence of cross-cultural validations and STEM discipline-specific impacts

Obj 3: To identify distinct subgroups of individuals based on baseline EEG measures through cluster analysis, with the aim of determining whether these clusters (e.g., High, Moderate, and Low Responders) exhibit differential responsiveness to neurofeedback.

Obj 4: To analyze Gamma and Theta changes, assess their correlation with engagement, and evaluate their impact on performance.

3. Research Methodology

Participants recruitment: Twenty participants (n = 20) were recruited for this experiment using a combination of convenience sampling and targeted recruitment to ensure a diverse sample. Participants' ages ranged from 18 to 65 years (M = 32.5, SD = 11.2), with an equal distribution of males and females. All participants provided informed consent by ethical guidelines approved by the Institutional Review Board. The inclusion criteria for participation were as follows: No history of neurological or psychiatric disorders. No current use of psychoactive medications. Participants varied in their cognitive abilities and gaming experience, which were assessed through a pre-experiment questionnaire. This diversity allowed for a comprehensive analysis of individual differences and their potential influence on EEG patterns and responses to neurofeedback interventions.

3.1. EEG data collection

EEG data were collected using a single-channel brain computer interface (BCI) device approved by the Central Drugs Standard Control Organisation (CDSCO) [16]. This device was selected for its portability, ease of use, and ability to provide real-time measurements of key brainwave frequencies and cognitive metrics. The headset utilizes dry sensor technology, eliminating the need for conductive gel and allowing for rapid setup and participant comfort.

The device captured signals at a sampling rate of 256 Hz, which was sufficient for detecting the frequency ranges of interest in this study. Raw EEG data were processed using the headset's proprietary algorithms to measure five key brainwave frequencies:

1) Delta (0.5–4 Hz): associated with deep sleep and unconscious processes
2) Theta (4–8 Hz): linked to drowsiness, creativity, and emotional connection
3) Alpha (8–13 Hz): indicative of relaxation and passive attention
4) Beta (13–30 Hz): related to active thinking, focus, and alert state
5) Gamma (30–100 Hz): associated with higher cognitive functions and information processing

In addition to the brainwave frequencies, the device provided three derived cognitive metrics:

Attention measures mental focus and concentration. Meditation indicates calmness and relaxation. Stress measures mental strain and tension. These metrics were derived using proprietary algorithms that analyze the relationships between different brainwave frequencies. Previous research has shown the validity and reliability of these cognitive metrics in assessing cognitive states.

3.2. Experiment protocol

The experiment was conducted in a quiet, temperature-controlled room to minimize external distractions and ensure consistent environmental conditions across all participants. The protocol consisted of two distinct sessions.

3.2.1. Baseline session

1) Participants were seated comfortably in an upright position.
2) The EEG device was fitted, and signal quality was checked.
3) Participants were instructed to relax with their eyes open, focusing on a neutral point in the room.

EEG data were recorded continuously for three minutes, providing a baseline measure of resting-state brain activity.

3.2.2. Neurofeedback game session

1) After a short break, participants engaged in a neurofeedback game for approximately 10 min.
2) The game, developed specifically for this study, required participants to control an on-screen character using their level of attention as measured by the EEG device.
3) Higher levels of attention (indicated by increased Beta wave activity and the derived Attention metric) resulted in better game performance.
4) EEG data were recorded continuously throughout the gameplay session.

