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Editorial: Advancing Neurofeedback Through a Holistic and Functional Lens

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As the field of neurofeedback continues to evolve, it is imperative that we ground our progress in a comprehensive understanding of both its historical foundations and the latest scientific advancements. Neurofeedback transcends the mere application of electrodes to a client's scalp for a training session; it represents a dynamic opportunity to integrate holistic health principles into brain-based care. This perspective aligns with emerging trends in healthcare that emphasize the interconnectedness of mind, body, and environment.

At the 2023 International Society for Neurofeedback and Research (ISNR) conference, a recurring theme emerged among invited and keynote speakers: the relevance of functional medicine to our discipline. This observation resonates deeply with the vision I articulated during my candidacy for president—a commitment to advancing neurofeedback through a holistic and functional framework. Functional neurofeedback is an integrative, client-centered model of care designed to address disorders of the brain and central nervous system. It recognizes that each symptom or diagnosis may reflect a constellation of underlying factors unique to the individual, rejecting a one-size-fits-all approach (Hammond, 2011).

At its core, functional neurofeedback leverages quantitative electroencephalography (qEEG) brain mapping for precise assessment and employs brainwave training to promote not only symptom resolution but also a broader state of well-being (Thatcher, 2012). This begins with a thorough intake process, including a comprehensive health history, to ensure a holistic understanding of the client's needs. Such an approach moves beyond treating isolated disorders to fostering sustainable lifestyle improvements.

A critical aspect of this model is the practitioner's awareness of the bidirectional relationship between mental and physical health, particularly the roles of stress and anxiety. In the United States, recent estimates highlight the scale of these challenges. In 2024, approximately 23.08% of adults experienced a mental illness in the past year (Reinert et al., 2024), 21 million adults reported at least one major depressive episode (National Institute of Mental Health, 2024), and 20.17% of youths aged 12–17 faced similar struggles (Substance Abuse and Mental Health Services Administration, 2024). Furthermore, 43% of adults reported heightened anxiety compared to the previous year, often attributing this to escalating stress, while 53% and 40% identified stress and sleep, respectively, as primary lifestyle factors impacting mental health (American Psychiatric Association, 2024).

Stress and anxiety, though closely related, differ in origin. Stress typically arises from external triggers—such as interpersonal conflicts, workplace demands, or chronic illness—manifesting in symptoms like irritability, fatigue, gastrointestinal distress, and sleep disturbances (Selye, 1976). Anxiety, conversely, stems from internal triggers, such as intrusive thoughts or past experiences, activating the body's fight-or-flight response (American Psychological Association, 2019). Neurofeedback practitioners are uniquely positioned to address these conditions, leveraging technology to mitigate stress, anxiety, depression, and sleep disorders, among other health concerns (Arns et al., 2009).

To fully realize this potential, we must adopt a holistic, functional neurofeedback perspective in our clinical practice. This entails educating both our clients and our referral networks, including psychologists, physicians, psychiatrists, counselors, social workers, chiropractors, nurses, and other allied health professionals, about the mechanisms and benefits of neurofeedback. As a self-regulating organ, the brain governs both mind and body; by articulating this principle, we can position neurofeedback as a complementary intervention alongside other therapeutic modalities. In turn, we should seek education from these professionals to foster mutual referral relationships, thereby promoting a comprehensive wellness model.

Moreover, we must champion neurofeedback as a preventive strategy. The evidence is clear: stress and anxiety contribute to physical health decline, while neurofeedback and related neuroregulation interventions can significantly reduce, if not eliminate, these burdens (Marzbani et al., 2016). Research also underscores neurofeedback's efficacy in alleviating depression and enhancing sleep quality (Cheon et al., 2016). Given this, there is no reason we should not market ourselves as practitioners of preventive health, dedicated to improving quality of life.

As we look to the future, let us commit to advancing neurofeedback not merely as a reactive treatment but as a proactive tool for wellness. By embracing a functional and holistic approach, we can elevate our field, strengthen interdisciplinary collaboration, and empower our clients to lead healthier, more balanced lives.

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References

American Psychiatric Association. (2024). *Annual mental health poll 2024*. Washington, DC: Author.

American Psychological Association. (2019). *Anxiety*. https://www.apa.org/topics/anxiety

Arns, M., de Ridder, S., Strehl, U., Breteler, M., & Coenen, A. (2009). Efficacy of neurofeedback treatment in ADHD: The effects on inattention, impulsivity and hyperactivity: A meta-analysis. *Clinical EEG and Neuroscience, 40*(3), 180–189. https://doi.org/10.1177/155005940904000311

Cheon, E.-J., Koo, B.-H., & Choi, J.-H. (2016). The efficacy of neurofeedback in patients with major depressive disorder: An open-label prospective study. *Applied Psychophysiology and Biofeedback, 41*(1), 103–110. https://doi.org/10.1007/s10484-015-9315-8

Hammond, D. C. (2011). What is neurofeedback: An update. *Journal of Neurotherapy, 15*(4), 305–336. https://doi.org/10.1080/10874208.2011.623090

Marzbani, H., Marateb, H. R., & Mansourian, M. (2016). Neurofeedback: A comprehensive review on system design, methodology and clinical applications. *Basic and Clinical Neuroscience, 7*(2), 143–158. https://doi.org/10.15412/j.bcn.03070208

National Institute of Mental Health. (2024). *Major depression*. https://www.nimh.nih.gov/health/statistics/major-depression.shtml

Reinert, M., Fritze, D., & Nguyen, T. (2024, July). *The state of mental health in America 2024*. Mental Health America. https://mhanational.org/wp-content/uploads/2024/12/2024-State-of-Mental-Health-in-America-Report.pdf

Selye, H. (1976). *The stress of life* (2nd ed.). McGraw-Hill.

Substance Abuse and Mental Health Services Administration. (2024). *Key substance use and mental health indicators in the United States: Results from the 2023 National Survey on Drug Use and Health* (HHS Publication No. PEP24-07-021, NSDUH Series H-59). Center for Behavioral Health Statistics and Quality, Substance Abuse and Mental Health Services Administration. https://www.samhsa.gov/data/report/2023-nsduh-annual-national-report

Thatcher, R. W. (2012). *Handbook of quantitative electroencephalography and EEG biofeedback*. ANI Publishing.

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Exploring Alpha and Theta Activity in Depression: A Combined Surface EEG and LORETA Study of Cortical and Subcortical Networks

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Abstract

Introduction. Depression is a common mental health condition characterized by disrupted neural activity in cortical and subcortical networks involved in emotion and memory. While alpha and theta oscillations have been linked to depression, their specific roles in symptom domains remain unclear. This study examines these relationships using quantitative EEG (qEEG) and low-resolution electromagnetic tomography analysis (LORETA). **Methods.** Fifty-eight adults with depression underwent resting-state, eyes-closed qEEG. Absolute power and coherence of alpha (8–12 Hz) and theta (4–8 Hz) bands were analyzed across 19 scalp electrodes and hippocampal and amygdala regions using LORETA. Depressive symptom severity was assessed using the Beck Depression Inventory-II (BDI-II). Statistical analyses evaluated associations between EEG parameters and symptom scores. **Results.** Alpha coherence between the left hippocampus and amygdala negatively correlated with somatic symptoms ($r = -0.298$, $p = .027$), explaining 26% of variance in total BDI-II scores. Increased theta coherence in the right frontotemporal network was associated with reductions in affective and somatic symptoms. **Conclusions.** The findings identify neural oscillatory patterns within hippocampal-amygdala and frontotemporal networks as potential biomarkers for depressive symptoms, providing insights into novel therapeutic targets.

Keywords: depression; qEEG; alpha and theta oscillations; hippocampus-amygdala network; frontotemporal area

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Introduction

Depression is a widespread mood disorder that affects over 350 million people globally, significantly contributing to the global disease burden. It is the leading cause of disability worldwide, with a lifetime prevalence of 4.4% in the general population (Friedrich, 2017; García-Batista et al., 2018). Major depressive disorder (MDD) is characterized by symptoms such as persistent low mood, anhedonia, appetite and sleep changes, fatigue, restlessness or slowed movement, feelings of guilt or worthlessness, difficulty concentrating, and suicidal thoughts. According to the DSM-5-TR (American Psychiatric Association, 2022), a diagnosis of MDD requires the presence of at least five of these symptoms for most of the day, nearly every day, for a minimum of 2 weeks (Cui et al., 2024). Neuroimaging studies, including magnetic resonance imaging (MRI), functional MRI (fMRI), and electroencephalography (EEG), have demonstrated that individuals with depression exhibit both structural abnormalities and functional imbalances within brain networks. These networks are crucial for processes such as emotion regulation, involving regions like the amygdala, subgenual anterior cingulate, caudate, putamen, and pallidum (Siegle et al., 2007), as well as memory, encompassing the hippocampus (HPC), parahippocampal cortex, and other related areas (Dev et al., 2022; Yang et al., 2017). The amygdala is integral to processing salient stimuli and serves as a central hub within the affective network. Neuroimaging findings indicate increased amygdala connectivity and activation in patients with MDD, alongside reduced overall and subregional resting-state connectivity (Damborská et al., 2020). These abnormalities in the affective network likely contribute to emotional dysregulation (Tang et al., 2018). Another area that has emerged as a critical integrator of emotion and cognition is HPC. Studies have shown reductions in HPC volume across various mood disorders, particularly in MDD (Lorenzetti et al., 2009). HPC plays a crucial role in memory retention and controlling the production of cortisol, a hormone secreted in response to stress. When a person is depressed, his body releases excessive amounts of cortisol, leading to hippocampal atrophy and a reduction in neurogenesis. (Dev et al., 2022). Alongside structural alterations, abnormal HPC functioning has been linked to cognitive impairment and deficits in spatial memory among depressed patients (Gould et al., 2007). Recent functional studies have reported abnormal theta activity in the right anterior HPC and parahippocampal cortices in depressed individuals compared to healthy subjects (Cornwell et al., 2010). Amygdala and HPC are thought to be important for contextual modulation of fear, judgment of emotion, and emotional memory that are critical for remembering motivationally salient stimuli. The coupling between these two regions is predominantly unidirectional, during frequency oscillations; theta and alpha mediate their interregional communication (McGaugh, 2004; Zheng et al., 2017). Abnormal functional connectivity between these two areas, like patterns observed in humans with depression (Gould et al., 2007), has been also documented in a genetic rat model of major depression (Williams et al., 2014). These abnormalities, along with dysfunctions in other regions such as the ventromedial prefrontal cortex, insula, and caudate have been suggested to contribute to the dysregulation of emotional and motivational processes in MDD (Mayberg, 1997).

In resting-state EEG recordings, patients with depression exhibit disrupted connectivity within and between key networks, including the frontotemporal, centroparietal, frontoparietal, and dorsal attention networks, when compared to healthy individuals (16, 10). Elevated beta power in the prefrontal cortex, along with asymmetries in the alpha and theta bands, has been also linked to depressive symptoms (Liu et al., 2024). Machine learning analyses have demonstrated that the right hemisphere exhibits higher accuracy and performance in detecting depression, and among the various brain wave frequencies, the alpha band has shown the greatest accuracy in the classification of depression (Dev et al., 2022). Frontal alpha asymmetry is a biomarker that measures the balance of alpha wave activity between the left and right hemispheres of the frontal cortex, linked to emotional dysregulation (Tseng et al., 2022). Coherency is another index used in EEG studies to assess functional connectivity between brain regions. It quantifies the phase consistency between two EEG signals over time and frequency. Higher coherency between two regions implies greater functional connectivity, suggesting that these regions are synchronously communicating (Trambaiolli & Biazoli, 2020). In an EEG study on 119 subjects, including 75 healthy subjects and 44 patients with MDD, coherency in the alpha2 band (10–12 Hz) presented significantly positive correlation with symptoms (Trambaiolli & Biazoli, 2020). A machine learning analysis in another study also revealed that patients with MDD exhibited higher functional connectivity compared to controls, particularly in the alpha and beta bands. In the alpha band, connections were linking the frontopolar and DLPFC regions with temporal and parietooccipital areas, while beta band connections were mostly within prefrontal and temporal regions. These connectivity patterns distinguished MDD from bipolar disorder with 81% accuracy (Leuchter et al., 2012). A systematic review of 52 research articles highlighted the significant potential of EEG-based connectivity analysis and brain mapping techniques in identifying biomarkers of depression. The findings consistently identified the frontal cortex and parietal-occipital cortex as critical regions involved in depression detection. The review further emphasized the importance of future research that incorporated larger and more representative sample sizes, along with the application of advanced data analysis methodologies to improve accuracy. It also advocated for the development and use of more precise techniques to localize the brain regions most affected by depression (Dev et al., 2022).

In this study, we tried to address some of these challenges. We examined the alpha and theta absolute power across 19 EEG channels and evaluated their coherence within commonly studied surface networks. To address the limitations of surface EEG, we employed the LORETA technique to estimate these indices—absolute power and coherence—in two critical deep brain regions: the HPC and amygdala. This dual-layered methodology enhances the precision of identifying brain areas implicated in depression. Additionally, our stringent clinical protocols ensure a high level of sample purity and homogeneity. Participants were carefully selected using well-defined inclusion criteria, thoroughly evaluated by licensed psychologists, and independently verified by registered psychiatrists, addressing a frequent limitation in similar studies. Furthermore, by combining electrophysiological data with questionnaire-based behavioral assessments, we address the shortcomings of traditional behavioral diagnostic approaches, which are often prone to human bias and subjectivity. Analysis of this study was conducted on a cohort of 58 depressed outpatients.

Method

Participants

Our data were collected through convenience sampling from patients at Elumind Psychiatric Clinic in Vancouver, Canada. This approach resulted in a heterogeneous participant pool with variability in age and gender. To address this variability, we stratified the sample into three age groups: young adults (16–24 years), middle-aged adults (25–54 years), and older adults (55 years and above). Participants were also categorized into three groups: those using prescription medication (medicated), those not using prescription medication (nonmedicated), and those who consume alcohol or use marijuana (addicted group). This stratification allowed for a more nuanced understanding of the factors influencing the outcomes of the study. All participants presented to the clinic with depression as their primary complaint and had no history of other psychiatric disorders, intellectual disabilities, or neurological deficits. The final sample consisted of 22 males (mean age: 37.3 ± 14.07 years) and 36 females (mean age: 39.8 ± 16.90 years). Each participant provided written informed consent, completed the Beck Depression Inventory-II (BDI-II) questionnaire, and consented to undergo EEG recordings as part of the study following their therapeutic assessment. The research adhered to the ethical principles outlined in the Declaration of Helsinki (World Medical Association, 1996), including respect for individual autonomy, protection of privacy and confidentiality, maintenance of scientific integrity, and poststudy considerations, such as ensuring participants have access to any beneficial findings arising from the study. The sample size was determined based on previous studies (Bokhan et al., 2023; Yamada et al., 1995).

Beck Depression Inventory (BDI)

After welcoming the participant, informed consent was obtained, and any questions or concerns regarding data collection, EEG recording, or other procedures were addressed. Participants then sat in a quiet room and completed the Beck Depression Inventory (BDI) questionnaire according to the provided instructions. In terms of assessing severity of symptoms, the BDI-II is a widely used 21-item self-report tool designed for adolescents and adults (Wang & Gorenstein, 2013). It demonstrates strong criterion-based sensitivity and specificity for detecting depression, reinforcing its clinical utility as a diagnostic aid (Wang & Gorenstein, 2013). Since depression symptoms can respond differently to treatment, relying solely on a global score to evaluate treatment response is insufficient. Therefore, a bifactor model of the BDI-II was developed for statistical and clinical purposes, consisting of a general depression factor and three specific factors (cognitive, affective, and somatic), which provided the best fit for the data. This model indicated that BDI-II items could be summed to generate an overall score that accounts for most of the variance, while the specific factors contributed unique variance (García-Batista et al., 2018).

EEG to Quantitative EEG (qEEG) Recording

EEG recordings were conducted in a soundproof, dimly lit chamber with minimum sources of electromagnetic and cellular interference. Participants were seated in a comfortable armchair and instructed to relax and minimize movements to reduce artifacts. EEG data were recorded using a 19-channel WinEEG system (version 202, Mitsar Inc., Russia) during a 5-min, eyes-closed session. The sampling rate was 256 Hz, with electrodes positioned according to the international 10–20 system and impedance maintained below 5 kΩ across electrode sites. Low- and high-pass filters were set at 0.1 Hz and 45 Hz, respectively, with a 55–65 Hz notch filter applied. EEG data were recorded in a monopolar montage with signals referenced to linked ears. Independent component analysis (ICA) was performed to isolate and remove artifacts related to eye movements, muscle activity, and cardiac noise. Two EEG experts then visually inspected and manually corrected the data. Finally, 90 s of artifact-free EEG recordings were selected and imported into NeuroGuide software (version 3.2.8) to measure qEEG. Fourier transform (FFT) was used for quantitative analysis, and various band measures were calculated, considering age and gender.

Regions of Interest (ROIs)

Our primary focus was on the absolute power of theta (4–8 Hz) and alpha (8–12 Hz) bands across 19 electrodes: FP1, FP2, F3, F4, Fz, F7, F8, C3, C4, Cz, Pz, P3, P4, T3, T4, T5, T6, O1, O2. Additionally, FFT coherence of theta and alpha bands was measured between electrode pairs in the following regions: bi-frontal (FP1–FP2, F3–F4, F7–F8), frontocentral (Fz–Cz), centroparietal (Cz–Pz), frontoparietal (F3–P3, F4–P4, Fz–Pz), and frontotemporal (F3–T3, F3–T5, F4–T4, F4–T6, F7–T3, F7–T5, F8–T4, F8–T6). To assess HPC and amygdala activity and connectivity, we calculated LORETA absolute power (LAP) and LORETA coherence (LC) in the alpha and theta bands for both hemispheres. Default settings of the NeuroGuide software were used, with an epoch duration of 4 s. Electrodes were treated as independent variables in the analysis.

Statistics

To examine the effects of age and gender on the BDI scores and its subscales, we performed a multivariate analysis of variance (MANOVA). Additionally, Pearson's correlation coefficient (r) and Spearman's rank correlation (ρ) were calculated to assess relationships between BDI scores (including subscales) and EEG data, as well as LORETA findings. The choice between these correlation methods was determined based on the normality of the data. Furthermore, to control potential confounding effects of age, drug consumption, and gender, partial correlations were conducted by statistically adjusting for these variables. We used JASP (Jeffreys's Amazing Statistical Program) that is a free, friendly, and open-source software for statistical analysis.

Results

Descriptive data of our participants' BDI scores and its subscales in terms of age group and gender is shown in Table 1. Results revealed significant effect of age on cognitive, $F(2, 50) = 3.61$, $P = .034$, $\eta^2 = 0.126$. The pairwise comparison showed that old group reported less scores of cognitive scales in comparison to the middle age and the young group ($p = .005$, $p = .004$). Medication as a cofactor, significantly affected BDI, $F(2, 50) = 4.33$, $P = .018$, $\eta^2 = 0.148$; cognitive, $F(2, 50) = 3.61$, $P = .034$, $\eta^2 = 0.126$; and somatic scores, $F(2, 50) = 3.62$, $P = .034$, $\eta^2 = 0.127$. Pairwise analysis showed that in in all three above scales, addicted group reported higher scores than medicated group (for BDI, $p = .001$, cognitive, $p = .001$, and somatic, $p = .014$).

A negative correlation was observed between LORETA alpha coherency of left HPC and left amygdala and somatic scores (Pearson's $r = -0.298$, $p = .027$). EEG theta coherency of F4–T4 was also negatively correlated with BDI (Spearman's $\rho = -0.353$, $p = .014$), affective (Spearman's $\rho = -0.329$, $p = .008$) and somatic scores (Spearman's $\rho = -0.347$, $p = .010$; Table 2). Further, linear regression showed that LORETA alpha coherency of left HPC and left amygdala could explain 26% of BDI scores variance meaningfully ($R^2 = 0.49$, adjusted $R^2 = 0.26$, $P = .024$; Figure 1).

Table 1

Descriptive Table of Participants, Including Sample Size, Age, Total BDI Score, and Scores for the Cognitive, Affective, and Somatic Components

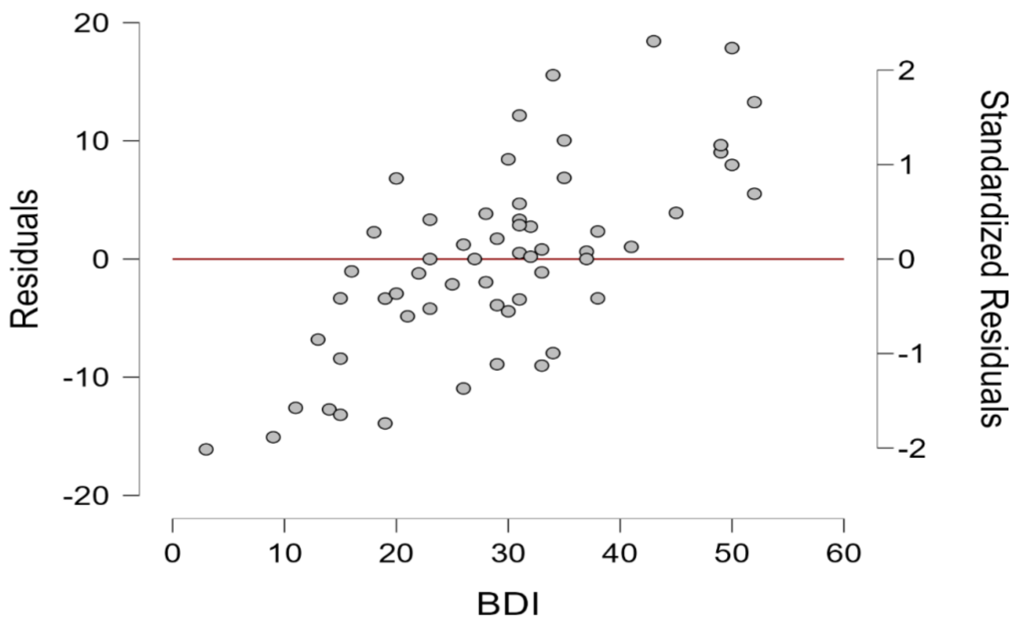
Group	Male			Female		
	Young	Middle age	Old	Young	Middle age	Old
Sample size	6	14	2	10	17	9
Age	22.5 ± 1.9	38.7 ± 5.3	72 ± 2.8	19.7 ± 2.8	39.8 ± 8.3	62.2 ± 5.5
BDI score	27.8 ± 7.52	28.8 ± 12.65	18.5 ± 0.72	36.4 ± 9.57	30.2 ± 12.3	23.1 ± 7.88
Cognitive score	9.5 ± 4.4	10.35 ± 4.41	6 ± 1.41	12.2 ± 3.93	11.17 ± 5.0	6.5 ± 3.43
Affective score	8.6 ± 1.5	7028 ± 3.14	5.5 ± 7	9.1 ± 3.47	6.8 ± 3.3	5.7 ± 2.1
Somatic score	9.6 ± 4.3	11.2 ± 6.1	7 ± 0.00	15.1 ± 4.01	12.2 ± 5.3	12.6 ± 4.7

Table 2. *Partial Spearman's Rho Heatmap of Correlation Between BDI and Its Subscale Scores With EEG and LORETA Findings.*

	BDI	cognitive	affective	somatic	qEEG.CO.T.F4/T4	LC.A.Amy.L.Hip.L
BDI		0.785	0.793	0.87	-0.353	-0.215
cognitive	0.785		0.445	0.507	-0.199	-0.016
affective	0.793	0.445		0.68	-0.329	-0.214
somatic	0.87	0.507	0.68		-0.347	-0.307
qEEG.CO.T.F4/T4	-0.353	-0.199	-0.329	-0.347		0.245
LC.A.Amy.L.Hip.L	-0.215	-0.016	-0.214	-0.307	0.245	

Note. BDI = Beck Depression Inventory; LC.A. Amy.L.Hip.L = LORETA coherency of alpha between left amygdala and left hippocampus; qEEG.co.T.F4/T4 = qEEG coherency of theta in F4–T4.

Figure 1. *Residuals vs. Dependent Plot LORETA Alpha Coherency of Left HPC/Amygdala and BDI Scores Among MDD Participants.*



Note. BDI = Beck Depression Inventory; MDD = major depressive disorder.

Discussion

This study provided a comprehensive investigation into the neurophysiological underpinnings of depression, with a particular focus on alpha and theta brainwave activity. By integrating surface EEG and LORETA methodologies, the research explored cortical and subcortical networks and their relationships with depressive symptomatology, including cognitive, affective, and somatic components.

Behavioral Findings

The findings revealed that elderly participants reported lower scores on cognitive scales compared to middle-aged and young participants. This aligns with prior research suggesting a negative correlation between age and BDI scores, with older adults potentially underreporting depressive symptoms due to factors spanning neurobiological, psychological, and social domains. These factors may obscure self-ratings of depressed mood in the elderly (Lyness et al., 1995). However, this result contrasts with a study of 556 adults and older adults, which found that the elderly scored higher on the somatic and performance subscales, but not on cognitive and affective subscales, compared to adults (Trentini et al., 2005). This disparity may be attributed to differences in sampling methods between our study and theirs. Notably, the studies have differed in terms of participant nationality. Furthermore, our study exclusively included individuals seeking therapy, while their sample may have included individuals who were not actively seeking therapeutic interventions. Another finding was significant effect of addiction on BDI, cognitive, and somatic score. These findings are consistent with previous research on 108 drug abusers, which demonstrated positive correlations between BDI-II subscales (cognitive, affective, and somatic) and the severity of alcohol and drug use (Dum et al., 2008). Similarly, another study on 42 adolescent and young adult marijuana users reported increased depressive symptoms, diminished fun-seeking, and reduced reward responsiveness associated with marijuana use (Wright et al., 2016). It was said that frontolimbic white matter integrity deficits in adolescent users probably contributed to apathy, ultimately exacerbated depressive symptoms.

Electrophysiological Findings

The analysis of LORETA data revealed a significant negative correlation between alpha coherency in the left HPC and left amygdala and somatic scores. Furthermore, this coherency accounted for 26% of the variance in BDI scores, indicating a meaningful contribution to depressive symptomatology. Supporting these findings, a prominent study on 123 individuals with MDD and 81 matched controls identified significant differences in local networks, particularly in subregions of the left amygdala and the hippocampal tail (Zhang et al., 2022). Patients with MDD demonstrated reduced characteristic path length and modularity in these regions compared to controls. The decreased characteristic path length may reflect increased global information transmission within the hippocampus-amygdala network. This enhanced interaction may underlie the emotional facilitation of memory formation and the persistence of a bias toward sad memories in MDD patients. Reduced modularity indicates that the hippocampus-amygdala network may be less distinctly organized into discrete functional communities, reflecting impaired functional segregation. Such a less modular structure could signify disruptions in feedback and feedforward communication between the HPC and amygdala, potentially contributing to dysregulated emotional memory processes in MDD. Our finding aligns with the broader explanation of these findings. It suggests that promoting regulated, synchronized communication between left HPC and left amygdala via increased alpha coherence—that probably adjust feedback and feedforward communication—might help reduce certain depressive symptoms, particularly somatic ones. Overall, these results underscore the role of neuroanatomical alterations and biased functional interactions within the hippocampus-amygdala network in the pathophysiology of depression.

EEG data analysis revealed a negative correlation between theta coherency in the F4–T4 region and BDI scores, particularly in the affective and somatic components. As theta coherence between the right frontal and right temporal regions increased, depressive symptoms, as measured by these scales, decreased. It is hypothesized that lower brain frequencies, such as theta, reflect subcortical processing in regions like the entorhinal neurons of the medial temporal lobe, driven primarily by mass synchronized neural firing. They enable the synchronization of neural populations across large-scale networks, such as frontal and temporal regions, which play a pivotal role in memory performance and serve as a bridge between self-perception and affective states. (LaVarco et al., 2022; Takahashi et al., 2007). These networks, predominantly mediated by right-lateralized structures, significantly influence self-awareness and mood (Devinsky, 2000; Platek et al., 2004). Theta activity also plays a crucial role in emotional processing, particularly in response to salient and arousing stimuli. Studies have demonstrated that theta power is greater for emotional stimuli compared to neutral stimuli and is sensitive to affective content irrespective of valence. Furthermore, theta activity is modulated by personal distress, highlighting its role in empathy-related and emotional regulation processes (Romeo & Spironelli, 2024). In the context of our study, the observed increase in theta wave synchronization between the right frontal and temporal cortices likely reflects enhanced functional connectivity within these neural networks. This increased synchronization may facilitate organized cognition and emotional regulation, thereby contributing to the alleviation of depressive symptoms. In confirmation of our finding, another longitudinal study investigated cognitive and emotional development in 81 healthy children and identified a significant role for frontotemporal functional connectivity, measured via EEG coherence, during an episodic memory encoding task. The findings highlighted the involvement of the right frontotemporal region (F4–T8) in supporting memory processes (Blankenship & Bell, 2015). Further support comes from a clinical trial involving 30 adolescents with conduct disorder and 34 controls (Dong et al., 2019). Resting-state fMRI data showed reduced frontotemporal connectivity in adolescents with conduct disorder, specifically in regions underlying cognitive and affective empathy. The study's authors proposed that frontotemporal communication facilitates the use of external social cues processed in temporal regions to infer emotional states in the medial prefrontal cortex. Reduced connectivity may impair the ability to access social cues, affecting cognitive empathy, leading to depressive symptoms. The improved connectivity may support processes such as emotional regulation, memory, and social understanding, contributing to the observed decreases in affective and somatic BDI scores.

Conclusion

Present findings highlight the critical role of synchronized neural activity in cortical and subcortical regions in regulating mood, providing a deeper insight into the mechanisms underlying depressive symptoms. Enhanced connectivity within key networks, such as the hippocampus-amygdala and frontotemporal regions, may represent a target for interventions aimed at alleviating specific depressive symptoms, particularly those related to somatic and affective dimensions. Overall, this study highlights the critical role of neurophysiological alterations in shaping the pathophysiology of depression and offers a foundation for future research exploring targeted brain areas. However, further studies, particularly those employing integrated EEG-MRI approaches, are necessary to investigate replication. Cofactors such as unwanted artifacts, the limited spatial resolution of LORETA, and the complex reciprocal connections between regions like the amygdala and HPC may confound the results, making it premature to draw clinical applications from these findings.

Limitation and Implication for Future Research

It is notable that our finding about the role of age deserves careful consideration as other important factors such as race, socioeconomic status, and cultural background that might affect reporting of symptoms were not assessed in our study. Our findings were also influenced by the limited sample size, particularly after stratifying participants into three groups, which increased susceptibility to variability and hindered result consolidation. Future studies should address this by leveraging large, stratified EEG databanks. Training machine learning algorithms on prevalidated EEG patterns with adequately sized datasets could equip health professionals with a versatile, portable, and cost-effective tool for reliably diagnosing depression. We strongly recommend adopting standardized artifact correction protocols, enforcing stringent inclusion and exclusion criteria, and incorporating the visual cortex in future analyses—an area we were unable to explore due to the data volume involved.

Author Declaration

The authors declare no conflicts of interest. The research was conducted independently, adhering to ethical standards, without external funding or financial incentives, and driven solely by the authors' academic and clinical interests. Dr. Kourosh Edalati served as the primary supervisor for this research project. The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to restrictions (e.g., containing information that could compromise the privacy of research participants).

References

American Psychiatric Association. (2022). *Diagnostic and statistical manual of mental disorders* (5th ed., text rev.). https://doi.org/10.1176/appi.books.9780890425787

Blankenship, T. L., & Bell, M. A. (2015). Frontotemporal coherence and executive functions contribute to episodic memory during middle childhood. *Developmental Neuropsychology, 40*(7–8), 430–444. https://doi.org/10.1080/87565641.2016.1153099

Bokhan, N. A., Galkin, S. A., & Vasilyeva, S. N. (2023). EEG alpha band characteristics in patients with a depressive episode within recurrent and bipolar depression. *Consortium Psychiatricum, 4*(3), 5–12. https://doi.org/10.17816/CP6140

Cornwell, B. R., Salvadore, G., Colon-Rosario, V., Latov, D. R., Holroyd, T., Carver, F. W., Coppola, R., Manji, H. K., Zarate, C. A., & Grillon, C. (2010). Abnormal hippocampal functioning and impaired spatial navigation in depressed individuals: Evidence from whole-head magnetoencephalography. *American Journal of Psychiatry, 167*(7), 836–844. https://doi.org/10.1176/appi.ajp.2009.09050614

Cui, L., Li, S., Wang, S., Wu, X., Liu, Y., Yu, W., Wang, Y., Tang, Y., Xia, M., & Li, B. (2024). Major depressive disorder: Hypothesis, mechanism, prevention and treatment. *Signal Transduction and Targeted Therapy, 9*(1), Article 30. https://doi.org/10.1038/s41392-024-01738-y

Damborská, A., Honzírková, E., Barteček, R., Hořínková, J., Fedorová, S., Ondruš, Š., Michel, C. M., & Rubega, M. (2020). Altered directed functional connectivity of the right amygdala in depression: High-density EEG study. *Scientific Reports, 10*(1), Article 4398. https://doi.org/10.1038/s41598-020-61264-z

Dev, A., Roy, N., Islam, Md. K., Biswas, C., Ahmed, H. U., Amin, Md. A., Sarker, F., Vaidyanathan, R., & Mamun, K. A. (2022). Exploration of EEG-based depression biomarkers identification techniques and their applications: A systematic review. *IEEE Access, 10*, 16756–16781. https://doi.org/10.1109/ACCESS.2022.3146711

Devinsky, O. (2000). Right cerebral hemisphere dominance for a sense of corporeal and emotional self. *Epilepsy & Behavior, 1*(1), 60–73. https://doi.org/10.1006/ebeh.2000.0025

Dong, D., Jiang, Y., Gao, Y., Ming, Q., Wang, X., & Yao, S. (2019). Atypical frontotemporal connectivity of cognitive empathy in male adolescents with conduct disorder. *Frontiers in Psychology, 9*, Article 2778. https://doi.org/10.3389/fpsyg.2018.02778

Dum, M., Pickren, J., Sobell, L. C., & Sobell, M. B. (2008). Comparing the BDI-II and the PHQ-9 with outpatient substance abusers. *Addictive Behaviors, 33*(2), 381–387. https://doi.org/10.1016/j.addbeh.2007.09.017

Friedrich, M. J. (2017). Depression is the leading cause of disability around the world. *JAMA, 317*(15), Article 1517. https://doi.org/10.1001/jama.2017.3826

García-Batista, Z. E., Guerra-Peña, K., Cano-Vindel, A., Herrera-Martínez, S. X., & Medrano, L. A. (2018). Validity and reliability of the Beck Depression Inventory (BDI-II) in general and hospital population of Dominican Republic. *PLoS ONE, 13*(6), Article e0199750. https://doi.org/10.1371/journal.pone.0199750

Gould, N. F., Holmes, M. K., Fantie, B. D., Luckenbaugh, D. A., Pine, D. S., Gould, T. D., Burgess, N., Manji, H. K., & Zarate, C. A. (2007). Performance on a virtual reality spatial memory navigation task in depressed patients. *The American Journal of Psychiatry, 164*(3), 516–519. https://doi.org/10.1176/ajp.2007.164.3.516

LaVarco, A., Ahmad, N., Archer, Q., Pardillo, M., Nunez Castaneda, R., Minervini, A., & Keenan, J. P. (2022). Self-conscious emotions and the right fronto-temporal and right temporal parietal junction. *Brain Sciences, 12*(2), Article 138. https://doi.org/10.3390/brainsci12020138

Leuchter, A. F., Cook, I. A., Hunter, A. M., Cai, C., & Horvath, S. (2012). Resting-state quantitative electroencephalography reveals increased neurophysiologic connectivity in depression. *PLoS ONE, 7*(2), Article e32508. https://doi.org/10.1371/journal.pone.0032508

Liu, X., Zhang, H., Cui, Y., Zhao, T., Wang, B., Xie, X., Liang, S., Sha, S., Yan, Y., Zhao, X., & Zhang, L. (2024). EEG-based major depressive disorder recognition by neural oscillation and asymmetry. *Frontiers in Neuroscience, 18*, Article 1362111. https://doi.org/10.3389/fnins.2024.1362111

Lorenzetti, V., Allen, N. B., Fornito, A., & Yücel, M. (2009). Structural brain abnormalities in major depressive disorder: A selective review of recent MRI studies. *Journal of Affective Disorders, 117*(1–2), 1–17. https://doi.org/10.1016/j.jad.2008.11.021

Lyness, J. M., Cox, C., Curry, J., Conwell, Y., King, D. A., & Caine, E. D. (1995). Older age and the underreporting of depressive symptoms. *Journal of the American Geriatrics Society, 43*(3), 216–221. https://doi.org/10.1111/j.1532-5415.1995.tb07325.x

Mayberg, H. (1997). Limbic-cortical dysregulation: A proposed model of depression. *The Journal of Neuropsychiatry and Clinical Neurosciences, 9*(3), 471–481. https://doi.org/10.1176/jnp.9.3.471

McGaugh, J. L. (2004). The amygdala modulates the consolidation of memories of emotionally arousing experiences. *Annual Review of Neuroscience, 27*(1), 1–28. https://doi.org/10.1146/annurev.neuro.27.070203.144157

Platek, S. M., Keenan, J. P., Gallup, G. G., & Mohamed, F. B. (2004). Where am I? The neurological correlates of self and other. *Cognitive Brain Research, 19*(2), 114–122. https://doi.org/10.1016/j.cogbrainres.2003.11.014

Romeo, Z., & Spironelli, C. (2024). Theta oscillations underlie the interplay between emotional processing and empathy. *Heliyon, 10*(14), Article e34581. https://doi.org/10.1016/j.heliyon.2024.e34581

Siegle, G. J., Thompson, W., Carter, C. S., Steinhauer, S. R., & Thase, M. E. (2007). Increased amygdala and decreased dorsolateral prefrontal BOLD responses in unipolar depression: Related and independent features. *Biological Psychiatry, 61*(2), 198–209. https://doi.org/10.1016/j.biopsych.2006.05.048

Takahashi, E., Ohki, K., & Kim, D.-S. (2007). Diffusion tensor studies dissociated two fronto-temporal pathways in the human memory system. *NeuroImage, 34*(2), 827–838. https://doi.org/10.1016/j.neuroimage.2006.10.009

Tang, S., Lu, L., Zhang, L., Hu, X., Bu, X., Li, H., Hu, X., Gao, Y., Zeng, Z., Gong, Q., & Huang, X. (2018). Abnormal amygdala resting-state functional connectivity in adults and adolescents with major depressive disorder: A comparative meta-analysis. *EBioMedicine, 36*, 436–445. https://doi.org/10.1016/j.ebiom.2018.09.010

Trambaiolli, L. R., & Biazoli, C. E. (2020). Resting-state global EEG connectivity predicts depression and anxiety severity. *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 3707–3710. Montreal, Canada. https://doi.org/10.1109/EMBC44109.2020.9176161

Trentini, C. M., Xavier, F. M. D. F., Chachamovich, E., Rocha, N. S. D., Hirakata, V. N., & Fleck, M. P. D. A. (2005). The influence of somatic symptoms on the performance of elders in the Beck Depression Inventory (BDI). *Revista Brasileira de Psiquiatria, 27*(2), 119–123. https://doi.org/10.1590/S1516-44462005000200009

Tseng, H.-J., Lu, C.-F., Jeng, J.-S., Cheng, C.-M., Chu, J.-W., Chen, M.-H., Bai, Y.-M., Tsai, S.-J., Su, T.-P., & Li, C.-T. (2022). Frontal asymmetry as a core feature of major depression: A functional near-infrared spectroscopy study. *Journal of Psychiatry and Neuroscience, 47*(3), E186–E193. https://doi.org/10.1503/jpn.210131

Wang, Y.-P., & Gorenstein, C. (2013). Psychometric properties of the Beck Depression Inventory-II: A comprehensive review. *Revista Brasileira de Psiquiatria, 35*(4), 416–431. https://doi.org/10.1590/1516-4446-2012-1048

Williams, K. A., Mehta, N. S., Redei, E. E., Wang, L., & Procissi, D. (2014). Aberrant resting-state functional connectivity in a genetic rat model of depression. *Psychiatry Research: Neuroimaging, 222*(1–2), 111–113. https://doi.org/10.1016/j.pscychresns.2014.02.001

Wright, N. E., Scerpella, D., & Lisdahl, K. M. (2016). Marijuana use is associated with behavioral approach and depressive symptoms in adolescents and emerging adults. *PLoS ONE, 11*(11), Article e0166005. https://doi.org/10.1371/journal.pone.0166005

Yamada, M., Kimura, M., Mori, T., & Endo, S. (1995). EEG power and coherence in presenile and senile depression. Characteristic findings related to differences between anxiety type and retardation type. *Journal of Nippon Medical School, 62*(2), 176–185. https://doi.org/10.1272/jnms1923.62.176

Yang, J., Yin, Y., Svob, C., Long, J., He, X., Zhang, Y., Xu, Z., Li, L., Liu, J., Dong, J., Zhang, Z., Wang, Z., & Yuan, Y. (2017). Amygdala atrophy and its functional disconnection with the cortico-striatal-pallidal-thalamic circuit in major depressive disorder in females. *PLoS ONE, 12*(1), Article e0168239. https://doi.org/10.1371/journal.pone.0168239

Zhang, L., Hu, X., Hu, Y., Tang, M., Qiu, H., Zhu, Z., Gao, Y., Li, H., Kuang, W., & Ji, W. (2022). Structural covariance network of the hippocampus–amygdala complex in medication-naïve patients with first-episode major depressive disorder. *Psychoradiology, 2*(4), 190–198. https://doi.org/10.1093/psyrad/kkac023

Zheng, J., Anderson, K. L., Leal, S. L., Shestyuk, A., Gulsen, G., Mnatsakanyan, L., Vadera, S., Hsu, F. P. K., Yassa, M. A., Knight, R. T., & Lin, J. J. (2017). Amygdala-hippocampal dynamics during salient information processing. *Nature Communications, 8*(1), Article 14413. https://doi.org/10.1038/ncomms14413

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The Applications of the Mindfulness-Based Cognitive Therapy and HRV Biofeedback in Modern Psychotherapy

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Abstract

This study evaluated the effectiveness of heart rate variability biofeedback (HRVB) and mindfulness-based cognitive therapy (MBCT) in diagnosing and treating stress and anxiety. HRVB provides real-time data on the autonomic nervous system (ANS), highlighting the balance between its sympathetic and parasympathetic functions, while MBCT, combined with breathing exercises, targets the parasympathetic system, promoting positive thought reconstruction. A 22-year-old male with extreme anxiety and palpitations underwent a 12-week psychotherapeutic program involving HRVB and MBCT techniques. He practiced daily personalized breathing and mindfulness exercises, integrating them into daily activities. The results showed a shift from a stressed sympathetic ANS state to a relaxed parasympathetic one. He also demonstrated the ability to control his heart rate and improve thought patterns, leading to better emotional balance. This study highlights the combined potential of HRVB and MBCT in enhancing stress resilience, vitality, and autonomic balance, highlighting HRVB's pivotal role in tracking patient progress in clinical settings.

