Investigating the Relationship Between Alpha, Beta and Gamma Neurofeedback and Cognitive Performance to Predict Training Outcomes

Grant Proposal

Rddhima Bora

Massachusetts Academy of Math & Science

Worcester, MA

Abstract (RQ) or Executive Summary (Eng)

Neurofeedback training (NFT) is a noninvasive technique that enables individuals to self-regulate neural activity and has shown potential for enhancing cognitive performance. However, NFT outcomes vary substantially across individuals, and there is currently no reliable method for predicting who will benefit from specific neurofeedback protocols. This variability represents a critical knowledge gap in the field and limits the efficiency and personalization of NFT interventions. In particular, the relationship between early-session EEG dynamics and long-term cognitive outcomes remains poorly understood.

This project investigates whether early changes in EEG activity across alpha, beta, and gamma frequency bands can serve as predictors of neurofeedback trainability and subsequent cognitive improvement. Participants undergo multiple NFT sessions while EEG data are collected continuously, and cognitive performance is assessed throughout training. Early-session neural features, including baseline spectral power, short-term learning slopes, and stability in amplitude change, are analyzed to determine their predictive value for later cognitive gains. By comparing outcomes across different frequency-band–specific training protocols, this study seeks to identify neural markers that distinguish responders from non-responders.

The findings of this research aim to address the gap between neurofeedback implementation and outcome predictability by establishing early EEG markers of training success. Identifying these markers could enable adaptive, individualized NFT protocols that optimize cognitive enhancement while minimizing ineffective training. Ultimately, this work contributes to the development of more reliable and personalized neurofeedback systems, with potential applications in cognitive optimization, education, and clinical intervention.

Keywords: neurofeedback training, electroencephalography, alpha, beta, gamma, cognitive performance, trainability, predictive biomarkers

Investigating the Relationship Between Alpha, Beta and Gamma Neurofeedback Training and Cognitive Performance to Predict Training Outcomes

The human brain communicates through rhythmic electrical oscillations known as brainwaves, which can be measured using electroencephalography (EEG). Each of the five frequency bands correspond to a different state of consciousness or cognitive state. Alpha, beta, and gamma waves are different brainwave frequency bands, and they are closely related to functions in the brain like optimized cognitive performance, thinking, focus, and mental sharpness (Marzbani et al., 2016). Neurofeedback training is a type of biofeedback which uses sensors to monitor real-time brainwave activity through EEG signals. Neurofeedback training (NFT) has been used with different protocols, or brain waves, to provide effective treatment for many diseases. Originally used to treat conditions like epilepsy, NFT has evolved to be applied in extensive areas, like enhancing cognitive function (Vernon et al., 2003; Egner et al., 2004). Across different people, however, the effects of NFT can vary, which can make it difficult to predict if certain protocols are going to be more beneficial than others for every individual. Thus, this project aims to find out whether early EEG changes can help predict long-term neurofeedback outcomes.

Neurofeedback and Brain Oscillations

EEG signals indicate the brain’s electrical activity, with different frequency bands that correspond to different cognitive and behavioral states. NFT utilizes this by providing participants with feedback on the amplitudes of their brainwaves and allows the brain to self-regulate through various stimuli (Zoefel at al., 2011). Over time, individuals can modify the amplitudes of specific frequency bands, which lead to measurable changes in cognitive outcomes.

Alpha Band Activity

The alpha frequency band (8-13 Hz) is closely associated with being a strong marker of cognitive control and inhibition (Hanslmayr et al. 2005). Within this frequency band, *upper alpha* (UA) activity is specifically related to memory performance and improved cognitive performance (Zoefel et al., 2011).

Hanslmayr et al. (2005) provided key evidence which suggests that increasing upper alpha power through NFT can directly boost cognitive performance. In the study, participants who were trained through NFT to increase UA amplitude demonstrated significant improvements in their scores in mental ability tests. These tests were taken across participants who did and did not receive NFT to qualify performance results. From this study, Zoefel et al. (2011) conducted further sessions of NFT and found that subjects who were able to successfully increase UA amplitude showed much greater gains in cognitive tasks than the control participants. It is important to note that UA increases were independent from those of other frequency bands like lower beta, or lower alpha.