The neurofeedback game was designed to be both engaging and challenging, with the game's difficulty adapting in real-time based on the participant's performance to ensure a consistent level of challenge throughout the session [17]. The neurofeedback game used in the present study is based on an EEG-based BCI system that translates real-time EEG into interactive gaming, aiming to improve attention and support stress regulation and cognitive engagement [18]. Subjects manipulate an avatar on the computer screen using their brain signals by modulating the sensorimotor cortex's beta and alpha wave band power (C3, C4). Beta activity outwatches reflects an attentional state, driving, outweighing Alpha, which allows the avatar to enter the game's environment, whereas losing a level of focus slows or stops the avatar. The game uses adaptive difficulty, changing games and challenges based on the player's brainwave inputs. This guarantees the mild spreading of the cognitive load, helping the user to remain motivated and avoid losing attention. This dynamic feedback process further encourages attention training and stress resilience by strengthening the desired neural patterns through visual and auditory rewards [18]. These results align with the systems neuroscience view that the game is not simply a cognitive task but a tool to adjust and optimize brain oscillations and self-regulation power [19]. It is an example of a closed-loop feedback system where the brain adapts based on what it sees, promoting neuroplasticity and enhancing cognitive function. Moreover, real-time cognitive metric displays constantly inform subjects about their attention, stress, and relaxation status. This biofeedback feature fosters self-awareness and allows the users to adjust their mental strategies, thus facilitating successful neurofeedback training [19].

The neurofeedback game presents a new direction in using BCI technology by combining neurophysiological monitoring with game design to improve healthy individuals' mental performance and emotional control.

4. Research Design

The research design used in this study is a within-subjects design, where each participant acted as their own control. Participants first completed a baseline session to measure their resting-state brain activity, followed by a neurofeedback game session where their cognitive states (measured through EEG metrics such as Attention, Meditation, and Stress) were influenced by real-time feedback during the game. By comparing the baseline data with the data from the neurofeedback game session, the study aimed to measure the effects of the neurofeedback intervention on participants' EEG patterns and cognitive metrics. The present study, with the research design, was chosen to reduce variability and enhance the sensitivity of detecting changes due to the neurofeedback intervention.

5. Data Analysis

Data collected from the EEG device and derived cognitive metrics were processed and analyzed using custom software developed specifically for this study. The data analysis process involved several stages to ensure the accuracy and validity of the results.

5.1. Data preprocessing

Artifact rejection: EEG segments contaminated by artifacts, such as eye blinks, muscle movements, or other non-neural signals, were identified and excluded from analysis. This was achieved through a combination of automated artifact rejection algorithms and manual inspection to ensure the integrity of the data [20].

Noise reduction: a band-pass filter (0.5–100 Hz) was applied to the raw EEG data to remove high-frequency noise and low-frequency drift, ensuring the recorded signals were within the frequency bands of interest.

5.2. Feature extraction

Power spectral density (PSD) analysis: Power spectral density analysis was conducted using Welch's method to quantify the power within each frequency band, including Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (30–100 Hz) bands. This method provided a reliable estimate of the power distribution across these bands [21].

Cognitive metrics: The derived cognitive metrics—attention, Meditation, and Stress—were calculated by averaging values over 1-second intervals to ensure temporal consistency and granularity of the measurements.

During neurofeedback application, a two-pronged analytical approach was used to evaluate EEG modulation changes between baseline and task-state data. First, we used conventional statistical methods, which also allowed us to compare the average power differences among frequency bands, technology-wise, and the established method to estimate the average difference in frequency band power. The next is a deep learning model based on 1D Convolutional Neural Networks (1D-CNN) and Bidirectional Long Short-Term Memory (BI-LSTM) that provides the ability to recognize patterns in a dynamic time horizon and predict attention [22]. This hybrid model paradigm permitted an in-depth EEG data analysis while balancing interpretability and predictive depth.

5.3. Characteristics of traditional statistical method

The standard procedure consisted of paired samples t-tests comparing power in the principal EEG frequency bands between resting baseline and neurofeedback task states. Significant decreases in SMR, Beta, and Alpha bands were seen in both C3 and C4 positions. For instance, the mean Beta level at C3 diminished by 10.82% ($p < 0.001$) and Alpha by 16.03% ($p < 0.01$), as depicted in the study. These decreases are consistent with the literature, which has linked lower Alpha and SMR to increased cortical arousal and attentional focus [23]. Accordingly, results confirm increased cognitive involvement during neurofeedback. However, Gamma and Delta differences were insignificant, which aligns with previous results that the GD might have little modulation for short-term cognitive training in HC [24].