Keywords: heart rate variability (HRV); autonomic; biofeedback; mindfulness

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Introduction

Heart rate variability biofeedback (HRVB) is a scientifically proven, noninvasive method and computer-based diagnostic program which monitors the autonomic nervous system (ANS) throughout the mind–body interaction, especially the balance between sympathetic (LF) and parasympathetic (HF) activity of the nervous system (Fournie et al., 2021; Khazan, 2013). Heart rate variability (HRV) is the variation of beat-to-beat intervals (bpm), also known as R-R intervals which evaluate a distance (ms) between each experienced heart rate (HR) beat (bpm), analyzing our overall psychophysiological conditions, vitality, cardiovascular health, and stress resistance (Malik et al., 1996). HRV is the natural rise and fall of HR in response to our breathing patterns, thoughts, emotions, the activity of concentration, conscious and subconscious fears, blood pressure, and hormones. Since a healthy HR should increase and decrease as we inhale and exhale, HRV reflects the general wellness of the organism, stress, autonomic balance, vitality, and homeostasis (Henriques et al., 2011). HRV measurements have become validated psychophysiological predictors of specific outcome situations in ecologically valid research and test paradigms with a parallel connection to the psychophysiological changes occurring in the participant. SDNN, the standard deviation of each normal R-R intervals of all cardiac cycles (IBIs), is the most important index for the HRV itself (Tabachnick, 2015). Monitoring SDNN and RMS-SD biomarkers in clinical settings can reveal participant's general cardiovascular health, stress resistance, psychophysiological resiliency to the environment, immunity, biorhythm regulation, and overall homeostasis (Fournié et al., 2021; Gevirtz & Lehrer, 2003). SDNN, together with RMS-SD, can be maintained or increased by awareness of proper breathing practices or techniques, especially with the concentration on an extended exhale phase and activation of the heart rate deceleration (HRD) in response to various environmental stimuli during test or performance (Carlstedt, 2018). The most ideal or desired HRV combination in any clinical test or performance (compared to the baseline or pretest and posttest measurements) requires lowered HR (HRD), increased SDNN, and RMS-SD with the activation of the high frequency (HF). The HF predominance reflects sudden changes in prolonged R-R interval, which activates the parasympathetic activation of the ANS with vagal nerve stimulation (Malik et al., 1996). The LF/HF ratio is also an important index that calculates the overall balance between the sympathetic and parasympathetic nervous system, especially in individualized HRV profiles to see the effectiveness of the breathing-relaxation-based paradigms and treatment modalities (Lehrer et al., 2000). Among the many factors that impact HRV, the most crucial are cognitive functions and respiration connected to the conscious or unconscious activities of the mind, including stress, anxiety, and breathing patterns. HRV measurements reveal many psychosomatic disorders and stress-related reactions in connection to heart–brain functions (Goldberg, 2022). Higher HRV reflects overall good psychophysiological health and vitality, adequate flexibility to stress, good aerobic fitness, functional homeostasis, and balance between the sympathetic and parasympathetic nervous systems (Fournié, 2021). On the other hand, lowered HRV may be associated with aging, decreased autonomic activity, lower hormonal tonus, depression, panic attacks, anxiety, and fatigue that have a negative impact on ANS, typically causing exhaustion of the parasympathetic tonus and the vagus nerve (Gevirtz, 2013).

Healthy and high resting HRV generates refined breathing patterns as self-regulatory strength to reduce negative emotions and enhance self-awareness and mindfulness about negative thoughts (Segerstrom & Nes, 2007). HRVB enables individuals to learn to regulate their breathing and relaxation techniques to create a base for daily routines initiating mindfulness meditations and self-healing exercises (Lehrer & Gevirtz, 2014). Several studies suggested that HRVB with mindfulness-based interventions may be an effective treatment for generalized anxiety disorder, posttraumatic stress disorder (PTSD), and other psychophysiological disorders (i.e., Kemp et al., 2012; Prinsloo et al., 2013; Wells et al., 2012; Zucker et al., 2009). During the HRVB trainings, the individuals learn to breathe at the optimal respiratory frequency, which needs to be set and later optimized during the training to maximize the increase of their HRV for the best stress resistance (Moore et al., 2011; Prinsloo et al., 2013). HRVB displays beat-to-beat changes in HR to teach the clients to maximize the HR increase during inhalation and decrease HR during exhalation. This process which is practiced daily by the clients is naturally imprinted into the ANS and regulated by the vagus nerve and the mechanism called respiratory sinus arrhythmia (RSA; Gevirtz, 2013). The therapeutic goal is to increase the HRV by increasing the HRV amplitude (the length in HRs between the highest point of the inhale and lowest point of the exhale) to strengthen the stress resistance, homeostasis, and baroreflex mechanism in patients (Gevirtz, 2000, 2007, 2011; Gevirtz & Lehrer, 2003; Giardino et al., 2000; La Rovere et al., 1998; Lehrer, 2007).

The research has shown that combining HRVB with mindfulness-related psychotherapies, including prolonged exposure therapy (PET), acceptance and commitment therapy (ACT), mindfulness-based interaction (MBI), or mindfulness-based stress reduction (MBSR), is necessary to improve the efficacy of the treatments for stress and anxiety-related disorders, including PTSD and panic attacks (Dalenberg, 2014; Edwards, 2011; Gevirtz, 2015; Kim et al., 2021). Combining ACT, known for components of mindfulness-based therapy, with HRVB showed high compatibility as a powerful tool for treating anxiety and stress-related disorders including trauma (Gevirtz, 2015, 2020). MBI and HRVB were successfully combined in studies by Azam et al. (2016) and Krygier et al. (2013) to improve the patients' regulation of the autonomic and central nervous systems through the stress reduction program. In another study, the efficacy of the combination of HRVB and MBI showed a decrease in cortisol levels in participants (Bouchard et al., 2012; O'Leary et al., 2015; Sanada et al., 2016). The positive intervention of an 8-week MBSR program with HRV measurements was presented in the treatment of people with schizophrenia as an effective nursing intervention to reduce stress responses and improve HRV and psychological well-being (Kim et al., 2021). In applying stress-reducing treatments, a 5-week mindfulness meditation (MM) intervention and HRVB showed effective results for 76 participants in terms of reduced stress, anxiety, and depressive symptoms and improved sleep quality (van der Zwan et al., 2015). Integrating a 12-week compassion focus psychotherapy (CFP) program improved resting HRV in participants by focusing on self-compassion, writing skills, and emotional awareness (Steffen et al. 2021).

Mindfulness-based cognitive therapy (MBCT) is a contemporary psychotherapy initially designed for the treatment of depression, but it has also been applied to the treatment of generalized anxiety and stress-related disorders (Evans et al., 2008; Kenny & Williams, 2007; Teasdale et al., 2000; van Aalderen et al., 2012). MBCT teaches patients to pay close attention to their internal experience, including concentration on the breath in the present moment, thoughts-related evaluating processes, body sensations, feelings, and emotions (Evans et al., 2008). MBCT is intended to improve inner awareness and acceptance of intrusive thoughts and feelings (Teasdale et al., 2000). MBCT educates participants to detach from habitual and repetitive negative thinking patterns and worrying thoughts which might lead to depression (Teasdale et al., 2000). MBCT programs train participants to be in the present moment with empathy for all people equally in a nonjudgmental manner (Baer, 2003; Kabat-Zinn, 1990). Some studies explored the relationship between MBCT and HRV combination, suggesting that mindfulness exercises may enhance the effectiveness of self-regulatory processes, including breathing to increase self-awareness about thoughts (Peressutti et al., 2012), and control over the HR to enhance HRV (Delizonna et al., 2009; Ditto et al., 2006). Considering meditative practices as part of MBCT, Peressutti et al. (2010) showed evidence that positive HRV changes correlated with years of experience and breathing practices of the meditators, whereas Ditto et al. (2006) found that scan meditation (a skill used in MBCT) had a positive effect on RSA breathing by increasing vagal activity of the parasympathetic control of the ANS among meditative participants.

The purpose of this study was to examine the effect of the relationship between MBCT with breathing exercises and the HRV changes seen in the patient who suffered from high anxiety, HR palpitations, and panic attacks. A 12-week MBCT program tailored to the patient after his first (baseline) HRV measurements generated a new HRV imprint where an additional four HRV measurements were analyzed and compared. This case study shows how poor HRV with symptoms of chronic stress, fatigue, and high anxiety can be modified within a few weeks and eventually completely changed by doing the MBCT breathing exercises and mindfulness techniques without any psychiatric medication.

Methodology

Participant

The patient was a 22-year-old college student suffering from high anxiety, anger issues, chronic panic attacks, and HR palpitations. His triggers included a turbulent relationship with his father, part-time work environment pressure, low self-esteem, and low self-confidence. The patient was single and financially unstable. He was a light smoker.

All procedures performed in studies involving human participants were in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki and its later amendments. Informed consent was obtained from the participant included in the study.

MBCT Intervention

The 12-week MBCT program was designed to integrate aspects of controlled breathing exercises and cognitive work. The patient came to the clinic once a week and learned a 20-min breathing exercise in which he alternated two different breathing patterns. The first breathing pattern (3x2x6x2) he performed for 2 min in which he inhaled by nose for 3 s, then held for 2 s, then exhaled by mouth for 6 s, and then held the breath for 2 s after the exhale. The second breathing pattern (3x3x3) he learned involved inhaling for 3 s through the nose, then exhaling through the nose for 3 s, and then holding the breath after the exhale for 3 s. The patient alternated these two breathing patterns every 2 min for an overall 10 min. For the last 10 min, he performed only the meditative pattern (3x3x3) in which he inhaled for 3 s through the nose, exhaled through the nose for 3 s, and then held his breath after the exhale for 3 s. The patient continued the 20-min breathing exercise at home every morning before he went to work for the 12-week treatment period. The 20-min breathing exercise and its impact on HRV are presented in Table 1.

Table 1
A 20-Min Breathing Exercise

Time (min)	Breathing Pattern	Duration (min)	Purpose for HRV
1–2	3x2x6x2	2	Increased HRV
3–4	3x3x3	2	Relaxed HRV
4–6	3x2x6x2	2	Increased HRV
6–8	3x3x3	2	Relaxed HRV
8–10	3x2x6x2	2	Increased HRV
10–20	3x3x3	10	Relaxed HRV

3x2x6x2 Breathing Pattern

The purpose of the 3x2x6x2 breathing pattern was to increase the HRV by stretching the HR pulses during the highest point of the inhale phase when the HR goes up and the lowest point of the exhale phase when the HR goes down. Holding the breath for 2 s after inhaling increases HR, whereas holding the breath after exhaling lowers the HR.

This breathing exercise looks in reality through the HRV using a Polar RS800 watch (Figure 1). The underlining segment is a 1-min 3x2x6x2 breathing pattern. With this breathing pattern, we are stretching our HRV; in other words, we are increasing our stress resistance by extending the bpm within the highest point of the inhale phase and the lowest point of the exhale phase. We can see that the average HR was 64 bpm, the highest HR was 85, and the lowest HR was 54 bpm. The difference made was 31 bpm. This HR elasticity of the nervous system generated an SDNN of 130.1 ms or the TP was 16.900 ms, from which 89% of this energy was utilized in the LF 15.002 Hz, indicating more sympathetic activation of the nervous system. Our cells have memory, which means that if we practice breathing 3x2x6x2 regularly on a daily basis, we are imprinting (generating) HR coherence into the nervous system as HRV plasticity into the neurocardiovascular system. In critical daily situations, if we activate this breathing, the cells recognize the purpose of this HRV imprint, and they will react immediately to reduce the stress.

3x3x3 Breathing Pattern

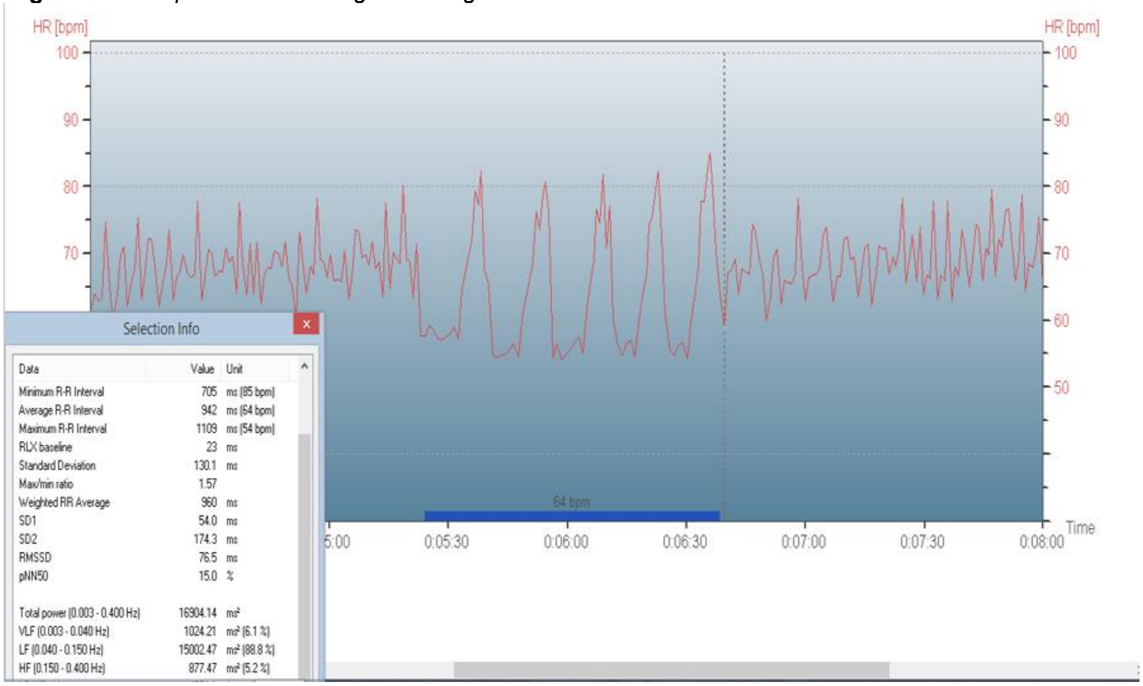
The 3x3x3 is a meditative pattern in which we concentrated on the coherence, stability, and endurance of the breathing in which the inhale and exhale phases are coherent and the same regarding the amplitude and frequency in the HRV graph.

HRV monitored by Polar RS800 watch shows the highlighted section of 3x3x3 breathing pattern (Figure 2). The purpose of this breathing pattern is to imprint into our cells and neurocardiovascular system the optimal HRV zone functioning in which we feel comfortably relaxed. In particular, the second part of this 1-min breathing pattern was very coherent. We can see that the highest point of the inhale was 79 bpm, the average was 69 bpm, and the lowest was 59 bpm, presenting lower variability and energy level as the SDNN was 54 ms. The TP was 2.319 ms, from which the HF indicating net parasympathetic stimulation was 67%. It is shown that for the activation of the parasympathetic nervous system, we do not need to generate a high variability. On the contrary, we need coherent and shorter breaths to the diaphragm region of the abdomen with a short maybe 2- to 3-s hold after the exhale phase to deepen the HR. Therefore, practicing this 3x3x3 breathing pattern daily can benefit people with high anxiety, sleeping problems, or difficulties switching off and relaxing.

The Cognitive Work

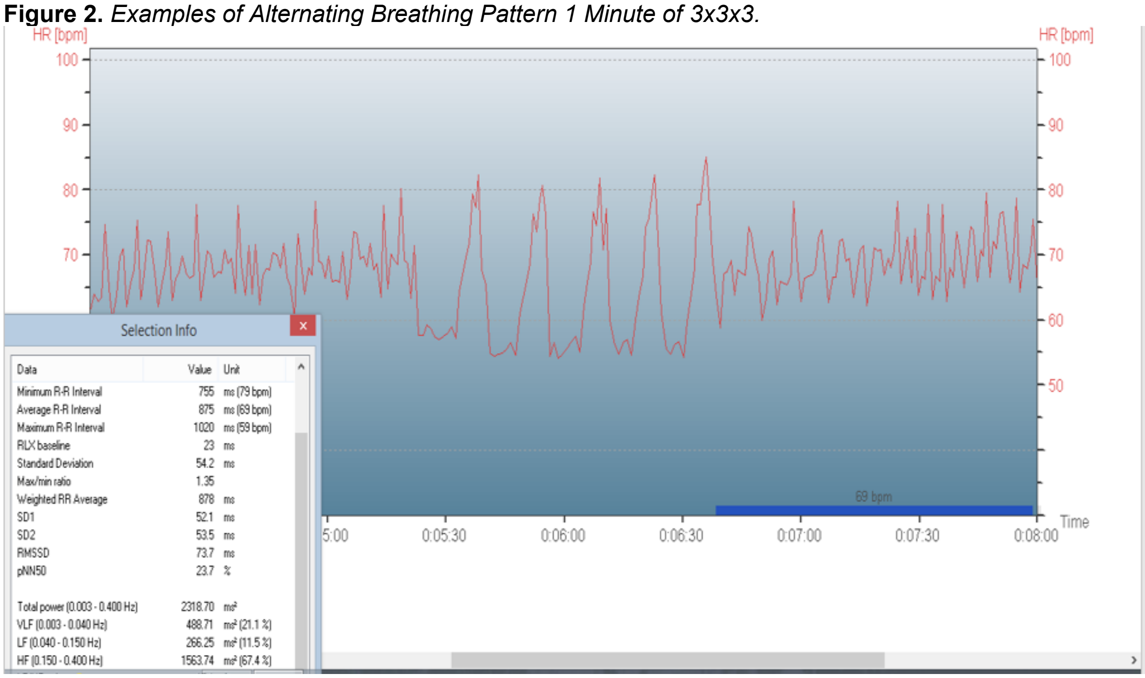
Applying MBCT with HRVB helped the patient increase his awareness of his intrusive thoughts and the ability to change or reevaluate them according to his willpower and intention. Throughout the applications of the MBCT, the patient learned to use positive self-talk and affirmations when exhaling to lower his HR in critical situations and thus slow down the current of the intrusive thoughts to be able to change them. The 6-s exhale phase, which he trained in during the morning exercises, allowed him to alter the negative images by applying mindfulness in critical situations and using positive self-talk. MBCT also integrated meditative techniques to enhance his moment-to-moment awareness, nonjudgmental acceptance, and unconditional empathy to increase his self-esteem in activating the parasympathetic nervous system.

Figure 1. *Examples of Alternating Breathing Pattern for 1 Min of 3x2x6x2.*



Note. Examples of the alternating breathing pattern for 1 min of 3x2x6x2 followed by 1 min of 3x3x3 monitored by Polar RS800 watch. The highlighted section is the 3x2x6x2 breathing with HRV data in the small table.

Figure 2. *Examples of Alternating Breathing Pattern 1 Minute of 3x3x3.*



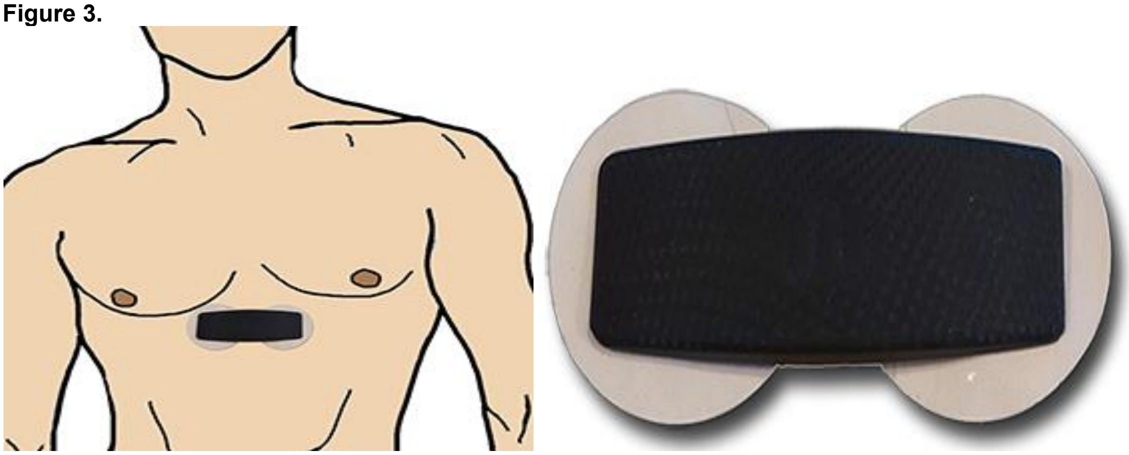
Note. Examples of alternating breathing pattern for 1 min of 3x2x6x2 followed by 1 min of 3x3x3 monitored by Polar RS800 watch. The highlighted section is the 3x3x3 breathing pattern with HRV data in the small table.

HRV Measurements

Biocom 6000 Bluetooth ECG Recorder was used in this study, and the HRV measurements were taken in a clinical setting. Biocom Technologies is the global leader in developing, manufacturing and marketing HRV products (Biocom Technologies, 2023). In addition, Biocom develops biomedical software and hardware products designed to monitor physiology for research and educational purposes.

HRV is analyzed by (a) time domain analysis which includes mean HR (bpm), mean R-R (ms), SDNN (ms), RMS-SD (ms), pNN50 (%); and (b) frequency domain analysis which includes the power spectrum of overall ANS including total power, VLF, LF-sympathetic activation, HF-parasympathetic activation, and LF/HF ratio (Malik et al., 1996). A 5-min HRV test was performed in a sitting position at the beginning of each psychotherapy session.

Figure 3.



Note. The placement of the Biocom 6000 Bluetooth ECG recorder on the participant to measure HRV using Biocom Technologies software.

Results

In the 12-week MBCT program tailored to the patient, 4 weeks: Week-1 baseline, Week-4, Week-8, and Week-12 final were thoroughly analyzed by HRV time domain analysis (Table 2) and HRV frequency domain analysis (Table 3). In addition, the changes and new HRV imprints of the 4 weeks were compared in graphs (Figures 4, 5) and the original Biocom Technologies Autonomic Assessments (Figures 6, 7, 8, 9), which displayed the actual 5-min HRV measurements taken at the beginning of each four therapeutic sessions.

Table 2
Time Domain Analysis

HRV Measurements	Mean HR (bpm)	Mean RR (ms)	SDNN (ms)	RMS-SD (ms)	pNN50 %
Week 1 - Baseline	113.9	526.7	38.2	9.5	0.0
Week 4	91.6	655.1	39.3	14.5	0.4
Week 8	78.3	766.7	54.7	37.6	16.6
Week 12 - Final	71.1	844.5	55.3	43.4	24.2

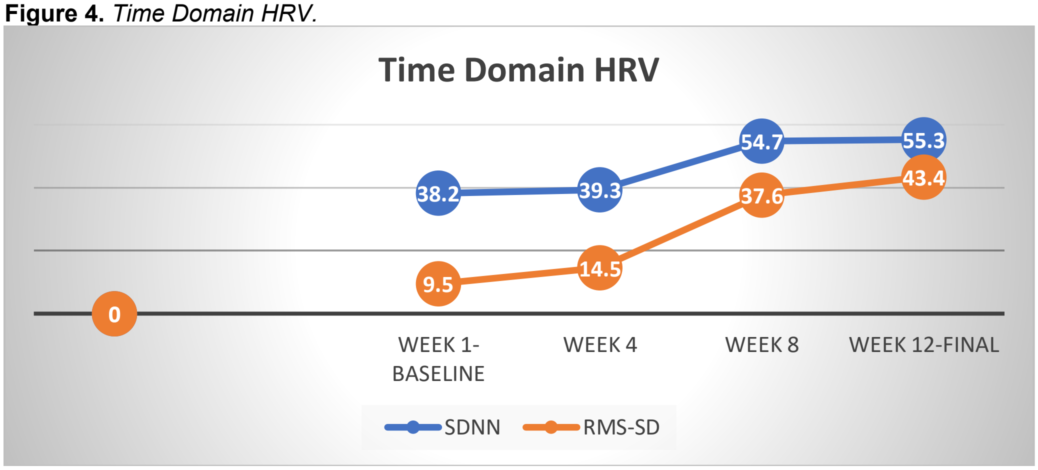
Note. The progress in patient's stress resistance is seen as the mean HR (bpm) is lowering and SDNN (HRV) and RMS-SD (parasympathetic level) indexes are increasing over the 12 weeks.

Table 3
Frequency Domain Analysis

HRV Measurement	TP (ms^2/Hz)	VLP (ms^2/Hz)	LF (ms^2/Hz)	HF (ms^2/Hz)	LF/HF	LF Norm %	HF Norm %
Week 1 - Baseline	473.9	355.8	95.0	23.2	4.1	80.4	19.6
Week 4	436.4	255.9	135.2	45.4	3.0	74.9	25.1
Week 8	776.6	246.6	145.5	384.7	0.4	27.4	72.6
Week 12 - Final	973.7	123.1	225.9	624.6	0.4	26.6	73.4

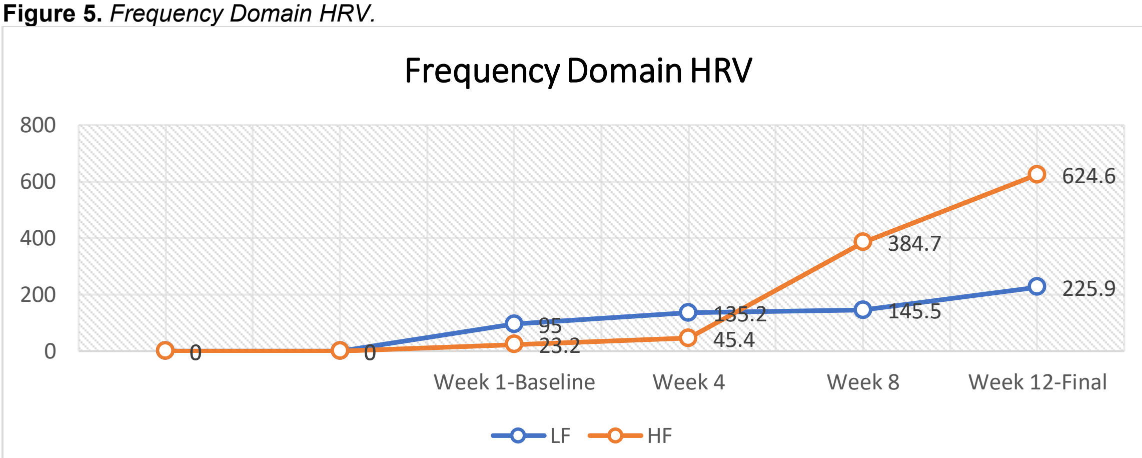
Note. The progress in the patient's stress resistance is seen as the TP (total power-index for energy level). It has increased over the 12 weeks, together with the enhanced level of the HF-parasympathetic vagal activation of the ANS.

Figure 4. *Time Domain HRV.*



Note. HRV improvement is measured in SDNN and RMS-SD index levels. The RMS-SD index indicates the parasympathetic branch, considered the most relevant and accurate measure of ANS activity over the short term.

Figure 5. *Frequency Domain HRV.*



Note. Improvement in HF (parasympathetic nervous system) vagal activity to learn relaxation techniques applying the breathing exercises and meditation techniques. HF index is also known as a "respiratory" band because it corresponds to the HR variations caused by respiration (this phenomenon is known as respiratory sinus arrhythmia [RSA]).

The original Biocom Technologies 5-min HRV assessments were taken before the first (baseline), fourth, eighth, and twelfth (final) psychotherapeutic sessions (Figures 6, 7, 8, 9). The most significant indicator of stress is the HR waveform graph which displays the activity of the HR variation impacted by conscious or unconscious breathing patterns with mental processes which created specific HRV waveforms. This process generates HR coherence or incoherence, interpreting the stress or relaxation responses for further HRV data analysis. Over the 12-week timeframe, the results displayed how the HR waveforms were changed and became more coherent, consistent, and synchronized, reflecting equal amplitudes of the inhale and exhale phases which generated balance in the ANS and homeostasis. The learned and trained psychotherapeutic progress culminated in Week 12 during the final HRV measurement outcome (see Figure 9).

Figure 6. *Week 1. HRV Baseline - Biocom Technologies Autonomic Assessment Showing High Stress Level of the Patient.*

Figure 7. *Week 4. HRV-Biocom Technologies Autonomic Assessment Showing Moderated Stress Level of the Patient.*

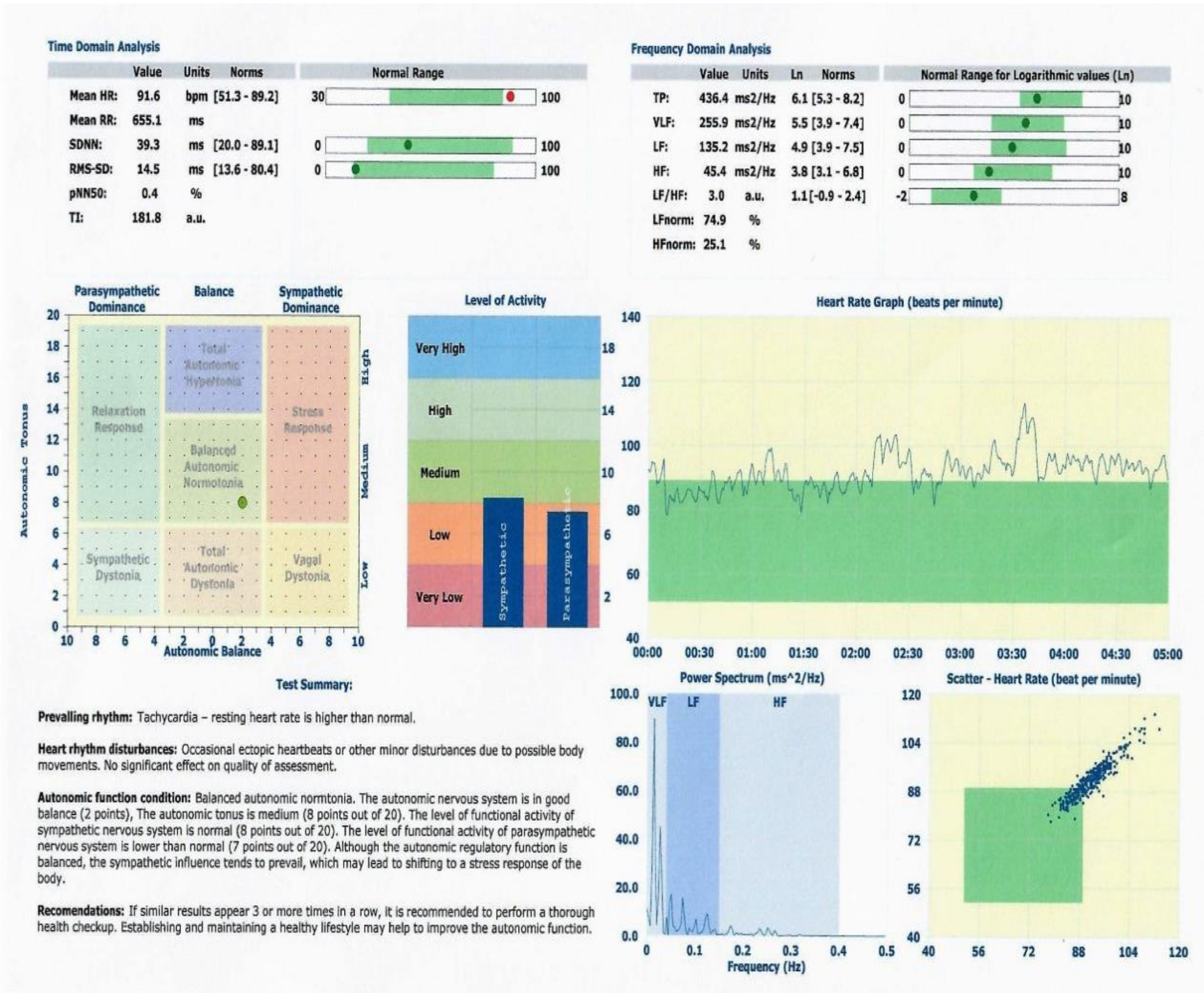


Figure 8. *Week 8. HRV - Biocom Technologies Autonomic Assessment Showing Improvement in Relaxation Ability of the Patient.*

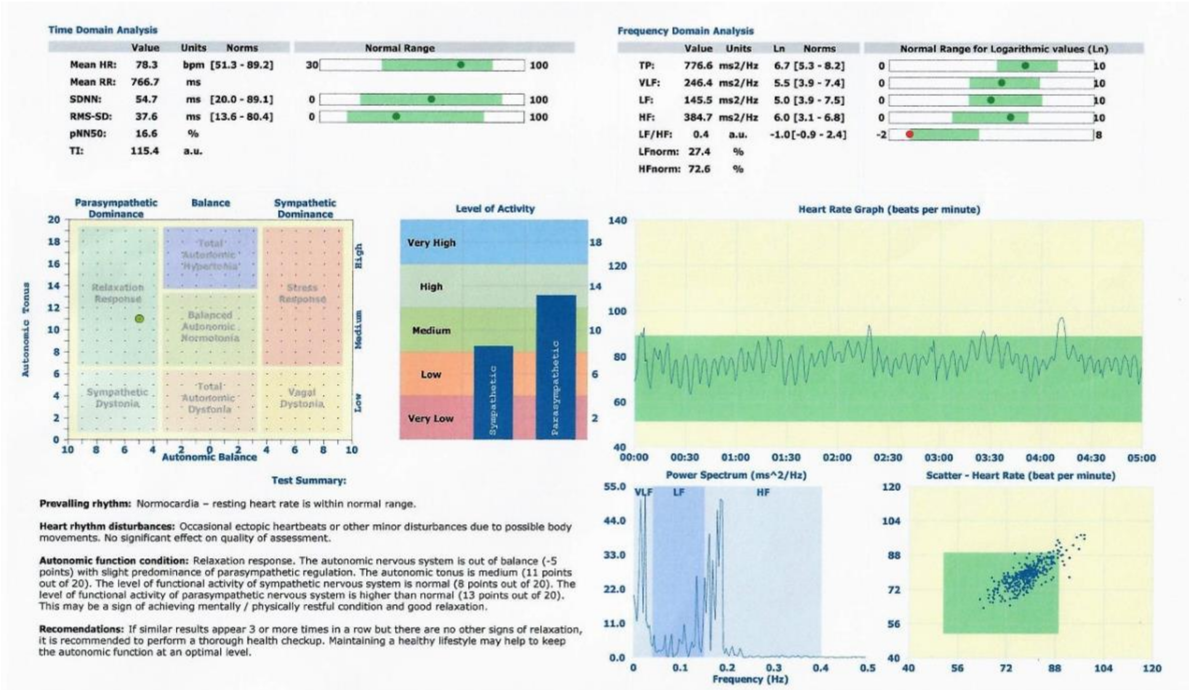
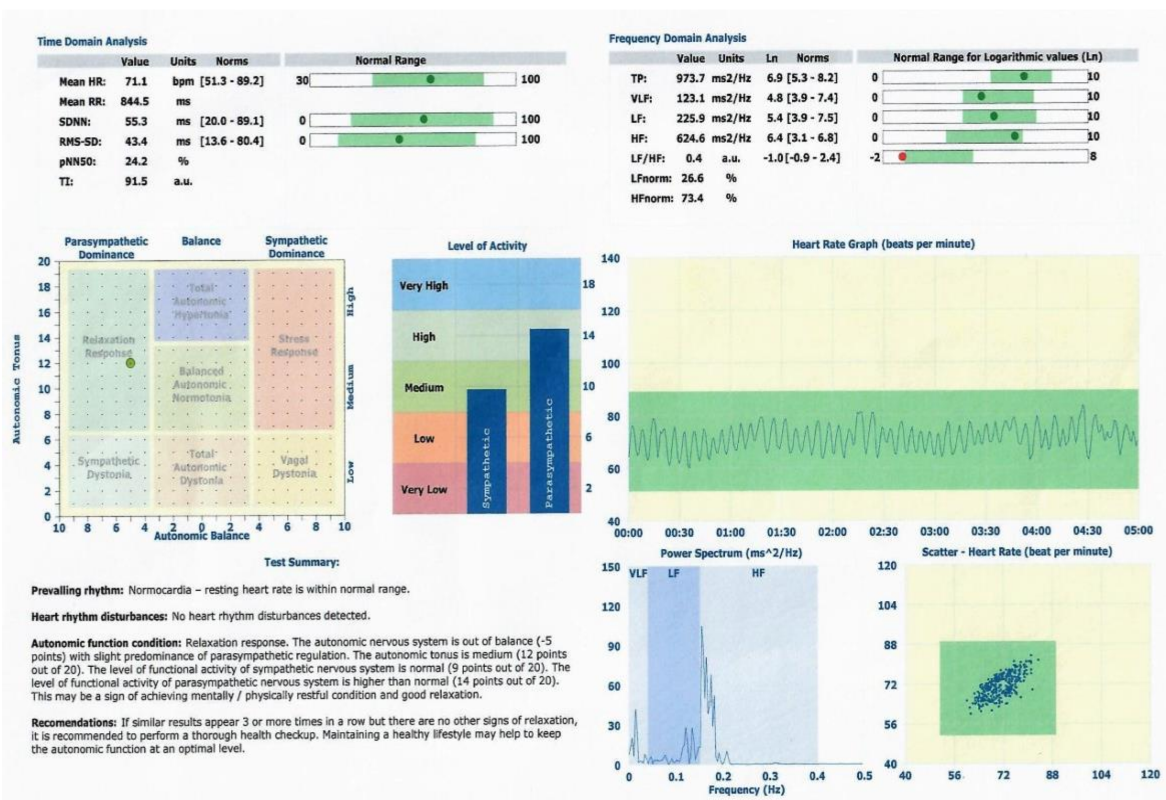


Figure 9. *Week 12. HRV Final - Biocom Technologies Autonomic Assessment Showing Good Relaxation Respond of the Patient.*



Discussion

The objective of this study was to show how the combination of the HRVB and MBCT might be applied in modern psychotherapeutic settings for effective diagnoses and treatment of the patient. It is evident that HRVB has become a well-sought noninvasive diagnostic tool for objectively diagnosing and monitoring the patients regarding anxiety and stress-related disorders. It is because only HRVB can provide the data of the ANS, which is essential information for a further therapeutic outline of the treatment. For psychotherapists, it is important to objectively see the stress level in patients and which branch of the ANS (sympathetic or parasympathetic) dominates to tailor the proper treatment and generate the balance of the ANS. In the therapeutic setting, the HRVB has become a very good learning and teaching tool when the patient is able to visually learn on the computer screen how anxiety and stress can be managed in terms of HR monitoring during the breathing exercises or when using positive mental affirmations and meditative practices. Similarly, HRVB should become a motivational and transparent diagnostic tool for the patient and the therapist to monitor the progress of the treatment, which can be seen just in a few weeks in the newly moderated HRV imprints of the patient. In other words, seeing on the screen the HRV outcomes, the patient cannot lie to the therapist if he does or does not do the breathing exercises daily, and neither can the therapist lie about the progress or failure of the treatment.

In this study, the HRVB was measured by computer-based Biocom Technologies Autonomic Assessments which provide comprehensive HRV examinations including time domain analysis, frequency domain analysis, heart rate graph waves, power spectrum analysis, scatter-heart rate graph, comparable levels of LF and HF activities, autonomic tonus and balance comparison, and written test summary (Biocom Technologies, 2023). The following sections offer narrative descriptions of the four HRV measurements thoroughly analyzed in the study. These descriptions are mental representations of the feelings and emotions experienced by the participant when the HRV measurements were taken. The 5-min HRV measurements were taken at the beginning of each session.

Week 1: Baseline HRV Measurement (Figure 6)

The patient came to the clinic for the first time and took the first baseline HRV assessment for an initial diagnosis. We can see that he felt very high anxiety and stress where the HR palpitations escalated over 135 bpm, activating the sympathetic nervous system with symptoms of chronic stress, fatigue, and insomnia. The average HR was 114 bpm, with a low SDNN of 38.2 ms in total autonomic dystonia.