Beta Band Activity

The beta frequency band (15–32 Hz) is associated with active cognitive processing, focused attention, and task engagement. Beta frequency increases when individuals perform tasks that require fast decision-making and sustained concentration. Particularly, lower frequency beta activity (15-20 Hz) is linked to maintaining more attentional focus, while higher frequency beta activity is tied to working memory updating and executive functioning (Engel & Fries, 2010; Spitzer & Haegens, 2017).

For the purpose of this study, beta-band neurofeedback is a potential target for improving aspects of cognitive performance that rely on sustained alertness. Beta oscillations respond quickly to task demands, and thus they may also serve as an early predictor of neurofeedback trainability. Individuals who indicate faster increases in beta power during initial training sessions can show greater cognitive gains across the training period. Observing whether beta-band responsivity predicts future treatment outcomes can help identify participants who are most likely to benefit from a beta-focused neurofeedback protocol.

Gamma Band Activity

Gamma oscillations (generally 32-100+ Hz) are among the fastest brain rhythms and have been associated with high-level cognitive integration. Gamma activity is believed to support the binding of information across neural networks, enabling processes such as complex attention, feature integration, working memory maintenance, and conscious perception (Jensen et al., 2007). Increased gamma power is often observed during tasks involving mental effort, cross-modal processing, and the formation of coherent percepts from distributed neural representations.

For this project, gamma activity represents an important comparative frequency band, particularly in understanding whether higher-frequency oscillations provide additional predictive power for identifying strong neurofeedback responders. If early EEG signals for gamma waves correlate with cognitive improvements later in training, gamma-band responsiveness may be a useful biomarker of better cognitive performance. Conversely, limited early gamma trainability may indicate that lower-frequency protocols like alpha or beta may be more effective for a participant. Evaluating gamma-band behavior along with alpha and beta rhythms can therefore help determine whether individualized neurofeedback prescriptions can be optimized based on early EEG signals.

Predicting Neurofeedback Training Outcomes

Recent evidence suggests that neurofeedback training (NFT) outcomes can be predicted after only a few sessions by examining early changes in neural activity and baseline EEG characteristics. Studies such as Hanslmayr et al. (2005) and Zoefel et al. (2011) found that participants who showed early increases in individually defined upper alpha (UA) amplitude were more likely to achieve long-term gains in both UA regulation and cognitive performance. A systematic review by Weber et al. (2020) further supported this, identifying baseline power in the trained frequency band and early session performance as key predictors of NFT success. Individuals who exhibit stronger resting UA activity or early positive trends in UA modulation tend to become “responders,” showing greater cognitive improvements over time.

While alpha-frequency predictors are the most well-established, emerging evidence suggests that beta and gamma frequency bands exhibit similar early indicators of trainability. Beta rhythms, which reflect attentional engagement and task preparation, often demonstrate rapid changes during the first few NFT sessions. Early increases in beta power have been associated with later improvements in cognitive tasks requiring focus and inhibitory control (Engel & Fries, 2010; Spitzer & Haegens, 2017). This means that participants who show initial responsivity to beta-based feedback may be more capable of long-term beta modulation and associated cognitive gains. Conversely, individuals with minimal early changes in beta activity typically demonstrate weaker overall NFT outcomes, suggesting that beta-band responsiveness may function as an early biomarker of attentional trainability.

Gamma oscillations, though more challenging to measure and train, also show potential as predictors of NFT outcomes. Gamma activity reflects high-level cognitive integration, including working memory maintenance and perceptual binding (Jensen et al., 2007). Participants who exhibit early gamma responsivity may later show enhanced performance on tasks involving complex attention or cognitive performance.

For this study, tracking early EEG changes across these three frequency bands will help identify which participants are most likely to be “responders” to each protocol. More importantly, this information will help determine which frequency band is best suited to improving an individual's cognitive performance.

By using early neural indicators to predict NFT outcomes, this project aims to contribute to the development of personalized neurofeedback, where protocols are selected based on each individual’s neurophysiological profile and early training performance rather than a one-size-fits-all approach.