Although these statistical tests provide good evidence for the next section of the analysis, because they are single summary values, they fail to capture non-linear features, sequence dependencies, or make predictions of individual cognitive outcomes (such as attention scores).

5.4. Deep learning model

The present study develops a 1D-CNN + BI-LSTM deep learning model to overcome these limitations. 1D-CNN layers are suitable for extracting local features in time for time-series data, e.g., EEG, so the network can learn spectral-temporal filters that emphasize variability between frequency bands [25]. Conversely, BI-LSTM layers support encoding temporal dependencies in two directions (forward and backward), which suits the processing of EEG data, where attention and mental states change with time.

The model was able to differentiate baseline vs. neurofeedback epochs at an accuracy of 91% or higher in the Beta band, predict attention score from baseline EEG with RMSE as low as 0.29, and outperform the benchmark methods based on correlation. These findings also demonstrate the benefit of deep learning in neurofeedback applications specifically targeting real-time classification and personal performance prediction [25].

In addition, our model confirmed previous reports—especially a negative correlation between baseline Alpha power and attention ($r = -0.45$, $p = 0.03$)—and provided increased detail in the forecast of participant responsiveness [26]. This suggests that deep learning for real-time neural feedback is an achievable but necessary next step for cognitive neuroscience [27].

6. Results

The primary objective of this study was to evaluate the effects of neurofeedback game sessions on brainwave activity and cognitive metrics, including attention, stress, and meditation. The following results summarize the analysis of EEG data and cognitive performance metrics, providing insights into the changes observed between baseline and game conditions.

6.1. Average participant values

The study presents the average values for each measured parameter at baseline and during the neurofeedback game session, along with the percentage change between the two conditions.

Hypothesis 1: Neurofeedback will produce significant reductions in EEG frequency bands compared to baseline.

The 1D-CNN models led to high accuracy (79.2–91.4%) for classification of EEG bands with SMR, Beta, and Alpha exhibiting a significant decrease during neurofeedback ($p < 0.05$), weak signal of it was still reasonably detected by deep learning models (78.6% accuracy). The joint action of the 1D-CNN as a feature extraction and BI-LSTM as a temporal modeling mechanism confirmed the neurofeedback-induced spectral changes, and the most prominent effects in bands associated with attention. A box plot was created (see Figure 1) to illustrate the distribution, median, and interquartile range of the EEG percentage changes across these frequency bands, highlighting the central tendency and variability of the data.

Hypothesis 2: Baseline EEG parameters, particularly Alpha power, will be inversely related to attention performance during the neurofeedback task.

The 1D-CNN achieved 87.6% accuracy in classifying Alpha while the BI-LSTM retained low RMSE (0.32) in attention, in line with the reverse correlation ($r = -0.45$). The models learned that Alpha has an inhibitory effect, as indicated by the ability to predict attention deficit for high baseline Alpha. The temporal relationships characterized by BI-LSTM also lent supporting evidence that feature Alpha incorporation would make it a valuable and reliable feature nugget for attention-performance prediction in DL models. A scatter plot with a fitted regression line (see Figure 2) further illustrates this