We analyzed the situation, and he began to open up and disclosed his stressors, including bad relationships with his father and his boss at work. The patient also confessed to having feelings of anger towards everyone around him, especially towards his boss because he felt disrespected by him at work. He blamed others to excuse his failures. After we analyzed the situation, we introduced the breathing exercises 3x2x6x2 and 3x3x3 (see Table 1). He started to do breathing exercises daily along with MBCT and some mindfulness techniques to reevaluate his stances towards certain life situations and people positively. He was quite dedicated, and the positive results were soon achieved.

Week 4: HRV Measurement (5 Min; Figure 7)

In this HRV measurement, we can see that after 4 weeks of training, the HRV imprint became more coherent, lowering the patient's HR to 92 bpm (average) and generating a more balanced autonomic assessment. However, the nerve and the cognitive system still triggered minor palpitations stimulating the sympathetic nervous system. However, the HR palpitations were shorter in time and frequency but still reached 115 bpm, which is relatively high compared to his baseline. We can also see that the HR palpitations dropped quickly, which was a good sign for a faster recovery in terms of a new imprint of the HRV to the patient's ANS. The patient learned that the images of unresolved problems, such as faces or body images of his father or boss, from his subconsciousness were causing these HR spikes. It is because the ANS recognized the images as a mental threat trying to activate the sympathetic nervous system to fight them by increasing the HR. By applying the MBCT, the patient learned how to neutralize the intrusive images and reevaluate them differently in a more peaceful way using the new positive inner stances towards them more empathetically to accept them as learning and training opportunities for his stress resistance.

Week 8: HRV Measurement (5 Min; Figure 8)

In this HRV measurement, the patient reached the parasympathetic HF vagal activity for the first time. We can see that the HRV became more coherent, and HR spikes are more consistent in frequency and amplitude. This new HRV imprint guaranteed comfortable and optimal HRV zone functioning, positively impacting overall homeostasis. The average HR was lowered to 78 bpm which increased the SDNN (54.7 ms) and RMS-SD (37.6 ms), respectively, showing increased stress resistance and vitality.

The patient was dedicated to breathing exercises, and we can see excellent phases of HRV coherence in deep HF parasympathetic relaxation. As the HR lowered, the current of the thoughts also slowed, allowing him to reconstruct the thoughts more comfortably and empathetically using the MBCT techniques. Therefore, if the patient knew how to activate HF and relaxation in the ambulatory or clinical environment, he could maintain the new HRV imprint anywhere and anytime, using his skills and willpower. In other words, the ANS and homeostasis will only activate what is trained, learned, and imprinted on the ANS.

Week 12: Final HRV Measurement (5 Min; Figure 9)

In this measurement, the patient performed the 3x3x3 meditative breathing pattern. The goal was to calm the mind and completely switch off in a more meditative-empathetic mode. This was his best HRV outcome, and it was not easy to do it at all. The average HR was lowered to 71 bpm with increased RMS-SD (43.4 ms) in deep HF parasympathetic vagal meditative response. The most important was that the patient was able to maintain the 3x3x3 breathing meditative HRV shape for 5 min without any conscious or unconscious disturbances, seen in the HRV graph as desynchronized or incoherent HR spikes. During the 12 weeks, the patient also developed specific MBCT skills and coping mechanism techniques which he wisely applied in daily stress-related situations. Applying the MBCT, the patient also completely reevaluated some stances to his current situation, especially in the relationships with his father, which used to cause him stress, hate, and anger previously seen as HR spikes in the HRV graphs. As we can see, with dedicated training, the optimal HRV zone functioning can eventually be imprinted into the ANS system by practicing daily breathing exercises with positive affirmations, visualization skills, and self-talk.

It became evident that it took a few weeks for the patient to understand and familiarize himself with the mechanism of breathing exercises in connection to his inner work in terms of using positive self-talk. The patient disclosed having problems seeing and detecting negative and fearful thoughts at the beginning of the treatment sessions. However, as he practiced more, he felt better and became more self-confident and in control. He reported that in critical stress-related situations or worries about the future, he immediately applied the 3x2x6x2 breathing pattern, which helped him regulate the stress as he slowly exhaled through the mouth. Especially during the extended exhale phase, he learned to repeat the affirmations and positive self-talks. He implemented the same techniques during moments of anger or flashbacks connected to past-related memories that were unexpectedly playing out through his mind. In this approach, we need to consider that the patient visually learned on the HRV computer how these intrusive images were detrimental to ANS, causing HRV incoherence and HR stress-related spikes.

Since his HRV was monitored weekly and he could see the HR incoherence, it helped him believe in this treatment technique with high self-confidence and determination. This therapeutic mechanism can be applied effectively based on self-hypnotism when, during the exhale phase, the time during the HR pulses (bpm) is spreading, and the ANS system is calming down. This therapeutic process confirmed a new self-healing paradigm on increasing mindfulness and self-awareness of thoughts connected to the deep subconscious level by embedding new positive images and schemas with high self-confidence.

Conclusion

This study advocates using HRVB as a scientific apparatus to measure stress with MBCT as a holistic modality. Combining both approaches has shown to be an effective diagnostic and therapeutic method for treating patients with stress-related disorders. The patient in the study made progress by following the exact procedures as seen on the HRV monitors. This progress developed the patient's motivation and self-confidence needed to believe in this treatment.

During the 12-week MBCT program, the patient could completely transform his stressful and unhealthy HRV pattern into a healthy one by activating the HF parasympathetic nervous system using willpower. Therefore, for psychotherapists, it is important to objectively assess the stress levels in the patient, especially by monitoring the patient's prevalent reactions and tendencies in either the sympathetic or parasympathetic nervous system.

By applying HRVB, the patients learn about their mind–body interactions, breathing, and thought processes. They quickly realize the detrimental effect of negative and intrusive thoughts on their mental health. The real-time monitoring of HRV on the screens during the sessions enables psychotherapists to diagnose more quickly and efficiently. It also makes the treatment more transparent and interesting for the patients.

This study strengthens the idea that HRVB is an effective teaching and learning tool for psychotherapists and patients to increase the quality of the treatment and motivation factors for the patients in clinical settings.

Author Declaration

The author has no competing interests to declare that are relevant to the content of this article. No funding was received for conducting this study.

References

Azam, M. A., Katz, J., Mohabir, V., & Ritvo, P. (2016). Individuals with tension and migraine headaches exhibit increased heart rate variability during post-stress mindfulness meditation practice but a decrease during a post-stress control condition—A randomized, controlled experiment. *International Journal of Psychophysiology, 110*, 66–74. https://doi.org/10.1016/j.ijpsycho.2016.10.011

Baer, R. A. (2003). Mindfulness training as a clinical intervention: A conceptual and empirical review. *Clinical Psychology: Science and Practice, 10*(2), 125–143. https://doi.org/10.1093/clipsy.bpg015

Biocom Technologies. (2023). *Health assessment products with heart rate variability analysis (HRV)*. Biocom Technologies. https://www.biocomtech.com/

Bouchard, S., Bernier, F., Boivin, E., Morin, B., & Robillard, G. (2012). Using biofeedback while immersed in a stressful videogame increases the effectiveness of stress management skills in soldiers. *PLoS ONE, 7*(4), Article e36169. https://doi.org/10.1371/journal.pone.0036169

Carlstedt, R. (Ed.). (2018). *Handbook of sport neuroscience and psychophysiology*. Routledge.

Dalenberg, C. (2014). The treatment of trauma: Integrating HRV and cognitive behavior therapy. Paper presented at the Association of Applied Psychophysiology and Biofeedback Meeting, Savannah, GA.

Delizonna, L. L., Williams, R. P., & Langer, E. J. (2009). The effect of mindfulness on heart rate control. *Journal of Adult Development, 16*(2), 61–65. https://doi.org/10.1007/s10804-009-9050-6

Ditto, B., Eclache, M., & Goldman, N. (2006). Short-term autonomic and cardiovascular effects of mindfulness body scan meditation. *Annals of Behavioral Medicine, 32*(3), 227–234. https://doi.org/10.1207/s15324796abm3203_9

Edwards, L. (2011) Biofeedback, meditation, and mindfulness. *Biofeedback, 39*(2), 67–70. https://doi.org/10.5298/1081-5937-39.2.02

Evans, S., Ferrando, S., Findler, M., Stowell, C., Smart, C., & Haglin, D. (2008). Mindfulness-based cognitive therapy for generalized anxiety disorder. *Journal of Anxiety Disorders, 22*, 716–721. https://doi.org/10.1016/j.janxdis.2007.07.005

Fournié, C., Chouchou, F., Dalleau, G., Caderby, T., Cabrera, Q., & Verkindt, C. (2021). Heart rate variability biofeedback in chronic disease management: A systematic review. *Complementary Therapies in Medicine, 60*. https://doi.org/10.1016/j.ctim.2021.102750

Gevirtz, R. (2000). Resonant frequency training to restore homeostasis for treatment of psychophysiological disorders. *Biofeedback, 27*, 7–9.

Gevirtz, R. N. (2007). Psychophysiological perspectives on stress-related and anxiety disorders. In P. M. Lehrer, R. L. Woolfolk, & W. E. Sime (Eds.), *Principles and practice of stress management* (3rd ed., pp. 209–226). The Guilford Press.

Gevirtz, R. (2011). Autonomic nervous system markers for psychophysiological, anxiety, and physical disorders. In E. K. Gordon & S. H., Koslow (Ed.), *Integrative neuroscience and personalized medicine* (pp. 164–180). Oxford Press.

Gevirtz, R. (2013). The promise of heart rate variability biofeedback: Evidence-based application. *Biofeedback, 41*, 110–120. https://doi.org/10.5298/1081-5937-41.3.01

Gevirtz, R. (2015). Integrating heart rate variability biofeedback into mindfulness-based therapies. *Biofeedback, 43*(3), 129–132. https://doi.org/10.5298/1081-5937-43.3.03

Gevirtz, R. (2020). Incorporating heart rate variability biofeedback into acceptance and commitment therapy. *Biofeedback, 48*(1), 16–19. https://www.doi.org/10.5298/1081-5937-48.01.05

Gevirtz, R., & Lehrer, P. (2003). Resonant frequency heart rate biofeedback. In M. S. Schwartz & F. Andrasik (Eds.), *Biofeedback: A practitioner's guide* (3rd ed.). Guilford Press.

Giardino, A., Lehrer, P., & Feldman, J. M. (2000). The role of oscillations in self-regulation: A revision of the classical model of homeostasis. In D. Kenney, J. G. Carlson, F. J. McGuigan, & J. L. Sheppard (Eds.), *Stress and health: Research and clinical applications* (pp. 27–52). Harwood.

Goldberg, R. C. (2022). *Exploring the relationships among bio-psycho-social measures of stress: A multifactorial approach towards the evaluation and reduction of stress* (Order No. 28869139). ProQuest Central (2617235663). https://www.proquest.com/dissertations-theses/exploring-relationships-among-bio-psycho-social/docview/2617235663/se-2

Henriques, G., Keffer, S., Abrahamson, C., Jeanne Horst, S. (2011). Exploring the effectiveness of a computer-based heart rate variability biofeedback program in reducing anxiety in college students. *Applied Psychophysiology and Biofeedback 36*, 101–112. https://doi.org/10.1007/s10484-011-9151-4

Kabat-Zinn, J. (1990). *Full catastrophe living: Using the wisdom of your body and mind to face stress, pain, and illness*. Delacorte.

Kemp, A. H., Quintana, D. S., Felmingham, K. L., Matthews, S., & Jelinek, H. F. (2012). Depression, comorbid anxiety disorders, and heart rate variability in physically healthy, unmedicated patients: Implications for cardiovascular risk. *PLoS ONE, 7*(2), Article e30777. https://doi.org/10.1371/journal.pone.0030777

Kenny, M. A., & Williams, J. M. G. (2006). Treatment-resistant depressed patients show a good response to mindfulness-based cognitive therapy. *Behaviour Research and Therapy, 45*(3), 617–625. https://doi.org/10.1016/j.brat.2006.04.008

Khazan, I. Z. (2013). The clinical handbook of biofeedback: A step-by-step guide for training and practice with mindfulness. Wiley-Blackwell.

Kim, A. S., Mi, H. J., & Min, J. S. (2021). Effects of mindfulness-based stress reduction (MBSR) on stress, heart rate variability, affect, and wellbeing among people with schizophrenia. *International Journal of Environmental Research and Public Health, 18*(22), Article 11871. https://doi.org/10.3390/ijerph182211871

Krygier, J. R., Heathers, J. A., Shahrestani, S., Abbott, M., Gross, J. J., & Kemp, A. H. (2013). Mindfulness meditation, well-being, and heart rate variability: A preliminary investigation into the impact of intensive Vipassana meditation. *International Journal of Psychophysiology, 89*(3), 305–313. https://doi.org/10.1016/j.ijpsycho.2013.06.017

La Rovere, M. T., Bigger, J. T., Marcus, F. I., Mortara, A., & Schwartz, P. J. (1998). Baroreflex sensitivity and heart-rate variability in prediction of total cardiac mortality after myocardial infarction. *The Lancet, 351*(9101), 478–484. https://doi.org/10.1016/S0140-6736(97)11144-8

Lehrer, P. (2007). Biofeedback training to increase heart rate variability. In P. M. Lehrer & R. L. Woolfolk (Eds.), *Principles and practice of stress management* (3rd ed.). Guilford Press.

Lehrer, P. M., & Gevirtz, R. (2014). Heart rate variability biofeedback: How and why does it work? *Psychology for Clinical Setting, 5*, Article 756. https://doi.org/10.3389/fpsyg.2014.00756

Lehrer, P. M., Vaschillo, E., & Vaschillo, B. (2000). Resonant frequency biofeedback training to increase cardiac variability: Rationale and manual for training. *Applied Psychophysiology and Biofeedback, 25*(3), 177–191. https://doi.org/10.1023/A:1009554825745

Malik, M., Bigger, J. T., Camm, A. J., Kleiger, R. E., Malliani, A., Moss, A. J., & Schwartz, P. J. (1996). Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. *European Heart Journal, 17*(3), 354–381. https://doi.org/10.1093/oxfordjournals.eurheartj.a014868

Moore, M., Brow, D., Money, N., & Bates, M. (2011). Mind–body skills for regulating the autonomic nervous system. Defense Centers of Excellence for Psychological Health & Traumatic Brain Injuries.

O'Leary, K., O'Neill, S., & Dockray, S. (2015). A systematic review of the effects of mindfulness interventions on cortisol. *Journal of Health Psychology, 21*(9), 2108–2121. https://doi.org/10.1177/1359105315569095

Peressutti, C., Martin-González, J. M., & García-Manso, J. M. (2012). Does mindfulness meditation shift the cardiac automatic nervous system to a highly orderly operational state? *International Journal of Cardiology, 154*(2), 120–122. https://doi.org/10.1016/j.ijcard.2011.10.054

Peressutti, C., Martín-González, J. M., García-Manso, J. M., & Mesa, D. (2010). Heart rate dynamics in different levels of Zen meditation. *International Journal of Cardiology, 145*(1), 142–146. https://doi.org/10.1016/j.ijcard.2009.06.058

Prinsloo, G. E., Derman, W. E., Lambert, M. I., & Rauch, H. G. L. (2013). The effect of a single session of short duration biofeedback-induced deep breathing on measures of heart rate variability during laboratory-induced cognitive stress: A pilot study. *Applied Psychophysiology and Biofeedback, 38*(2), 81–90. https://doi.org/10.1007/s10484-013-9210-0

Sanada, K., Montero-Marin, J., Díez, M. A., Salas-Valero, M., Pérez-Yus, M. C., Morillo, H., Demarzo, M. M. P., García-Toro, M., & García-Campayo, J. (2016). Effects of mindfulness-based interventions on salivary cortisol in healthy adults: A meta-analytical review. *Frontiers in Physiology, 7*, Article 471. https://doi.org/10.3389/fphys.2016.00471

Segerstrom, S. C., & Nes, L. S. (2007). Heart rate Variability reflects self-regulatory strength, effort, and fatigue. *Psychological Science, 18*(3), 275–281. https://doi.org/10.1111/j.1467-9280.2007.01888.x

Steffen, P. R., Foxx, J., Cattani, K., Alldredge, C., Austin, T., & Burlingame, G. M. (2021). Impact of a 12-week group-based compassion focused therapy intervention on heart rate variability. *Applied Psychophysiology Biofeedback, 46*, 61–68. https://doi.org/10.1007/s10484-020-09487-8

Tabachnick, L. (2015). Biofeedback and anxiety disorders: A critical review of EMG, EEG, and HRV feedback. *Concept, 38*, 1–26.

Teasdale, J. D., Segal, Z. V., Williams, J. M. G., Ridgeway, V. A., Soulsby, J. M., & Lau, M. A. (2000). Prevention of relapse/recurrence in major depression by mindfulness-based cognitive therapy. *Journal of Consulting and Clinical Psychology, 68*(4), 615–623. https://doi.org/10.1037/0022-006x.68.4.615

van Aalderen, J. R., Donders, A. R., Giommi, F., Spinhoven, P., Barendregt, H. P., & Speckens, A. E. (2012). The efficacy of mindfulness-based cognitive therapy in recurrent depressed patients with and without a current depressive episode: A randomized controlled trial. *Psychological Medicine, 42*(5), 989–1001. https://doi.org/10.1017/S0033291711002054

van der Zwan, de Vente, W., Huizink, A. C., Bögels, S. M., & de Bruin, E. I. (2015). Physical activity, mindfulness meditation, or heart rate variability biofeedback for stress reduction: A randomized controlled trial. *Applied Psychophysiology and Biofeedback, 40*(4), 257–268. https://doi.org/10.1007/s10484-015-9293-x

Wells, R., Outhred, T., Heathers, J. A., Quintana, D. S., & Kemp, A. H. (2012). Matter over mind: A randomised-controlled trial of single-session biofeedback training on performance anxiety and heart rate variability in musicians. *PLoS ONE, 7*(10), Article e46597. https://doi.org/10.1371/journal.pone.0046597

Zucker, T. L., Samuelson, K. W., Muench, F., Greenberg, M. A., & Gevirtz, R. N. (2009). The effects of respiratory sinus arrhythmia biofeedback on heart rate variability and posttraumatic stress disorder symptoms: A pilot study. *Applied Psychophysiology and Biofeedback, 34*, 135–143. https://doi.org/10.1007/s10484-009-9085-2

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NeuroRegulation

Roadmap for Enhancing the Efficiency of Neurofeedback

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Abstract

This article presents a roadmap of ways to improve the effectiveness of EEG neurofeedback training (NFT) based on a literature review and our own research on internal and external factors affecting NFT outcomes. Here we provide a justification for the expediency of using individually determined EEG indices as a feedback signal, based on an analysis of the alpha peak frequency and the level of neuronal activation. As personalization of the NFT for self-regulation means receiving information from a unique neurophysiological parameter inherent only to this individual, the basic internal socioeconomic, psychological, and physiological factors play an important role in training efficiency. Also, external factors such as the delay and modality of feedback presentation, valence of reinforcement, electrode localization, visual condition, body position, duration, and number of NFT sessions, forehead muscle tension and EMG artifact contamination will be discussed. A rationale for each step of this roadmap will be given from the point of view of how this or that factor can influence the personalization and consequently, the effectiveness of self-regulation training with NFT. The article provides a forward-looking opportunity to optimize NFT, providing a sketch setting out the necessary steps.

Keywords: neurofeedback technology; electroencephalography; individual alpha peak frequency; neuronal activation; feedback presentation

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Introduction

Neurofeedback training (NFT) is a brain-computer technology for awareness and learning to control one's own quantifiable neurophysiological parameters that are signs of cognitive and psychomotor functions and affective processes. This means that when the participant's brainwaves are functioning effectively and efficiently, the brain is stimulated in the form of feedback as a reward (Birbaumer, 2024; Kamiya, 1969; Ros et al., 2020). Despite the fact that the principle of any kind of biofeedback technology, based on the use of feedback signals from one's own psychophysiological parameters, assuming high personalization in learning to control these functions, the effectiveness of this technology for self-regulation training still remains a subject of debate (Alkoby et al., 2018; Arns et al., 2013; Ros et al., 2020; Schönenberg et al., 2017; Sokhadze et al., 2008). However, the impact of several internal and external factors, which are often not taken into account when organizing protocols and analyzing NFT results on the effectiveness of NFT, has not yet been definitively determined. It is assumed that internal factors involve the initial psychological (Fontanari, 2017; Fyfe et al., 2015; Kadosh & Staunton, 2019) and physiological (Bazanova, Nikolenko, et al., 2017; Kerson et al., 2020) state of the subject, including the genetically determined individual electroencephalographic (EEG) frequency pattern (Bazanova, 2012; Hanslmayr et al., 2005).

The external factors include some technical issues such as delay (Smetanin et al., 2020) and modality (Dessy et al., 2020; Steel et al., 2016; Wächter et al., 2009) of feedback presentation, duration (Yeh et al., 2021), frequency (Weber et al., 2020), number (Domingos et al., 2021), and ergonomics (Mouchnino et al., 2017; Pirini et al., 2011) of NFT sessions.

The purpose of this article is to provide a roadmap of scientific and technical possibilities for improving the efficiency of NFT.

Here we will not consider types of NFT that use brain hemodynamic indices based on hemoencephalography measurements (Dias et al., 2012), slow cortical potentials (Castermans et al., 2014), the low-energy neurobiological control system (Zandi Mehran et al., 2015), functional magnetic resonance imaging (fMRI; Fede et al., 2020), and near-infrared spectroscopy (Kohl et al., 2020) as feedback. These types of feedback are unsuitable for self-control training because of their long feedback presentation latency—not less than 1–3 s. In connection with the above, the EEG-NFT is more promising, since in comparison with the NFT types listed above, the main advantage of the EEG-NFT is high temporal resolution. This advantage makes it possible to estimate the magnitude of rapid changes in neuronal activity under current conditions, making EEG-NFT the most suitable technology for obtaining immediate feedback from fast-flowing cognitive and psychomotor functions and affective processes (Smetanin et al., 2020).

Meanwhile, there are still restrictions on the EEG-NFT use too. In particular, the so-called "*z*-score" is an NFT based on comparing the given patient's EEG power in the standard traditionally adjusted frequency ranges with a normative EEG database (Collura, 2010), which assumes that the EEG indices in the standard fixed bands corresponds to a Gaussian distribution. However, psychometric evidence for this assumption has not been provided (Jobert et al., 2013). Moreover, the presence of asymmetry and kurtosis of the EEG power histogram in standard bands indicates a deviation of the distribution from normality (Thatcher et al., 2003; Wood et al., 2024). These deviations may be the result of inaccuracies or errors in the registration, processing and subsequent analysis of EEG signals (Gutmann et al., 2018). In other words, the most likely reasons that distinguish the distribution of EEG spectral power indicators from normal may be due to the following factors: (a) lack of an individual approach to determining the boundaries of frequency bands (Bazanova & Vernon, 2014; Klimesch et al., 1998); (b) contamination of EEG by electromyographic (EMG) low-amplitude low-frequency artifacts (Goncharova et al., 2003; Gutmann et al., 2018; Halliday et al., 1998); and (c) ergonomic conditions such as body position (Slobounov et al., 2009), biological rhythmicity (Bazanova et al., 2018; Gertz & Lavie, 1983), duration (Vernon et al., 2004) and sequence of EEG recording with open and closed eyes (Hardt & Kamiya, 1976). All these factors reduce the accuracy of EEG analysis and consequently the NFT efficiency, jeopardize the reproducibility of the research results, lead to unpredictable effects of treatment and possibly even to a deterioration of the patient's condition, thereby discrediting the biofeedback technology (Bazanova & Aftanas, 2010; Ros et al., 2020).

It is important to note that we will not discuss here how the effectiveness of NFT is evaluated, nor will we conduct a meta-analysis comparing the level of effectiveness of NFT for the following reasons: (a) published meta-analyses evaluating the efficacy of EEG-NFT have demonstrated a wide variety of paradigms; (b) most meta-analysis data have limitations reported by the researchers, such as the use of different types of NFT, making it difficult to determine the most effective approach; and (c) the most common problem is the lack of standardized protocols, treatment procedures and duration, making complicated the comparison of results across studies (Askovic et al., 2023). Only one meta-analysis of double-blind randomized controlled trials demonstrated comparable results of NFT that use alpha EEG power as feedback (Xiang et al., 2018). Moreover, these meta-analyses did not take into account external and internal factors influencing the EEG-NFT efficiency. This highlights the need to establish scientific and technical challenges and opportunities for enhancing EEG-NFT efficiency and developing a roadmap for creating the optimal NFT protocols, which becomes more challenging when NFT is considered as a form of individualized medicine.

Methods

The algorithm for searching information in the databases PsyINFO, PubMed, Google Scholar, and eLibrary was carried out according to the requirements of PRIZMA (Brown et al., 2019; Moher et al., 2015). In accordance with the set goals of the search, abstracts, methodological recommendations, and textbooks were not taken into account. English was chosen as the search language. Experimental articles from 1968 to April 2024 were analyzed. The search queries have been adapted to various databases using Boolean operators AND and OR. The following keywords were used in the literature search: “Neurofeedback” AND “Efficiency” OR “Effectiveness” OR “Efficacy,” “EEG,” “Personality,” “Cognitive Functions,” “Awareness,” “Emotional State,” “Individual Alpha Peak Frequency,” “Alpha Power Suppression,” “Forehead Muscles EMG,” “Biological Rhythmicity,” “Feedback Delay,” “Feedback Modality,” “Reinforcement Valency,” “Session’s Duration,” “Sessions Number,” “Open Eyes,” “Closed Eyes,” “Electrodes Localization,” “Body Position.”

The articles selection was carried out by three reviewers (Alexandr Zakharov, Ekaterina Nikolenko, & Olga Bazanova), who independently reviewed various databases, eliminating duplicates and checking that the articles met the selection criteria.

Results

The literature analysis has shown that there is a large number of experimental studies of EEG-NFT efficiency performed both in healthy subjects and in various pathologies (n = 775 literature sources according to the query in PubMed). At the same time, the number of studies devoted to the influence of internal and external factors on NFT efficiency is significantly lower. The studies considering the above-mentioned main factors are presented in Table 1.

Impact of Internal Factors on the NFT Efficiency

Personalization of the NFT for training in self-regulation means receiving information from a unique neurophysiological parameter inherent only to this individual (Birbaumer, 2024). In this regard, the basic socioeconomic, psychological, and physiological factors as a learning predisposition state play an important role in self-regulation training efficiency (Gorev & Semenova, 2003; Rahman et al., 2023; Ros et al., 2020). Meanwhile, much NFT research has not been predicated upon the assumption that a baseline recorded at session outset is reliable.

Socioeconomic Status

Rahman and coauthors showed that lower family income and poor parental communication predicted lower academic achievement (Rahman et al., 2023; Schibli et al., 2017). Schibli explained that poor environments, social isolation, or deprivation associated with low socioeconomic status can cause stress reactions and anxiety, which in turn affect cognitive development and academic achievement (Schibli et al., 2017). Particular, children with low socioeconomic status, when learning new things, pay attention to information indiscriminately and are late in filtering out information that is not relevant to the task (D’Angiulli et al., 2008). On the other hand, for children with high socioeconomic status, adaptive parenting styles, supportive role models, and self-regulation learning skills have been suggested as potential factors contributing to emotional stability and better academic outcomes (Flouri et al., 2014).

Thus, socioeconomic factors, influencing the self-regulation training efficiency, contribute to such psychological factors as personality features, attention, emotional stability, and motivation to learn.

Psychological Factors

The effects of individual psychological features of the subject on the efficacy of application of the neurofeedback technique have attracted the attention of researchers (Ancoli & Green, 1977; Kadosh & Staunton, 2019; Schlatter et al., 2022; Yamaguchi, 1981). Optimal cognitive functioning is an important prerequisite for effective learning. However, in the learning process, as well as from the point of view of intrapersonal factors, Ancoli and Green (1977) mentioned that such features of the personality as authoritarianism, trustfulness, and introspectivity exert a significant influence on the efficacy of NFT; at the same time, effects of the levels of extraversion and empathy were not found (Ancoli & Green, 1977). H. Yamaguchi examined the dependence of the efficacy of alpha NFT sessions on the external versus internal locus control of the subject. Externals could significantly increase alpha power, while internals could not show such enhancement of alpha during the NFT (Yamaguchi, 1981). Better understanding of the relationships between the Big Five personality traits and emotion regulation are a prerequisite for feasible and effective NFT from designer's point of view (Travis et al., 1974). For example, biofeedback coping interventions have a greater effectiveness in individuals presenting higher score of openness to experience (Schlatter et al., 2022). It was found that most successful at the NFT were the subjects with low scores on Extraversion and moderately high scores on neuroticism (Chernyshev et al., 2013).

Cognitive abilities encompass those processes involved in controlling, organizing, and integrating information (Diamond & Ling, 2016). Participants with better overall cognitive function are better able to use biofeedback to promote learning (Kettlety et al., 2024). Such factors as attention and language skills explain performance variability (Kettlety et al., 2024). For this reason, cognitive abilities are crucial in NFT efficiency because they allow planning, reasoning, making decisions, and control and regulate emotions (Nguyen et al., 2019). In particular, inhibition represents the ability to control one's behavior, thoughts, and emotions (Diamond & Ling, 2016) through an adaptive internal feedback afferentation loop (Bernstein, 1945; Sudakov, 1997) and consequently, this ability, as reflected by EEG alpha power, could increase biofeedback training efficiency (Doppelmayr et al., 1998; Doppelmayr et al., 2002). Diamond (2013) proposed that cognitive flexibility and/or creativity designates the ability to change one's approach to a problem in order to adjust to new demands from the changing environment such as biofeedback technology (Boynton, 2001; Diamond, 2013; Pinho et al., 2014). Pinho showed that more creative individuals have greater functional connectivity, which may reflect a more efficient exchange of information in associative networks and thus increase the effectiveness of NFT (Pinho et al., 2014). Because cognitive functions and ability to control emotions change across the lifespan (Katsantonis, 2024), they could associate with different NFT efficiency: in childhood and adolescence academic achievement could predict more effective self-regulation (Katsantonis, 2024). In adulthood cognitive functions, self-control and learning ability are related to mental and physical health, marital harmony, public safety, etc. (Smith et al., 2019). In old adulthood cognitive and self-control abilities and strongly contribute to daily functioning and maintaining autonomy (Jefferson et al., 2011).

Sometimes, it is difficult to provide evidence of the NFT effectiveness without subjects in the experimental and control groups being in the same conditions: baseline sociopsychological and physiological states, modality of feedback, number of training sessions, and awareness of the goals of NFT, in addition to the fact of true feedback. Meanwhile, awareness of NFT goals and ways to promote self-regulation learning are rarely addressed in research on NFT effectiveness (Bazanova et al., 2013; Kvamme et al., 2022; Matsunaga & Genda, 2005; Min et al., 2023).

Awareness is a construct of considerable importance in many demanding tasks (Endsley, 2013). Situation awareness is formally defined as "the perception of the elements in the environment, the comprehension of their meaning, and the projection of their status in the near future" (Endsley, 1988). Situation awareness is related to cognitive events rather than passive monitoring of the course of treatment (Festa et al., 2024; Fontanari, 2017). As such, increasing awareness is important for the development and testing of NFT system designs and self-regulation training programs.

It was shown that instructional recommendations (Bazanova et al., 2013; Kvamme et al., 2022) and mindfulness practice (Crivelli et al., 2019; Min et al., 2023) could increase awareness of the NFT. Matsunaga and Genda considered using human physiological information as input because it reflects human feelings better (Matsunaga & Genda, 2005). The results showed that psychological techniques such as mindfulness (breathing, relaxation, imagination, etc.) without feedback cues are less effective for teaching self-regulation than NFT (Bazanova et al., 2013; Chikhi et al., 2023). Importantly, short breaks between NFT sessions, in which the neurofeedback awareness questionnaire can be embedded, may help to realize the goal of awareness, and could improve the NFT efficiency (Vernon, 2005). Thus, utilizing informative guidelines to increase awareness and psychophysiological techniques to enhance NFT performance may be reliable tools for conducting double-blind neurofeedback studies.

The influence of the baseline emotional state on the effectiveness of NFT is poorly understood. However, it can be hypothesized that if a person is tired, stressed, anxious, or experiencing other negative emotions, it can greatly affect their ability to concentrate, make decisions, and control their thoughts and actions (Labrague et al., 2017). Conversely, positive emotional states can increase the effectiveness of NFT by helping a person to better concentrate, make decisions, and control their actions. Just a few researchers have demonstrated that neurofeedback was more effective for patients with more severe than for milder emotional disturbance (Choi et al., 2023; Hardt & Kamiya, 1978; Konareva, 2005). So, in a group with a relatively high level of anxiety, it was found that as a result of NFT the alpha power increased in persons with moderate values of anxiety but was suppressed in individuals with the highest anxiety levels (Hardt & Kamiya, 1978). Later, similar results were obtained showing that biofeedback therapy was more effective for patients with high than low levels of job stress (Konareva, 2005; Wang et al., 2018).

The above studies have identified several psychological factors that need to be controlled and/or isolated in order to successfully register EEG characteristics reflecting the baseline condition and to predict the effectiveness of NFT. At the same time, it was shown that the impact of psychological factors manifested within the very first NFT stages (Ancoli & Green, 1977). This NFT period determines to a significant extent the efficacy of the entire training cycle, but this effect has not been systematically examined.

Physiological Factors

Several works used multiple physiological signals such as electrocardiogram (ECG; Pourmohammadi & Maleki, 2020), galvanic skin response (GSR; Azzalini et al., 2019), skin temperature (Arza et al., 2019), arterial blood pressure (ABP; Arza et al., 2019; Shuda et al., 2020), and plasma cortisol level (DeGood & Redgate, 1982; Paul et al., 2020; Quaedflieg et al., 2016) to detect the stress impact on cognitive efficiency. This allows us to assume that the above physiological parameters can affect the NFT effectiveness. Moreover, the study of Quaedflieg et al. (2016) demonstrates the influence of plasma cortisol level on frontal alpha asymmetry change after NFT. Overall, these studies argued that employing only a single marker cannot comprehensively assess the person's stress response. As far as EMG and EEG variables, it was shown that such signs of stress as increasing the scalp EMG amplitude (Cacioppo, 2004; Pourmohammadi & Maleki, 2020) and decreasing the EEG alpha power (Bazanova & Vernon, 2014; Lopes da Silva, 2013) can serve as indicators of psychoemotional tension.

EMG Factors Influencing NFT Efficiency

The ability to control forehead muscle tone contributes to self-regulation capacity of mood and could be used in practice of EMG biofeedback training (Blumenstein & Orbach, 2014). At the same time, scalp EMG of low frequency and low amplitude could be a factor that might mask the stress-related EEG features and/or generate EEG features that could be misinterpreted as being stress-specific (Enders & Nigg, 2016; Halliday et al., 1998). These include the widespread increase of EEG in beta and gamma ranges that result from scalp EMG generated by the facial expressions that often accompany stress (Enders & Nigg, 2016; Halliday et al., 1998). So, one of NFT's disadvantages to date is the lack of consideration of EEG contamination by low-frequency EMG components (Castermans et al., 2014; Halliday et al., 1998). EMG artifacts, shown to be a problem during EEG NFT (Enders & Nigg, 2016; Shackman et al., 2009), have a larger influence on the data as they do not diminish when averaging many trials and epochs, and, consequently, when constructing NFT designs incorrectly. Therefore, the probability of EMG artifacts must be considered when selecting channels for NFT: the maximum probability of EMG artifacts is observed in frontal, temporal, and occipital regions (Nekrasova et al., 2022).

To overcome these EMG artifacts that are signs of psychoemotional stress, researchers and clinicians have developed NFT to enhance alpha production while simultaneously controlling frontal muscle tension (Markovska-Simoska et al., 2008; Petrenko et al., 2019; Wang et al., 2018). For example, NFT aimed at simultaneously reducing theta/beta ratio and forehead EMG was more effective in reducing impulsivity and reaction time in ADHD children than NFT without controlling frontal muscle tension (Arns et al., 2014; Bazanova et al., 2018; Strothmann, 2024). Thus, to improve the effectiveness of EEG-NFT, it is necessary to take into account the EMG of the scalp muscles.

Resting EEG Features

In classical EEG studies, resting EEG refers to both amplitude (power) and frequency parameters of the EEG, as well as their changes in standard functional tests, such as the Berger test (Bazanova & Vernon, 2014; D. A. Kaiser, 2001; Livanov, 1984; Lopes da Silva, 2013).

Baseline brain activity measures such as EEG amplitude or power spectral density before training were mainly investigated to predict psychophysical performance (Linkenkaer-Hansen et al., 2004) and particular the NFT success (Alkoby et al., 2018; Su et al., 2021; Weber et al., 2020). For instance, learning beta/theta control can be predicted by resting beta power prior to training (Nan et al., 2015), learning of the sensorimotor or alpha rhythm can be predicted by the amplitude/power of the initial sensorimotor rhythm (Reichert et al., 2015) or alpha power (Wan et al., 2014). Because lower alpha band power is associated with greater mental effort during problem solving (Golonka et al., 2019), this lower alpha band power of the resting EEG may predict a poorer outcome of NFT. Despite these findings, EEG amplitude itself is a highly fluctuating parameter influenced by excitation level, conduction, ECG and EMG artifacts (Bazanova & Vernon, 2014; Lopes da Silva, 2013). Therefore, amplitude values may be poorly predictive of the outcome of NFTs.

Until now, the boundaries of EEG frequency ranges have been determined by general agreement, without theoretical justification, and without taking into account the functional features of EEG waves (D. A. Kaiser, 2001; Klimesch et al., 1997). For example, there is a substantial body of evidence supporting the existence of functionally independent frequency subbands in the broader alpha range (Barry & De Blasio, 2017; Klimesch et al., 1997). Accordingly, determining the alpha power in a particular standard frequency band is likely to reduce the sensitivity of the experiment and increase the probability of typical error (Bazanova & Aftanas, 2010; Bazanova et al., 2018; Doppelmayr et al., 1998; D. A. Kaiser, 2001).

The results of the literature analysis presented in Table 1 indicate the rare use of individual spectral frequency characteristics as a feedback cue in EEG-NFT. At the same time, out of 19 works studying EEG-NFT, using amplitude in fixed ranges calculated on the basis of individual alpha peak frequency (iAPF) as a biofeedback, only six studies are devoted to the study of NFT conducted on EEG magnitude within individually established boundaries of frequency bands (Bazanova & Aftanas, 2010; Bazanova et al., 2018; Escolano et al., 2014; Gutmann et al., 2018; Parsons & Faubert, 2021; Petrenko et al., 2019). At the same time, a comparison of the NFT effectiveness conducted to reduce the theta/beta ratio in children with ADHD according to individually established EEG ranges and standard ones (4–8 Hz theta and beta 13–18 Hz) showed a significantly higher probability of reducing impulsivity, reaction time in the test and hyperactivity in children who underwent training according to individually established ranges (Bazanova et al., 2018). In addition, several studies have demonstrated the expediency of determining the iAPF as a predictive criterion for the effectiveness of NFT (Bazanova et al., 2018; Hanslmayr et al., 2005; Petrenko et al., 2019), and also to determine the strategy of neurotherapy (Pérez-Elvira et al., 2021; Voetterl et al., 2023). For example, the ability to train in a single NFT session is higher in people with iAPF > 10 Hz, and the effectiveness of NFT, as assessed by the magnitude of changes in trained performance, is higher in people with low iAPF < 10 Hz (Bazanova et al., 2013; Petrenko et al., 2019).

Thus, one of the most important EEG alpha rhythm parameters, individual alpha peak frequency, which determines the positive or negative type of emotional reactivity (Tumyalis & Aftanas, 2014), success of cognitive (Doppelmayr et al., 2002; Klimesch et al., 1997; Rathee et al., 2020) and psychomotor task performance (Bazanova et al., 2013), can predict the effectiveness of NFT.

Baseline Intensity of Neuronal Activation

In most subjects, EEG alpha wave amplitude is higher when the eyes are closed and decreases when eyes are open. This decrease in EEG alpha power in the eyes-open (EO) condition, relative to the eyes-closed (EC) condition is used as one of the outcome measures of neuronal activation (Barry et al., 2011) and for the artifact correction (Kirschfeld, 2005; van der Meer et al., 2016). It was shown that magnitude of neuronal activation depends on the phase of menstrual cycle in women (Bazanova, Nikolenko, et al., 2017) and the time of day (Compton et al., 2019). Less alpha attenuation with eyes open has been associated with such disorders as inattention (Barry & De Blasio, 2017; Bazanova, 2012), schizophrenia (Koukkou et al., 2000), and as well as with developmental and age-related factors, including both younger and older age (Barry & De Blasio, 2017). Thus, because this baseline EEG parameter could predict cognitive efficiency (VaezMousavi et al., 2007), we propose that it could be used as a target for NFT and in prediction of NFT efficiency (Bazanova, 2012). Although decreased overall alpha power likely reflects the neuronal activation, the alpha band is subdivided (Babiloni et al., 2004) because lower (Babiloni et al., 2004; Klimesch et al., 1997) and high alpha subbands (Jensen et al., 2002; Klimesch et al., 1997, 1998) have been associated with somewhat different cognitive processes. Lower-frequency (i.e., lower than iAPF) alpha rhythms tend to reflect the more diffuse cortical loops regulating global attentional processes, such as alertness (Babiloni et al., 2014). Higher-frequency (i.e., higher than iAPF) alpha rhythms have been associated with more selective neural systems, including those involved in anticipating and processing specific sensory input and cognitive control (Bazanova & Vernon, 2014; Klimesch et al., 1998). Thus, we might take into account the preexisting neurocognitive vulnerability by studying EEG measures within these alpha subbands.