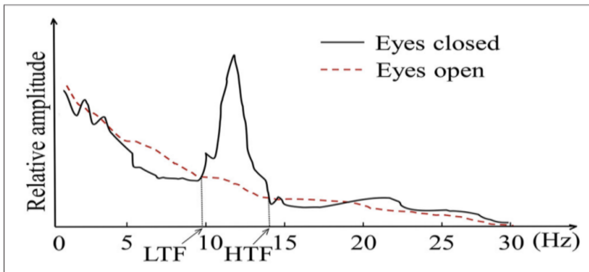

FIGURE 1 | The illustration of individual alpha frequency band.

Figure 1: Illustration of an individual alpha frequency band

Research by Wan et al. (2014) provides strong evidence that early brainwave characteristics can reliably predict an individual’s neurofeedback learning ability, supporting the aims of the current project. In their study, resting-state alpha amplitude within their individual alpha frequency band (ex: Figure 1) was shown to be a significant predictor of how well participants learned to modulate alpha activity over the course of multiple neurofeedback sessions. Individuals with higher baseline alpha demonstrated larger training gains, faster learning slopes, and more effective long-term modulation of the trained frequency band. This finding reinforces the central premise of the present research: that early neural markers can be used to forecast neurofeedback responsiveness.

Overall, the graph of the mean alpha amplitude across all subjects showed a positive increase, as seen in Figure 2. By extending this predictive framework beyond alpha into the beta and gamma bands, the current project builds on Wan et al.'s foundation by examining whether early EEG signatures in multiple frequency ranges can help determine the most effective neurofeedback protocol for improving cognitive performance in each individual. If early beta or gamma responsiveness similarly predicts long-term outcomes, this would further validate the use of early-session EEG patterns as a tool for personalized neurofeedback design, similar to the predictive mechanisms identified by Wan et al. (2014).

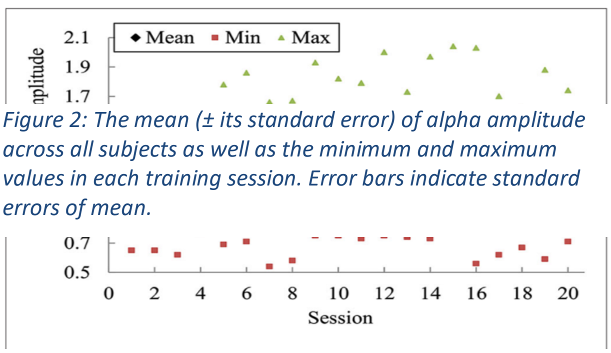

Figure 2: The mean (± its standard error) of alpha amplitude across all subjects as well as the minimum and maximum values in each training session. Error bars indicate standard errors of mean.

This evidence suggests that it is possible to forecast neurofeedback outcomes within a few sessions, allowing researchers to tailor training parameters for each participant. For the current study, tracking early UA amplitude changes will help estimate the individual's ability to be trained and determine the amplitude adjustments most likely to enhance attention and cognitive performance.

Section II: Specific Aims

This proposal's objective is to determine whether early EEG changes during neurofeedback (NFT) can predict long-term training responsiveness and cognitive performance improvements. By examining individual differences in trainability across beta, upper-alpha, and gamma frequency bands, this project seeks to identify which neural markers and training protocols produce the most reliable cognitive benefits.

The long-term goal is to establish a framework for personalized neurofeedback, where training protocols are selected based on each participant's early neural response patterns. The central hypothesis of this proposal is that early-session EEG indicators—such as initial spectral power modulation, the slope of neural learning, and baseline frequency characteristics—will reliably predict later cognitive improvement and overall NFT success. The rationale is that neurofeedback outcomes vary widely across individuals, and current NFT protocols lack data-driven methods for determining which participants will benefit most—or which frequency bands they should train.

The work proposed here will help identify predictive neural markers that allow researchers to efficiently tailor NFT protocols which reduce time, cost, and ineffective training while maximizing cognitive enhancement outcomes.

Specific Aim 1: Identify early EEG markers of neurofeedback trainability across multiple frequency bands.

Examine spectral power changes, initial learning slopes, and baseline neural characteristics during the first two NFT sessions. This aim will determine whether early neural responses can distinguish participants who are likely to modulate the target band consistently from those who do not.

Specific Aim 2: Evaluate the relationship between frequency-band–specific training (beta, upper alpha, gamma) and cognitive performance outcomes.