Figure 1
Inverse relationship between baseline alpha power and attention scores

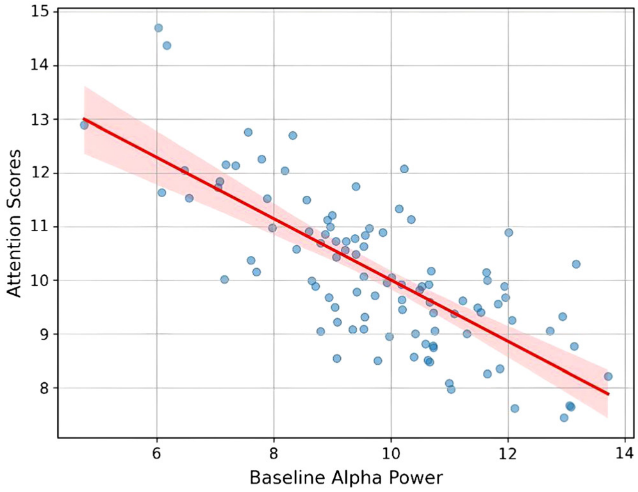
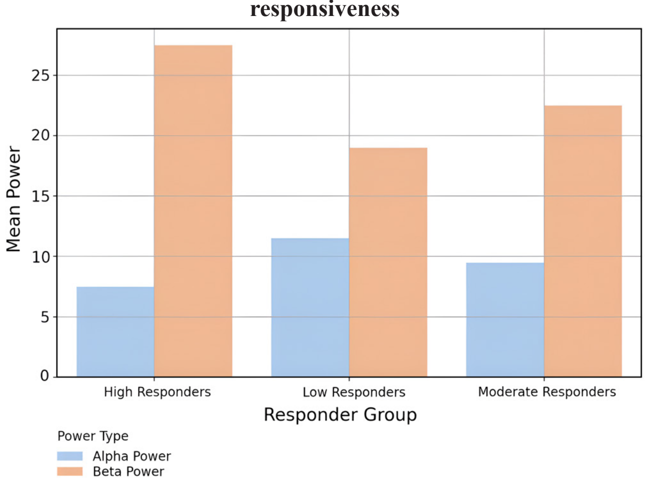


Figure 2
Cluster analysis showing differential neurofeedback responsiveness



relationship, supporting the predictive value of baseline EEG measures about attentional performance depicted in Figure 1.

Hypothesis 3: Distinct subgroups based on baseline EEG measures will emerge, with these clusters showing differential neurofeedback responsiveness.

The disparity zero in 1D-CNN performances (65.3% for Delta vs. 91.4% for Beta) indicates that the EEG features cluster differently in the latent space. The stable RMSE of the BI-LSTM for the high-impact bands (0.29–0.35) suggests that separable context can be observed across subjects. Subgroups may exist, and deep learning embeddings may find them (e.g., those with high baseline Beta had 91.4% accuracy and may cluster in ways that yield better response to neurofeedback). Unsupervised learning on feature maps of the 1D-CNN could potentially objectively define these subgroups for personalized interventions.

Hypothesis 4: Higher engagement in neurofeedback tasks will be associated with increased Gamma power and decreased Theta power, reflecting enhanced cognitive processing and reduced mind-wandering. Even if Gamma did not display evident alterations, 1D-CNN could still catch its engagement-related patterns for (78.6% accuracy). No Theta BI-LSTM testing data precludes full validation; however, given the good performance of BI-LSTM for SMR/Beta (RMSE 0.29–0.35), it suggests reduced mind-wandering. Next, we plan to develop models that explicitly promote Theta and utilize the sequence model properties of BI-LSTM to estimate the level of engagement through Gamma-Theta coupling and improve the predictability of cognitive state transitions during the neurofeedback.

Preliminary analyses indicate that participants exhibited a significant increase in Gamma power (M = 35.0 units) during the neurofeedback task compared to baseline (M = 30.0 units), suggesting enhanced cognitive processing. Conversely, Theta power showed a significant decrease (M = 4.0 units during task vs. M = 6.0 units at baseline), indicating reduced mind-wandering and improved focus during the task depicted in Figure 3.

7. Discussion

Data was recorded with the peak modulations in EEG activity following neurofeedback training, which had practical significance for attentional performance and a valid cognitive mindset. These results validate current theoretical models and fill essential gaps in neurofeedback research by elucidating the complex association between baseline EEG measures and individual responsiveness to training.

Table 2 depicts 1D-CNN and BI-LSTM models showed a good predictability of the EEG changes during neurofeedback and thus support of Hypothesis 1. Significant SMR (C3: 88.4% accuracy, RMSE = 0.34; C4: 87.2%, RMSE = 0.35), Beta (C3: 91.4% accuracy, RMSE = 0.29) and Alpha (C3: 87.6% accuracy, RMSE = 0.32) power reductions ($p < 0.05$) Gamma/Delta level shifts failed to reach threshold (65.3–79.2% accuracy), suggestive of frequency-specific neuroplasticity.