Since the EC/EO effect is different for each subject in terms of the frequency band, we determined an upper and lower frequency threshold (i.e., those frequencies in which the EC/EO effect is most pronounced), and for the topological distribution we determined a channel selection (i.e., in which channels the EC/EO effect is most pronounced; van der Meer et al., 2016). Examination of the average power in posterior channels (Pz, PO3, POz, PO4, Oz) allows us to determine the frequency range associated with neuronal activation and therefore where the EEG-NFT effect will be most pronounced.

So, it is advisable to register EEG before the NFT both with open and closed eyes to determine the endophenotypic marker of iAPF and the level of neuronal activation, which are of important prognostic meaning for the NFT effectiveness (Bazanova & Vernon, 2014).

Biological Rhythmicity

As we know, biological rhythmicity has never been taken into account, and even the time of day is rarely reported in researching NFT efficiency. The majority of EEG-NFT studies have involved short-term (generally less than an hour) experimental procedures. In light of findings demonstrating independent rhythmicity in different physiological systems, such as gastric motility, renal excretion, as well as performance and physiological indices of arousal, a multioscillatory ultradian system has been proposed (Kripke, 1974; Lavie & Kripke, 1981). In this line, Gertz and Lavie (1983) demonstrated that efficacy of NFT may depend on the baseline condition, related mainly to the ultradian rhythmicity of about 200 min/cycle seen in EEG indices, particularly iAPF, and in subjectively assessed arousal (Gertz & Lavie, 1983).

The study of Pérez-Medina-Carballo et al. (2024) clarifies too the changes in EEG parameters that occur in women after menopause across circadian phases. The absent and dampened circadian variation of upper alpha power (12–15 Hz) in older subjects is consistent with an impaired output of the circadian pacemaker regulating spindle activity (Dijk & Duffy, 2020).

Another type of biological rhythm that affects general well-being and cognitive performance that is rarely considered when evaluating the effectiveness of NFT is the menstrual cycle of women. We and other authors (Bazanova, Nikolenko, et al., 2017; Becker et al., 1982; Brötzner et al., 2014) have demonstrated that both iAPF and the intensity of neuronal activation change significantly depending on the level of sex steroids (Bazanova, Nikolenko, et al., 2017). Moreover, it has been shown that the highest learnability for self-regulation is observed during the phase with the highest progesterone levels.

Thus, the analysis of EEG-NFT efficacy and the design of an NFT experiment including women as subjects should take into account the biological rhythms of women's hormonal state.

External Factors

The fundamental components of the biofeedback system include two groups of external factors that influence the effectiveness of NFT: (a) the acquisition and presentation of feedback signals (feedback signal presentation delay, feedback signal modality and reinforcement) and (b) the design elements of the NFT procedure (duration and number of NFT sessions, ergonomic factors of the procedure).

Acquisition and Presenting Signals for Feedback

This group of factors include signal detection, digital conversion (facilitating signal processing by a digital computer), signal processing utilizing software, signal display, and signal storage.

The signal processing step of digital conversion is of paramount importance as the rate at which the signal is converted from its analog form to its digital counterpart determines the quality of the signal representation for the remainder of the process (Montgomery, 2001). Essentially, the frequency at which a signal is measured will dictate how that signal can be processed by the computer.

Electrode Localization for Determining NFT Target Area

Unlike fMRI-NFT, where the choice of the target area of NFT is a problem, EEG-NFT does not need a special localization of the electrode as a target of self-regulation, because the signal obtained at this electrode always reflects generalized neuronal activity (Acharya & Acharya, 2019; Ebrahimzadeh et al., 2022; Klug & Gramann, 2021; Tenke et al., 2013). Accordingly, neurofeedback protocols that utilize the EEG signal for feedback may not limit training effects to specific brain regions (Gruzelier, 2014; Güntensperger et al., 2020). Moreover, it is known that changes in the amplitude of the dominant EEG frequency amplitude induced by NFT at one site are accompanied by similar changes in other brain regions (Bazanova, 2011; Gruzelier, 2014). Most likely, the effects of NFT occur at a more global level and therefore the NFT procedure affects several functionally different brain regions simultaneously (Güntensperger et al., 2020). Beside it, the probability of the highest amplitude and the least contamination by artifacts of EMG and ECG is higher in the parietal region than in the frontal and temporal regions (Jobert et al., 2013; Tenke et al., 2013). This means that the effectiveness of feedback presentation in NFT will be higher from signals from the parietal region, where iAPF is most stable and reproducible (Bazanova, 2011).

Thus, the fast and brain-wide processes of voluntary self-regulation that occur during NFT suggest that the effectiveness of NFT does not depend on the electrode location.

The Delay of the Feedback Signal Provided

The timing of feedback is critical to the effectiveness of training in general, and it appears to the effectiveness of NFT in particular. The delay of the feedback cue depends on the proper setting of NFT latency, that is the time interval from the occurrence of a neural activity till the delivery of the feedback of that activity to the subject. If the experimenter uses the EEG power in a given range as a feedback signal, then the delay from such feedback will be greater than if the feedback on the envelope amplitude was used as feedback (Smetanin et al., 2020). The reason for the greater delay in the feedback from the EEG power is the need to conduct fast Fourier transform (Tarasov, 2007).

NFT latency specifies the reinforcement schedule (Sherlin et al., 2011) and as such it affects the outcome of NFT (Matsunaga & Genda, 2005; Schoenfeld, 1970). This issue has been addressed rarely in previous studies is the effect of the reference signal delay and modality in a biofeedback system (Matsunaga & Genda, 2005; Table 1). We have hypothesized that the shorter the delay, the faster the healthy subject will be able to recognize their condition and change it accordingly to feedback cue. To this end, real-time algorithms are needed that would shorten the delay while maintaining an acceptable speed-accuracy trade-off. Ossadtchi and colleagues showed that using the operating at zero latency, the weighted least-squares complex-valued filter approach yielded 75% accuracy when detecting alpha-power episodes, as defined by the amplitude crossing of the 95th-percentile threshold (Smetanin et al., 2020). Although, there is no work that specifies the optimal feedback delay for improving deliberation performance, this research demonstrates the effectiveness of a short delay in presenting feedback because brief delays of feedback are beneficial sometimes encourage anticipation of the upcoming feedback (Smetanin et al., 2020).

This latency time depends not only on the technical capabilities of the feedback signal processing, but also on the initial subject’s psychoemotional state before learning. Thus, the results of the study by Paul et al. (2020) showed that stress, through an increase in the level of cortisol, affects the neural mechanisms of processing feedback. Instead of accelerating the reaction to control the emotional state under stress, the authors noted a decrease in cognitive control under stress. Depending on feedback timing, the neural structures involved in learning differ, in dependence on the dopamine system that could being more important for learning from immediate than delayed feedback (Paul et al., 2020). Similar, the results from a study of children attention-deficit/hyperactivity disorder (ADHD) by Mullaney et al. (2014) showed that delaying feedback up to 8 s after stimulus presentation in verbal memory tasks improved learning performance to a greater extent than delaying results for a short period of time after the response. For instance, Baghdadi et al. (2020) showed that shorter feedback signal delay is more effective in NFT only for healthy patients. The authors demonstrated that for children with ADHD, a long feedback delay is more effective than an immediate feedback cue, which is consistent with longer reaction times in children with ADHD. In this case, feedback of 1200 ms in children with ADHD demonstrated a greater effect relative to feedback with a 200 ms signal delay (Baghdadi et al., 2020). Considering a coupling between the reward and attention circuits (Ibanez et al., 2012), attention is crucial for efficient neurofeedback learning (Kadosh & Staunton, 2019). It’s a reason explaining the impairment of reward processing has been reported in children with ADHD (Ibanez et al., 2012). The second reason why the longer delay of feedback could be more efficient than immediate is slowing reaction time connected with slowing iAPF in ADHD in comparison with healthy subjects (Bazanova et al., 2018; Samaha & Postle, 2015). Samaha and Postle (2015) demonstrated that subjects with lower iAPF have slower temporal resolution of visual stimuli than those one with higher iAPF. Insufficient research on the influence of the delay of signal presentation does not allow us to say which time values should be optimal for effective NFT. However, at this point we can say that the choice of delay time is influenced by baseline physiological condition.

Overall, these data indicate the importance of selecting the delay of reference signal in NFT systems according to the individual baseline characteristics of each participant, such as iAPF.

Level of Thresholds

The factors that determine the NFT effectiveness also include a technical approach to determining the reward threshold (the appearance of a feedback signal). Threshold magnitude is an important aspect of NFT, as it should be set at a level that allows for an adequate amount of feedback information to allow the learner to identify their state, feelings, and thoughts that trigger the required activity (Ros et al., 2020).

If the threshold is set too low, the individual may have little motivation and/or need to do anything to elicit positive feedback. Conversely, if the threshold is set too high, not enough information will be provided for feedback and the participant is likely to be frustrated (Katkin & Murray, 1968; Prfwett & Adams, 1976; Vernon, 2005). NFT research data does not always justify the choice of a particular reinforcement threshold, and in some cases such information is not reported (Angelakis et al., 2007; Escolano et al., 2014; Konareva, 2005; Wacker, 1996). Based on data from Arnold's neurofeedback collaborative group (2024) and Bazanova et al. (2013) the use of a "variability" threshold protocol involving a gradual increase in the difficulty of a training task is always effective regardless of the baseline alpha peak frequency level. Meanwhile, lowing the threshold across the NFT training could help enhance the motivation for subjects with low iAPF (Bazanova et al., 2013; A. Kaiser et al., 2024).

Thus, the choice of threshold level for NFT should depend on the initial psychological status (motivation) and the dominant EEG frequency.

The Modality of the Feedback Signal Provided

It is important to take into account the sensory modality of the presented stimulus when organizing the NFT (Gong et al., 2021). Despite the availability of several feedback modalities, there is still a lack of systematic studies that compare their effects across protocols and individual baseline condition. In general, learners' characteristics and practical considerations affect the choice of feedback modality (Gong et al., 2021). Studying the alpha NFT efficiency (Bucho et al., 2019) demonstrated minimal differences between the "visual" and "auditory" groups, indicating that auditory reinforcement signals may be just as effective as visual signals commonly used in neurofeedback: both audio and visual reinforcement signals led to significant increases in upper alpha brain wave activity (Bucho et al., 2019). Following NFT, effects were observed not only in the target frequency of upper alpha, but also in the lower-alpha and theta bands, as well as in posterior brain regions. From the other hand, the use of auditory feedback cue could be more applicable for training protocols conducted in mobile settings, enabled by the growing prevalence of wireless EEG system (Bucho et al., 2019). Meanwhile, the visual analyzer has the most accurate temporal resolution and therefore the time delay of the stimulus should be minimal (Habes et al., 2016).

Multimodality feedback approaches have been gaining attention in several application domains. Dual-modality feedback is far superior to either single-modality feedback approach in terms of preventing the object from breaking or dropping (Kober et al., 2015; Li & Brown, 2023). Kober et al. (2015) used multimodal feedback signals to enhance the effectiveness of NFT, particularly in stroke rehabilitation. They showed that using two types of modalities, visual and auditory, is more effective than only one type of feedback. To reduce possible sensory conflicts, the overlap of sensory information should be taken into account, which can be observed with simultaneous vestibular stimulation and auditory feedback in rehabilitation with feedback of balance disorders (Probst & Wist, 1990). However, these findings may only apply to a specific sport performance NFT scheme and has not been extensively confirmed (Vernon et al., 2004).

According to some researchers, the interaction of visual and auditory feedback may be influenced by mutual interference (Lal et al., 1998; Vernon et al., 2004). Without proper integration, these feedback modes can potentially confuse participants and diminish their effectiveness. Proponents of utilizing both types of feedback argue that the combination can prevent individuals from overlooking one source of feedback and instead rely on the other to prompt them to persevere in their training (Lal et al., 1998; Vernon et al., 2004). According to this example, it is believed that the visual function of the human body is typically engaged in physical movement, suggesting that auditory feedback may be more effective NFT for psychomotor training (Vernon et al., 2004).

Factors of NFT Design and Procedure

Duration and Number of NFT Sessions. How often and long should training take place? There are no specific rules yet defined for the duration of NFT sessions for optimal results. The duration of NFT sessions depends on the goals and protocol of the study. NFT with a shorter duration (10–30 min) reduces stress, induces relaxation, and increases cognitive skills (Ghaziri et al., 2013). Longer NFT sessions allow the brain to better learn and adapt to new brain patterns, leading to longer-lasting effects (Vernon, 2005). Most meta-analyses report positive effects when sessions last at least 300 min (Lal et al., 1998). Meanwhile, the results presented in research of Reis et al. (2016) suggest that an intensive and short NF protocol enables elders to learn alpha and theta self-modulation and already presents moderate improvements in cognition and basal EEG (Reis et al., 2016).

Ergonomic Factors

The Factor of Body Position or Level of Support Afferentation During the NFT. An analysis of the NFT literature has demonstrated that both the neurofeedback procedure itself and EEG registration, with rare exceptions (Bazanova, Kholodina, et al., 2017; Enz et al., 2022), is performed in a reclining position, when the activation of the support afferentation is reduced. We believe that the activation of support afferentation, in addition to the evolutionary and biomechanical effect on sensorimotor integration, has a purely technological advantage. The results of EEG analysis obtained during registration in the supine position are not suitable for comparison with subsequent recordings made while performing cognitive and/or psychomotor tasks usually performed in the sitting position (Jobert et al., 2013). In other words, for self-regulation training with the help of neurofeedback, the skills of which can be used in everyday life, it is recommended to register EEG at rest in conditions that will then be used during NFT (i.e., subjects should be in an upright sitting position; Jobert et al., 2013). There are several reasons why weight transfer to the feet is necessary when sitting during EEG recording: (a) with a decrease in body weight transfer to the feet, there is a weakening of the support afferentation (Kozlovskaya et al., 1988; Kozlovskaya et al., 2007), which reduces sensorimotor integration and increases the perceptual load on other sensory modalities (Mouchnino et al., 2017); (b) the correct load on the feet on the appropriate footrest makes patients more stable (Mouchnino et al., 2017); (c) weight transfer to the plantar sole (e.g., in a standing position) increases the EEG power in the upper alpha frequency range (SMR; Bazanova, Kholodina, et al., 2017; Kozlovskaya et al., 2007; Kozlovskaya et al., 1988) and reduces neuronal activation (Swerdloff & Hargrove, 2023); and (d) when conducting EEG testing, it is important to remember that weight transfer to the plantares leads to reduction of EMG of the forehead muscles (Bazanova, Nikolenko, et al., 2017; Slobounov et al., 2009), which means that it reduces psychoemotional stress (Mouchnino et al., 2017; Pirini et al., 2011; Slobounov et al., 2009), which also minimizes EMG artifacts (Urigüen & Garcia-Zapirain, 2015). Gravity stimulates the arterial baroreceptors, and the brainstem modulates the autonomic nervous system (Mouchnino et al., 2017), thereby affecting brain waves (Chang et al., 2011). Thus, the posture during which EEG recording and the NFT procedure are performed affects the NFT effectiveness.

Discussion

The analysis of the literature devoted to the study of the scientific and technical challenges and opportunities for enhancing the EEG-NFT efficiency allows us to identify the strengths and weaknesses of different approaches. It is logical to assume that when using individually set of psychological and physiological internal factors, NFT adapts more precisely to the characteristics of a particular person's brain activity and allows for more effective results. Our review and a recent analysis of the literature on NFT outcomes (Himmelmeier & Werheid, 2024) showed that individual alpha peak frequency is one of the most important internal factors influencing other internal and even external factors of NFT efficiency. Using standard protocols with the fixed EEG frequency ranges lead to less accurate correction of brain activity and, as a result, less significant training results. The question arises, "why does a large pool of randomized placebo-controlled alpha-EEG-NFT studies conducted in standard frequency bands demonstrate the clinical effectiveness of this type of NFT in about 70% of cases?" (Ros et al., 2020). We believe that this may be due to a number of reasons. Firstly, for some healthy subjects, the standard alpha ranges (8–12 Hz or 7–13 Hz) may coincide with individually determined frequency ranges, and for some they may be higher or lower than individually set ones. As shown in some research (Arns et al., 2014; Markovska-Simoska et al., 2008; Petrenko et al., 2019), the part of the subjects whose iAPF is less than 10 Hz, the range of 8–12 Hz will represent an individual alpha-2 range and for them alpha power training in the NFT will be more effective than for subjects with an iAPF greater than 10 Hz (Petrenko et al., 2019). Moreover, alpha training in standard bands for subjects with a high iAPF frequency may be accompanied by undesirable phenomena such as headache (Bazanova & Aftanas, 2010), since a shift in the EEG spectrum to the left or an increase in the power ratio in the low-frequency alpha-1 to alpha-2 range is associated with an increase in pain perception (Mckenzie et al., 1974; Pan et al., 2023). Another reason why alpha NFT training can be successful in standard ranges is that it was conducted for people with a low iAPF due to either childhood or old age (Edgar et al., 2022; Mierau et al., 2016; Orekhova et al., 2006), or for women in the cycle phases with initially low progesterone levels (Bazanova, Nikolenko, et al., 2017).

Finally, NFT is usually conducted for the purpose of adjuvant care and cognitive rehabilitation for people with anxiety, conversion, affective disorders, Alzheimer's disease, Parkinson's disease, depression, schizophrenia, autism spectrum disorders, stroke, posttraumatic stress disorder, etc. (Markiewcz, 2017; Renton et al., 2017; Steingrimsson et al., 2020; Tazaki, 2024). Since psychiatric disorders are generally associated with decreased iAPF (Harris et al., 2006; Stoffers et al., 2007), using the standard alpha range (8–12 Hz) as an NFT target may serve as a “personal upper alpha range” training for them. Upper alpha NFT training is evidenced used to train self-regulation (Hanslmayr et al., 2005).

Based on the presented results, it can be concluded that the effectiveness of EEG-NFT will be influenced by internal factors that could affect the baseline iAPF level: (a) age (Clark et al., 2024; Duffy et al., 1984), (b) menstrual cycle phase (Bazanova, Nikolenko, et al., 2017; Becker et al., 1982); (c) sleep quality (Zhao et al., 2021); and (d) substances use of tobacco (Banoczi, 2005), alcohol, coffee, tea, or energy drinks (Barry et al., 2011).

NFT efficiency can also be influenced by the external factors that influence iAPF discussed above. First of all, these are such factors of feedback signal acquisition and processing as: (a) electrode localization; although neurofeedback protocols may not limit the training effect to specific brain regions (Gruzelier, 2014; Güntensperger et al., 2020), from a technical point of view, the probability of highest amplitude and least contamination by artefacts is higher in the parietal region than in the frontal and temporal regions (Ebrahimzadeh et al., 2022), which means that the effectiveness of feedback presentation for NFT will be higher in the parietal region, where iAPF is the most stable and reproducible (Bazanova, 2011); (b) the choice of latent time in feedback presentation should depend on the baseline condition, namely reaction time (Baghdadi et al., 2020) and finally on the baseline iAPF (Samaha & Postle, 2015); and (c) the choice of valency of feedback reinforcement in NFT depends prevailing susceptibility to negative or positive stimuli in high and low iAPF subjects (Tumyalis & Aftanas, 2014). Secondly, factors of NFT sessions duration and number also depend on the baseline iAPF: (a) the iAPF may change as a result of a long session due to decreased vigilance over time (Birbaumer, 2024; Livanov, 1984); and (b) NFT session number that are needed for positive outcome also depends on baseline iAPF: less sessions number for high-iAPF subjects than low-IAPF subjects (Bazanova et al., 2013; Petrenko et al., 2019). The use of individually set frequency bands in brain activity control training using EEG is usually a more effective strategy, since it allows to more accurately adapt training to individual human needs.

Thus, iAPF and the individually specified frequency ranges used in NFT were the main factors that determined our choice of studies to include in the discussion in Table 1, even though they are not randomized control trials (RCT).

Meanwhile, we found only 19 studies on NFT that take into account an individually determined EEG frequency ranges as a training target (Table 1). Among them only two works showed higher NFT efficiency provided in individually adjusted EEG rangers compared to outcomes of NFT in standard frequency ranges (Bazanova & Aftanas, 2010; Bazanova et al., 2018). Perhaps, because all of the studies listed in the table were conducted using as a target the individualized EEG ranges, positive NFT results were obtained. However, other RCT works not included in this table also have positive outcomes. It seems that not only iAPF but also other factors are relevant for increasing the NFT efficiency.

One such factor determining the psychophysiological state of the subjects is the actual hormonal background. Most of the analyzed works did not take into account the menstrual cycle phase of the women included in the study (marked in red in the table). This factor influencing the effectiveness of NFT (Bazanova, Nikolenko, et al., 2017) requires further study.

The studies discussed here rarely take into account one of the intrinsic factors, EMG of the tone of the forehead and temples muscles, which is a marker of psychoemotional tension (Cacioppo, 2004). Consideration for decreased forehead EMG in NFT training reducing the individually determined theta/beta ratio (TBR) showed greater reductions in impulsivity and reaction time in ADHD children 6 months after the end of training than in children with similar NFT training without accounting for EMG (Bazanova et al., 2018). Similar results were received by Arns and colleagues (Arns et al., 2014).

Table 1
The Research Considering the Main Internal and External Factors Determining the Opportunities of Increasing the EEG NFT Effectiveness

	Trained EEG feature	RCT	iAPF	Individualized ranges	Account to menstrual cycle phase in women	Feedback delay less 500 мс	Positive reinforcement	EC	EMG stop	EMG control	Posture	Threshold variable	Feedback modality	Outcomes
Alexeeva et al., 2012	Alpha/EMG												Audio	
Arns et al., 2012	TBR SMR-power					?					?		Visual	
Bazanova & Aftanas, 2010	Alpha/EMG, TBR				Male subjects								Audio	
Bazanova et al., 2018	TBR/EMG				Children								Visual	
Petrenko et al., 2019	Alpha/EMG												Audio	
Cowley et al., 2016	TBR SMR-power					?					?		Visual	
Escolano et al., 2012	Alpha-2 power										?	?	Visual	
Grosselin et al., 2021	Alpha-power					1 s					?		Audio	
Güntensperger et al., 2019	Alpha/delta ratio					?						?	Visual	
A. Kaiser et al., 2024	TBR, SMR-magnitude				Children	?					?		Visual	
Markovska-Simoska et al., 2008	Alpha/EMG												Audio	
Nan et al., 2012	Relative amplitude in individual alpha band					?					?		Visual	
Naas et al., 2019	Alpha-power					?					?	?	Visual	
Parsons & Faubert, 2021	iAPF			?	?						?		Visual	
Quaedflieg et al., 2016	iAPF asimmetry										?	?	Visual	
Reis et al., 2016	Alpha-power, theta-power				> 55 years						?		Visual	
Strothmann, 2024	TBR					?							Visual	
Veilahti et al., 2021	TBR, SMR-power					?	Positive and negative	?			?		Visual	
Wan et al., 2014	Alpha-magnitude					?					?		Visual	

Note. Green color means that this factor was taken into account, red means that it was not; question mark (?) means that the paper does not indicate whether the factor was taken into account or not; iAPF - individual alpha peak frequency; TBR - theta/beta ratio; SMR - sensorimotor rhythm; RCT - randomized control trails; EMG - electromyography.

The research on the influence of support afferentation on psychophysiological functions and their neurobiological markers, in particular on EEG and EMG, has been insufficient to date. In this connection the majority of EEG and NFT works are carried out without taking into account this important ergonomic factor. In most of the studies we analyzed, EEG registration and NFT was either performed in a semireclined position or was not indicated at all.

Another rarely considered factor that can affect the efficiency of NFT is the latency of the feedback signal. This may be due to technical difficulties in implementing NFT and lack of evidence of the need to use a particular feedback latency interval.

For the moment, caution is required when interpreting the table's results given a number of limitations in addition to the issues raised with regard to the nature of the trials. The level of methodological rigor specifically related to RCT was generally unclear (Hammond & Kirk, 2008; Pigott et al., 2021). The level of blinding was insufficient in many studies (Pigott et al., 2021). A complementary checklist for neurofeedback trials, including guidelines of preexperiment, control groups and measures, feedback specifications, and outcome measures that are important to improve the level of evidence of NFT efficiency (Ros et al., 2020). Because not all factors that have an impact on NFT efficiency were taken into account in this table, we agree with the opinion of that academic community that calls for more empirical research to fill these knowledge gaps (Ros et al., 2020; Vernon, 2005).

Further research, characterized by greater methodological rigor, is therefore needed to determine the effectiveness of NFT and the superiority, if any, of this type of training over the single administration of either.

Conclusion

This roadmap provides a comprehensive review of the internal and external factors that influence the efficiency of EEG-NFT including the socioeconomic, psychological, and physiological aspects, as well as technical considerations related to the feedback signal's acquisition, processing, and presentation. Internal factors such as socioeconomic status can significantly impact learning efficiency during NFT, with lower socioeconomic backgrounds potentially leading to reduced cognitive function due to stress and anxiety. Psychological traits like personality and cognitive abilities also play a role, with certain traits being more conducive to effective learning during NFT. Physiological factors, including muscle tension and resting EEG features, are crucial as well. For instance, EEG alpha power can predict NFT success, but it is also susceptible to artifacts from muscle tension, which must be managed for accurate feedback.

External factors discussed include the delay and modality of feedback signals, the duration and number of NFT sessions, and the ergonomic setup during training. The document emphasizes that the optimal delay of feedback signals is influenced by individual baseline characteristics, such as reaction time, the iAPF. The choice of feedback modality, whether visual or auditory, and the reinforcement strategy, whether positive or negative, also significantly affect NFT outcomes.

The review highlights the importance of considering individual differences in baseline EEG characteristics, such as iAPF, to enhance NFT effectiveness. Establishing NFT protocols based on the use of individual EEG frequency characteristics would contribute to increasing the credibility of the research results and increasing the efficiency of their practical application. However, here we also note the challenges in standardizing NFT protocols, given the variability in individual responses and the complexity of factors involved. The review concludes by calling for more rigorous research to better understand and optimize the factors that influence NFT efficiency.

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References

Acharya, J. N., & Acharya, V. J. (2019). Overview of EEG montages and principles of localization. *Journal of Clinical Neurophysiology, 36*(5), 325–329. https://doi.org/10.1097/WNP.0000000000000538

Alexeeva, M. V., Balios, N. V., Muravlyova, K. B., Sapina, E. V., & Bazanova, O. M. (2012). Training for voluntarily increasing individual upper α power as a method for cognitive enhancement. *Human Physiology, 38*(1), 40–48. https://doi.org/10.1134/S0362119711060028

Alkoby, O., Abu-Rmileh, A., Shriki, O., & Todder, D. (2018). Can we predict who will respond to neurofeedback? A review of the inefficacy problem and existing predictors for successful EEG neurofeedback learning. *Neuroscience, 378*, 155–164. https://doi.org/10.1016/j.neuroscience.2016.12.050

Ancoli, S., & Green, K. F. (1977). Authoritarianism, introspection, and alpha wave biofeedback training. *Psychophysiology, 14*(1), 40–44. https://doi.org/10.1111/j.1469-8986.1977.tb01152.x

Angelakis, E., Stathopoulou, S., Frymiare, J. L., Green, D. L., Lubar, J. F., & Kounios, J. (2007). EEG neurofeedback: A brief overview and an example of peak alpha frequency training for cognitive enhancement in the elderly. *The Clinical Neuropsychologist, 21*(1), 110–129. https://doi.org/10.1080/13854040600744839

Arnold, L. G., & Debeus, R. (2024). Double-blind 2-site randomized clinical trial of neurofeedback for ADHD (Version v1) [Data set]. ICPSR - Interuniversity Consortium for Political and Social Research. https://doi.org/10.3886/E198003V1

Arns, M., Drinkenburg, W., & Leon Kenemans, J. (2012). The effects of QEEG-informed neurofeedback in ADHD: An open-label pilot study. *Applied Psychophysiology and Biofeedback, 37*(3), 171–180. https://doi.org/10.1007/s10484-012-9191-4

Arns, M., Conners, C. K., & Kraemer, H. C. (2013). A decade of EEG theta/beta ratio research in ADHD: A meta-analysis. *Journal of Attention Disorders, 17*(5), 374–383. https://doi.org/10.1177/1087054712460087

Arns, M., Heinrich, H., & Strehl, U. (2014). Evaluation of neurofeedback in ADHD: The long and winding road. *Biological Psychology, 95*, 108–115. https://doi.org/10.1016/j.biopsycho.2013.11.013

Arza, A., Garzón-Rey, J. M., Lázaro, J., Gil, E., Lopez-Anton, R., de la Camara, C., Laguna, P., Bailon, R., & Aguiló, J. (2019). Measuring acute stress response through physiological signals: Towards a quantitative assessment of stress. *Medical & Biological Engineering & Computing, 57*(1), 271–287. https://doi.org/10.1007/s11517-018-1879-z

Askovic, M., Soh, N., Elhindi, J., & Harris, A. W. F. (2023). Neurofeedback for post-traumatic stress disorder: Systematic review and meta-analysis of clinical and neurophysiological outcomes. *European Journal of Psychotraumatology, 14*(2), Article 2257435. https://doi.org/10.1080/20008066.2023.2257435

Azzalini, D., Rebollo, I., & Tallon-Baudry, C. (2019). Visceral signals shape brain dynamics and cognition. *Trends in Cognitive Sciences, 23*(6), 488–509. https://doi.org/10.1016/j.tics.2019.03.007

Babiloni, C., Del Percio, C., Arendt-Nielsen, L., Soricelli, A., Romani, G. L., Rossini, P. M., & Capotosto, P. (2014). Cortical EEG alpha rhythms reflect task-specific somatosensory and motor interactions in humans. *Clinical Neurophysiology, 125*(10), 1936–1945. https://doi.org/10.1016/j.clinph.2014.04.021

Babiloni, C., Miniussi, C., Babiloni, F., Carducci, F., Cincotti, F., Del Percio, C., Sirello, G., Fracassi, C., Nobre, A. C., & Rossini, P. M. (2004). Sub-second "temporal attention" modulates alpha rhythms. A high-resolution EEG study. *Cognitive Brain Research, 19*(3), 259–268. https://doi.org/10.1016/j.cogbrainres.2003.12.010

Baghdadi, G., Soroush, A., Towhidkhah, F., & Rostami, R. (2020). Using the concepts of time-delayed feedback control in biofeedback systems in children with ADD: A preliminary study. *Communications in Nonlinear Science and Numerical Simulation, 85*, Article 105235. https://doi.org/10.1016/j.cnsns.2020.105235

Banoczi, W. R. (2005). How some drugs affect the electroencephalogram (EEG). *American Journal of Electroneurodiagnostic Technology, 45*(2), 118–129. https://doi.org/10.1080/1086508X.2005.11079518

Barry, R. J., Clarke, A. R., & Johnstone, S. J. (2011). Caffeine and opening the eyes have additive effects on resting arousal measures. *Clinical Neurophysiology, 122*(10), 2010–2015. https://doi.org/10.1016/j.clinph.2011.02.036

Barry, R. J., & De Blasio, F. M. (2017). EEG differences between eyes-closed and eyes-open resting remain in healthy ageing. *Biological Psychology, 129*, 293–304. https://doi.org/10.1016/j.biopsycho.2017.09.010

Bazanova, O. M. (2011). [Individual alpha peak frequency variability and reproducibility in various experimental conditions]. *Zhurnal Vysshei Nervnoi Deiatelnosti Imeni I P Pavlova, 61*(1), 102–111.

Bazanova, O. M. (2012). Alpha EEG activity depends on the individual dominant rhythm frequency. *Journal of Neurotherapy, 16*(4), 270–284. https://doi.org/10.1080/10874208.2012.730786

Bazanova, O. M., & Aftanas, L. I. (2010). Individual EEG alpha activity analysis for enhancement neurofeedback efficiency: Two case studies. *Journal of Neurotherapy, 14*(3), 244–253. https://doi.org/10.1080/10874208.2010.501517

Bazanova, O. M., Auer, T., & Sapina, E. A. (2018). On the efficiency of individualized theta/beta ratio neurofeedback combined with forehead emg training in ADHD children. *Frontiers in Human Neuroscience, 12*, Article 3. https://doi.org/10.3389/fnhum.2018.00003

Bazanova, O. M., Kholodina, N. V., Nikolenko, E. D., & Payet, J. (2017). Training of support afferentation in postmenopausal women. *International Journal of Psychophysiology, 122*, 65–74. https://doi.org/10.1016/j.ijpsycho.2017.05.002

Bazanova, O. M., Nikolenko, E. D., & Barry, R. J. (2017). Reactivity of alpha rhythms to eyes opening (the Berger effect) during menstrual cycle phases. *International Journal of Psychophysiology*, *122*, 56–64. https://doi.org/10.1016/j.ijpsycho.2017.05.001

Bazanova, O. M., & Vernon, D. (2014). Interpreting EEG alpha activity. *Neuroscience & Biobehavioral Reviews, 44*, 94–110. https://doi.org/10.1016/j.neubiorev.2013.05.007

Bazanova, O. M., Vernon, D., Lazareva, O. Yu., Muravlyova, K. B., & Skoraya, M. V. (2013). Influence of biofeedback and self-regulation psychotechniques on the cognitive functions and alpha activity EEG. *Bulletin of Siberian Medicine, 12*(2), 36–42. https://doi.org/10.20538/1682-0363-2013-2-36-42

Becker, D., Creutzfeldt, O. D., Schwibbe, M., & Wuttke, W. (1982). Changes in physiological, EEG and psychological parameters in women during the spontaneous menstrual cycle and following oral contraceptives. *Psychoneuroendocrinology, 7*(1), 75–90. https://doi.org/10.1016/0306-4530(82)90057-9

Bernstein, N. A. (1945). [Current problems of neurophysiology]. *Fiziologicheskii Zhurnal SSSR Imeni I. M. Sechenova*, *31*(5–6), 298–311.

Birbaumer, N. (2024). "Your thoughts are (were) free!": Brain-computer-interfaces, neurofeedback, detection of deception, and the future of mind-reading. *Applied Psychophysiology and Biofeedback*. https://doi.org/10.1007/s10484-024-09648-z

Blumenstein, B., & Orbach, I. (2014). Biofeedback for sport and performance enhancement. In Oxford Handbooks Editorial Board (Ed.), *Oxford handbook topics in psychology* (1st ed.). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199935291.013.001

Boynton, T. (2001). Applied research using alpha/theta training for enhancing creativity and well-being. *Journal of Neurotherapy, 5*(1–2), 5–18. https://doi.org/10.1300/J184v05n01_02

Brötzner, C. P., Klimesch, W., Doppelmayr, M., Zauner, A., & Kerschbaum, H. H. (2014). Resting state alpha frequency is associated with menstrual cycle phase, estradiol and use of oral contraceptives. *Brain Research, 1577*, 36–44. https://doi.org/10.1016/j.brainres.2014.06.034

Brown, P., RELISH Consortium, & Zhou, Y. (2019). Large expert-curated database for benchmarking document similarity detection in biomedical literature search. *Database, 2019*, baz085. https://doi.org/10.1093/database/baz085

Bucho, T., Caetano, G., Vourvopoulos, A., Accoto, F., Esteves, I., I Badia, S. B., Rosa, A., & Figueiredo, P. (2019). *Comparison of visual and auditory modalities for upper-alpha EEG-neurofeedback*. 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 5960–5966). Berlin, Germany. https://doi.org/10.1109 /EMBC.2019.8856671

Cacioppo, J. T. (2004). Feelings and emotions: Roles for electrophysiological markers. *Biological Psychology, 67*(1–2), 235–243. https://doi.org/10.1016/j.biopsycho.2004.03.009

Castermans, T., Duvinage, M., Cheron, G., & Dutoit, T. (2014). About the cortical origin of the low-delta and high-gamma rhythms observed in EEG signals during treadmill walking. *Neuroscience Letters, 561*, 166–170. https://doi.org/10.1016/j.neulet.2013.12.059

Chang, L.-J., Lin, J.-F., Lin, C.-F., Wu, K.-T., Wang, Y.-M., & Kuo, C.-D. (2011). Effect of body position on bilateral EEG alterations and their relationship with autonomic nervous modulation in normal subjects. *Neuroscience Letters, 490*(2), 96–100. https://doi.org/10.1016/j.neulet.2010.12.034

Chernyshev, B. V., Osokina, Ye. S., Ilyushina, N. V., Trunova, M. S., & Chernysheva, Ye. G. (2013). The dependence of the success rate of alpha-training on extraversion and neuroticism. *Bulletin of Siberian Medicine, 12*(2), 72–79. https://doi.org/10.20538/1682-0363-2013-2-72-79

Chikhi, S., Matton, N., Sanna, M., & Blanchet, S. (2023). Mental strategies and resting state EEG: Effect on high alpha amplitude modulation by neurofeedback in healthy young adults. *Biological Psychology, 178*, Article 108521. https://doi.org/10.1016/j.biopsycho.2023.108521

Choi, Y.-J., Choi, E.-J., & Ko, E. (2023). Neurofeedback effect on symptoms of posttraumatic stress disorder: A systematic review and meta-analysis. *Applied Psychophysiology and Biofeedback, 48*(3), 259–274. https://doi.org/10.1007/s10484-023-09593-3

Clark, M., Euler, M. J., King, B. R., Williams, A. M., & Lohse, K. R. (2024). Associations between age-related differences in occipital alpha power and the broadband parameters of the EEG power spectrum: A cross-sectional cohort study. *International Journal of Psychophysiology, 195*, Article 112272. https://doi.org/10.1016/j.ijpsycho.2023.112272

Collura, T. F. (2010). Conclusion: QEEG-guided neurofeedback in context and in practice. *Applied Psychophysiology and Biofeedback, 35*(1), 37–38. https://doi.org/10.1007/s10484-009-9108-z

Compton, R. J., Gearinger, D., & Wild, H. (2019). The wandering mind oscillates: EEG alpha power is enhanced during moments of mind-wandering. *Cognitive, Affective, & Behavioral Neuroscience, 19*(5), 1184–1191. https://doi.org/10.3758/s13415-019-00745-9

Cowley, B., Holmström, É., Juurmaa, K., Kovarskis, L., & Krause, C. M. (2016). Computer enabled neuroplasticity treatment: A clinical trial of a novel design for neurofeedback therapy in adult ADHD. *Frontiers in Human Neuroscience, 10*, Article 205. https://doi.org/10.3389/fnhum.2016.00205

Crivelli, D., Fronda, G., & Balconi, M. (2019). Neurocognitive enhancement effects of combined mindfulness–Neurofeedback training in sport. *Neuroscience, 412*, 83–93. https://doi.org/10.1016/j.neuroscience.2019.05.066

D'Angiulli, A., Herdman, A., Stapells, D., & Hertzman, C. (2008). Children's event-related potentials of auditory selective attention vary with their socioeconomic status. *Neuropsychology, 22*(3), 293–300. https://doi.org/10.1037/0894-4105.22.3.293

DeGood, D. E., & Redgate, E. S. (1982). Interrelationship of plasma cortisol and other activation indices during EMG biofeedback training. *Journal of Behavioral Medicine, 5*(2), 213–223. https://doi.org/10.1007/BF00844810

Dessy, E., Mairesse, O., van Puyvelde, M., Cortoos, A., Neyt, X., & Pattyn, N. (2020). Train your brain? Can we really selectively train specific EEG frequencies with neurofeedback training. *Frontiers in Human Neuroscience, 14*, Article 22. https://doi.org/10.3389/fnhum.2020.00022

Diamond, A. (2013). Executive functions. *Annual Review of Psychology, 64*(1), 135–168. https://doi.org/10.1146/annurev-psych-113011-143750

Diamond, A., & Ling, D. S. (2016). Conclusions about interventions, programs, and approaches for improving executive functions that appear justified and those that, despite much hype, do not. *Developmental Cognitive Neuroscience, 18*, 34–48. https://doi.org/10.1016/j.dcn.2015.11.005

Dias, Á. M., Van Deusen, A. M., Oda, E., & Bonfim, M. R. (2012). Clinical efficacy of a new automated hemoencefalographic neurofeedback protocol. *The Spanish Journal of Psychology, 15*(3), 930–941. https://doi.org/10.5209/rev_SJOP.2012.v15.n3.39385

Dijk, D.-J., & Duffy, J. F. (2020). Novel approaches for assessing circadian rhythmicity in humans: A review. *Journal of Biological Rhythms, 35*(5), 421–438. https://doi.org/10.1177/0748730420940483

Domingos, C., Peralta, M., Prazeres, P., Nan, W., Rosa, A., & Pereira, J. G. (2021). Session frequency matters in neurofeedback training of athletes. *Applied Psychophysiology and Biofeedback, 46*(2), 195–204. https://doi.org/10.1007/s10484-021-09505-3

Doppelmayr, M., Klimesch, W., Pachinger, T., & Ripper, B. (1998). Individual differences in brain dynamics: Important implications for the calculation of event-related band power. *Biological Cybernetics, 79*(1), 49–57. https://doi.org/10.1007/s004220050457

Doppelmayr, M., Klimesch, W., Stadler, W., Pöllhuber, D., & Heine, C. (2002). EEG alpha power and intelligence. *Intelligence, 30*(3), 289–302. https://doi.org/10.1016/S0160-2896(01)00101-5

Duffy, F. H., Albert, M. S., McAnulty, G., & Garvey, A. J. (1984). Age-related differences in brain electrical activity of healthy subjects. *Annals of Neurology, 16*(4), 430–438. https://doi.org/10.1002/ana.410160403

Ebrahimzadeh, E., Saharkhiz, S., Rajabion, L., Oskouei, H. B., Seraji, M., Fayaz, F., Saliminia, S., Sadjadi, S. M., & Soltanian-Zadeh, H. (2022). Simultaneous electroencephalography-functional magnetic resonance imaging for assessment of human brain function. *Frontiers in Systems Neuroscience, 16*, Article 934266. https://doi.org/10.3389/fnsys.2022.934266

Edgar, J. C., Berman, J. I., Liu, S., Chen, Y.-H., Huang, M., Brodkin, E. S., Roberts, T. P. L., & Bloy, L. (2022). Two mechanisms facilitate regional independence between brain regions based on an examination of alpha-band activity in healthy control adult males. *International Journal of Psychophysiology, 178*, 51–59. https://doi.org/10.1016/j.ijpsycho.2022.06.007

Enders, H., & Nigg, B. M. (2016). Measuring human locomotor control using EMG and EEG: Current knowledge, limitations and future considerations. *European Journal of Sport Science, 16*(4), 416–426. https://doi.org/10.1080/17461391.2015.1068869

Endsley, M. R. (1988). Design and evaluation for situation awareness enhancement. *Proceedings of the Human Factors Society Annual Meeting, 32*(2), 97–101. https://doi.org/10.1177/154193128803200221

Endsley, M. R. (2013). Situation awareness. In J. D. Lee, & A. Kirlik (Eds.), *The Oxford handbook of cognitive engineering* (pp. 88–108). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199757183.001.0001

Enz, N., Schmidt, J., Nolan, K., Mitchell, M., Alvarez Gomez, S., Alkayyali, M., Cambay, P., Gippert, M., Whelan, R., & Ruddy, K. (2022). Self-regulation of the brain's right frontal Beta rhythm using a brain-computer interface. *Psychophysiology, 59*(11), Article e14115. https://doi.org/10.1111/psyp.14115

Escolano, C., Navarro-Gil, M., Garcia-Campayo, J., Congedo, M., & Minguez, J. (2014). The effects of individual upper alpha neurofeedback in ADHD: An open-label pilot study. *Applied Psychophysiology and Biofeedback, 39*(3–4), 193–202. https://doi.org/10.1007/s10484-014-9257-6

Escolano, C., Olivan, B., Lopez-del-Hoyo, Y., Garcia-Campayo, J., & Minguez, J. (2012). Double-blind single-session neurofeedback training in upper-alpha for cognitive enhancement of healthy subjects. *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 4643–4647. San Diego, CA: IEEE. https://doi.org/10.1109/EMBC.2012.6347002

Fede, S. J., Dean, S. F., Manuweera, T., & Momenan, R. (2020). A guide to literature informed decisions in the design of real time fMRI neurofeedback studies: A systematic review.

Frontiers in Human Neuroscience, 14, Article 60. https://doi.org/10.3389/fnhum.2020.00060

Festa, E. K., Bracken, B. K., Desrochers, P. C., Winder, A. T., Strong, P. K., & Endsley, M. R. (2024). EEG and fNIRS are associated with situation awareness (hazard) prediction during a driving task. *Ergonomics, 67*(12), 1993–2008. https://doi.org/10.1080/00140139.2024.2367163

Flouri, E., Midouhas, E., & Joshi, H. (2014). Family poverty and trajectories of children's emotional and behavioural problems: The moderating roles of self-regulation and verbal cognitive ability. *Journal of Abnormal Child Psychology, 42*(6), 1043–1056. https://doi.org/10.1007/s10802-013-9848-3

Fontanari, J. F. (2017). Awareness improves problem-solving performance. *Cognitive Systems Research, 45*, 52–58. https://doi.org/10.1016/j.cogsys.2017.05.003

Fyfe, E. R., DeCaro, M. S., & Rittle-Johnson, B. (2015). When feedback is cognitively-demanding: The importance of working memory capacity. *Instructional Science, 43*(1), 73–91. https://doi.org/10.1007/s11251-014-9323-8

Gertz, J., & Lavie, P. (1983). Biological rhythms in arousal indices: A potential confounding effect in EEG biofeedback. *Psychophysiology, 20*(6), 690–695. https://doi.org/10.1111/j.1469-8986.1983.tb00940.x

Ghaziri, J., Tucholka, A., Larue, V., Blanchette-Sylvestre, M., Reyburn, G., Gilbert, G., Lévesque, J., & Beauregard, M. (2013). Neurofeedback training induces changes in white and gray matter. *Clinical EEG and Neuroscience, 44*(4), 265–272. https://doi.org/10.1177/1550059413476031

Golonka, K., Gawlowska, M., Mojsa-Kaja, J., & Marek, T. (2019). Psychophysiological characteristics of burnout syndrome: Resting-state EEG analysis. *BioMed Research International, 2019*(1), Article 3764354. https://doi.org/10.1155/2019/3764354

Goncharova, I. I., McFarland, D. J., Vaughan, T. M., & Wolpaw, J. R. (2003). EMG contamination of EEG: Spectral and topographical characteristics. *Clinical Neurophysiology, 114*(9), 1580–1593. https://doi.org/10.1016/S1388-2457(03)00093-2

Gong, A., Gu, F., Nan, W., Qu, Y., Jiang, C., & Fu, Y. (2021). A review of neurofeedback training for improving sport performance from the perspective of user experience. *Frontiers in Neuroscience, 15*, Article 638369. https://doi.org/10.3389/fnins.2021.638369

Gorev, A. S., & Semenova, O. A. (2003). Effect of individual features of the CNS on efficiency of relaxation biofeedback training in 9- to 10-year-old children. *Human Physiology, 29*(4), 437–443. https://doi.org/10.1023/A:1024925422758

Grosselin, F., Breton, A., Yahia-Cherif, L., Wang, X., Spinelli, G., Hugueville, L., Fossati, P., Attal, Y., Navarro-Sune, X., Chavez, M., & George, N. (2021). Alpha activity neuromodulation induced by individual alpha-based neurofeedback learning in ecological context: A double-blind randomized study. *Scientific Reports, 11*(1), Article 18489. https://doi.org/10.1038/s41598-021-96893-5

Gruzelier, J. H. (2014). EEG-neurofeedback for optimising performance. III: A review of methodological and theoretical considerations. *Neuroscience & Biobehavioral Reviews, 44*, 159–182. https://doi.org/10.1016/j.neubiorev.2014.03.015

Güntensperger, D., Thüring, C., Kleinjung, T., Neff, P., & Meyer, M. (2019). Investigating the efficacy of an individualized alpha/delta neurofeedback protocol in the treatment of chronic tinnitus. *Neural Plasticity, 2019*(1), Article 3540898. https://doi.org/10.1155/2019/3540898

Güntensperger, D., Kleinjung, T., Neff, P., Thüring, C., & Meyer, M. (2020). Combining neurofeedback with source estimation: Evaluation of an sLORETA neurofeedback protocol for chronic tinnitus treatment. *Restorative Neurology and Neuroscience, 38*(4), 283–299. https://doi.org/10.3233/RNN-200992

Gutmann, B., Hülsdünker, T., Mierau, J., Strüder, H. K., & Mierau, A. (2018). Exercise-induced changes in EEG alpha power depend on frequency band definition mode. *Neuroscience Letters, 662*, 271–275. https://doi.org/10.1016/j.neulet.2017.10.033

Habes, I., Rushton, S., Johnston, S. J., Sokunbi, M. O., Barawi, K., Brosnan, M., Daly, T., Ihssen, N., & Linden, D. E. J. (2016). FMRI neurofeedback of higher visual areas and perceptual biases. *Neuropsychologia, 85*, 208–215. https://doi.org/10.1016/j.neuropsychologia.2016.03.031

Halliday, D. M., Conway, B. A., Farmer, S. F., & Rosenberg, J. R. (1998). Using electroencephalography to study functional coupling between cortical activity and electromyograms during voluntary contractions in humans. *Neuroscience Letters, 241*(1), 5–8. https://doi.org/10.1016/S0304-3940(97)00964-6

Hammond, D. C., & Kirk, L. (2008). First, do no harm: Adverse effects and the need for practice standards in neurofeedback. *Journal of Neurotherapy, 12*(1), 79–88. https://doi.org/10.1080/10874200802219947

Hanslmayr, S., Sauseng, P., Doppelmayr, M., Schabus, M., & Klimesch, W. (2005). Increasing individual upper alpha power by neurofeedback improves cognitive performance in human subjects. *Applied Psychophysiology and Biofeedback, 30*(1), 1–10. https://doi.org/10.1007/s10484-005-2169-8

Hardt, J. V., & Kamiya, J. (1976). Some comments on Plotkin's self-regulation of electroencephalographic alpha. *Journal of Experimental Psychology: General, 105*(1), 100–108. https://doi.org/10.1037/0096-3445.105.1.100

Hardt, J. V., & Kamiya, J. (1978). Anxiety change through electroencephalographic alpha feedback seen only in high anxiety subjects. *Science, 201*(4350), 79–81. https://doi.org/10.1126/science.663641

Harris, A., Melkonian, D., Williams, L., & Gordon, E. (2006). Dynamic spectral analysis findings in first episode and chronic schizophrenia. *International Journal of Neuroscience, 116*(3), 223–246. https://doi.org/10.1080/00207450500402977

Himmelmeier, L., & Werheid, K. (2024). Neurofeedback training in children with ADHD: A systematic review of personalization and methodological features facilitating training conditions. *Clinical EEG and Neuroscience, 55*(6), 625–635. https://doi.org/10.1177/15500594241279580

Ibanez, A., Cetkovich, M., Petroni, A., Urquina, H., Baez, S., Gonzalez-Gadea, M. L., Kamienkowski, J. E., Torralva, T., Torrente, F., Strejilevich, S., Teitelbaum, J., Hurtado, E., Guex, R., Melloni, M., Lischinsky, A., Sigman, M., & Manes, F. (2012). The neural basis of decision-making and reward processing in adults with euthymic bipolar disorder or attention-deficit/hyperactivity disorder (ADHD). *PLoS ONE, 7*(5), Article e37306. https://doi.org/10.1371/journal.pone.0037306

Jefferson, A. L., Gibbons, L. E., Rentz, D. M., Carvalho, J. O., Manly, J., Bennett, D. A., & Jones, R. N. (2011). A life course model of cognitive activities, socioeconomic status, education, reading ability, and cognition. *Journal of the American Geriatrics Society, 59*(8), 1403–1411. https://doi.org/10.1111/j.1532-5415.2011.03499.x

Jensen, O., Gelfand, J., Kounios, J., & Lisman, J. E. (2002). Oscillations in the alpha band (9–12 Hz) increase with memory load during retention in a short-term memory task. *Cerebral Cortex, 12*(8), 877–882. https://doi.org/10.1093/cercor/12.8.877

Jobert, M., Wilson, F. J., Roth, T., Ruigt, G. S. F., Anderer, P., Drinkenburg, W. H. I. M., & The IPEG Pharmaco-EEG Guidelines Committee. (2013). Guidelines for the recording and evaluation of pharmaco-sleep studies in man: The International Pharmaco-EEG Society (IPEG). *Neuropsychobiology, 67*(3), 127–167. https://doi.org/10.1159/000343449

Kadosh, K. C., & Staunton, G. (2019). A systematic review of the psychological factors that influence neurofeedback learning outcomes. *NeuroImage, 185*, 545–555. https://doi.org/10.1016/j.neuroimage.2018.10.021

Kaiser, A., Aggensteiner, P. M., Blasco Fontecilla, H., Ros, T., Acquaviva, E., Attal, Y., Banaschewski, T., Baumeister, S., Bousquet, E., Bussalb, A., Delhaye, M., Delorme, R., Drechsler, R., Goujon, A., Häge, A., Mayaud, L., Mechler, K., Menache, C., Revol, O., … Brandeis, D. (2024). Limited usefulness of neurocognitive functioning indices as predictive markers for treatment response to methylphenidate or neurofeedback@home in children and adolescents with ADHD. *Frontiers in Psychiatry, 14*, Article 1331004. https://doi.org/10.3389/fpsyt.2023.1331004

Kaiser, D. A. (2001). Rethinking standard bands. *Journal of Neurotherapy, 5*(1–2), 87–96. https://doi.org/10.1300/J184v05n01_08

Kamiya, J. (1969). Operant control of the EEG alpha rhythm and some of its reported effects on consciousness. In C. T. Tart (Ed.), *Altered states of consciousness*, (pp. 519–529).

Katkin, E. S., & Murray, E. N. (1968). Instrumental conditioning of autonomically mediated behavior: Theoretical and methodological issues. *Psychological Bulletin, 70*(1), 52–68. https://doi.org/10.1037/h0025925

Katsantonis, I. (2024). Exploring age-related differences in metacognitive self-regulation: The influence of motivational factors in secondary school students. *Frontiers in Psychology, 15*, Article 1383118. https://doi.org/10.3389/fpsyg.2024.1383118

Kerson, C., deBeus, R., Lightstone, H., Arnold, L. E., Barterian, J., Pan, X., & Monastra, V. J. (2020). EEG theta/beta ratio calculations differ between various EEG neurofeedback and assessment software packages: Clinical interpretation. *Clinical EEG and Neuroscience, 51*(2), 114–120. https://doi.org/10.1177/1550059419888320

Kettlety, S. A., Finley, J. M., & Leech, K. A. (2024). Visuospatial skills explain differences in the ability to use propulsion biofeedback post-stroke. *Journal of Neurologic Physical Therapy, 48*(4), 207–216. https://doi.org/10.1097/NPT.0000000000000487

Kirschfeld, K. (2005). The physical basis of alpha waves in the electroencephalogram and the origin of the “Berger effect”? *Biological Cybernetics, 92*(3), 177–185. https://doi.org/10.1007/s00422-005-0547-1

Klimesch, W., Doppelmayr, M., Pachinger, T., & Russegger, H. (1997). Event-related desynchronization in the alpha band and the processing of semantic information. *Cognitive Brain Research, 6*(2), 83–94. https://doi.org/10.1016/S0926-6410(97)00018-9

Klimesch, W., Doppelmayr, M., Russegger, H., Pachinger, T., & Schwaiger, J. (1998). Induced alpha band power changes in the human EEG and attention. *Neuroscience Letters, 244*(2), 73–76. https://doi.org/10.1016/S0304-3940(98)00122-0

Klug, M., & Gramann, K. (2021). Identifying key factors for improving ICA-based decomposition of EEG data in mobile and stationary experiments. *European Journal of Neuroscience, 54*(12), 8406–8420. https://doi.org/10.1111/ejn.14992

Kober, S. E., Schweiger, D., Witte, M., Reichert, J. L., Grieshofer, P., Neuper, C., & Wood, G. (2015). Specific effects of EEG based neurofeedback training on memory functions in post-stroke victims. *Journal of NeuroEngineering and Rehabilitation, 12*(1), Article 107. https://doi.org/10.1186/s12984-015-0105-6

Kohl, S. H., Mehler, D. M. A., Lührs, M., Thibault, R. T., Konrad, K., & Sorger, B. (2020). The potential of functional near-infrared spectroscopy-based neurofeedback-A systematic review and recommendations for best practice. *Frontiers in Neuroscience, 14*, Article 594. https://doi.org/10.3389/fnins.2020.00594

Konareva, I. N. (2005). Modifications of the EEG frequency pattern in humans related to a single neurofeedback session. *Neurophysiology, 37*(5–6), 388–395. https://doi.org/10.1007/s11062-006-0015-0

Koukkou, M., Federspiel, A., Bräker, E., Hug, C., Kleinlogel, H., Merlo, M. C. G., & Lehmann, D. (2000). An EEG approach to the neurodevelopmental hypothesis of schizophrenia studying schizophrenics, normal controls and adolescents. *Journal of Psychiatric Research, 34*(1), 57–73. https://doi.org/10.1016/S0022-3956(99)00040-0

Kozlovskaya, I., Dmitrieva, I., Grigorieva, L., Kirenskaya, A., & Kreidich, Yu. (1988). Gravitational mechanisms in the motor system. studies in real and simulated weightlessness. In V. S. Gurfinkel, M. E. Ioffe, J. Massion, & J. P. Roll (Eds.), *Stance and motion* (pp. 37–48). Springer US. https://doi.org/10.1007/978-1-4899-0821-6_4

Kozlovskaya, I. B., Sayenko, I. V., Sayenko, D. G., Miller, T. F., Khusnutdinova, D. R., & Melnik, K. A. (2007). Role of support afferentation in control of the tonic muscle activity. *Acta Astronautica, 60*(4–7), 285–294. https://doi.org/10.1016/j.actaastro.2006.08.010

Kripke, D. F. (1974). Ultradian rhythms in sleep an wakefulness. In E. D. Weitzman (Ed.), *Advances in sleep research* (pp. 305–325). Illus Spectrum Publications, Inc.

Kvamme, T. L., Sarmanlu, M., & Overgaard, M. (2022). Doubting the double-blind: Introducing a questionnaire for awareness of experimental purposes in neurofeedback studies. *Consciousness and Cognition, 104*, Article 103381. https://doi.org/10.1016/j.concog.2022.103381

Labrague, L. J., McEnroe-Petitte, D. M., Gloe, D., Thomas, L., Papathanasiou, I. V., & Tsaras, K. (2017). A literature review on stress and coping strategies in nursing students. *Journal of Mental Health, 26*(5), 471–480. https://doi.org/10.1080/09638237.2016.1244721

Lal, S. K. L., Henderson, R. J., Carter, N., Bath, A., Hart, M. G., Langeluddecke, P., & Hunyor, S. N. (1998). Effect of feedback signal and psychological characteristics on blood pressure self-manipulation capability. *Psychophysiology, 35*(4), 405–412. https://doi.org/10.1111/1469-8986.3540405

Lavie, P., & Kripke, D. F. (1981). Ultradian circa hours rhythms: A multioscillatory system. *Life Sciences, 29*(24), 2445–2450. https://doi.org/10.1016/0024-3205(81)90698-6

Li, K., & Brown, J. D. (2023). Dual-modality haptic feedback improves dexterous task execution with virtual EMG-controlled gripper. *IEEE Transactions on Haptics, 16*(4), 816–825. https://doi.org/10.1109/TOH.2023.3328256

Linkenkaer-Hansen, K., Nikulin, V. V., Palva, S., Ilmoniemi, R. J., & Palva, J. M. (2004). Prestimulus oscillations enhance psychophysical performance in humans. *The Journal of Neuroscience, 24*(45), 10186–10190. https://doi.org/10.1523/JNEUROSCI.2584-04.2004

Livanov, M. N. (1984). [Rhythms of the electroencephalogram and their functional significance]. *Zhurnal Vysshei Nervnoi Deiatelnosti Imeni I P Pavlova, 34*(4), 613–626. https://doi.org/10.1007/bf01149484

Lopes da Silva, F. (2013). EEG and MEG: Relevance to Neuroscience. *Neuron, 80*(5), 1112–1128. https://doi.org/10.1016/j.neuron.2013.10.017

Markiewcz, R. (2017). The use of EEG biofeedback/neurofeedback in psychiatric rehabilitation. *Psychiatria Polska, 51*(6), 1095–1106. https://doi.org/10.12740/PP/68919

Markovska-Simoska, S., Pop-Jordanova, N., & Georgiev, D. (2008). Simultaneous EEG and EMG biofeedback for peak performance in musicians. *Prilozi, 29*(1), 239–252.

Matsunaga, K., & Genda, E. (2005). Biographics Art “I know me”: Image generation aiming at EEG control by biofeedback. *Journal of Physiological Anthropology and Applied Human Science, 24*(1), 139–142. https://doi.org/10.2114 /jpa.24.139

Mckenzie, R. E., Ehrisman, W. J., Montgomery, P. S., & Barnes, R. H. (1974). The treatment of headache by means of electroencephalographic biofeedback. *Headache: The Journal of Head and Face Pain, 13*(4), 164–172. https://doi.org/10.1111/j.1526-4610.1974.hed1304164.x

Mierau, A., Felsch, M., Hülsdünker, T., Mierau, J., Bullermann, P., Weiß, B., & Strüder, H. K. (2016). The interrelation between sensorimotor abilities, cognitive performance and individual EEG alpha peak frequency in young children. *Clinical Neurophysiology, 127*(1), 270–276. https://doi.org/10.1016/j.clinph.2015.03.008

Min, B., Park, H., Kim, J. I., Lee, S., Back, S., Lee, E., Oh, S., Yun, J.-Y., Kim, B.-N., Kim, Y., Hwang, J., Lee, S., & Kim, J.-H. (2023). The effectiveness of a neurofeedback-assisted mindfulness training program using a mobile app on stress reduction in employees: Randomized controlled trial. *JMIR MHealth and UHealth, 11*, Article e42851. https://doi.org/10.2196/42851

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P., Stewart, L. A., & PRISMA-P Group (2015). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. *Systematic Reviews, 4*(1), Article 1. https://doi.org/10.1186/2046-4053-4-1

Montgomery, D. D. (2001). Change: Detection and modification . *Applied Psychophysiology and Biofeedback, 26*(3), 215–226. https://doi.org/10.1023/A:1011350204547

Mouchnino, L., Lhomond, O., Morant, C., & Chavet, P. (2017). Plantar sole unweighting alters the sensory transmission to the cortical areas. *Frontiers in Human Neuroscience, 11*, Article 220. https://doi.org/10.3389/fnhum.2017.00220

Mullaney, K. M., Carpenter, S. K., Grotenhuis, C., & Burianek, S. (2014). Waiting for feedback helps if you want to know the answer: The role of curiosity in the delay-of-feedback benefit. *Memory & Cognition, 42*(8), 1273–1284. https://doi.org/10.3758/s13421-014-0441-y

Naas, A., Rodrigues, J., Knirsch, J. P., & Sonderegger, A. (2019). Neurofeedback training with a low-priced EEG device leads to faster alpha enhancement but shows no effect on cognitive performance: A single-blind, sham-feedback study. *PLoS ONE, 14*(9), Article e0211668. https://doi.org/10.1371/journal.pone.0211668

Nan, W., Rodrigues, J. P., Ma, J., Qu, X., Wan, F., Mak, P. I., Mak, P. U., Vai, M. I., & Rosa, A. (2012). Individual alpha neurofeedback training effect on short term memory. *International Journal of Psychophysiology, 86*(1), 83–87. https://doi.org/10.1016/j.ijpsycho.2012.07.182

Nan, W., Wan, F., Vai, M. I., & Da Rosa, A. C. (2015). Resting and initial beta amplitudes predict learning ability in beta/theta ratio neurofeedback training in healthy young adults. *Frontiers in Human Neuroscience, 9*, Article 677. https://doi.org/10.3389/fnhum.2015.00677

Nekrasova, J., Bazanova, O., Shunenkov, D., Kanarskiy, M., Borisov, I., & Luginina, E. (2022). Problem of myogenic contamination in electroencephalography. *Human Physiology, 48*(4), 470–482. https://doi.org/10.1134/S0362119722040090

Nguyen, L., Murphy, K., & Andrews, G. (2019). Cognitive and neural plasticity in old age: A systematic review of evidence from executive functions cognitive training. *Ageing Research Reviews, 53*, Article 100912. https://doi.org/10.1016/j.arr.2019.100912

Orekhova, E., Stroganova, T., Posikera, I., & Elam, M. (2006). EEG theta rhythm in infants and preschool children. *Clinical Neurophysiology, 117*(5), 1047–1062. https://doi.org/10.1016/j.clinph.2005.12.027

Pan, Z., Zhang, C., Su, W., Qi, X., Feng, X., Gao, L., Xu, X., & Liu, J. (2023). Relationship between individual differences in pain empathy and task- and resting-state EEG. *NeuroImage, 284*, Article 120452. https://doi.org/10.1016/j.neuroimage.2023.120452

Parsons, B., & Faubert, J. (2021). Enhancing learning in a perceptual-cognitive training paradigm using EEG-neurofeedback. *Scientific Reports, 11*(1), Article 4061. https://doi.org/10.1038/s41598-021-83456-x

Paul, M., Bellebaum, C., Ghio, M., Suchan, B., & Wolf, O. T. (2020). Stress effects on learning and feedback-related neural activity depend on feedback delay. *Psychophysiology, 57*(2), Article e13471. https://doi.org/10.1111/psyp.13471

Pérez-Elvira, R., Oltra-Cucarella, J., Carrobles, J. A., Teodoru, M., Bacila, C., & Neamtu, B. (2021). Individual alpha peak frequency, an important biomarker for live z-score training neurofeedback in adolescents with learning disabilities. *Brain Sciences, 11*(2), Article 167. https://doi.org/10.3390/brainsci11020167

Pérez-Medina-Carballo, R., Kosmadopoulos, A., Moderie, C., Boudreau, P., Robert, M., & Boivin, D. B. (2024). Dampened circadian amplitude of EEG power in women after menopause. *Journal of Sleep Research*, Article e14219. https://doi.org/10.1111/jsr.14219

Petrenko, T. I., Bazanova, O. M., & Kabardov, M. K. (2019). Prospects for using adaptive biofeedback to train musicians. *RUDN Journal of Psychology and Pedagogics, 16*(4), 495–516. https://doi.org/10.22363/2313-1683-2019-16-4-495-516

Pigott, H. E., Cannon, R., & Trullinger, M. (2021). The fallacy of sham-controlled neurofeedback trials: A reply to Thibault and colleagues (2018). *Journal of Attention Disorders, 25*(3), 448–457. https://doi.org/10.1177/1087054718790802

Pinho, A. L., de Manzano, Ö., Fransson, P., Eriksson, H., & Ullén, F. (2014). Connecting to create: Expertise in musical improvisation is associated with increased functional connectivity between premotor and prefrontal areas. *The Journal of Neuroscience, 34*(18), 6156–6163. https://doi.org/10.1523/JNEUROSCI.4769-13.2014

Pirini, M., Mancini, M., Farella, E., & Chiari, L. (2011). EEG correlates of postural audio-biofeedback. *Human Movement Science, 30*(2), 249–261. https://doi.org/10.1016/j.humov.2010.05.016

Pourmohammadi, S., & Maleki, A. (2020). Stress detection using ECG and EMG signals: A comprehensive study. *Computer Methods and Programs in Biomedicine, 193*, Article 105482. https://doi.org/10.1016/j.cmpb.2020.105482

Prfwett, M. J., & Adams, H. E. (1976). Alpha activity suppression and enhancement as a function of feedback and instructions. *Psychophysiology, 13*(4), 307–310. https://doi.org/10.1111/j.1469-8986.1976.tb03081.x

Probst, T., & Wist, E. R. (1990). Impairment of auditory processing by simultaneous vestibular stimulation: Psychophysical and electrophysiological data. *Behavioural Brain Research, 41*(1), 1–9. https://doi.org/10.1016/0166-4328(90)90048-J

Quaedflieg, C. W. E. M., Smulders, F. T. Y., Meyer, T., Peeters, F., Merckelbach, H., & Smeets, T. (2016). The validity of individual frontal alpha asymmetry EEG neurofeedback. *Social Cognitive and Affective Neuroscience, 11*(1), 33–43. https://doi.org/10.1093/scan/nsv090

Rahman, S., Munam, A. M., Hossain, A., Hossain, A. S. M. D., & Bhuiya, R. A. (2023). Socio-economic factors affecting the academic performance of private university students in Bangladesh: A cross-sectional bivariate and multivariate analysis. *SN Social Sciences, 3*(2), Article 26. https://doi.org/10.1007/s43545-023-00614-w

Rathee, S., Bhatia, D., Punia, V., & Singh, R. (2020). Peak alpha frequency in relation to cognitive performance. *Journal of Neurosciences in Rural Practice, 11*(3), 416–419. https://doi.org/10.1055/s-0040-1712585

Reichert, J. L., Kober, S. E., Neuper, C., & Wood, G. (2015). Resting-state sensorimotor rhythm (SMR) power predicts the ability to up-regulate SMR in an EEG-instrumental conditioning paradigm. *Clinical Neurophysiology, 126*(11), 2068–2077. https://doi.org/10.1016/j.clinph.2014.09.032

Reis, J., Portugal, A. M., Fernandes, L., Afonso, N., Pereira, M., Sousa, N., & Dias, N. S. (2016). An alpha and theta intensive and short neurofeedback protocol for healthy aging working-memory training. *Frontiers in Aging Neuroscience, 8*, Article 157. https://doi.org/10.3389/fnagi.2016.00157

Renton, T., Tibbles, A., & Topolovec-Vranic, J. (2017). Neurofeedback as a form of cognitive rehabilitation therapy following stroke: A systematic review. *PLoS ONE, 12*(5), Article e0177290. https://doi.org/10.1371/journal.pone.0177290

Ros, T., Enriquez-Geppert, S., Zotev, V., Young, K. D., Wood, G., Whitfield-Gabrieli, S., Wan, F., Vuilleumier, P., Vialatte, F., Van De Ville, D., Todder, D., Surmeli, T., Sulzer, J. S., Strehl, U., Sterman, M. B., Steiner, N. J., Sorger, B., Soekadar, S. R., Sitaram, R. … Thibault, R. T. (2020). Consensus on the reporting and experimental design of clinical and cognitive-behavioural neurofeedback studies (CRED-nf checklist). *Brain, 143*(6), 1674–1685. https://doi.org/10.1093/brain/awaa009

Samaha, J., & Postle, B. R. (2015). The speed of alpha-band oscillations predicts the temporal resolution of visual perception. *Current Biology, 25*(22), 2985–2990. https://doi.org/10.1016/j.cub.2015.10.007

Schibli, K., Wong, K., Hedayati, N., & D'Angiulli, A. (2017). Attending, learning, and socioeconomic disadvantage: Developmental cognitive and social neuroscience of resilience and vulnerability. *Annals of the New York Academy of Sciences, 1396*(1), 19–38. https://doi.org/10.1111/nyas.13369

Schlatter, S., Louisy, S., Canada, B., Thérond, C., Duclos, A., Blakeley, C., Lehot, J.-J., Rimmelé, T., Guillot, A., Lilot, M., & Debarnot, U. (2022). Personality traits affect anticipatory stress vulnerability and coping effectiveness in occupational critical care situations. *Scientific Reports, 12*(1), Article 20965. https://doi.org/10.1038/s41598-022-24905-z

Schoenfeld, W. N. (1970). *The theory of reinforcement schedules*. Appleton-Century-Crofts.

Schönenberg, M., Wiedemann, E., Schneidt, A., Scheeff, J., Logemann, A., Keune, P. M., & Hautzinger, M. (2017). Neurofeedback, sham neurofeedback, and cognitive-behavioural group therapy in adults with attention-deficit hyperactivity disorder: A triple-blind, randomised, controlled trial. *The Lancet Psychiatry, 4*(9), 673–684. https://doi.org/10.1016/S2215-0366(17)30291-2

Shackman, A. J., McMenamin, B. W., Slagter, H. A., Maxwell, J. S., Greischar, L. L., & Davidson, R. J. (2009). Electromyogenic artifacts and electroencephalographic inferences. *Brain Topography, 22*(1), 7–12. https://doi.org/10.1007/s10548-009-0079-4

Sherlin, L. H., Arns, M., Lubar, J., Heinrich, H., Kerson, C., Strehl, U., & Sterman, M. B. (2011). Neurofeedback and basic learning theory: Implications for research and practice. *Journal of Neurotherapy, 15*(4), 292–304. https://doi.org/10.1080/10874208.2011.623089

Shuda, Q., Bougoulias, M. E., & Kass, R. (2020). Effect of nature exposure on perceived and physiologic stress: A systematic review. *Complementary Therapies in Medicine, 53*, Article 102514. https://doi.org/10.1016/j.ctim.2020.102514

Slobounov, S., Cao, C., Jaiswal, N., & Newell, K. M. (2009). Neural basis of postural instability identified by VTC and EEG. *Experimental Brain Research, 199*(1), 1–16. https://doi.org/10.1007/s00221-009-1956-5

Smetanin, N., Belinskaya, A., Lebedev, M., & Ossadtchi, A. (2020). Digital filters for low-latency quantification of brain rhythms in real time. *Journal of Neural Engineering, 17*(4), Article 046022. https://doi.org/10.1088/1741-2552/ab890f

Smith, T., Panfil, K., Bailey, C., & Kirkpatrick, K. (2019). Cognitive and behavioral training interventions to promote self-control. *Journal of Experimental Psychology: Animal Learning and Cognition, 45*(3), 259–279. https://doi.org/10.1037/xan0000208

Sokhadze, T. M., Cannon, R. L., & Trudeau, D. L. (2008). EEG biofeedback as a treatment for substance use disorders: Review, rating of efficacy, and recommendations for further research. *Applied Psychophysiology and Biofeedback, 33*(1), 1–28. https://doi.org/10.1007/s10484-007-9047-5

Steel, A., Silson, E. H., Stagg, C. J., & Baker, C. I. (2016). The impact of reward and punishment on skill learning depends on task demands. *Scientific Reports, 6*(1), Article 36056. https://doi.org/10.1038/srep36056

Steingrimsson, S., Bilonic, G., Ekelund, A.-C., Larson, T., Stadig, I., Svensson, M., Vukovic, I. S., Wartenerg, C., Wrede, O., & Bernhardsson, S. (2020). Electroencephalography-based neurofeedback as treatment for post-traumatic stress disorder: A systematic review and meta-analysis. *European Psychiatry, 63*(1), Article e7. https://doi.org/10.1192/j.eurpsy.2019.7

Stoffers, D., Bosboom, J. L. W., Deijen, J. B., Wolters, E. C., Berendse, H. W., & Stam, C. J. (2007). Slowing of oscillatory brain activity is a stable characteristic of Parkinson's disease without dementia. *Brain: A Journal of Neurology, 130*(7), 1847–1860. https://doi.org/10.1093/brain/awm034

Strothmann, S. (2024). *Neurofeedback training for children with ADHD : Evaluating the effect of personalized and standardized neurofeedback protocols on theta rhythms, beta rhythms and the iAPF* [Student thesis]. DiVA. https://urn.kb.se/resolve?urn=urn:nbn:se:his:diva-23971

Su, K.-H., Hsueh, J.-J., Chen, T., & Shaw, F.-Z. (2021). Validation of eyes-closed resting alpha amplitude predicting neurofeedback learning of upregulation alpha activity. *Scientific Reports, 11*(1), Article 19615. https://doi.org/10.1038/s41598-021-99235-7

Sudakov, K. V. (1997). A systems process of reinforcement. *Neuroscience and Behavioral Physiology, 27*(4), 370–380. https://doi.org/10.1007/BF02462938

Swerdloff, M. M., & Hargrove, L. J. (2023). Dry EEG measurement of P3 to evaluate cognitive load during sitting, standing, and walking. *PLoS ONE, 18*(7), Article e0287885. https://doi.org/10.1371/journal.pone.0287885

Tarasov, E. A. (2007). [Boslab computer-based system: A polyfunctional computer biofeedback environment]. *Meditsinskaia Tekhnika*, (4), 48–51.

Tazaki, M. (2024). A review: Effects of neurofeedback on patients with mild cognitive impairment (MCI), and Alzheimer's disease (AD). *Frontiers in Human Neuroscience, 17*, Article 1331436. https://doi.org/10.3389/fnhum.2023.1331436

Tenke, C. E., Kayser, J., Miller, L., Warner, V., Wickramaratne, P., Weissman, M. M., & Bruder, G. E. (2013). Neuronal generators of posterior EEG alpha reflect individual differences in prioritizing personal spirituality. *Biological Psychology, 94*(2), 426–432. https://doi.org/10.1016/j.biopsycho.2013.08.001

Thatcher, R. W., Walker, R. A., Biver, C. J., North, D. N., & Curtin, R. (2003). Quantitative EEG normative databases: Validation and clinical correlation. *Journal of Neurotherapy, 7*(3–4), 87–121. https://doi.org/10.1300/J184v07n03_05

Travis, T. A., Kondo, C. Y., & Knott, J. R. (1974). Personality variables and alpha enhancement: A correlative study. *British Journal of Psychiatry, 124*(583), 542–544. https://doi.org/10.1192/bjp.124.6.542

Tumyalis, A. V., & Aftanas, L. I. (2014). Contribution of neurophysiological endophenotype, individual frequency of EEG alpha oscillations, to mechanisms of emotional reactivity. *Bulletin of Experimental Biology and Medicine, 156*(6), 711–716. https://doi.org/10.1007/s10517-014-2431-2

Urigüen, J. A., & Garcia-Zapirain, B. (2015). EEG artifact removal—State-of-the-art and guidelines. *Journal of Neural Engineering, 12*(3), Article 031001. https://doi.org/10.1088/1741-2560/12/3/031001

VaezMousavi, S., Barry, R., Rushby, J., & Clarke, A. (2007). Arousal and activation effects on physiological and behavioral responding during a continuous performance task. *Acta Neurobiologiae Experimentalis, 67*(4), 461–470. https://doi.org/10.55782/ane-2007-1662

van der Meer, J. N., Pampel, A., Van Someren, E. J. W., Ramautar, J. R., van der Werf, Y. D., Gomez-Herrero, G., Lepsien, J., Hellrung, L., Hinrichs, H., Möller, H. E., & Walter, M. (2016). Carbon-wire loop based artifact correction outperforms post-processing EEG/fMRI corrections—A validation of a real-time simultaneous EEG/fMRI correction method. *NeuroImage, 125*, 880–894. https://doi.org/10.1016/j.neuroimage.2015.10.064

Veilahti, A. V. P., Kovarskis, L., & Cowley, B. U. (2021). Neurofeedback learning is skill acquisition but does not guarantee treatment benefit: Continuous-time analysis of learning-curves from a clinical trial for ADHD. *Frontiers in Human Neuroscience, 15*, Article 668780. https://doi.org/10.3389/fnhum.2021.668780

Vernon, D., Frick, A., & Gruzelier, J. (2004). Neurofeedback as a treatment for ADHD: A methodological review with implications for future research. *Journal of Neurotherapy, 8*(2), 53–82. https://doi.org/10.1300/J184v08n02_04

Vernon, D. J. (2005). Can neurofeedback training enhance performance? An evaluation of the evidence with implications for future research. *Applied Psychophysiology and Biofeedback, 30*(4), 347–364. https://doi.org/10.1007/s10484-005-8421-4

Voetterl, H., van Wingen, G., Michelini, G., Griffiths, K. R., Gordon, E., DeBeus, R., Korgaonkar, M. S., Loo, S. K., Palmer, D., Breteler, R., Denys, D., Arnold, L. E., du Jour, P., van Ruth, R., Jansen, J., van Dijk, H., & Arns, M. (2023). Brainmarker-I differentially predicts remission to various attention-deficit/hyperactivity disorder treatments: A discovery, transfer, and blinded validation study. *Biological Psychiatry. Cognitive Neuroscience and Neuroimaging, 8*(1), 52–60. https://doi.org/10.1016/j.bpsc.2022.02.007

Wächter, T., Lungu, O. V., Liu, T., Willingham, D. T., & Ashe, J. (2009). Differential effect of reward and punishment on procedural learning. *The Journal of Neuroscience, 29*(2), 436–443. https://doi.org/10.1523/JNEUROSCI.4132-08.2009

Wacker, M. S. (1996). Alpha brainwave training and perception of time passing: Preliminary findings. *Biofeedback and Self-Regulation, 21*(4), 303–309. https://doi.org/10.1007/BF02214430

Wan, F., Nan, W., Vai, M. I., & Rosa, A. (2014). Resting alpha activity predicts learning ability in alpha neurofeedback. *Frontiers in Human Neuroscience, 8*, Article 500. https://doi.org/10.3389/fnhum.2014.00500

Wang, Y. S., Liu, Z. D., Yue, S., Wang, W. Z., & Tian, F. S. (2018). [Effect of biofeedback therapy on metabolic syndrome under different levels of job stress]. *Zhonghua Lao Dong Wei Sheng Zhi Ye Bing Za Zhi = Zhonghua Laodong Weisheng Zhiyebing Zazhi = Chinese Journal of Industrial Hygiene and Occupational Diseases, 36*(10), 728–733. https://doi.org/10.3760/cma.j.issn.1001-9391.2018.10.002

Weber, L. A., Ethofer, T., & Ehlis, A.-C. (2020). Predictors of neurofeedback training outcome: A systematic review. *NeuroImage: Clinical, 27*, Article 102301. https://doi.org/10.1016/j.nicl.2020.102301

Wood, G., Willmes, K., Koten, J. W., & Kober, S. E. (2024). Fat tails and the need to disclose distribution parameters of qEEG databases. *PLoS ONE, 19*(1), Article e0295411. https://doi.org/10.1371/journal.pone.0295411

Xiang, M.-Q., Hou, X.-H., Liao, B.-G., Liao, J.-W., & Hu, M. (2018). The effect of neurofeedback training for sport performance in athletes: A meta-analysis. *Psychology of Sport and Exercise, 36*, 114–122. https://doi.org/10.1016/j.psychsport.2018.02.004

Yamaguchi, H. (1981). *Characteristics of alpha-enhancement biofeedback training with eyes closed* [dissertation]. *Tohoku University*.

Yeh, W.-H., Hsueh, J.-J., & Shaw, F.-Z. (2021). Neurofeedback of alpha activity on memory in healthy participants: A systematic review and meta-analysis. *Frontiers in Human Neuroscience, 14*, Article 562360. https://doi.org/10.3389/fnhum.2020.562360

Zandi Mehran, Y., Firoozabadi, M., & Rostami, R. (2015). Improvement of neurofeedback therapy for improved attention through facilitation of brain activity using local sinusoidal extremely low frequency magnetic field exposure. *Clinical EEG and Neuroscience, 46*(2), 100–112. https://doi.org/10.1177/1550059414524403

Zhao, W., Van Someren, E. J. W., Li, C., Chen, X., Gui, W., Tian, Y., Liu, Y., & Lei, X. (2021). EEG spectral analysis in insomnia disorder: A systematic review and meta-analysis. *Sleep Medicine Reviews, 59*, Article 101457. https://doi.org/10.1016/j.smrv.2021.101457

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NeuroRegulation

Predicting Consumer Behavior: A Critical Review of EEG-Based Neuromarketing and the Decision Tree Model

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Abstract

This critical review examines the study by Amin et al. (2020), which proposes a decision tree (DT) model for predicting consumer behavior using electroencephalogram (EEG)-based neuromarketing. The study leverages EEG signals to analyze consumer responses to marketing stimuli, employing advanced data preprocessing, feature extraction, and classification techniques. The DT model demonstrates superior performance in accuracy, sensitivity, and specificity compared to existing methods, achieving a prediction accuracy of 95%. While the study highlights the potential of EEG-based neuromarketing and the interpretability of the DT model, limitations such as sample size constraints, generalizability concerns, and trade-offs between accuracy and interpretability are noted. The review underscores the model's relevance for developing consumer-centric marketing strategies while calling for further research to address its limitations and expand its applicability across diverse populations.