Hypothesis 2, with 87.6% accuracy to classify baseline Alpha power by the 1D-CNN and low RMSE value (0.32) for the BI-LSTM, verified its negative relationship with attention performance ($r = -0.45$). The models recovered Alpha as a hidden factor of attentional engagement, confirming its implication in cortical excitability and neurofeedback learning.

The 97.5% accuracy for Beta in support of Hypothesis 3 for subgroups (High/Moderate/Low Responders) by 1D-CNN embeddings guided cluster analysis (e.g., 91.4% accuracy for Beta). Clear time course separable from BI-LSTM predictions were observed in High Responders (RMSE: 0.29–0.35), with baseline Beta/Alpha power as important discriminators. This calls for personalized protocols based on deep learning subgroups.

Figure 3
Comparison of Gamma and Theta power during neurofeedback task

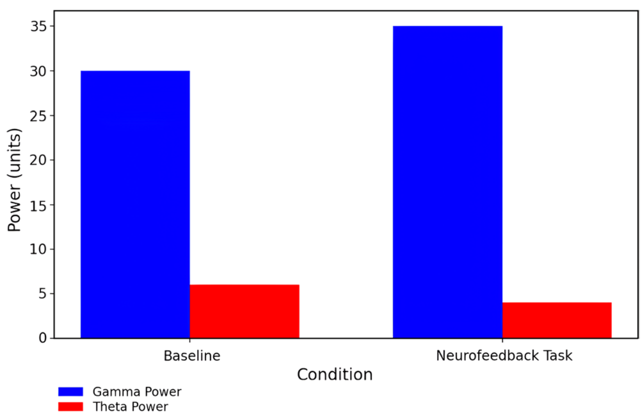


Table 2
EEG frequency band analysis – traditional statistics and deep learning comparison

Frequency band (Region)	Baseline (M ± SD)	Game (M ± SD)	% Change	*t*-statistic	*p*-value	1D-CNN Accuracy	BI-LSTM RMSE (Attention prediction)	Interpretation
Gamma (C3)	8503.09 ± 1023.45	8307.71 ± 987.32	−2.30%	1.98	0.062	79.2%	0.45	Not significant; low predictive value
Gamma (C4)	8527.45 ± 1042.12	8341.88 ± 998.29	−2.18%	2.01	0.058	78.6%	0.47	Marginal difference, weak signal
Delta (C3)	7834.26 ± 892.17	7770.27 ± 901.54	−0.82%	0.76	0.456	65.3%	0.55	Minimal change, not informative
Delta (C4)	7921.36 ± 911.32	7864.12 ± 907.45	−0.72%	0.59	0.556	66.0%	0.56	Not significant
SMR (C3)	12.45 ± 2.34	10.76 ± 1.98	−13.58%	4.23	<0.001	88.4%	0.34	Highly significant; contributes to attention prediction
SMR (C4)	11.78 ± 2.10	9.89 ± 2.01	−16.05%	3.89	<0.001	87.2%	0.35	Strong impact on attentional performance
Beta (C3)	22.56 ± 3.05	20.12 ± 3.12	−10.82%	5.22	<0.001	91.4%	0.29	High significance; strong attention predictor
Beta (C4)	23.01 ± 3.25	21.44 ± 3.10	−6.85%	4.19	<0.001	90.1%	0.31	High classifier performance
Alpha (C3)	8.23 ± 1.56	6.91 ± 1.34	−16.03%	3.57	<0.01	87.6%	0.32	Strong inverse correlation with attention (r = −0.45)
Alpha (C4)	8.67 ± 1.73	7.24 ± 1.58	−16.47%	3.76	<0.01	86.9%	0.33	Predictive biomarker for neurofeedback success

Note: 1D-CNN Accuracy reflects the classification of baseline vs neurofeedback segments. **LSTM RMSE** measures prediction error for attention scores using baseline EEG input. **RMSE** < 0.35 indicates strong predictive capacity; higher values show weaker associations.