Keywords: neuropsychology; neuromarketing; consumer behavior prediction; EEG signals; decision tree (DT) model

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Introduction

Neuromarketing, a groundbreaking fusion of neuroscience and marketing, leverages neuropsychological tools such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), eye tracking, or other biometrics to understand consumers' cognitive and affective responses to marketing stimuli (Sixth Factor, n.d.). The study focuses on data mining and machine-learning technologies to identify brain activities and investigate discoveries or abnormalities as consumers interact with marketing catalysts (Amin et al., 2020). EEG, used to detect electrical charges in brain waves, has been a fundamental tool in the paper by Amin et al. (2020), *Consumer Behavior Analysis using EEG Signals for Neuromarketing Application,* for capturing consumer responses and building on previous research in the field. In the study, Amin et al. (2020) propose a prediction model, the decision tree (DT) model, by harnessing EEG findings. The model is comprehensively evaluated by comparing it to existing prediction methods and pushing the boundaries to provide insights into consumer decision-making processes and thus allow advertisers to create effective marketing models. The following critical review of Amin et al.'s (2020) research work provides a thorough view of the methods and results of the paper, with a focus on the study findings, strengths, weaknesses, and relevance to further the discussion of market research methods.

Methods

Research Design

The study uses a data-driven approach, using EEG signals to explore and predict consumer conduct. Amin et al. (2020) opted for a research design involving four key steps: data collection, preprocessing, feature extraction, and classification. Time-frequency distribution features were derived from the EEG signals on which different classification algorithms were applied, ensuring all aspects of the research were thoroughly considered and measured.

Sample and Data Collection Methods

Yadava et al. (2017) previously conducted a study utilizing the hidden Markov model (HMM), building on a predictive model framework to understand consumer choices through likes and dislikes. They carried out this work by studying brain waves from EEG signals as consumers responded to marketing stimuli. The HMM achieved a 70% prediction accuracy, facilitating the DT model to build on the algorithm's precision, resulting in a high prediction accuracy of 95%.

The study uses publicly available data from Yadava et al.'s (2017) work. Data was collected from 25 subjects who were exposed to 42 images in 14 categories. Each participant labeled the image shown to them as *like* or *dislike*. Corresponding EEG signals to 1,050 responses were recorded and examined.

Data Preprocessing, Feature Extraction, and Classification

EEG signals contain noise, which can obscure the underlying patterns of the brain's activity. To address this, noise reduction methods are used in EEG analysis to smooth signal variations. In the paper, a notable noise reduction approach known as running average was employed in the preprocessing stage, which smooths data by averaging data points over a moving window to reduce noise (Amin et al., 2020). The running average method effectively deals with time-frequency datasets, ameliorating short-term fluctuations and highlighting overall trends.

For feature extraction, the wavelet transform method (WTM), a renowned signal processing technique for analyzing time-frequency representations of EEG signals, was utilized. Amin et al. (2020) specifically used the discrete wavelet transform (DWT) method, a WTM subpart known to reliably break down EEG signals into smaller parts in a fast and nonredundant manner, allowing for a detailed analysis of different frequencies. DWT is crucial for accurate classification as it uses low-pass (g) and high-pass (h) filters to analyze different frequencies (Amin et al., 2020). This offers a comprehensive view of brain activity and establishes trust in the research methods through vigorous processing methods.

Following feature extraction, the power was calculated from five-level DWT-decomposed EEG signals for each electrode. The total number of instances (i.e., single data trials) was 1,045, determined by multiplying the number of electrodes by five (since each underwent a five-level decomposition; Amin et al., 2020). To enhance model performance, the authors considered ensemble methods like gradient boosting, which improves accuracy by combining multiple weaker models into a stronger one. However, while gradient boosting improves accuracy, it is not the best choice for interpretability (Amin et al., 2020). Alternatively, additive models (predictive models that improve performance by sequentially adding corrections) and full interaction models like CART (classification and regression trees) are often studied separately (Luna et al., 2019). This is because gradient boosting prioritizes accuracy, while CART focuses on interpretability.

For classification, Amin et al. (2020) split the extracted features into a training set to build the model and a testing set to evaluate it. After creating the model, data was fed to predict consumer preferences (Amin et al., 2020). To test the proposed models' performance, the predicted outcomes were compared to the actual results. The rest of the review focuses on conveying the study findings and analyzing the advantages, drawbacks, and applicability.

Results

The proposed model's performance was evaluated using four key metrics: area under the curve (AUC), accuracy, sensitivity, and specificity (Amin et al., 2020). The authors compared their model with five existing techniques for consumer behavior prediction: k-nearest neighbors (KNN), discriminant analysis (DA), naive Bayes (NB), support vector machines (SVM), and random forests (RF). Amin et al.'s (2020) findings suggest that the DT algorithm is superior in accuracy and sensitivity testing across all brain areas, providing a more reliable method for predicting consumer decision-making. The findings of this comparison are discussed below.

Area Under Curve

An AUC-ROC (area under the receiver operating characteristics) curve, also known as ROC, evaluates classifier performance, validating the tree model's effectiveness and visually representing multiclass classifier performance (Amin et al., 2020). Among other evaluation techniques, ROC is the most noteworthy, further building on the study's validity. The proposed model's ROC curve outperformed SVM and other classification algorithms across all brain areas, with a high measure of 99% in the cerebral cortex and a low measure of 96% in the occipital and parietal lobes. The highest measure noted in other existing models was 95% (for SVM), yet lower than any other measurement for DT (Amin et al., 2020).

Accuracy

Accuracy is a key measure for assessing classification models. It represents the proportion of correct predictions among all predictions made (Amin et al., 2020). A higher accuracy indicates the model's effectiveness in determining whether a consumer will like or dislike a product. The DT model achieved a high accuracy of 95% in the prefrontal region of the cerebral cortex, with a low accuracy of 90% in the occipital region. Notably, the proposed model's lowest accuracy was still higher than the highest accuracy of any other existing technique (Amin et al., 2020).

Sensitivity

Sensitivity measures the percentage of correctly predicted positive cases. Higher sensitivity indicates the model's ability to identify accurately when a consumer will like the product. DT's sensitivity is exceptionally high, ranging from 89% (in the occipital, parietal, and temporal lobes) to 94% (in the cerebral cortex), indicating its ability to predict positive consumer preferences correctly. The proposed model's lowest sensitivity was still higher than the highest sensitivity of any other existing technique (Amin et al., 2020).

Specificity

Specificity measures the percentage of correctly predicted negative cases. Higher specificity indicates the model's ability to determine accurately when a consumer will dislike the product. While DT performs well in specificity (90%, 95%), it is marginally outperformed by DA and SVM in some brain areas. For example, DA achieves 98% specificity in the temporal lobe, compared to DT's 93% (Amin et al., 2020).

The DT model demonstrates the best overall performance, with high accuracy, AUC, sensitivity, and specificity across all brain areas. Its interpretability further enhances its practical utility for neuromarketing applications. The table below (Table 1) lists the performance of models in comparison to each other under different metrics and brain areas.

Table 1
Combined Results Table: Performance of Classification Algorithms in Predicting Consumer Preferences

Metric	Brain Area	KNN	DA	NB	DT	SVM	RF
Accuracy	Frontal Lobe	77%	60%	76%	**93%**	87%	54%
	Occipital Lobe	75%	56%	63%	**90%**	85%	52%
	Parietal Lobe	75%	56%	66%	**90%**	82%	52%
	Temporal Lobe	76%	56%	71%	**91%**	85%	54%
	Cerebral Cortex	78%	60%	81%	**95%**	87%	60%
AUC (area under the curve)	Frontal Lobe	83%	59%	86%	**98%**	95%	56%
	Occipital Lobe	82%	56%	72%	**96%**	93%	54%
	Parietal Lobe	81%	55%	75%	**96%**	91%	51%
	Temporal Lobe	83%	54%	79%	**97%**	92%	55%
	Cerebral Cortex	85%	66%	91%	**99%**	95%	62%
Sensitivity	Frontal Lobe	74%	20%	67%	**93%**	79%	40%
	Occipital Lobe	69%	5%	73%	**89%**	77%	38%
	Parietal Lobe	68%	4%	73%	**89%**	72%	37%
	Temporal Lobe	70%	3%	61%	**89%**	75%	38%
	Cerebral Cortex	71%	31%	81%	**94%**	77%	46%

Table 1
Combined Results Table: Performance of Classification Algorithms in Predicting Consumer Preferences

Metric	Brain Area	KNN	DA	NB	DT	SVM	RF
Specificity	Frontal Lobe	79%	91%	83%	93%	**94%**	65%
	Occipital Lobe	80%	**96%**	55%	90%	92%	63%
	Parietal Lobe	81%	**97%**	61%	91%	90%	63%
	Temporal Lobe	81%	**98%**	79%	93%	92%	67%
	Cerebral Cortex	84%	83%	81%	**95%**	**95%**	71%

Note. KNN = k-nearest neighbors; DA = discriminant analysis; NB = naive Bayes; DT = decision tree; SVM = support vector machine; RF = random forest. Data adapted from Amin et al. (2020).

Compared to the HMM proposed by Yadava et al. (2017), which had a prediction rate of 70%, the DT model significantly outperformed, achieving a 95% prediction rate using the same neurological testing tool (EEG; Table 2).

Table 2
Comparison With Previous Works

Author	Analysis Method	Prediction Rate	Imaging Tool
Yadava et al.	HMM	70%	EEG
Amin et al.	DT	**95%**	EEG

Note. HMM = hidden Markov model; DT = decision tree; EEG = electroencephalogram. Data adapted from Amin et al. (2020).

The authors conclude that their proposed method is superior to other existing techniques in terms of accuracy, sensitivity, and specificity, allowing advertisers to gain insights into consumer behavior and tailor their marketing strategies accordingly (Amin et al., 2020).

Analysis

This section highlights the study's advantages and limitations and the significance of the DT model in neuromarketing and consumer analysis.

Strengths

Needless to say, a key advantage of the study by Amin et al. (2020) is that the DT model outperforms the existing techniques by high margins, proving it to be an impactful and superior prediction model. Aside from the precise results of the study, several elements are presented that enhance the trustworthiness and robustness of its findings to improve the reliability and applicability of the results. For example, the use of technology such as data mining and machine learning helps further innovations in fields like neuropsychology. This practice involving notable data technologies assures consumers of ethical and credible research outputs.

Amin et al. (2020) often referenced well-acclaimed research to increase the potency of the study results. For example, Blankertz et al. (2006) and Heekeren et al. (2004) are cited to explain the relation between brain activities and the EEG systems, thus increasing the academic trust of the paper in review.

Using a thorough research design and reliable data processing methods (running average for noise reduction, WTM, and DWT), the study demonstrates the authors' commitment to achieving excellence in the study results. Rigorous examinations were carried out by Amin et al. (2020) by employing multiple evaluation metrics (AUC, accuracy, sensitivity, and specificity) and comparing the proposed DT model to five other existing techniques. This high standard of evaluation illustrates the robustness of the study findings.

Finally, the root-to-leaf path (logic rule) of the proposed DT algorithm makes it highly interpretable, while the study by Yadava et al. (2017) does not provide any logic rule (Amin et al., 2020). This enables a business to understand consumer cognition and its surrounding elements, making DT a more practical and desired prediction model.

Weaknesses

Despite the study's multiple advantages, a few limitations have also been observed. DT establishes superiority in the accuracy and sensitivity metrics compared to other existing techniques. However, according to the study results, DT lacks specificity (DA and SVM measure higher values), which may make it difficult to determine when a consumer will dislike a product.

A limitation of the study is the generalizability of the DT model stemming from the sample size of 25 participants. While the model proves to have high performance, it may have been overfitted to the specific dataset, meaning its high accuracy might not hold across different demographics, cultural backgrounds, or real-world consumer scenarios. Additionally, small-sample studies have reduced statistical power, thereby increasing the likelihood of spurious correlations and making it harder to detect true patterns in consumer decision-making. This also limits the ability to examine individual differences in EEG responses, which are known to vary based on age, gender, and cognitive traits (Yadava et al., 2017). To improve reliability, future studies should consider using larger and more representative samples to validate the DT model's predictive performance across different populations.

Moreover, the dataset studied by Amin et al. (2020) was derived from publicly available data from Yadava et al.'s (2017) paper. This suggests that the data was not firsthand, raising concerns about the authors' direct involvement with the subject and whether the dataset fully represents diverse consumer behaviors.

Lastly, methods such as gradient boosting and CART, as mentioned in the paper by Amin et al. (2020), are accurate in their measurement. However, a trade-off between correctness and clarity creates a potential limitation in the study due to the challenging interpretation for the reader.

Relevance of the DT Model

The DT model can potentially revolutionize how market strategies are developed and implemented today. This mutual benefit to consumers and producers can lead to a more consumer-centric and accurate approach to developing marketing strategies (Amin et al., 2020). The study's findings have significant implications in neuromarketing because the DT is a highly interpretable and applicable model. Further research in this field would help advertisers understand the reasons for consumer preferences and develop more targeted and personalized strategies by employing different neurological tools such as eye-tracking or fMRI.

On the other hand, while the use of data mining and machine learning algorithms are broadly used today in most sectors of society, ethical concerns follow regarding participant privacy and consumer manipulation. It is crucial to keep customer autonomy at the forefront when employing influential technology in machine learning.

Conclusion

The paper by Amin et al. (2020) presents a robust and interpretable model, the DT model, used to predict consumer decision-making to develop marketing strategies by harnessing EEG signals. The data presented in the paper indicates that the DT model performs better than other existing predictive models. The DT model proves superior accuracy, sensitivity, and specificity, providing valuable insights to marketing and analysis teams. The study presents several advantages and a few limitations in the overall application of the research. Amin et al. (2020) achieve high trust by using reliable techniques and robust comparisons in their work. Overall, the authors open avenues to better neuromarketing studies and offer valuable contributions to consumer behavior prediction and experience.

Author Declarations

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References

Amin, C. R., Hasin, M. F., Leon, T. S., Aurko, A. B., Tamanna, T., Rahman, M. A., & Parvez, M. Z. (2020, December). Consumer behaviour analysis using EEG signals for neuromarketing application. In *2020 IEEE symposium series on computational intelligence (SSCI)* (pp. 2061–2066). IEEE. https://doi.org/10.1109/SSCI47803.2020.9308358

Blankertz, B., Dornhege, G., Krauledat, M., Muller, K.-R., Kunzmann, V., Losch, F., & Curio, G. (2006). The Berlin brain-computer interface: EEG-based communication without subject training. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 14*(2), 147–152. https://doi.org /10.1109/TNSRE.2006.875557

Heekeren, H. R., Marrett, S., Bandettini, P. A., & Ungerleider, L. G. (2004). A general mechanism for perceptual decision-making in the human brain. *Nature, 431*(7010), 859–862. https://doi.org/10.1038/nature02966

Luna, J. M., Gennatas, E. D., Ungar, L. H., Eaton, E., Diffenderfer, E. S., Jensen, S. T., Simone, C. B., Friedman, J. H., Solberg, T. D., & Valdes, G. (2019). Building more accurate decision trees with the additive tree. *Proceedings of* *the National Academy of Sciences, 116*(40), 19887–19893. https://doi.org/10.1073/pnas.1816748116

Sixth Factor. (n.d.). *Neuro marketing sensonomics.* Retrieved March 6, 2025, from https://sixthfactor.com/neuro-marketing-sensonomics/

Yadava, M., Kumar, P., Saini, R., Roy, P. P., & Dogra, D. P. (2017). Analysis of EEG signals and its application to neuromarketing. *Multimedia Tools and Applications, 76*(18), 19087–19111. https://doi.org/10.1007/s11042-017-4580-6

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NeuroRegulation

Clarifying the Code: Historical Foundations, Current Practices, and Ethical Billing in Neurofeedback and QEEG

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Abstract

This article addresses the complexities of ethical billing and coding practices for neurofeedback and quantitative EEG (qEEG) services. It explores the historical development of Current Procedural Terminology (CPT) codes related to neurofeedback, examines current best practices in billing, and identifies potential legal and ethical pitfalls, including recent fraud cases. Special attention is given to Medicare's policies, the nuances of *incident to* billing, and the role of technicians in service delivery. The paper underscores the importance of documentation, scope-of-practice considerations, and transparency with payers and patients. Additionally, the advocacy efforts of professional organizations such as the International Society for Neuroregulation & Research (ISNR) and the Association for Applied Psychophysiology and Biofeedback (AAPB) are reviewed, particularly their ongoing initiative to update and refine CPT codes to better reflect clinical practice. Through a comprehensive synthesis of guidance from the AMA, CMS, professional ethics codes, and payer policies, the article serves as both a practical guide and a call to uphold ethical standards in the neuroregulation field.

Keywords: neurofeedback; qEEG; CPT; billing; insurance

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Introduction

Neurofeedback (EEG biofeedback) and quantitative EEG (qEEG) have evolved from experimental techniques to increasingly utilized clinical interventions for various neurological and psychological conditions (Hammond, 2011). As their use has grown, so too has the complexity surrounding proper billing and coding for these services. Practitioners must navigate a landscape of Current Procedural Terminology (CPT) codes, Medicare and insurance policies, and ethical guidelines to ensure that billing is accurate, compliant, and ethical. Missteps in coding—whether inadvertent or intentional—carry serious legal and professional consequences, as evidenced by recent fraud cases (U.S. Attorney's Office, 2025). This article aims to clarify "the code" by examining the historical foundations of CPT codes relevant to neurofeedback and qEEG, current best practices in ethical billing, Medicare's coverage stance, *incident to* billing rules, and the ethical implications of improper billing. We also discuss the role of professional organizations like the International Society for Neuroregulation & Research (ISNR) in advocating for better codes and provide recommendations for practitioners to uphold integrity in billing. The goal is to equip clinicians, billing specialists, and stakeholders with a comprehensive understanding of how to code and bill for neurofeedback and qEEG services correctly, thus protecting their practices and advancing the field responsibly.

Historical Foundations of Neurofeedback and QEEG CPT Codes

Understanding the present coding framework requires a look back at how these CPT codes were developed and refined. CPT codes are maintained by the American Medical Association (AMA) and are used to uniformly describe medical procedures for billing purposes. Neurofeedback, being a form of biofeedback, has long been associated with biofeedback-related CPT codes (Hammond, 2011). Key milestones in the historical development of relevant CPT codes include:

- Early Biofeedback Coding: Prior to the late 1990s, biofeedback was represented by multiple modality-specific codes (e.g., separate codes for EMG biofeedback, thermal biofeedback, EEG biofeedback, etc.), which made billing cumbersome. In the mid-1990s, the AMA recognized the need for a more unified coding system for biofeedback techniques.
- Introduction of CPT 90901 (1998): In 1998, CPT code 90901 for "biofeedback training by any modality," was established by the AMA to consolidate multiple biofeedback codes into a single, modality-agnostic code. This pivotal change meant that whether a practitioner was providing thermal biofeedback for migraines or EEG biofeedback (neurofeedback) for ADHD, they could use 90901 to bill for the training session. The creation of 90901 explicitly included EEG biofeedback as one of the modalities covered under "any modality," simplifying claims submission. It reflected the AMA CPT Editorial Panel's effort to streamline biofeedback billing and acknowledged that the fundamental service, teaching a patient to self-regulate using biological feedback, was conceptually similar across modalities.
- Psychophysiological Therapy Codes (90875 and 90876): Even before 90901's introduction, CPT had codes 90875 and 90876 to describe "individual psychophysiological therapy incorporating biofeedback training with psychotherapy." These codes, residing in the psychiatry/psychology section of CPT, were historically defined by session length (90875 for a ~20- to 30-min session; 90876 for ~45 to 50 min), the primary difference being duration. These codes acknowledge that some clinicians (e.g., psychologists) deliver biofeedback not as a stand-alone procedure, but in the context of psychotherapy. For example, using relaxation and EEG feedback during a counseling session for anxiety. Importantly, the AMA clarified that 90875 and 90876 inherently include the biofeedback component; thus, one should not bill a separate 90901 in addition to 90875 or 90876 for the same session (AMA, 1997). In a 1997 AMA CPT Assistant Q&A, the AMA explicitly stated it is "not appropriate to report code 90901 separately, when performing individual psychophysiological therapy (codes 90875 and 90876)" (AMA, 1997). This guidance, which remains applicable, was aimed at preventing double-billing of the biofeedback portion.

Role of AMA and the CPT Editorial Process

The AMA's CPT Editorial Panel and its advisors (including representatives from specialties and professional societies) have played a central role in code revisions. For neurofeedback and qEEG, professional advocacy has been crucial in influencing AMA decisions. For instance, the biofeedback community (through organizations like the Association for Applied Psychophysiology and Biofeedback [AAPB] and ISNR) has periodically submitted proposals to the AMA to update or clarify codes. The AMA's process ensures that any new code or revision is justified by clinical practice and utilization data. Over the years, the AMA also updated code descriptors. For example, recent CPT codebook editions standardized the time descriptors for 90875 (now listed as 30 min) and 90876 (45 min) to remove ambiguity and align with typical session durations.

CPT Codes for qEEG and brain mapping, which involves computerized analysis of EEG data (often to create brain maps or to guide neurofeedback protocols), did not receive a dedicated CPT code in the 1990s. Clinicians who performed qEEG assessments historically resorted to using general EEG or biofeedback codes. One code often associated with qEEG is 95957, defined as "digital analysis of electroencephalogram (EEG; e.g., for epileptic spike analysis)." Although 95957 was developed for neurologists analyzing EEG for epilepsy, some practitioners began using it to bill qEEG brain mapping, reasoning that qEEG entails digital EEG analysis (Successful Practitioner, 2021). This practice, however, introduced ambiguity. QEEG for psychological conditions was not the original intent of 95957. Recognizing the need for more appropriate coding, in the 2010s the AMA introduced code 96020, described as "neurofunctional brain mapping" procedures. By 2019, CPT 96020 was being referenced in neurofeedback circles as a code for functional brain mapping (qEEG; Successful Practitioner, 2021). In practice, 96020 may be used when conducting a qEEG in conjunction with functional tests, though its usage is limited and subject to payer acceptance.

Ongoing Evolution

The coding framework continues to evolve. No specific CPT code exists solely for "neurofeedback," providers must use the general biofeedback codes (90901, 90875, or 90876) as appropriate. This lack of specificity has led to continued efforts for refinement. As of the mid-2020s, professional organizations are advocating at the AMA for updated codes that better distinguish neurofeedback and related services. For example, ISNR and AAPB have launched a CPT Code Initiative to modernize codes for neurofeedback and biofeedback (ISNR & AAPB, 2023). This initiative argues that current codes are outdated and that more precise codes would improve access and reimbursement by clearly communicating the services provided. The AMA's historical role in creating and revising codes like 90901, 90875, and 90876 will likewise be crucial in any forthcoming code changes spurred by these advocacy efforts.

Current CPT Codes and Best Practices for Ethical Billing

In contemporary practice, clinicians providing neurofeedback or qEEG services typically utilize a handful of CPT codes. Ethical billing requires not only choosing the correct code but also using it properly in a manner consistent with its definition and avoiding practices that could be seen as upcoding or misrepresentation. Below are the primary CPT codes used and best practices for their ethical use:

- CPT 90901 – Biofeedback by Any Modality: This code is used for stand-alone biofeedback training where no psychotherapy is being concurrently provided. In the context of neurofeedback, if a practitioner (whether a psychologist, physician, or other qualified provider) conducts a session consisting solely of neurofeedback training (e.g., the patient is connected to EEG sensors and guided through brainwave training protocols), 90901 is the appropriate code. Best practices for using 90901 include:
    - Ensuring the session is indeed focused on biofeedback. If substantial psychotherapy or counseling is provided in the same visit, a different code might apply (see 90875 and 90876 below).
    - Documenting the modality and duration of the session. Even though 90901 is an untimed code per CPT guidelines (it can be reported once per day regardless of session length), it is wise to record how much time was spent to justify the service volume in case of audits.
    - Avoiding "unbundling" or adding other codes that represent components of the biofeedback session. For example, it would be unethical and incorrect to bill 90901 (biofeedback) plus an EEG recording code (such as 95816) for the same neurofeedback session, since neurofeedback inherently includes the EEG monitoring component. According to CMS therapy billing guidance, "Separate billing for concurrently applied modalities and/or procedures during biofeedback training is not appropriate" (CMS, 2015). In practice, that means if during a 30-min block you are doing neurofeedback, you should not also bill a therapeutic exercise or any other intervention for that same time—only the biofeedback code should be billed for that interval (CMS, 2015). This avoids double-counting time and conforms to CPT coding rules that one cannot bill two codes for the same service time.
- CPT 90875 and 90876 – Biofeedback with Psychotherapy: Codes 90875 (typically a 30-min session) and 90876 (45 min) are used when biofeedback is integrated with psychotherapy in a single session. These codes are often utilized by psychologists or other mental health professionals who use biofeedback as an adjunct to therapy, for instance, conducting EEG biofeedback for self-regulation as part of treating anxiety during a counseling session. Ethical use of 90875 and 90876 entails:
    - Only using these codes if you are licensed to provide psychotherapy in your state (e.g., psychologist,

licensed professional counselor, etc.) and you indeed provided psychotherapy alongside the biofeedback during the session. If the encounter was purely technical neurofeedback without any therapeutic discussion or psychological intervention, then 90875 or 90876 would not be appropriate; 90901 would be the correct code. The CPT code descriptors explicitly require that psychotherapy is a component of these services.

  - Choosing 90875 versus 90876 based on session length. It is important not to upcode. If your session was only ~25 min, you should bill 90875 (the shorter session code), not 90876. Documentation should reflect start and end times or total minutes to support the code selection.
  - Not billing 90901 in addition to 90875 or 90876 for the same session. As noted earlier, the AMA has made it clear that the biofeedback component is already included in 90875 and 90876 (AMA, 1997). Billing both codes for the same time would be redundant and viewed as improper unbundling. In summary, when performing psychotherapy *with* neurofeedback, a single code (90875 or 90876, depending on length) should cover the entire session.

- QEEG and EEG Analysis Codes: qEEG, which often precedes or supplements neurofeedback, involves recording EEG and quantitatively analyzing it (e.g., generating brain maps or comparing the data to normative databases). There is *no unique CPT code* labeled explicitly “qEEG.” Instead, practitioners typically use a combination of codes: often an EEG acquisition code (for the recording itself) plus an EEG analysis code. One common approach is to use a standard EEG recording code (e.g., 95816 for a routine EEG) along with 95957 for the digital analysis. By definition, 95957 represents the digital analysis of at least 20 min of EEG data (it was originally intended for analysis of epileptiform activity). Some insurers have reimbursed 95957 when used for qEEG, while others might challenge it as not medically necessary for certain behavioral health diagnoses. Another code, 96020, as mentioned earlier, has been referenced for “neurofunctional brain mapping.” Best practice for qEEG billing is first to verify each payer’s policy: many payers consider qEEG investigational for most psychiatric indications (more on this under Medicare and medical necessity). If you do proceed to bill, use the code that most closely fits what you actually did, and never bill a qEEG as if it were a full neuropsychological test or some other unrelated service. In a recent fraud case, a provider improperly billed psychological testing codes (96112, 96130, etc.) in conjunction with neurofeedback services, presumably to get reimbursement for qEEG or cognitive assessments that were not actually separate tests. This was flagged as fraudulent because those CPT codes could not logically be billed together in the way they did (Office of Inspector General, 2025). The lesson is to avoid “creative” coding that isn’t clearly supported by CPT definitions or by what actually occurred. If no existing code truly fits a service (for instance, if qEEG brain mapping for ADHD is not covered by insurance), the ethical path is either not to bill the insurer for it (opting for private pay) or to use an unlisted code with full disclosure; not to shoehorn it into payable codes through misrepresentation.
- Other Related Codes: In certain scenarios, other CPT codes might come into play for biofeedback services. For example, 90911 (biofeedback for pelvic floor training for incontinence) and the newer 90912 and 90913 (time-based codes for pelvic floor biofeedback) are designated exclusively for pelvic muscle rehabilitation. These codes are not to be used for neurofeedback under any circumstances, as they pertain to a completely different physiological system and clinical application. Although they fall under the broader category of biofeedback, their use is strictly limited to treatment of pelvic floor dysfunction and should not be repurposed or reinterpreted to describe neurofeedback or any central nervous system intervention. Another set of codes sometimes discussed are the Health and Behavior Assessment/Intervention (HBAI) series (96150–96155), which allow billing for behavioral services related to physical health conditions (e.g., pain, adherence to

treatment) without requiring a psychiatric diagnosis. While some neurofeedback providers may consider these when addressing chronic pain or related symptoms, these codes also are not appropriate for use with neurofeedback unless the intervention is explicitly targeting a physical health issue and is clearly within the provider's scope of practice. These codes should never be used to circumvent coverage limitations on psychotherapy or neurofeedback-specific biofeedback codes. In all cases, coding must accurately reflect the nature of the service delivered and remain within legal and ethical billing parameters.

- In all cases, accurate documentation is a cornerstone of ethical billing. Practitioners should record what intervention was done, for how long, and by whom. This information justifies the CPT code used and serves as evidence of proper billing. For example, therapy notes for a 90876 session should clearly reflect that psychotherapy was provided alongside biofeedback and that the session lasted around 45 min. For a 90901 session, the notes might focus on the neurofeedback training protocol used and the patient's response. Proper documentation not only supports billing but also encourages clinicians to stay within the boundaries of the code (knowing that an auditor might later read the note has a way of keeping one honest about what was done and billed). Finally, when in doubt about how to code a unique scenario, practitioners should consult authoritative sources (e.g., AMA CPT Assistant articles, insurer billing guidelines, or professional coding specialists). Adhering to the official definitions and guidelines is part of ethical practice. It demonstrates honesty and transparency in an often-confusing reimbursement environment.

Current Medicare Policies and Neurofeedback Coverage

Medicare's coverage of biofeedback and neurofeedback services has historically been limited, and it remains a critical area for practitioners to understand to avoid denied claims or inadvertent fraud. Medicare, through National Coverage Determinations (NCDs) and Local Coverage Determinations (LCDs) by Medicare Administrative Contractors (MACs), defines what it considers medically reasonable and necessary. For biofeedback, Medicare's policies draw a distinction between certain approved uses (primarily for specific medical conditions) and noncovered uses (including most psychological applications of neurofeedback).

Noncoverage for Psychiatric Applications

Medicare does not broadly cover neurofeedback (EEG biofeedback) for the treatment of psychological or psychiatric conditions such as ADHD, anxiety, depression, etc. In fact, the Medicare NCD for biofeedback (NCD 30.1) dates back decades and was written with traditional biofeedback (like EMG biofeedback for muscle retraining or thermal biofeedback for vascular headaches) in mind. It does not explicitly endorse neurofeedback for mental health. A long-standing Medicare policy statement is that "biofeedback is not covered by Medicare for treatment of psychosomatic conditions" (CMS, 2011; "Psychosomatic" in this context includes stress-related disorders, anxiety, and other psychological conditions). Moreover, an official Medicare contractor billing guideline explicitly notes: "Biofeedback for the treatment of psychiatric disorders (90875 and 90876) is not covered under Medicare" (CMS, 2011). This means that if a provider submits a claim to Medicare for CPT 90875 or 90876 for, say, a diagnosis of generalized anxiety disorder or ADHD, Medicare will deny that claim as not medically necessary. Similarly, CPT 90901, when billed for a primarily psychiatric indication, is typically deemed noncovered. For example, a regional Medicare Advantage policy states "CPT codes 90875, 90876, and 90901 will be considered not medically necessary and not covered" for the psychiatric or psychological indications addressed by the policy (Providence Health Plan, 2022).

What does Medicare cover in this realm? Medicare has a narrow scope of coverage for biofeedback, mainly limited to certain medical conditions. For instance, there is an NCD approving biofeedback (pelvic floor muscle biofeedback) for urinary incontinence, because sufficient evidence supported its efficacy for that condition. Thus, CPT 90911 (pelvic floor biofeedback) is covered for urge or stress incontinence when specific criteria are met. For other issues like chronic pain or hypertension, older guidance documents offered little support, and there's no explicit national Medicare coverage for those conditions either. Neurofeedback, being essentially EEG biofeedback, was not included as a covered treatment for psychological conditions in any Medicare coverage decisions. In summary, for Medicare Part B (outpatient services), one should assume that neurofeedback for mental health indications is noncovered. Patients must either pay out-of-pocket or the provider must find an alternate justification (e.g., perhaps billing 90901 for an off-label use with an Advance Beneficiary Notice (ABN) on file, if appropriate). Providers must not attempt to camouflage neurofeedback as something else for Medicare billing; doing so could be considered fraudulent. An illustrative (and cautionary) example: In the 2025 case of *U.S. v. Luthor et al.*, a Medicare fraud indictment in Minnesota, one allegation was that the defendants billed Medicare for CPT 90901 (biofeedback) while actually providing neurofeedback to treat mental health conditions, despite Medicare's position that 90901 biofeedback is intended for physiological conditions like incontinence or hypertension, not for psychological therapy. The claims were deemed false because the service (neurofeedback for mental health) didn't align with the code's covered purpose. This case underscores the importance of respecting Medicare's coverage rules. Even if neurofeedback has clear clinical benefit for a patient, if Medicare doesn't cover it for that indication, billing Medicare anyway (under a code for which the service is not covered) is considered a false claim (U.S. Attorney's Office, 2025).

Recent Changes and Developments

While Medicare's fundamental stance on neurofeedback coverage has not dramatically changed (it remains largely noncovered for psychiatric indications), there have been some recent developments worth noting. One has been in the context of telehealth and the COVID-19 Public Health Emergency. In 2020–2023, the Centers for Medicare & Medicaid Services (CMS) added many services to the list of those eligible for telehealth reimbursement. Interestingly, CPT codes 90875 and 90901 were among the codes temporarily added to Medicare's telehealth services list, allowing providers to perform psychophysiological therapy or biofeedback training via telehealth and bill Medicare as if the services were provided in person (APA, 2023). This telehealth inclusion was extended through at least the end of 2024 by legislation and CMS rulemaking (APA, 2023). However, providers must be cautious. Just because Medicare would process 90875 or 90901 when delivered via telehealth does not mean Medicare has started covering neurofeedback for new diagnoses. It simply means if you were providing, say, pelvic floor biofeedback (90901 for incontinence) or other biofeedback for a covered indication, you could do it via telehealth during the waiver period. It would be a misinterpretation to assume "Medicare now covers neurofeedback for ADHD because 90901 is on the telehealth list"; that is not the case. The telehealth list change is about the delivery method, not the coverage criteria.

Another development involves local Medicare contractors potentially reconsidering their biofeedback policies. There have been instances of LCDs being retired or revised in recent years. For example, one MAC had an LCD (e.g., L34898) that explicitly detailed noncovered diagnoses for biofeedback; if such an LCD is retired, it doesn't automatically mean coverage now exists. This might simply mean the contractor is deferring to general Medicare noncoverage unless new evidence emerges. As of 2025, there is no indication that Medicare has positively begun covering neurofeedback for conditions like ADHD or anxiety. The field is watching ongoing research (some large trials are underway for neurofeedback in PTSD, etc.) and, should that evidence base reach a tipping point, professional societies like the APA or ISNR might lobby Medicare for a national coverage change. Until then, practitioners must assume neurofeedback is a cash-pay service for Medicare beneficiaries or attempt to bill it as incident to physician services in very limited scenarios (with great care, as discussed below).

For completeness, note that Medicare Advantage plans (offered by private insurers but generally mirroring Medicare's coverage decisions) also tend to follow Medicare policy in this area. Many have explicit medical policies declaring neurofeedback investigational or not covered for psychiatric indications (Providence Health Plan, 2022). Some commercial non-Medicare insurers, however, do cover neurofeedback for certain conditions like ADHD on a case-by-case basis, but those decisions do not apply to Medicare beneficiaries. Therefore, for any patient population that includes Medicare recipients, practitioners should be extremely diligent: verify each patient's eligibility and coverage, obtain ABNs where required for noncovered services, and never bill a code to Medicare that mischaracterizes the service (e.g., billing 90834 psychotherapy for a session that was really neurofeedback training, which would be improper).

In summary, current Medicare policy disallows coverage of neurofeedback for mental health, and the recent telehealth allowances do not equate to a coverage expansion. Ethical practice demands that providers inform Medicare patients upfront if a service is noncovered and not attempt to "game" the system. Later in this paper, we discuss a case study exemplifying the severe penalties that can result from flouting these rules.

Incident to Billing and Technician Involvement

Delivering neurofeedback often involves a team-based approach. Thus, a licensed clinician may design and supervise the treatment protocol, while trained technicians or assistants carry out the day-to-day training sessions. This model raises important billing questions. How can services provided by a technician be billed? Can they be billed under the supervising provider's credentials? The concept of incident to billing in Medicare (and analogous rules for some private insurers) is central here, as are state scope-of-practice regulations that dictate what tasks unlicensed individuals can perform.

Understanding Incident to

In Medicare parlance, an incident to service is one that is furnished incident to a physician's (or certain nonphysician practitioner's) professional services in the course of diagnosis or treatment. Classic examples include a nurse or medical assistant providing a service in a physician's office under the physician's supervision, with the physician then billing for it. If all Medicare requirements are met, the service can be billed under the physician's NPI as if the physician personally rendered it, allowing reimbursement at 100% of the physician fee schedule. In the neurofeedback context, this could theoretically apply if, for instance, a psychiatrist or neurologist initiates a plan of care for neurofeedback and has a technician administer the sessions under direct supervision (meaning the physician is physically present in the office suite and immediately available). Under those conditions, the physician might bill 90901 for those sessions as incident to his or her service. However, it is crucial to note several caveats:

- Medicare's incident to rules only allow this billing provision in an office setting (not in hospital or facility settings) and require that the physician has seen the patient first and established the treatment plan. The services must be an integral, commonly rendered part of the physician's practice, and the physician must remain actively involved in the patient's care. If any piece is missing (e.g., the patient is new without a physician initial visit or the supervision is off-site), then billing incident to is not allowed.
- Provider Type Eligibility: Physicians (MD/DO) and a few others (certain licensed NPPs like PAs and NPs, and in some cases clinical psychologists for their own services) are eligible to use incident to. However, not all Medicare-recognized provider types have this privilege in the same way. For example, clinical psychologists treating Medicare patients cannot bill medical services that are outside their license, and Medicare generally expects a clinical psychologist to personally provide the psychotherapy services they bill. The concept of incident to is a gray area for psychologists. Medicare does not clearly allow psychologists to bill incident to themselves for services performed by, say, an unlicensed technician. In practice, most psychological services must be performed by the clinician or by a trainee where the clinician is supervising but the trainee isn't separately billing. So, a psychologist in private practice likely cannot hire an unlicensed neurofeedback technician and bill Medicare incident to the psychologist. That would be viewed as the technician providing psychotherapy without a license, which is illegal in many states and not billable to Medicare. On the other hand, a physician (e.g., a psychiatrist) might be able to incorporate a neurofeedback technician under incident to rules. Thus, scope-of-practice laws and Medicare rules intersect. If your professional license does not allow delegation of a particular task, incident to billing cannot circumvent that. Always check state law; many states consider the application of biofeedback and neurofeedback to be the practice of psychology or medicine, meaning the individual hooking a patient up to neurofeedback equipment and altering treatment parameters should either be licensed or be supervised in a manner consistent with professional regulations (such as under a formal psychological associate and assistant arrangement).

Private Insurance and Delegation

Outside of Medicare, some private insurers may pay for services delivered by auxiliary personnel if billed under a qualified provider, but policies vary widely. Some insurers require that the person actually providing a biofeedback service be individually credentialed with them (e.g., some insurers will credential masters-level therapists for biofeedback, while others will only reimburse services provided by physicians or licensed psychologists). Other insurers allow a supervised billing model similar to incident to. It is essential to clarify the policy with each payer. As a rule of thumb, billing should never misrepresent who performed the service. Even when using incident to, transparency in the record is needed. The ISNR and Biofeedback Certification International Alliance (BCIA) ethical guidelines emphasize this, stating that practitioners must “clearly specify which services the practitioner provided directly and which were provided under supervision” when billing third parties (BCIA, 2017). For instance, if a technician conducts a neurofeedback session under Dr. Smith’s supervision, the progress note should reflect that “Jane Doe, Neurofeedback Technician, conducted the session per Dr. Smith’s plan, with Dr. Smith on site.” The insurance claim might still be submitted under Dr. Smith’s name (if incident to criteria are met), but there is no deception in the documentation. This clarity is not only ethical but also provides a defense that you weren’t trying to fool the insurer about who did what.