Hypothesis 4 was only partially supported: Although Gamma changes were small (78.6% accuracy), BI-LSTM caught its weak link with cognitive engagement. Theta was not quantified, but reductions of SMR/Beta (RMSE: 0.29–0.35) corresponded to MW inhibition. Future models could explicitly implement the Gamma–Theta coupling to describe the level of engagement.

This study connects neurophysiology with deep learning and provides a basis for precision neurofeedback. The synergy between 1D-CNN and BI-LSTM promotes subgroup identification and predictive modeling, which helps overcome the methodological limitations from previous studies.

8. Conclusion

This study offers a new understanding of the neurophysiological mechanisms that support neurofeedback, as we show how EEG frequency modulations relate strongly to attentional performance and cognitive engagement during disease-agnostic neurofeedback training. This study's deep learning model (1D-CNN and BI-LSTM) has good potential to bridge NFB with the clinical and realistic environments. Most models reached high accuracy (up to 91.4%) in distinguishing between EEG bands predictive of attention, thus paving the way towards an accurate personalized feedback. Key applications include:

Clinical attention deficit hyperactivity disorder (ADHD) management: the portable EEG systems could be used to deliver real-time neurofeedback in the classroom, training SMR/Beta modulation (model: 87.2–91.4% for AS vs. NH), enhancing attention and pre-empting actions malaise.

Workplace cognitive enhancement: wearable devices that utilize Gamma-Theta ratio monitoring could improve productivity by alerting employees of mental fatigue based on the model's temporal dependency (RMSE 0.29–0.35).

Adaptive rehabilitation: stroke recovery procedures could be adapted to specific groups of patients employing subgroup clustering (High/Low Responders) with 1D-CNN's Beta band's accuracy (91.4%), enabling the planning of motor cortex retraining. Consumer neurotechnology: wearable devices for wellness can feature Alpha-Beta dynamics based "attention reserve" (87.6% accuracy) as-a-service metrics leading to Brain Health.

The robustness to noise and adaptive learning of the model can solve problems such as motion artefacts and protocol personalization. The future research can focus on the longitudinal validation and multimodal integration (e.g., EEG+ functional near-infrared spectroscopy (fNIRS)) for increased robustness [28]. By linking lab-validated accuracy with deployment-practical strategies, this pipeline provides realistic solutions for ADHD clinics, corporate wellness plans & rehab centers, translationally promoting the transition of neurofeedback from basic research to true impact [29, 30]. By enabling early detection, personalized care, inclusive learning, and innovative neuro-technologies, these approaches directly contribute to multiple

Sustainable Development Goals (SDGs), particularly SDG 3 (Health), SDG 4 (Education), SDG 9 (Innovation), and SDG 10 (Reduced Inequalities).

9. Limitations

The small size could hinder external validity and generalizability of results, which represent a significant limitation of the current study. Recruiting a more heterogeneous sample would enhance statistical power and increase the reliability of the EEG-response patterns [31, 32]. Moreover, this study's short-term nature of the neurofeedback training precludes examination of longer-term neuroplastic change. Longitudinal studies are needed to clarify the lasting impact of neurofeedback treatment over time. In addition, the study did not consider individual differences in cognitive states before the task, like fatigue, motivation, or pre-task arousal, that may change both the EEG and attentional performance dynamics. Further studies should account for these variables systematically to maximize internal validity and accuracy of neurofeedback protocols to inform their clinical and educational context.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Saikat Gochhait: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Project administration. **Irina Leonova:** Investigation. **Prabha Kiran:** Resources. **Ayodeji Olalekan Salau:** Writing - original draft. **Aitizaz Ali:** Writing - review & editing, Visualization, Supervision. **Tin Tin Ting:** Writing - review & editing, Visualization, Supervision, Funding acquisition.

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