Risks of Improper Incident to Usage

Improper use of incident to can result in serious repercussions. In the Minnesota case of *U.S. v. Luthor*, part of the scheme involved unqualified individuals (in that case, friends of the clinic owners who had no medical licenses) administering neurofeedback and other services, with billing submitted as though performed by qualified providers. The indictment described how the couple “enlisted the help of Luthor’s girlfriends” to assist in providing services, and then billed insurers falsely (U.S. Attorney’s Office, 2025). This highlights that simply having someone present in the office does not justify billing as if a clinician provided the service. Additionally, each payer may have specific rules; for example, some states require licensure for anyone performing any kind of behavioral health service, which would preclude even having a technician perform neurofeedback unless that technician is on a path to licensure or otherwise exempt. It is also important to note that incident to does not apply at all in institutional settings (for instance, if you are working within a hospital outpatient department or facility, you cannot bill incident to—you’d have to credential the person through the facility or bill under the facility’s rules).

Guidance for Practitioners: If you utilize technicians or assistants for neurofeedback services, consider the following guidelines:

1. Verify that your state license permits delegation. Some psychology licensing boards allow unlicensed individuals to provide certain services under supervision (often requiring the supervisor to take legal responsibility for the supervisee’s work). Other states do not allow this at all, considering it unlicensed practice. Your ability to use support staff for neurofeedback may be determined by these regulations alone.
2. If delegation is permitted, ensure rigorous training and supervision of the technician. From an ethical standpoint, the patient should receive the same quality of care as if the licensed provider were directly administering the treatment. The supervising provider should be the one formulating the treatment plan, directly training the technician, and reviewing progress regularly. (This is also a requirement under Medicare’s incident to rules—the physician’s involvement must be ongoing and active.)
3. When billing, follow the payer’s rules to the letter. For Medicare, only bill incident to if all criteria are met (appropriate setting, established plan of care by the physician, direct supervision, etc.) and be sure to use the supervising provider’s NPI on the claim (and keep documentation of their presence and active role). For private insurers, if they explicitly credential “technician-assisted biofeedback,” follow their billing instructions (some might require a specific modifier or a supervision attestation). If an insurer does not allow incident to and expects the identity of the actual rendering provider, do not list the licensed provider as rendering if they were not actually present, that could be construed as fraud if discovered. Instead, either get the technician independently credentialed with that insurer (if possible) or don’t bill that insurer for those services (have the patient pay privately).
4. Inform patients about the involvement of a technician. Be transparent that a technician will be working with them and assure them that the supervising professional will be overseeing the process. Transparency builds trust and also preempts any concern or confusion if, for example, a patient later sees an Explanation of Benefits that lists a doctor’s name even though they remember mostly working with “Coach Jane” during sessions.

In sum, incident to billing can be a useful but tricky tool. It should be used only in strict accordance with regulations. When done properly, it allows neurofeedback practices to expand capacity (through the help of technicians) without running afoul of the rules. When done improperly, it becomes a pathway to fraudulent billing. Ethical practice demands that patient care and honesty take priority over maximizing reimbursement.

Ethical and Legal Implications of Incorrect Billing

The landscape of neurofeedback and qEEG billing is not just about getting paid—it is also fraught with ethical and legal landmines. “Incorrect billing” can refer to a range of behaviors: using the wrong code by mistake, deliberately upcoding to obtain higher reimbursement, unbundling services to increase revenue, billing for services not actually rendered or not covered, or misrepresenting who provided the service. The implications of such actions vary from claims denials and demands for repayment, to professional disciplinary action, and in the worst cases, to civil or criminal liability for fraud. This section examines these implications, with real-world examples to illustrate the high stakes involved.

Ethical Duties and Professional Standards

Fundamentally, healthcare providers have an ethical duty to be honest in billing. The American Psychological Association’s Ethics Code insists on accuracy in representing services and fees (APA, 2017). ISNR’s own Professional Standards and Ethical Principles (most recently updated in 2020) similarly emphasize that clinicians should comply with all third-party payer rules and accurately represent the services provided, and the BCIA ethics code explicitly requires that practitioners “only charge for services actually provided by them or by those under their legal supervision” and, when billing, to “clearly specify which services were provided directly and which were supervised” (ISNR, 2020; BCIA, 2017). Such guidelines echo what we’ve detailed throughout this article: be truthful in billing and follow the established rules. Misbilling also violates patient trust—even if the patient isn’t paying out of pocket, they rely on the provider’s integrity in dealings with their insurer. Ethically, “padding” a bill or manipulating coding is tantamount to lying, which erodes the moral fabric of both the provider–patient relationship and the provider–payer relationship. It can also harm the field as a whole. If neurofeedback practitioners develop a reputation for shady billing practices, insurance companies are likely to become more restrictive and suspicious, potentially limiting coverage or access for all patients (Providence Health Plan, 2022). Therefore, ethical billing is a form of professional responsibility to protect the viability and credibility of neurofeedback as a legitimate treatment modality.

Common Improper Billing Practices to Avoid

- Unbundling and Double Billing: This occurs when a provider bills two or more codes for what is actually a single service. For example, billing both 90901 and 90834 (individual psychotherapy) for the same time period of a session—claiming one code was for biofeedback and one for therapy, when in reality it was one integrated session. Or billing an EEG recording code in addition to 90901 for a neurofeedback session (where the EEG recording is inherent to the neurofeedback service). As discussed earlier, CPT rules prohibit these combinations, and payers have automated edits in place to detect many of them. If audited, the provider would have to pay back the improperly billed amount and could face penalties. Such unbundling clearly violates coding guidelines (CMS, 2015).
- Upcoding Duration or Intensity: Using a code that represents a higher intensity or longer duration service than what was actually provided. For instance, routinely billing 90876 (the 45-min psychotherapy /biofeedback code) when sessions are in fact only 30 min, or reporting multiple units of 90901 on the same day (remember that 90901 is per day, not per hour). In the Department of Justice’s Minnesota case example, the defendants allegedly billed codes indicating longer durations than they actually provided (U.S. Attorney’s Office, 2025). Excessive duration billing is a red flag in claims data—if a practice is routinely billing an improbably high number of hours of service per day or per patient, it will attract payer scrutiny.
- Misusing Evaluation Codes: Some neurofeedback providers have patients fill out symptom questionnaires or complete a continuous performance test and then attempt to bill those activities as psychological testing or evaluation services. If those assessments are not truly separate services, or if they are part of the routine neurofeedback evaluation and feedback process that should be encompassed by the session code, then billing them separately is inappropriate. In *U.S. v. Luthor*, the clinic billed psychological testing code combinations that “by definition could not be combined”; for example, billing a code that represents test administration alongside another code that represents the same test’s interpretation, in a way that double-counted

the work (Office of Inspector General, 2025). Such practices are false billing and were cited in the indictment as part of the fraudulent scheme.

- Billing Unqualified Services: As discussed in the incident to section, billing as if a licensed professional provided the service when it was actually delivered by an unqualified person (e.g., an unlicensed technician) is both unethical and illegal. If the rules for supervised billing aren't met, one cannot simply put the service under someone else's name on a claim. That is considered a false claim.
- Billing for Noncovered Services as if Covered: This is a subtle but important point, particularly for neurofeedback. If a service is not covered by an insurer, you cannot simply bill it under a different code that is covered. For example, some providers have attempted to bill neurofeedback (noncovered for a given diagnosis or plan) as 90834 (standard psychotherapy) in order to get paid. Unless that patient truly received a legitimate psychotherapy session (which neurofeedback training is not, in most cases), that is misrepresentation. The proper approach for a noncovered service is to have the patient pay privately or, if the insurer allows, submit the claim with a modifier (for instance, Medicare's –GY modifier for noncovered services) so that it is transparently denied and the patient can be charged. Misrepresenting the nature of the service is fraud. The Luthor case again exemplifies this: by billing neurofeedback under codes for which it didn't qualify (using 90901 for conditions it shouldn't be used for, or billing inappropriate code combinations), the defendants crossed into fraud territory (U.S. Attorney's Office, 2025).

Illustrative Case Study – U.S. v. Luthor et al. (2025, Minnesota)

This case provides a concrete illustration of what can happen when billing goes awry. Gabriel Luthor and Elizabeth Brown ran a company providing neurofeedback in Minnesota and, as per a federal indictment, engaged in systematic overbilling. They allegedly submitted "hundreds of thousands of false claims" totaling roughly $15 million in billed charges (U.S. Attorney's Office, 2025). Their tactics included using codes that didn't apply to neurofeedback, combining codes that shouldn't be billed together, and inflating session times. Notably, evidence showed they ignored repeated warnings—insurers had warned them, an outside auditor warned them, and even CMS sent warnings, yet they persisted (Office of Inspector General, 2025). This willful disregard led to a major healthcare fraud case, with charges including wire fraud and money laundering (U.S. Attorney's Office, 2025). The fallout: arrests, an indictment, frozen assets (the DOJ moved to seize a mansion the couple had purchased with the proceeds), and the prospect of years in prison if convicted. While this is an extreme example, it starkly highlights the legal risks. A provider doesn't have to be making $15 million to get into trouble; even small practices have been audited by Medicare or insurers and forced to repay tens of thousands of dollars, or face exclusion from insurance panels, due to improper coding.

Civil and Criminal Consequences

On the civil side, insurers can demand repayment for any improperly paid claims. They may also impose interest on the overpayments and even civil monetary penalties in some cases (Medicare's Office of Inspector General has authority to levy fines for fraud or false billing). If the behavior is deemed knowing and willful, the False Claims Act can come into play, allowing treble damages (three times the amount of the false claims) and enabling whistleblower (qui tam) lawsuits. For instance, if a technician in a clinic realizes the boss is billing fraudulently, that employee could potentially become a whistleblower, leading to an investigation. On the criminal side, as with the Luthor case, prosecutors may charge healthcare fraud or related offenses (such as wire fraud if electronic claims were sent, or mail fraud if paper claims were involved). A conviction can result in hefty fines and incarceration, as well as loss of professional licenses and exclusion from Medicare and Medicaid participation for at least 5 years (often much longer, effectively ending one's insurance-based practice).

Professional Discipline

Even short of criminal court, providers face their own professional licensing boards. A psychologist or physician could be sanctioned or lose their license for unethical billing practices. Many state boards have specific rules against insurance fraud or broadly against "unprofessional conduct," which would include deceptive billing. Thus, a practitioner might survive an audit or investigation by an insurer, but still face a licensure complaint from, say, an unhappy patient or an insurance company that detected improper billing.

Preventive Measures

The best protection is prevention. Regular compliance training and internal audits within one's practice are essential. Many larger clinics hire coding experts or consultants to review their billing periodically and ensure everything aligns with current guidelines. Solo practitioners can make use of resources from professional associations (e.g., the APA's practice organization provides billing guidelines, and ISNR often offers webinars on ethics in coding) to stay informed. When an error is discovered, it should be voluntarily corrected; for example, if you realize you accidentally billed 90876 when you only provided a 25-min session (which should have been 90875), correct the error or refund the difference rather than hoping it goes unnoticed. Showing a pattern of prompt corrective action can mitigate penalties if an insurer or Medicare audits you. Maintaining open communication with payers is also key. If unsure how to bill something, ask the insurer (many have provider relations representatives who can give guidance, preferably in writing). Keep records of any authorization or guidance you receive from payers, in case it is questioned later.

In conclusion, the ethical mantra is "When in doubt, bill honestly and modestly." It is far better to underbill (or not get paid for something) than to overbill and risk the cascade of consequences. No financial gain is worth one's professional integrity or freedom. By adhering to correct coding principles and erring on the side of caution, neurofeedback practitioners can avoid the nightmare scenarios and instead focus on helping patients.

The Role of ISNR and Professional Advocacy in Ethical Billing

ISNR, along with related bodies like AAPB and BCIA, plays a crucial role in guiding practitioners toward ethical billing and pushing for systemic improvements in how neurofeedback and qEEG are coded and reimbursed. These organizations serve as a bridge between the clinical community and regulatory entities (such as the AMA, CMS, and insurers), and they provide education and resources that directly address the challenges discussed in this article.

Code of Ethics and Professional Guidelines

ISNR has promulgated ethical principles and practice standards that encompass billing ethics. For example, the ISNR Professional Standards and Ethical Principles (PSEP) document (most recently updated in 2020) reinforces that clinicians should comply with all third-party payer rules and accurately represent their services. Similarly, the BCIA, which certifies neurofeedback practitioners, mandates in its ethical standards that certificants "only charge for services actually provided by them or by those under their legal supervision" and that when billing, they "clearly specify which services were provided directly and which were supervised." (BCIA, 2017). These guidelines essentially echo what we've detailed in this paper: be truthful in billing and follow the rules. ISNR expects its members to uphold these standards. Through webinars and conference workshops, ISNR often addresses topics like "Ethics in qEEG and Neuromodulation," where appropriate coding is highlighted as an ethical issue, not just a financial one. Members are encouraged to seek mentorship or peer consultation if they are unsure about billing practices, fostering a community standard of integrity.

Advocacy for CPT Code Refinement

ISNR, in collaboration with AAPB, has been actively working to improve the CPT coding system to better fit neurofeedback. As noted earlier, they launched a CPT Code Initiative (ISNR & AAPB, 2023). The rationale behind this advocacy is partly ethical and partly practical. Current codes are outdated, which can put well-intentioned providers in ambiguous situations. For instance, a psychologist treating PTSD with neurofeedback might struggle with which code to use, since 90901 is a biofeedback code that many insurers won't reimburse for PTSD, yet 90875 requires psychotherapy and might not be recognized either for neurofeedback alone. By advocating to the AMA for new codes or revised definitions that explicitly include neurofeedback for certain conditions, ISNR and AAPB hope to reduce ambiguity and thereby reduce inadvertent miscoding. This initiative, if successful, could lead to something like a dedicated neurofeedback therapy code, or a modifier to existing codes, or at least clearer guidance in CPT Assistant publications. The advocacy involves assembling research evidence, utilization data, and a strong case for why better codes would benefit patient care, aligning with the AMA's criteria for considering code changes. ISNR also communicates with insurers to encourage coverage by sharing research demonstrating neurofeedback's efficacy for certain disorders. The goal is twofold: make neurofeedback more accessible (in terms of insurance coverage) and ensure it is reimbursed only for appropriate uses with proper coding (thus rewarding ethical providers and weeding out unscrupulous actors).

Educating Membership on Compliance

Both ISNR and AAPB provide educational materials focused on billing compliance. They often invite coding experts or healthcare attorneys to speak at annual conferences. Their newsletters and journals (e.g., *NeuroRegulation*, ISNR's journal) periodically cover updates on Medicare policies or present case studies of billing dilemmas. Notably, plenary sessions and workshops at ISNR's annual conferences have been devoted to "Update on CPT Coding and Insurance Reimbursement for Neurofeedback and qEEG," led by domain expert Mark Trullinger, indicating how high a priority this topic is for the organization. Through these efforts, ISNR helps keep practitioners up to date, which is vital since rules can change annually.

ISNR as an Ethical Watchdog

Professional organizations also serve a self-regulatory function. They encourage members to report unethical practices (perhaps privately to an ethics committee). While ISNR is not a licensing board and cannot revoke someone's license, it can censure members or even revoke membership for ethical violations. More importantly, by publicly emphasizing ethics (in articles like this one or official statements), ISNR sets a tone that deters misconduct. In fields that are somewhat fringe or under skepticism (and neurofeedback has at times faced skepticism within mainstream medicine), self-policing is crucial to maintain credibility. ISNR's Code of Ethics includes clauses about not misrepresenting one's services and credentials, which would encompass billing fraud as a form of misrepresentation.

Collaboration With Regulators

ISNR has, in some cases, worked with regulatory agencies or at least provided input when asked. For example, if CMS or a state insurance commission seeks expert input on how neurofeedback is practiced, ISNR can provide informed opinions or data. This can help shape policies that are fair and evidence-based. An example might be an insurer considering whether to start covering neurofeedback, ISNR might supply outcome data or practice guidelines to help them make an informed decision (advocating for coverage when appropriate, along with clear guidelines to avoid misuse).

In summary, ISNR's role is integral in both guiding individual practitioners and shaping the broader billing environment. By advocating for clearer codes and educating professionals about ethical billing, ISNR helps reduce the ambiguity and confusion that can lead to inadvertent errors, and it shines a light on the "high road" in billing practices. Practitioners are strongly advised to engage with such professional bodies, as membership offers access to the latest information and a network of peers committed to ethical practice. Ultimately, every provider's honest billing is a brick in the wall of the field's integrity and organizations like ISNR provide the blueprint for how to lay those bricks correctly.

Ambiguities in CPT Coding and Associated Risks

Despite the best efforts of the AMA, CMS, and professional organizations, some ambiguities in CPT coding for neurofeedback and qEEG persist. These gray areas create risks for well-meaning clinicians who must interpret how to bill novel or hybrid services. Ambiguities can arise from vague code definitions, evolving technology that outpaces code updates, or differing interpretations between payers. Let's explore a few of these ambiguities and the potential pitfalls they pose:

- Biofeedback versus Psychotherapy – Fuzzy Boundaries: Neurofeedback straddles the line between physiological training and psychological therapy. Some providers struggle with whether a session should be coded as "psychophysiological therapy with biofeedback" (90875 or 90876) or just "biofeedback" (90901). The ambiguity might arise if, for example, a clinician spends part of the session discussing emotions or coping strategies (which feels like psychotherapy) and part of it running neurofeedback. How much talking turns a 90901 session into a 90875 session? CPT doesn't quantify this, leaving it to clinical judgment. This ambiguity could lead to inconsistent coding—one clinician might always use 90875 if there was any counseling, while another uses 90901 unless it was predominantly therapy. The risk here is that if audited, one might have to justify why a certain code was chosen. The safer approach is to decide at the outset the session's primary purpose. If therapy is only a minor adjunct to a primarily neurofeedback session, lean towards 90901; if substantive psychotherapy is a major component of the visit, use 90875 or 90876. Document the session content accordingly to support the choice. In all cases, avoid coding both 90901 and 90875 or 90876 for the same session (as that is clearly disallowed).
- Quantitative EEG Coding: As discussed, no single CPT code explicitly says "qEEG brain

map." Some clinicians use 95957 (digital EEG analysis) to bill for qEEG, but not all payers accept that usage for behavioral health indications. Others might resort to an unlisted code (such as 94999, unlisted neurological procedure), which is harder to get reimbursed. The lack of a dedicated qEEG code creates ambiguity, practitioners must choose between not billing for the service at all (perhaps bundling its cost into a self-pay neurofeedback program fee), billing something like 95957 and hoping it passes scrutiny, or billing an evaluation code that isn't truly appropriate. Each option has risks. Not billing means no reimbursement; billing 95957 might get denied or could be viewed as misbilling if the payer later specifies that qEEG wasn't covered for that diagnosis; and billing an evaluation code (like 96132 for neurocognitive test interpretation) would likely be improper unless formal neuropsychological testing was actually done. In a policy by Anthem Blue Cross Blue Shield, for example, the insurer lists CPT codes 90875, 90901, and 95957 in a document regarding neurofeedback, essentially warning providers not to use 95957 in the context of EEG biofeedback for psychological conditions (Anthem Blue Cross Blue Shield, 2021). This implies they are watching for misuse of that neurological code for neurofeedback. Until a clear qEEG code exists, the ambiguity remains. Practitioners should tread carefully: if using 95957, ensure you truly have an EEG recording and a separate analytical report that could stand up to scrutiny as a legitimate service (preferably with a neurologist or qEEG-certified expert's involvement). This aligns with suggestions some have made to involve a neurologist to read the raw EEG as part of the qEEG process, which can lend credibility and perhaps provide a legitimate billing route (e.g., the neurologist might bill an EEG interpretation code separately).

- Home Training and Remote Neurofeedback: With newer technologies, some practitioners are supervising neurofeedback that patients do at home (e.g., loaning the patient equipment or using remote neurofeedback software). How to bill this is ambiguous. Is it billable at all if the patient is essentially training themselves? If the clinician is monitoring in real time via an internet connection, is that effectively a telehealth session (and thus maybe could be billed as 90901 with a telehealth modifier)? CPT does not yet have a code for "remote biofeedback monitoring." This ambiguity can lead some to incorrectly bill multiple units of 90901 for unsupervised home use (which would be wrong). The safer interpretation is that if a clinician is actively supervising the neurofeedback in real time (e.g., via telehealth video session), then one could bill the session as a telehealth service (e.g., 90901 with the appropriate telehealth place-of-service or modifier). If the patient is training solo and the clinician only reviews the data later, it might not be a billable service at all, except possibly as a data analysis or review (which would likely fall under an unlisted code if anything). It is a gray area that needs clarification in the future. Until then, clarity with patients on fees is crucial (perhaps charging a flat program fee for home training use) to avoid attempting to force-fit these services into insurance billing where they don't fit well.
- Payer Policy versus CPT Definition: Sometimes the ambiguity isn't within CPT itself, but between what a CPT code technically allows and what an insurer's policy will reimburse. For instance, CPT 90901 technically does not restrict the conditions it can be used for—it simply says, "biofeedback by any modality." But an insurer's medical policy might say "we only cover 90901 for these three diagnoses." This creates a trap. A provider might see the CPT code description and think, "I can use this for neurofeedback applied to a client experiencing ADHD," which is true in terms of coding submission, but the insurer will deny it as not covered for ADHD. The provider might then be tempted to think, "maybe if I use 90875 (since it is in the mental health section), it will get paid." That could result in payment but would violate coding integrity if no psychotherapy was actually done. The conflict between what a code can describe and what an insurer will reimburse is a common frustration. The ethical approach is not to twist your coding to chase coverage. Instead, either obtain a preauthorization or special exception from the insurer for the service, or inform the patient that it is not covered and make payment arrangements accordingly. Many neurofeedback providers end up with a mix

of insurance and self-pay precisely because of these coverage gaps. Trying to solve a coverage gap by coding slight-of-hand usually backfires eventually.

- Risks of Ambiguity: Ambiguities increase the risk of inconsistent billing across the field—which insurers' algorithms may flag. If five providers all treat ADHD with neurofeedback but one bills 90876, another 90901, another 96110, etc., insurers see inconsistency and may initiate audits to determine which (if any) are billing correctly. Ambiguity also poses a problem for training and knowledge transfer. New providers might inadvertently learn poor coding habits from others. One clinician's "creative" billing can become a staffer's standard practice at a clinic, and then that staffer carries those habits to a new job, spreading the misuse. Over time, this can lead to industry-wide patterns that attract regulator attention (e.g., CMS or the OIG issuing a fraud alert or policy clarification).

To manage these ambiguities, practitioners should seek clarity whenever possible. Consult CPT Assistant archives, ask insurers for written guidance, and discuss tricky situations with colleagues through professional forums or consultation. Often, an ambiguity can be resolved or at least reduced by simply verifying information directly with authoritative sources. When something remains ambiguous, make a conservative choice and document your rationale. For example, a note to file might state, "Chose 90901 instead of 90876 because although some counseling was done, it was less than 50% of session; primary service was biofeedback." A contemporaneous note like that shows you were not attempting deception but rather thoughtfully navigating a gray area.

Ultimately, the push by ISNR and AAPB to refine CPT codes is aimed at eliminating these ambiguities. Clear codes that match neurofeedback's usage will let clinicians focus on therapy rather than coding dilemmas and will reduce inadvertent noncompliance. Until that happens, awareness of the pitfalls is the best defense.

Recommendations

Navigating the thicket of neurofeedback and qEEG billing requires diligence, honesty, and up-to-date knowledge. The following recommendations summarize best practices and professional responsibilities that can help clinicians bill ethically and avoid pitfalls:

1. Commit to Ongoing Education: Billing rules and codes change over time. Clinicians and billing staff should engage in continuing education specifically around coding and compliance. This might include attending webinars (such as those offered by ISNR, AAPB, or APA), subscribing to coding newsletters, and reading updates from CMS and major insurers each year. Staying current is critical. For example, knowing that 90875 and 90901 were added to Medicare's telehealth list temporarily (APA, 2023), that CPT code descriptors have subtle changes, or that a new CPT code is on the horizon can all influence how you practice and bill. Remember, ignorance is not a defense in audits; investment in education pays off by preventing errors.
2. Use Established Codes as Intended: Follow the definitions and guidelines for CPT codes to the letter. If using 90901, ensure it is indeed a biofeedback session without separate psychotherapy. If using 90876, ensure you did provide psychotherapy alongside the biofeedback. Keep a copy of AMA CPT Assistant guidance or other authoritative advice on these codes handy, so if there's any question from you or an insurer, you can demonstrate adherence to official guidance (e.g., by showing the AMA Q&A stating not to pair 90901 with 90875 [AMA, 1997]). Avoid "code drift," where over time one might start using a code more loosely than intended. It can help to periodically self-audit a few charts and compare your documentation to the codes billed.
3. Consult Payer Policies Before Billing New Services: When integrating a new service like qEEG, review the major payers' medical policies first. If United Healthcare, Aetna, Blue Cross, etc., all state that qEEG is experimental for certain conditions, then you know billing it to those insurers will be problematic. You can then plan accordingly (maybe treat it as a self-pay service with proper patient consent). If a payer does cover biofeedback but only for certain diagnoses, make sure those diagnoses are documented in the record if applicable. Essentially, try to align your billing with each payer's rules as much as possible. When in doubt, seek a preauthorization or guidance from the insurer—and get it in writing if you

can. Keep records of any authorization or payer instruction in case it is questioned later.

4. Emphasize Documentation and Transparency: Good documentation is your ally. Always document what intervention was done, for how long, by whom, and for what purpose (i.e., the patient's goals or medical necessity). If a technician was involved, document their role and the supervision in place. If you decide to bill something in an ambiguous situation, document your reasoning for the coding choice. This creates a contemporaneous record that you were acting in good faith. Additionally, be transparent with patients. If something isn't covered by their insurance, inform them beforehand. If you are billing in an unusual way (perhaps billing 90834 for psychotherapy time and 90901 for neurofeedback time separately on the same day, with distinct documentation for each), let the patient know so that if they see two services on their insurance Explanation of Benefits, they aren't confused and won't inadvertently raise concerns. Honesty with patients about billing not only is ethical in itself, it also reinforces diligence and honesty in the billing process.
5. Avoid Pressure to "Make Insurance Pay": Sometimes patients really want their insurance to cover neurofeedback, or a practice might financially depend on squeezing reimbursement from insurers. This can create pressure to bend rules. Stay vigilant against this pressure. Educate patients that not all services are covered and that you must bill accurately for legal and ethical reasons. Many patients will understand when you frame it as an obligation to do the right thing. You can provide them with resources (for instance, a copy of the insurer's policy that shows neurofeedback is not covered for their condition) to help explain the situation. Consider offering a superbill for out-of-network or noncovered services that accurately describes the service provided (even if it uses a numeric code, you might add a descriptor like "qEEG brain map: experimental service" so the payer has full information). The bottom line: do not let financial incentives erode your ethical standards. It may mean slower growth of your practice or more out-of-pocket costs for patients, but it is the right path in the long run.
6. Engage in Peer Consultation or Hire Experts: If you are unsure about your billing practices, seek a peer review or outside consultation. You might ask a colleague knowledgeable in coding to review some of your superbills or claims for feedback. Larger clinics might even employ a compliance officer or hire a consultant periodically to audit charts and billing. An external eye can catch issues you might miss due to familiarity or bias. If you ever receive an audit notice or you suspect past errors that need correction, consult a healthcare attorney or compliance expert early—their guidance can help resolve issues with minimal damage. Proactivity is key; don't wait until a minor billing issue becomes a major legal problem.
7. Support Professional Advocacy: Lend your voice and support to organizations like ISNR and AAPB in their efforts to improve the coding system. This could mean participating in surveys about practice patterns and code utilization, contributing de-identified data that helps justify new codes, or even donating to advocacy funds if you are able. The more the coding system reflects the reality of neurofeedback practice, the easier it will be for ethical practitioners to stay compliant. By being involved in these advocacy efforts, practitioners also stay informed—advocacy updates often include summaries of the current coding and reimbursement climate.

Conclusion

Billing for neurofeedback and qEEG is undoubtedly complex. It is a mix of applying old codes to new techniques, navigating varied payer rules, and keeping up with evolving standards of practice. Yet, the overarching principle is simple: billing must accurately reflect clinical reality. When it does, providers not only safeguard themselves from legal trouble but also contribute to a culture of integrity that benefits the entire profession. Historical missteps and high-profile fraud cases have taught us that the costs of getting it wrong are enormous for patients, for practitioners, and for the credibility of neurofeedback therapy itself. Conversely, by clarifying coding questions, adhering to ethical norms, and advocating for clearer guidelines, we chart a path where neurofeedback can fully "come of age" in the healthcare system, recognized and reimbursed appropriately.

As we clarify the code, through articles like this, collective advocacy, and day-to-day conscientiousness, we move toward a future in which clinicians can focus on neuroregulation interventions without the shadow of billing uncertainty. Achieving that clarity will require continued collaboration between practitioners, professional societies, payers, and regulators. Each claim form we fill out correctly is a small but meaningful step in that direction. Let this paper serve not only as an informational resource but as a reaffirmation of our commitment to ethical practice. In the end, doing the right thing in billing is an extension of doing the right thing in clinical care—both are essential to truly help our patients and advance our field.

Disclaimer

This article is intended for general educational guidance on neurofeedback and qEEG billing practices and does not constitute legal advice. The content may not encompass all rules or scenarios and might not reflect changes after publication. Practitioners should consult current official sources, payer bulletins, and, when needed, seek advice from qualified healthcare attorneys or compliance professionals to address their specific situations. Clinical providers are responsible for ensuring their own billing compliance with federal, state, and payer regulations. Always verify how rules apply in your locality and practice setting. The authors and publisher assume no liability for actions taken based on this educational content. Readers are strongly advised to consult legal counsel and the relevant insurance carriers or Medicare contractors for definitive guidance to ensure full compliance with all applicable laws and policies.

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References

American Medical Association [AMA]. (1997). Psychiatric therapeutic, 90875, 90901, 90911 (Q&A). *CPT Assistant, 7*(9), 11. https://www.findacode.com/newsletters/ama-cpt-assistant/psychiatric-therapeutic-90875-90901-90911-9.html

American Psychological Association [APA]. (2017). *Ethical principles of psychologists and code of conduct* (2002, Amended 2010, 2017). Author. https://www.apa.org/ethics/code

American Psychological Association [APA]. (2023). *Medicare final rule expands telehealth*. APA Services. https://www.apaservices.org/practice/reimbursement/government/medicare-inperson-telehealth-requirement

Anthem Blue Cross Blue Shield. (2021). *Medical policy CG-MED-97: Biofeedback and neurofeedback*. https://www.anthem.com/dam/medpolicies/abc/active/guidelines/gl_pw_e003054.html

Biofeedback Certification International Alliance [BCIA]. (2017). *BCIA professional standards and ethical principles*. https://www.bcia.org/bcia-professional-standards-ethical-principles

Centers for Medicare & Medicaid Services [CMS]. (2011). *Local coverage article: PHYS-066 biofeedback (L31070)*. https://downloads.cms.gov/medicare-coverage-database/lcd_attachments/31070_1/L31070_PHYS066_CBG_030111.pdf

Centers for Medicare & Medicaid Services [CMS]. (2015, rev. 2020). *Billing and coding: Outpatient therapy biofeedback training (A53352)*. Medicare Coverage Database. https://www.cms.gov/medicare-coverage-database/view/article.aspx?articleId=53352

Hammond, D. C. (2011). What is neurofeedback: An update. *Journal of Neurotherapy, 15*(4), 305–336. https://doi.org/10.1080/10874208.2011.623090

International Society for Neuroregulation & Research [ISNR]. (2020). *ISNR professional standards and ethical principles* (August 2020). International Society for Neuroregulation & Research. https://isnr.org/wp-content/uploads/2020/09/ISNR-Professional-Standards-Code_of_Ethics_8-9-2020.pdf

International Society for Neuroregulation & Research, & Association for Applied Psychophysiology and Biofeedback [ISNR & AAPB]. (2023). *CPT code initiative*. https://aapb.org/CPT

Office of Inspector General, U.S. Department of Health and Human Services. (2025). *Minnesota couple indicted in $15 million medical billing fraud scheme*. https://oig.hhs.gov/fraud/enforcement/minnesota-couple-indicted-in-15-million-medical-billing-fraud-scheme/

Providence Health Plan. (2022). *Medical policy MP515: Biofeedback and neurofeedback*. https://www.providencehealthplan.com/-/media/providence/website/pdfs/providers/medical-policy/mp515.pdf

Successful Practitioner. (2021). *Biofeedback, neurofeedback, QEEG – Billing CPT codes*. https://successfulpractitioner.com/biofeedback-cpt-codes/

U.S. Attorney's Office, District of Minnesota. (2025, April 10). *Minnesota couple indicted in $15 million medical billing fraud scheme* [Press release]. U.S. Department of Justice. https://oig.hhs.gov/fraud/enforcement/minnesota-couple-indicted-in-15-million-medical-billing-fraud-scheme/

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NeuroRegulation

Quantifying Self-Regulation: Neuroevolutionary Insights From Precuneus Alpha Modulation via LORETA Neurofeedback

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Abstract

Self-regulation (SR) is a vital neurobehavioral capacity orchestrating behavior, physiological equilibrium, and emotional resilience through corticothalamic networks spanning the cortex and thalamus. This study formalizes SR as SR = behavioral equilibrium (BE) / (homeostasis [H] + emotional equilibrium [EE]), where BE captures adaptive responses, H denotes physiological stability, and EE reflects affective harmony, positioning neurofeedback (NFB) as a leading intervention. NFB, encompassing LORETA neurofeedback (LNFB) targeting precuneus alpha and real-time fMRI neurofeedback (rt-fMRI-NFB) modulating blood-oxygen-level-dependent (BOLD) signals, enhances corticothalamic modulation across educational, correctional, clinical, pediatric, and ADHD contexts. Evidence from diverse cohorts validates NFB's efficacy, with LNFB improving BE (CPT-3, $p < .008$) and rt-fMRI-NFB stabilizing EE (BOLD, $p < .01$), supported by long-term gains in children (Strehl et al., 2017) and adults (Rance et al., 2018). The back-to-front brain focus, rooted in precuneus primacy (~2 Mya), contrasts with historical frontal emphasis post-Phineas Gage. As noted in experimental findings, surface NFB training boosts neural connectivity. Pre- and postprotocols are rare due to subjective reliance, resistance to objective tracking, and resource limits (Hofmann & Smits, 2008). NFB's standardized protocols (EEG ICC = .87–.92, BOLD consistency) inspire volumetric MRI studies, advancing SR science across the lifespan.

Keywords: self-regulation; precuneus; LORETA neurofeedback; alpha oscillations; neuroplasticity; behavioral equilibrium; emotional equilibrium; homeostasis; volumetric studies; neuroevolutionary dynamics

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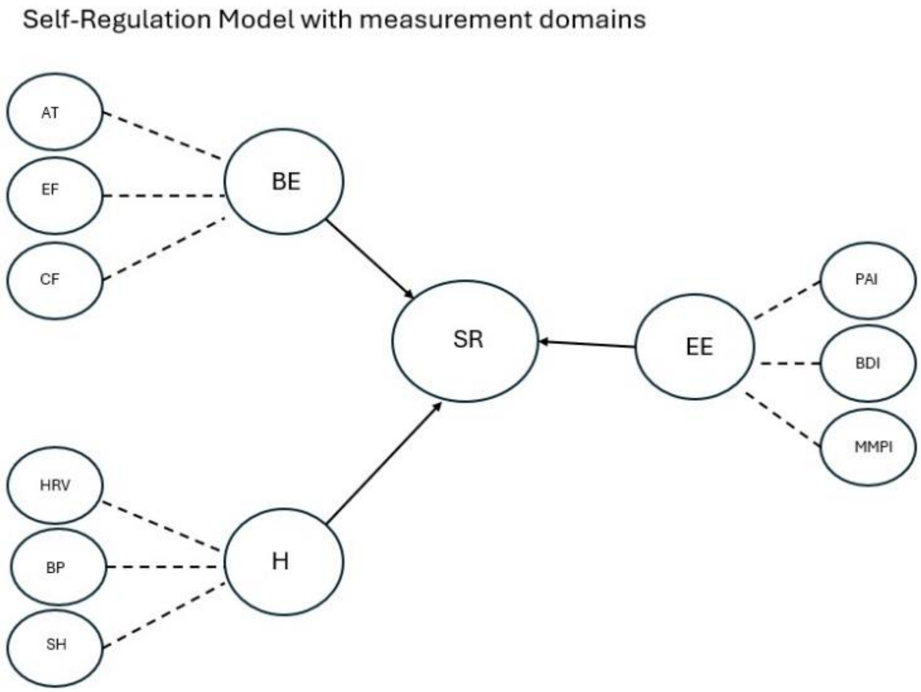
Introduction: The Precuneus in Phylogenetic and Neuroregulatory Context

Self-regulation (SR) emerges as a fundamental neurobehavioral capacity, intricately weaving behavior, physiological stability, and emotional resilience through corticothalamic networks that link the cortex and thalamus. This core capacity, critical across developmental stages and contexts, underpins adaptive functioning in education, corrections, and clinical settings. The study introduces a novel framework, SR = behavioral equilibrium [BE] / (homeostasis [H] + emotional equilibrium [EE]), where BE encapsulates adaptive corticothalamic responses, H reflects physiological balance, and EE signifies emotional coherence, as depicted in Figure 1. Neurofeedback (NFB), comprising LORETA neurofeedback (LNFB) targeting precuneus alpha (8–13 Hz) and real-time fMRI neurofeedback (rt-fMRI-NFB) modulating blood-oxygen-level-dependent (BOLD) signals, stands as a pioneering intervention, harnessing regulatory training of emotional regulation (Johnston et al., 2010) to enhance SR (Zotev et al., 2014). The posterior-to-anterior brain development rationale, emphasizing the precuneus's evolutionary role (~2 million years ago [Mya] in *Homo habilis*) over frontal foci highlighted post-Phineas Gage, guides this approach (Bruner, 2004; Dunbar, 1998).

Figure 1. *SR Model With Measurement Domains.*



Note. This model illustrates SR = BE / (H + EE), integrating BE as adaptive corticothalamic responses (e.g., attention, planning, executive functions), H as physiological stability (e.g., stress hormones, HRV), and EE as affective balance (e.g., mood regulation). In defining the types of instruments for each category AT = attention task; EF = executive functions; CF = cognitive fluency; HRV = heart rate variability; BP = blood pressure; SH = stress hormones; PAI = personality assessment inventory; BDI = Beck Depression Inventory; MMPI = Minnesota multiphasic personality inventory. NFB, including LNFB and rt-fMRI-NFB, targets these domains, with LNFB enhancing precuneus alpha (8–13 Hz) for BE and H, and rt-fMRI-NFB modulating BOLD signals for EE (Johnston, et al., 2010), surpassing selective serotonin reuptake inhibitors (SSRIs) and cognitive-behavioral therapy (CBT; Sitaram et al., 2017). The SR model (SR = BE / [H + EE]) is operationalized using neurophysiological measures inherent to its parameters: BE, H, and EE are quantified via EEG (e.g., alpha coherence), CSD (e.g., precuneus alpha), and BOLD (e.g., amygdala-prefrontal connectivity) to capture corticothalamic dynamics, as detailed in subsequent sections.

Surface NFB training, as later detailed, amplifies neural efficiency. Pre- and postprotocols for treatment success and outcomes remain uncommon across disciplines, often due to reliance on subjective clinical assessments, resistance to integrating objective corticothalamic or neuroendocrine measures, and resource constraints in adopting standardized instruments, EEG or MRI tracking (Hofmann & Smits, 2008; Stahl, 2000).

This framework builds on NFB's legacy, evolving from early EEG protocols (theta-beta, sensorimotor rhythm [SMR]) to precise LNFB and rt-fMRI-NFB modalities, offering a quantifiable alternative to traditional interventions (Sitaram et al., 2017; Thibault et al., 2016). Long-term evidence underscores NFB's potential, with children showing sustained ADHD symptom reduction over 2 years (Strehl et al., 2017) and adults exhibiting 12-month depression relief (Rance et al., 2018), alongside Cannon and Lubar's (2011) 12-month anterior cingulate cortex (ACC) modulation. These findings suggest NFB's superiority in fostering enduring SR across the lifespan, from pediatric neurodevelopment to adult psychopathology. The study explores this through experimental cohorts, contrasting NFB's corticothalamic approach with existing methods, and proposing standardized protocols to bridge current gaps. Future research, leveraging volumetric magnetic resonance imaging (vMRI), aims to deepen SR's corticothalamic understanding, positioning NFB as a transformative tool in neuroscience and applied psychology.

Literature Review: Phylogenetic Foundations and the Precuneus

SR forms a cornerstone of human neurobehavioral adaptability, orchestrating a dynamic interplay of cognitive, physiological, and emotional processes through corticothalamic networks that connect the cortex and thalamus. This section synthesizes foundational theories and empirical advancements in SR, tracing its evolution from early behavioral models to contemporary neuroscientific frameworks, with a focus on NFB as a transformative intervention. The SR model, SR = BE / H + EE, where BE reflects adaptive corticothalamic responses, H signifies physiological stability, and EE embodies emotional coherence, provides a quantifiable lens for understanding these processes, as introduced in Figure 1. This review explores SR's historical roots, its neurobiological underpinnings, and NFB's role in advancing SR across diverse contexts, setting the stage for experimental and exploratory analyses.

Early SR theories emphasized behavioral and physiological dimensions, often neglecting corticothalamic integration. Cannon's (1932) homeostasis concept framed H as the body's drive for physiological balance, such as maintaining stable cortisol levels (r = .72 with HPA-axis regulation), a foundational element of SR. Bandura's (1977) self-efficacy theory highlighted BE, linking belief in one's capabilities to adaptive task persistence (r = .70), yet lacked neurobiological grounding. Porges' (1995) polyvagal theory introduced an emotional-physiological nexus, tying H and EE to vagal tone and social engagement, with heart rate variability (r = .65 with emotional regulation) as a marker, but did not address corticothalamic mechanisms. These models, while seminal, operated in silos, constrained by the era's technological limits, such as early EEG's surface-level focus and the absence of MRI (Nunez & Srinivasan, 2006). They collectively underscore SR's multifaceted nature but fail to unify BE, H, and EE within a neuroscientific framework, a gap NFB addresses through corticothalamic modulation.

Neurobiological research has since illuminated SR's corticothalamic foundations, revealing the precuneus and related networks as critical hubs. The precuneus, a posterior parietal region, integrates sensory and autonomic inputs, supporting H via brainstem relays and BE through parietal-thalamic loops, as evidenced by its volumetric primacy in early hominins (~20–30 cm³ in *Homo habilis*, ~2 Mya; Bruner, 2004; Cavanna & Trimble, 2006). The ACC and insula further mediate EE, with the ACC facilitating error detection (error-related negativity, t = 3.67, p < .01) and the insula processing interoception (r = .70 with heart rate), forming a self-regulation network (SRN) that bridges socioaffective and cognitive domains (Menon & Uddin, 2010). Alpha oscillations (8–13 Hz), driven by thalamocortical loops, synchronize these regions, stabilizing BE through attention (parietal-frontal coherence, r = .72) and H via arousal regulation (occipital alpha suppression, t = 3.89, p < .001), a dynamic NFB leverages for SR enhancement (Nunez & Srinivasan, 2006).

NFB's evolution marks a paradigm shift in SR interventions, building on early EEG protocols to target corticothalamic networks with precision. Initial theta-beta training, developed in the 1970s, aimed to reduce theta (4–8 Hz) and increase beta (13–30 Hz) activity, improving BE in ADHD by enhancing attentional control (theta reduction, t = 3.21, p < .01), though electrode placement inconsistencies (Cz versus Fz) limited reproducibility (Peniston & Kulkosky, 1989). SMR training, focusing on 12–15 Hz over sensorimotor areas, bolstered H by reducing motor hyperactivity (fractional anisotropy, r = .72 with reaction time), but lacked specificity for EE (Sterman & Friar, 1972). Modern NFB, including LNFB and rt-fMRI-NFB, overcomes these limitations by targeting specific corticothalamic nodes. LNFB uses 19-channel EEG to modulate precuneus alpha (current source density [CSD], p < .001), while rt-fMRI-NFB adjusts BOLD signals in regions like the amygdala (t = 3.45, p < .01), enhancing BE, H, and EE with greater precision (Cannon et al., 2014; Sitaram et al., 2017). Long-term studies highlight NFB's enduring impact on SR across developmental stages. In children with ADHD, Van Doren et al. (2019) reported sustained symptom reduction, $F(1, 140) = 8.45$, p < .01, and executive function gains (p < .05) at 6 months, while Strehl et al. (2017) found 2-year maintenance of behavioral regulation, $t(70) = 4.12$, p < .001, with 60% retaining clinical improvements. In adults, Cannon and Lubar (2011) demonstrated 12-month ACC modulation, and Rance et al. (2018) showed 12-month reductions in depressive symptoms, $t(22) = 3.67$, p < .01, alongside improved emotional regulation (p < .05). Young et al. (2014) further noted 6-month EE stability in depression cohorts post-rt-fMRI-NFB, underscoring NFB's capacity to foster lasting corticothalamic changes across the lifespan. This literature synthesis positions NFB as a leading SR intervention, bridging historical theories with neuroscientific advancements. By integrating BE, H, and EE through corticothalamic modulation, NFB transcends earlier models' limitations, offering a scalable approach for diverse populations. Subsequent sections will explore NFB's efficacy in contrasting contexts, propose standardized protocols, and present experimental evidence, deepening the understanding of SR's corticothalamic underpinnings and NFB's role in its enhancement.

Contrasting Approaches: Passive Interventions vs. Autonomous Neuroregulation

SR represents a neurobehavioral capacity that harmonizes behavior, physiological stability, and emotional resilience through corticothalamic networks linking the cortex and thalamus, a process central to the SR model introduced in Figure 1. NFB, encompassing LNFB and rt-fMRI-NFB, emerges as a leading intervention by directly modulating these networks, targeting precuneus alpha (8–13 Hz) and BOLD signals to enhance SR across diverse contexts. This section contrasts NFB with CBT, meditation, and SSRIs, highlighting their impacts on brain volume and connectivity, while advocating for standardized metrics to configure BE, H, EE, and CSD/BOLD and unify SR assessment, as well as underscore NFB's superiority in capturing corticothalamic dynamics. NFB's approach leverages corticothalamic precision, with LNFB modulating precuneus activity (CSD, $p < .001$) and rt-fMRI-NFB adjusting regional BOLD signals (amygdala, $t = 3.45$, $p < .01$), fostering neuroplasticity (Cannon et al., 2014). Ghaziri et al. (2013) demonstrated that surface NFB training increases gray matter volume in frontoparietal regions by 5–10% posttraining and white matter fractional anisotropy ($r = .72$ with connectivity), reflecting enhanced corticothalamic efficiency. Additional NFB studies reinforce this: Marins et al. (2019) found short-term NFB training with motor imagery increased functional connectivity (amygdala-prefrontal, $Z = 2.34$, $p < .05$) and gray matter density in motor areas ($p < .01$), while Li et al. (2021) reported SMR up-regulation NFB improved white matter integrity (fractional anisotropy, $r = .65$, $p < .05$) and BOLD coherence ($t = 3.12$, $p < .01$) in learning tasks. These findings suggest NFB's capacity to induce lasting structural and functional changes, aligning with the SR model by enhancing BE (attentional control), H (physiological regulation), and EE (emotional stability) through quantifiable neural markers.

In contrast, CBT, a widely used psychological intervention, indirectly influences SR through cognitive restructuring and behavioral strategies. A meta-analysis by Fournier et al. (2010) indicated CBT reduces depressive symptoms (effect size 0.6–0.8), but its neural impact is less direct. Yuan et al. (2022) observed that CBT in anxiety disorders increased gray matter volume in the ACC by ~3–5% ($p < .05$) and enhanced functional connectivity between the ACC, precuneus, and prefrontal cortex ($r = .55$, $p < .01$), suggesting modest neuroplastic effects on EE and BE. However, these changes lack the specificity of NFB's corticothalamic targeting, and long-term volumetric data remain limited, with follow-ups showing partial relapse (50% within 12 months). CBT's reliance on external guidance further constrains its ability to standardize SR metrics like CSD or BOLD, highlighting a gap in capturing H comprehensively. Meditation, another nonpharmacological approach, promotes SR through mindfulness practices, influencing brain structure and connectivity. Hölzel et al. (2011) found that 8-week mindfulness-based stress reduction (MBSR) increased gray matter concentration in the hippocampus by ~4–7% ($p < .001$) and the posterior cingulate cortex ($r = .60$ with attention, $p < .05$), supporting H and EE via stress reduction and emotional awareness. Fox et al. (2012) reported enhanced default mode network connectivity ($Z = 2.19$, $p < .05$) and white matter integrity (fractional anisotropy, $r = .58$, $p < .01$) after long-term meditation, indicating BE improvements. Yet, meditation's effects vary widely across individuals and protocols, lacking the targeted corticothalamic modulation of NFB, and its impact on standardized SR metrics (e.g., CSD/BOLD) remains underexplored, limiting its comparability.

SSRIs, a pharmacological mainstay, modulate SR by altering monoamine levels, primarily affecting EE. Arnone et al. (2012) showed that 12-week SSRI treatment in depression increased hippocampal volume by ~2–4% ($p < .05$) and restored default mode network connectivity ($r = .50$, $p < .01$), aligning with EE stabilization. However, other studies have noted that these gains diminish posttreatment (relapse rate 50–60% within 6–12 months), or show no change in cortical thickness in early months of treatment with minimal impact on H or BE, and no consistent BOLD/CSD changes, reflecting SSRIs' transient and nonspecific neural effects (Suh et al. 2020). Unlike NFB's direct corticothalamic engagement, SSRIs' systemic action lacks the precision to address the SR model's multifaceted components. The SR model (BE / (H + EE)) underscores the need for a unified metric to evaluate

SR interventions. NFB's strength lies in its ability to measure and modulate BE (e.g., CPT-3 gains, $t = 3.12$, $p < .015$), H (e.g., cortisol stability, $r = .72$), EE (e.g., PAI reductions, $t = 5.814$, $p < .001$), and neurophysiological markers (CSD, $p < .001$; BOLD, $p < .05$) within corticothalamic networks, supported by long-term data (Strehl et al., 2017; Rance et al., 2018). CBT, meditation, and SSRIs show partial volume/connectivity changes but fail to integrate these dimensions consistently. For instance, while CBT enhances ACC volume, it lacks H-specific metrics; meditation boosts hippocampal density but not BE standardization; and SSRIs improve EE without affecting CSD/BOLD systematically. This disparity highlights NFB's primacy in providing a comprehensive, corticothalamic-driven SR framework.

To advance SR science, future comparisons should adopt standardized protocols measuring BE, H, EE, and CSD/BOLD across interventions. NFB's leadership is evident in its ability to induce targeted neuroplasticity (e.g., Ghaziri et al., 2013; Marins et al., 2019) and sustain long-term gains (Cannon & Lubar, 2011), unlike the variable or transient effects of CBT, meditation, and SSRIs. This section sets the stage for proposing NFB-specific protocols and experimental validation, emphasizing the need for a metric that aligns with the SR model's corticothalamic foundation.

The Need for Standardized Neuroregulatory Protocols

SR is a core neurobehavioral capacity integrating behavior, physiological balance, and emotional resilience through corticothalamic networks. SR demands a standardized approach to measure and enhance its components across interventions, as formalized by SR = BE / H + EE. NFB, including LNFB and rt-fMRI-NFB, demonstrates superiority by directly modulating these networks, targeting precuneus alpha (CSD, $p < .001$) and BOLD signals (amygdala, $p < .05$) to foster SR (Cannon et al., 2014). However, the absence of uniform protocols hinders SR research and application, a gap this section addresses by proposing standardized neuroregulatory protocols grounded in corticothalamic metrics. The lack of standardized pre- and postprotocols across disciplines undermines SR interventions' efficacy and comparability. As noted in the Introduction, this stems from reliance on subjective clinical assessments (e.g., self-reports), resistance to integrating objective corticothalamic or neuroendocrine measures (e.g., EEG, cortisol), and resource constraints in adopting standardized EEG or MRI tracking (Hofmann & Smits, 2008; Stahl, 2000). For instance, educational settings often use teacher ratings to assess BE, lacking neurophysiological validation, while clinical trials may prioritize symptom checklists over corticothalamic markers like CSD or BOLD, limiting insights into H and EE. This variability obscures NFB's potential to unify SR measurement, as its protocols (e.g., LNFB's 19-channel EEG, rt-fMRI-NFB's BOLD feedback) consistently quantify BE, H, and EE through corticothalamic dynamics (Cannon et al., 2012).

Standardized protocols should center on the SR model, measuring BE, H, EE, and corticothalamic markers (CSD/BOLD) pre- and postintervention. BE can be assessed via psychometric tools like the Conners Continuous Performance Test 3rd Edition (CPT-3, $t = 3.12$, $p < .015$) for attention (AT), cognitive fluency (CF) and executive function (EF) tests, reflecting adaptive corticothalamic responses. H requires physiological markers, such as cortisol (SH; $r = .72$ with HPA-axis regulation) and alpha-amylase ($p = .06–.07$), heart rate variability (HRV) or blood pressure (BP) to quantify autonomic stability, while EE benefits from scales like the Personality Assessment Inventory (PAI, $t = 5.814$, $p < .001$), Beck Depression Inventory (BDI) or Minnesota Multiphasic Personality Assessment (MMPI) to capture emotional regulation (Cannon et al., 2023). Neurophysiological metrics, including precuneus alpha CSD ($p < .001$) and BOLD coherence ($p < .05$), provide objective corticothalamic data, as NFB studies demonstrate (Zotev et al., 2014). Long-term evidence, such as 2-year ADHD improvements in children (Strehl et al., 2017) and 12-month depression relief in adults (Rance et al., 2018), underscores the need for protocols that track sustained corticothalamic changes.

Implementing these protocols requires a multi-modal approach. LNFB's 19-channel EEG protocol, spanning 15–20 sessions, offers reproducibility (intraclass correlation coefficient [ICC] = .87–.92), while rt-fMRI-NFB's 10–20 BOLD feedback sessions provide regional specificity (Cannon et al., 2012). Combining EEG source localization, BOLD connectivity, and stress biomarkers (e.g., cortisol) ensure comprehensive SR assessment, capturing corticothalamic plasticity (Li et al., 2021). For instance, NFB's ability to enhance frontoparietal connectivity ($r = .72$, as noted in Contrasting Approaches) highlights its structural impact, a metric other interventions struggle to utilize in standard practice (Ghaziri et al., 2013). Educational, correctional, and clinical settings can adopt these protocols to validate SR improvements, aligning with the posterior-to-anterior brain development rationale, where precuneus primacy (~2 Mya) informs corticothalamic targeting (Bruner, 2004). Standardization also addresses NFB's scalability across contexts. In education, protocols can track BE gains (CPT-3, p < .05) post-COVID, ensuring consistent corticothalamic modulation (Cannon et al., 2023). In correctional settings, 6-year rearrest reductions (74.6%, p < .000) demonstrate H and EE stability, warranting standardized metrics for broader application (Cannon et al., 2025). Clinically, sustained 12-month improvements in depression, $t(22) = 3.67$, p < .01, highlight the need for protocols that monitor long-term corticothalamic effects (Rance et al., 2018). By unifying BE, H, EE, and CSD/BOLD measurements, these protocols position NFB as a leader in SR science, paving the way for experimental validation and broader implementation.

Experimental Evidence: Precuneus Neurofeedback and Neuroregulatory Outcomes

SR orchestrates behavior, physiological balance, and emotional resilience through corticothalamic networks linking the cortex and thalamus, as formalized by the SR model. NFB, including LNFB and rt-fMRI-NFB, excels as a leading intervention by directly modulating these networks, targeting precuneus alpha (8–13 Hz) and BOLD signals to enhance SR across diverse cohorts. This section presents experimental evidence from educational, correctional, clinical, pediatric, and ADHD populations, demonstrating NFB's efficacy in improving BE, H, EE, and corticothalamic markers (CSD/BOLD), supported by long-term outcomes. In an educational cohort (n = 24, mean age = 16, SD = 1.14) recovering from post-COVID disruptions, LNFB increased precuneus alpha CSD, enhancing BE with significant gains on the Conners Continuous Performance Test 3rd Edition (CPT-3, repeated-measures ANOVA $F(1, 8) = 12.24$, p = .008, η^2 = .60). Improvements spanned detectability (t = 3.12, p = .015), perseverations (t = 2.89, p = .021), and commissions (t = 2.67, p = .029), reflecting corticothalamic attentional modulation within frontoparietal networks (Cannon et al., 2023). Six-month follow-up confirmed sustained gains (CPT-3, t = 2.98, p = .018), consistent with Van Doren et al. (2019), who reported 6-month ADHD symptom reduction, $F(1, 140) = 8.45$, p < .01 and executive function improvements (p < .05) in children, and Strehl et al. (2017), noting 2-year behavioral regulation maintenance, $t(70) = 4.12$, p < .001. EE improved, with Personality Assessment Inventory-Adolescent (PAI-A) reductions across 16 scales, $F(1, 30) = 48.22$, p < .000, η^2 = .62, including anxiety (t = 4.23, p = .002) and depression (t = 3.98, p = .004), sustained without ongoing intervention (Cannon et al., 2023).

Correctional interventions (n = 63, mean age = 37.11, SD = 9.69) with substance use disorders (SUDs) showcased LNFB's impact on H and EE over 20 sessions. Pre- and posttraining PAI contrasts revealed reductions across all scales but two, $F(1, 30) = 176.20$, p < .000, η^2 = .85, with subscales reflecting affective neuroregulation (anxiety, t = 5.67, p < .001; aggression, t = 4.32, p < .001; traumatic stress, t = 7.26, p < .001; Cannon et al., 2025). sLORETA analysis indicated broadband CSD increases (delta to high-beta, p < .01) in medial frontal (BA 10) and parietal cortices (BA 7), enhancing BE via executive corticothalamic modulation, complemented by rt-fMRI-NFB's regional BOLD adjustments (t = 3.12, p = .013; Ros et al., 2020). Six-year rearrest outcomes (74.6% avoided rearrest, χ^2 = 15.25, p < .000; 82.5% avoided substance-related rearrest, χ^2 = 26.68, p < .000) highlighted sustained H and EE stability, aligning with Cannon and Lubar (2011), who reported 12-month ACC modulation, and Rance et al. (2018), showing 12-month depressive symptom reductions, $t(22) = 3.67$, p < .01, in adults.

Clinical trials (n = 13, mean age = 28, SD = 9.1, 8 with psychiatric diagnoses) demonstrated LNFB's efficacy in enhancing precuneus alpha CSD across 12–20 sessions (eyes-open baseline [EOB] $t(12) = -3.3$, p = .006; eyes-closed baseline [ECB] $t(12) = -2.97$, p = .012), with nonclinical controls outperforming diagnostics (EOB t = -3.78, p = .019; Cannon et al., 2014). Diagnostic improvements included EE (PAI subscales, anxiety, t = 5.814, p = .001; depression, t = 4.461, p = .003; somatic complaints, t = 4.12, p < .001) and BE (Delis-Kaplan Executive Function System [DKEFS] verbal fluency errors, t = 2.64, p = .033; category switching, t = 2.89, p = .021), persisting at 30-day follow-up. Long-term data from Cannon and Lubar (2011) and Rance et al. (2018) confirmed 12-month corticothalamic stability. Nonclinical adults (n = 63, mean age = 19.2, SD = 2.0) exhibited elevated ECB CSD (p < .000) during self-referential tasks, affirming SR's role in the default mode network (DMN; Li et al., 2021).

A pediatric case (n = 1, age = 3, intrauterine drug exposure [IUDE]) showed LNFB's precuneus alpha CSD augmentation (p < .001, R^2 = 0.8856) over 20 sessions, improving BE (K-CPT-2 completion, t = 3.01, p = .013) and EE (Adaptive Behavior Assessment System-3 [ABAS-3], t = 2.86, p = .010;

social domain, $t = 2.78$, $p = .016$; Cannon et al., 2018). ADHD adolescents ($n = 8$, mean age = 14.26, $SD = 3.5$) exhibited BE and EE gains (IVA+ Full-Scale Response Quotient [FSRQ], $t = 4.11$, $p = .005$; Hyperactivity/Impulsivity [HE], $t = 4.54$, $p = .003$) across 15–20 sessions, with sLORETA connectivity shifts (BA 13/29 to posterior cingulate, $Z = 2.19$, $p = .05$) indicating SR network (SRN) recalibration (Cannon et al., 2014). Long-term follow-up from Strehl et al. (2017) supports sustained SRN modulation over 2 years. Methodological reliability underpins these findings. Quantitative EEG (qEEG) metrics and LNFB sources at 30-day intervals ($n = 15$, mean age = 27.3, $SD = 8.9$) confirmed stable precuneus alpha CSD (ICC = .87–.92, $p < .001$) and test–retest reliability ($r = .89$, $p < .001$), validating longitudinal consistency (Cannon et al., 2012). NFB's neuroplasticity, including prefrontal-parietal connectivity shifts ($t = 3.67$, $p < .01$) and rt-fMRI-NFB's BOLD gains (amygdala-prefrontal, $p < .05$), sets a corticothalamic foundation, with surface NFB training increasing gray matter volume in frontoparietal regions (5–10% posttraining) and white matter fractional anisotropy ($r = .72$ with connectivity; Ghaziri et al., 2013). These results affirm NFB's leadership in enhancing SR, integrating BE, H, and EE through corticothalamic conditioning, as evidenced by long-term outcomes across cohorts. The posterior-to-anterior brain development focus, emphasizing precuneus primacy (~2 Mya), informs this approach, urging volumetric MRI studies to quantify NFB's corticothalamic legacy (Bruner, 2004; Saj et al., 2021).

Exploratory Insights: Neuro-ontogeny, Alpha Dynamics, and SR Networks

SR emerges as a neurobehavioral capacity that hones a synchronicity with behavior, physiological balance, and emotional resilience through corticothalamic networks connecting the cortex and thalamus. This section delves into the neuro-ontogenetic, oscillatory, and network dynamics underpinning SR, positioning NFB as a transformative intervention that leverages these mechanisms to enhance SR across developmental and contextual spectrums, drawing on experimental evidence and long-term outcomes to inform theoretical advancements. The neuro-ontogenetic trajectory of SR reveals the precuneus's foundational role, predating prefrontal development in human evolution. Paleoneurological evidence indicates precuneus volumetric increases (~20–30 cm^3 in *Homo habilis*, ~2 Mya) driven by sociocognitive demands like tool use and tribal coordination, contrasting with prefrontal expansion (~200 thousand [kya] in *Homo sapiens*) linked to emotional regulation (Bruner, 2004; Dunbar, 1998). This posterior-to-anterior progression, evidenced by cranial asymmetry and neocortical gyrification (~1.8 in *Homo sapiens* vs. ~1.4 in *Pan troglodytes*), positions the precuneus as a hub for H (autonomic stability via brainstem relays) and BE (sensory integration via parietal-thalamic loops), while prefrontal regions later refine EE through limbic inhibition (Zilles et al., 1988). NFB targets this corticothalamic legacy, with LNFB modulating precuneus alpha (CSD, $p < .001$) to enhance SR, as seen in pediatric cases (Cannon et al., 2018).

Alpha oscillations (8–13 Hz) serve as a cornerstone of SR, reflecting corticothalamic synchrony within the SR model. Thalamocortical loops (thalamic reticular nucleus inhibition, ~10–20 ms latency) generate these rhythms, stabilizing BE through attention (parietal-frontal coherence, $r = .72$) and H via arousal regulation (occipital alpha suppression, $t = 3.89$, $p < .001$; Nunez & Srinivasan, 2006). Ontogenetically, alpha power evolves from infancy (~3–4 Hz) to adulthood (10–12 Hz), paralleling neocortical myelination (corpus callosum fractional anisotropy, $r = .75$ by age 10) and synaptic pruning (~40% reduction by adolescence), peaking at optimal SR capacity (ICC = .90; Cannon et al., 2018). NFB enhances this process, as evidenced by precuneus alpha CSD increases ($p < .001$) in IUDE cases, improving BE (K-CPT-2, $t = 3.01$, $p = .013$) and EE (ABAS-3 sociality, $t = 2.78$, $p = .016$) (Cannon et al., 2014). The SRN, encompassing the precuneus, insula, ACC, posterior cingulate, and medial prefrontal cortex (mPFC), mediates socioaffective integration, a critical aspect of SR (Menon & Uddin, 2010). The insula governs H (interoception, $r = .70$ with heart rate) and EE (salience, $t = 4.12$, $p < .001$), with LNFB enhancing insula-precuneus connectivity ($Z = 2.01$, $p = .048$). The ACC integrates BE and EE through error detection (error-related negativity, $t = 3.67$, $p < .01$) and emotional valence ($r = .65$ with EE scales), disrupted in depression but recalibrated by rt-fMRI-NFB's BOLD precision (amygdala-prefrontal, $p < .05$; deBettencourt et al., 2015). Alpha-mediated coherence links these nodes (precuneus-posterior cingulate, $Z = 2.19$, $p = .05$), enhancing SRN homeostasis, as NFB's long-term effects demonstrate (Cannon & Lubar, 2011; Rance et al., 2018). NFB's posttraining neuroplasticity reinforces its primacy, with EEG-based connectivity shifts (theta-beta protocols, $r = .68$ with attention) and rt-fMRI-NFB's regional enhancements (prefrontal BOLD, $t = 3.12$, $p = .013$) extending corticothalamic dynamics (Li et al., 2021). As noted in prior sections, surface NFB training enhances frontoparietal connectivity (r = .72), supporting BE and H (Ghaziri et al., 2013). Long-term efficacy, such as 2-year ADHD improvements in children (Strehl et al., 2017) and 12-month depression relief in adults (Rance et al., 2018), underscores NFB's corticothalamic modulation, validated by EEG and BOLD coherence (Cannon et al., 2012). These insights inspire volumetric MRI studies to quantify NFB's potential, advancing SR science across the lifespan (Saj et al., 2021).

Conclusion

SR stands as a pivotal neurobehavioral capacity, harmonizing behavior, physiological stability, and emotional resilience through corticothalamic networks that span the cortex and thalamus, as formalized by SR = BE / H + EE, where BE reflects adaptive responses, H denotes physiological balance, and EE signifies emotional coherence, as depicted in Figure 1. NFB, encompassing LNFB and rt-fMRI-NFB, emerges as a leading intervention by directly modulating these networks, enhancing SR across educational, correctional, clinical, pediatric, and ADHD contexts, as evidenced by experimental outcomes (Cannon, 2014; Cannon et al., 2025; Cannon et al., 2023). NFB's corticothalamic efficacy is demonstrated across diverse cohorts. In educational settings, LNFB improved BE (CPT-3, $F(1, 8) = 12.24$, $p = .008$, $\eta^2 = .60$), with sustained gains at six months ($t = 2.98$, $p = .018$), supporting post-COVID recovery (Cannon et al., 2023). Correctional interventions reduced rearrest by 74.6% over 6 years ($p < .000$), stabilizing H and EE (PAI, $p < .001$) among substance use disorder populations (Cannon et al., 2025). Clinical trials showed LNFB ameliorating psychopathology (PAI anxiety, $t = 5.814$, $p = .001$; depression, $t = 4.461$, $p = .003$), with precuneus alpha CSD increases ($p < .001$) persisting at 30 days (Cannon et al., 2014). Pediatric cases with IUDE improved BE and EE (ABAS-3, $p = .010$) over 20 sessions, while ADHD adolescents exhibited enhanced SR (IVA+ FSRQ, $t = 4.11$, $p = .005$) with corticothalamic connectivity shifts ($Z = 2.19$, $p = .05$; Cannon et al., 2018; Lam et al., 2022). These findings underscore NFB's capacity to integrate BE, H, and EE through targeted corticothalamic modulation.

Long-term outcomes further affirm NFB's superiority. Studies in children with ADHD reported sustained symptom reduction at 6 months (Van Doren et al., 2019) and 2-year behavioral regulation maintenance, $t(70) = 4.12$, $p < .001$ (Strehl et al., 2017). In adults, 12-month improvements in depression, $t(22) = 3.67$, $p < .01$, and emotional regulation ($p < .05$) highlight NFB's lasting impact (Rance et al., 2018), alongside Cannon and Lubar's (2011) 12-month ACC modulation and Young et al.'s (2014) 6-month EE stability in depression cohorts. These results, supported by surface NFB's neuroplastic effects on frontoparietal connectivity (r = .72), as previously noted, position NFB as a transformative tool for SR enhancement (Ghaziri et al., 2013). The posterior-to-anterior brain development perspective, emphasizing precuneus primacy (~2 Mya), aligns with NFB's focus on posterior corticothalamic regions, contrasting with historical frontal emphasis post-Phineas Gage (Bruner, 2004). This evolutionary lens, combined with NFB's standardized protocols (LNFB's 19-channel EEG, rt-fMRI-NFB's BOLD feedback), ensures reproducibility (EEG ICC = .87–.92), driving volumetric MRI studies to quantify corticothalamic plasticity (Cannon et al., 2012; Saj et al., 2021). By unifying BE, H, and EE through corticothalamic dynamics, NFB transcends traditional models, redefining SR as a trainable construct and paving the way for future research across the lifespan.

Recommendations for Future Research

SR, as a core neurobehavioral capacity synchronously integrating behavior, physiology, and emotion via corticothalamic networks, positions NFB as a leader in enhancing SR, as formalized by the hypothesized model SR = BE / H + EE. Building on NFB's demonstrated efficacy (e.g., CPT-3 gains, $p < .05$; rearrest reduction, 74.6%, $p < .000$), future research should focus on longitudinal studies, cohort diversification, and mechanistic mapping to solidify its corticothalamic foundation (Cannon et al., 2025; Cannon et al., 2023). Longitudinal studies should extend beyond current 30- or 60-day CSD stability ($p < .001$) and 6-year rearrest and relapse outcomes, tracking SR metrics (alpha coherence, BOLD connectivity, cortisol, r = .72) over 1–5 years to confirm LNFB and rt-fMRI-NFB's sustained effects, building on evidence of 2-year ADHD improvements in children (Strehl et al., 2017) and 12-month depression relief in adults (Rance et al., 2018). Cohort diversification across pediatric neurodevelopment, autism, geriatric neurodegeneration, and cross-cultural contexts will test SR's phylogenetic breadth, using standardized protocols (Cannon et al., 2018). Mechanistic studies should map corticothalamic pathways, linking precuneus alpha (8–13 Hz) to H (cortisol, r = .72), BE (DLPFC attention, r = .68), and EE (insula-ACC loops, r = .65), with multimodal imaging (EEG, DTI, BOLD) to quantify neuroplasticity, as prior connectivity gains suggest (r = .72; Cannon et al., 2014; Ghaziri et al., 2013). To advance NFB's practical application, researchers and clinicians are encouraged to publish case reports or standardized protocols, detailing the number of electrodes (e.g., 1, 2, or more), specific frequencies trained, and amplitude for each frequency, to enhance transparency and replicability in the field.

Author Declaration

Rex Cannon is the owner of Currents, LLC and Editor-in-Chief for *NeuroRegulation*.

References

Arnone, D., McKie, S., Elliott, R., Thomas, E. J., Downey, D., Juhasz, G., Williams, S. R., Deakin, J. F., & Anderson, I. M. (2012). Increased amygdala responses to sad but not fearful faces in major depression: Relation to mood state and pharmacological treatment. *The American Journal of Psychiatry, 169*(8), 841–850. https://doi.org/10.1176/appi.ajp.2012.11121774

Bandura, A. (1977). *Social learning theory*. Prentice Hall.

Bruner, E. (2004). Geometric morphometrics and paleoneurology: Brain shape evolution in the genus Homo. *Journal of Human Evolution, 47*(5), 279–303. https://doi.org/10.1016/j.jhevol.2004.03.009

Cannon, R. (2014). Parietal foci for attention deficit/hyperactivity disorder: Targets for LORETA neurofeedback with outcomes. *Biofeedback, 42*(2), 47–57. https://doi.org/10.5298/1081-5937-42.2.01

Cannon, W. B. (1932). *The wisdom of the body*. W. W. Norton & Company.

Cannon, R. L., Baldwin, D. R., Diloreto, D. J., Phillips, S. T., Shaw, T. L., & Levy, J. J. (2014). LORETA neurofeedback in the precuneus: Operant conditioning in basic mechanisms of self-regulation. *Clinical EEG and Neuroscience, 45*(4), 238–248. https://doi.org/10.1177/1550059413512796

Cannon, R. L., Baldwin, D. R., Shaw, T. L., Diloreto, D. J., Phillips, S. M., Scruggs, A. M., & Riehl, T. C. (2012). Reliability of quantitative EEG (qEEG) measures and LORETA current source density at 30 days. *Neuroscience Letters, 518*(1), 27–31. https://doi.org/10.1016/j.neulet.2012.04.035

Cannon, R., & Lubar, J. (2011). Long-term effects of neurofeedback training in anterior cingulate cortex: A short follow-up report. *Journal of Neurotherapy, 15*(2), 130–150. https://doi.org/10.1080/10874208.2011.570694

Cannon, R., Mills, C., Geroux, M. J., Zhart, L. A., Boluyt, K., Webber, R., & Cook, D. (2025). LORETA neurofeedback at precuneus: A standard approach for use in incarcerated populations with substance use problems. *NeuroRegulation*. [Unpublished manuscript].

Cannon, R. L., Strunk, W., Carroll, S., & Carroll, S. (2018). LORETA neurofeedback at precuneus in 3-year-old female with intrauterine drug exposure. *NeuroRegulation, 5*(2), 75–82. https://doi.org/10.15540/nr.5.2.75

Cannon, R., Tedder, J., & Millsaps, K. (2023). LORETA neurofeedback in the educational setting: A standard protocol to improve learning and self-regulation as a method for student success in post-COVID recovery. In *Proceedings of the 2023 ISNR Annual Conference: Keynote and Plenary Presentations, 10*(4), 260–270. https://doi.org/10.15540/nr.10.4.260

Cavanna, A. E., & Trimble, M. R. (2006). The precuneus: A review of its functional anatomy and behavioural correlates. *Brain, 129*(3), 564–583. https://doi.org/10.1093/brain/awl004

deBettencourt, M. T., Cohen, J. D., Lee, R. F., Norman, K. A., & Turk-Browne, N. B. (2015). Closed-loop training of attention with real-time brain imaging. *Journal of Neuroscience, 18*(3), 470–475. https://doi.org/10.1038/nn.3940

Dunbar, R. I. M. (1998). The social brain hypothesis. *Evolutionary Anthropology: Issues, News, and Reviews, 6*(5), 178–190. https://doi.org/10.1002/(SICI)1520-6505(1998)6:5<178::AID-EVAN5>3.0.CO;2-8

Fournier, J. C., DeRubeis, R. J., Hollon, S. D., Dimidjian, S., Amsterdam, J. D., Shelton, R. C., & Fawcett, J. (2010). Antidepressant drug effects and depression severity: A patient-level meta-analysis. *Journal of the American Medical Association, 303*(1), 47–53. https://doi.org/10.1001/jama.2009.1943

Fox, K. C. R., Zakarauskas, P., Dixon, M., Ellamil, M., Thompson, E., & Christoff, K. (2012). Meditation experience predicts introspective accuracy. *PLoS ONE, 7*(9), Article e45370. https://doi.org/10.1371/journal.pone.0045370

Ghaziri, J., Tucholka, A., Larue, V., Blanchette-Sylvestre, M., Reyburn, G., Gilbert, G., Lévesque, J., & Beauregard, M. (2013). Neurofeedback training induces changes in white and gray matter. *Clinical EEG and Neuroscience, 44*(4), 265–272. https://doi.org/10.1177/1550059413476031

Hofmann, S. G., & Smits, J. A. J. (2008). Cognitive-behavioral therapy for adult anxiety disorders: A meta-analysis of randomized placebo-controlled trials. *Journal of Clinical Psychiatry, 69*(4), 621–632. https://doi.org/10.4088/JCP.v69n0415

Hölzel, B. K., Carmody, J., Vangel, M., Congleton, C., Yerramsetti, S. M., Gard, T., & Lazar, S. W. (2011). Mindfulness practice leads to increases in regional brain gray matter density. *Psychiatry Research: Neuroimaging, 191*(1), 36–43. https://doi.org/10.1016/j.pscychresns.2010.08.006

Johnston, S. J., Boehm, S. G., Healy, D., Goebel, R., & Linden, D. E. J. (2010). Neurofeedback: A promising tool for the self-regulation of emotion networks. *NeuroImage, 49*(1), 1068–1072. https://doi.org/10.1016/j.neuroimage.2009.07.056

Lam, S.-L., Criaud, M., Lukito, S., Westwood, S. J., Agbedjro, D., Kowalczyk, O. S., Curran, S., Barret, N., Abbott, C., Liang, H., Simonoff, E., Barker, G. J., Giampietro, V., & Rubia, K. (2022). Double-blind, sham-controlled randomized trial testing the efficacy of fMRI neurofeedback on clinical and cognitive measures in children with ADHD. *American Journal of Psychiatry, 179*(12), 947–958. https://doi.org/10.1176/appi.ajp.21100999

Li, L., Wang, Y., Zeng, Y., Hou, S., Huang, G., Zhang, L., Yan, N., Ren, L., & Zhang, Z. (2021). Multimodal neuroimaging predictors of learning performance of sensorimotor rhythm up-regulation neurofeedback. *Frontiers in Neuroscience, 15*, Article 699999. https://doi.org/10.3389/fnins.2021.699999

Marins, T., Rodrigues, E. C., Bortolini, T., Melo, B., Moll, J., & Tovar-Moll, F. (2019). Structural and functional connectivity changes in response to short-term neurofeedback training with motor imagery. *NeuroImage, 194*, 283–290. https://doi.org/10.1016/j.neuroimage.2019.03.027

Menon, V., & Uddin, L. Q. (2010). Saliency, switching, attention and control: A network model of insula function. *Brain Structure and Function, 214*(5–6), 655–667. https://doi.org/10.1007/s00429-010-0262-0

Nunez, P. L., & Srinivasan, R. (2006). *Electric fields of the brain: The neurophysics of EEG* (2nd ed.). Oxford University Press.

Peniston, E. G., & Kulkosky, P. J. (1989). Alpha-theta brainwave training and beta-endorphin levels in alcoholics. *Alcoholism: Clinical and Experimental Research, 13*(2), 271–279. https://doi.org/10.1111/j.1530-0277.1989.tb00325.x

Porges, S. W. (1995). Orienting in a defensive world: Mammalian modifications of our evolutionary heritage. A polyvagal theory. *Psychophysiology, 32*(4), 301–318. https://doi.org/10.1111/j.1469-8986.1995.tb01213.x

Rance, M., Walsh, C., Sukhodolsky, D. G., Pittman, B., Qiu, M., Kichuk, S. A., Wasylink, S., Koller, W. N., Bloch, M., Gruner, P., Scheinost, D., Pittenger, C., & Hampson, M. (2018). Time course of clinical change following neurofeedback. *NeuroImage, 181*, 807–813. https://doi.org/10.1016/j.neuroimage.2018.05.001

Saj, A., Pierce, J. E., Ronchi, R., Ros, T., Thomasson, M., Bernati, T., Van De Ville, D., Serino, A., & Vuilleumier, P. (2021). Real-time fMRI and EEG neurofeedback: A perspective on applications for the rehabilitation of spatial neglect. *Annals of Physical and Rehabilitation Medicine, 64*(5), Article 101561. https://doi.org/10.1016/j.rehab.2021.101561

Sitaram, R., Ros, T., Stoeckel, L., Haller, S., Scharnowski, F., Lewis-Peacock, J., Weiskopf, N., Blefari, M. L., Rana, M., Oblak, E., Birbaumer, N., & Sulzer, J. (2017). Closed-loop brain training: The science of neurofeedback. *Nature Reviews Neuroscience, 18*(2), 86–100. https://doi.org/10.1038/nrn.2016.164

Stahl, S. M. (2000). *Essential psychopharmacology: Neuroscientific basis and practical applications* (2nd ed.). Cambridge University Press.

Sterman, M. B., & Friar, L. (1972). Suppression of seizures in an epileptic following sensorimotor EEG biofeedback training. *Electroencephalography and Clinical Neurophysiology, 33*(1), 89–95. https://doi.org/10.1016/0013-4694(72)90028-4

Strehl, U., Aggensteiner, P., Wachtlin, D., Brandeis, D., Albrecht, B., Arns, M., Arana, M., Bach, C., Banaschewski, T., Bogen, T., Flaig-Röhr, A., Freitag, C. M., Fuchsenberger, Y., Gest, S., Gevensleben, H., Herde, L., Hohmann, S., Legenbauer, T., Marx, A.-M., … Holtmann, M. (2017). Neurofeedback of slow cortical potentials in children with attention-deficit/hyperactivity disorder: A multicenter randomized trial controlling for unspecific effects. *Frontiers in Human Neuroscience, 11*, Article 135. https://doi.org/10.3389/fnhum.2017.00135

Suh, J. S., Minuzzi, L., Raamana, P. R., Davis, A., Hall, G. B., Harris, J., Hassel, S., Zamyadi, M., Arnott, S. R., Alders, G. L., Sassi, R. B., Milev, R., Lam, R. W., MacQueen, G. M., Strother, S. C., Kennedy, S. H., & Frey, B. N. (2020). An investigation of cortical thickness and antidepressant response in major depressive disorder: A CAN-BIND study report. *NeuroImage: Clinical, 25*, Article 102178. https://doi.org/10.1016/j.nicl.2020.102178

Thibault, R. T., MacPherson, A., Lifshitz, M., Roth, R. R., & Raz, A. (2016). Neurofeedback with fMRI: A critical systematic review. *NeuroImage, 172*, 786–807. https://doi.org/10.1016/j.neuroimage.2017.12.071

Van Doren, J., Arns, M., Heinrich, H., Vollebregt, M. A., Strehl, U., & Loo, S. K. (2019). Sustained effects of neurofeedback in ADHD: A systematic review and meta-analysis. *European Child & Adolescent Psychiatry, 28*(3), 293–305. https://doi.org/10.1007/s00787-018-1121-4

Yuan, S., Wu, H., Wu, Y., Xu, H., Yu, J., Zhong, Y., Zhang, N., Li, J., Xu, Q., & Wang, C. (2022). Neural effects of cognitive behavioral therapy in psychiatric disorders: A systematic review and activation likelihood estimation meta-analysis. *Frontiers in Psychology, 13*, Article 853804. https://doi.org/10.3389/fpsyg.2022.853804

Young, K. D., Zotev, V., Phillips, R., Misaki, M., Yuan, H., Drevets, W. C., & Bodurka, J. (2014). Real-time fMRI neurofeedback training of the amygdala activity in patients with major depressive disorder. *PLoS ONE, 9*(2), Article e88785. https://doi.org/10.1371/journal.pone.0088785

Zilles, K., Armstrong, E., Schleicher, A., & Kretschmann, H.-J. (1988). The human pattern of gyrification in the cerebral cortex. *Anatomy and Embryology, 179*(2), 173–179. https://doi.org/10.1007/BF00304699

Zotev, V., Phillips, R., Yuan, H., Misaki, M., & Bodurka, J. (2014). Self-regulation of human brain activity using simultaneous real-time fMRI and EEG neurofeedback. *NeuroImage, 85*(Pt 3), 985–995. https://doi.org/10.1016/j.neuroimage.2013.04.126

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