Participants will complete cognitive assessments before and after each NFT session. Quantify how different frequency bands influence attention, working memory, and general cognitive performance.

Specific Aim 3: Develop a predictive model that links early training neural responses to long-term cognitive improvement.

Using machine-learning or statistical modeling, integrate early EEG features with later behavioral outcomes. This model will determine whether early-session neural changes are reliable predictors of final cognitive gains, and whether different individuals benefit most from different NFT frequency targets.

Section III: Project Goals and Methodology

Relevance/Significance

Neurofeedback training has been shown to significantly enhance cognitive performance, but its effectiveness is largely variable across individuals. Some individuals are “non-responders,” meaning that NFT does not greatly affect them, which makes current NFT approaches inefficient and unable to be generalized. This project addresses this limitation, as it will be able to predict early responders to neurofeedback and which training protocols will be the most effective for an individual.

Innovation

Current neurofeedback training approaches often rely on standardized protocols that are applied uniformly across individuals, despite well-documented variability in training outcomes. The proposed research advances the field by shifting the focus from retrospective evaluation to early prediction of neurofeedback success using neurophysiological markers. Prior work has largely emphasized alpha-band neurofeedback and post-training performance assessment (Hanslmayr et al., 2005; Zoefel et al., 2011), whereas this study systematically examines early-session EEG changes across alpha, beta, and gamma frequency bands as predictors of cognitive improvement. Additionally, extending predictive analyses to beta and gamma bands addresses a significant gap in current research, as these frequencies are closely linked to attention, working memory, and integrative cognitive processing yet remain underexplored in outcome prediction studies (Engel & Fries, 2010; Jensen et al., 2007).

Methodology

1. Resting-state EEG will be collected to measure baseline alpha, beta, and gamma activity.
2. Participants will complete neurofeedback training targeting each frequency band (alpha, beta, or gamma) using real-time visual EEG feedback.
3. Standardized cognitive tasks assessing attention and working memory will be given before and after the training period.
    a. Steps 1-3 will be repeated for each of the training sessions
4. EEG changes during the first one to two neurofeedback sessions will be quantified to assess early modulation of the trained frequency band.
5. Early EEG changes and baseline neural activity will be statistically compared with later cognitive performance to identify predictors of neurofeedback responsiveness and frequency-specific effectiveness.

Specific Aim #1: Identify early EEG markers of neurofeedback trainability across multiple frequency bands

The goal is to identify EEG features (baseline power, early amplitude changes, learning slopes) during the first two NFT sessions that predict successful modulation of alpha, beta, or gamma activity.

Justification and Feasibility.

Previous studies have demonstrated that early changes in EEG activity, particularly in the alpha band, are strong predictors of neurofeedback success (Hanslmayr et al., 2005; Zoefel et al., 2011; Weber et al., 2020). EEG acquisition and spectral power analysis are non-invasive, well-established, and feasible using standard neurofeedback systems. Limiting analysis to the first two sessions reduces participant burden while capturing the most informative learning-related neural changes.

Expected Outcomes

This aim is expected to identify frequency-band–specific early EEG markers that differentiate responders from non-responders. The results will clarify whether early trainability varies across alpha, beta, and gamma bands and establish which neural features are most predictive of successful modulation.

Potential Pitfalls and Alternative Strategies

Early EEG recordings may be noisy or influenced by other factors, potentially obscuring learning-related changes. Additionally, if some participants exhibit delayed learning effects, data from an additional early session may be incorporated as a secondary analysis.

Specific Aim #2: Evaluate the relationship between frequency-band–specific training and cognitive performance outcomes

The goal of this aim is to determine how neurofeedback training targeting different frequency bands relate to changes in cognitive performance. Cognitive assessments will be used to evaluate attention, working memory, and overall cognitive function before and after neurofeedback training.

Justification and Feasibility

Alpha, beta, and gamma oscillations are known to support distinct cognitive processes, suggesting that training different bands may lead to frequency-specific cognitive effects (Engel & Fries, 2010; Jensen et al., 2007).

The selected cognitive tasks are validated, brief, and appropriate for repeated administration. This design allows for within-subject comparisons across sessions, making it feasible to track cognitive changes over time.

Expected Outcomes

Alpha-band training is expected to be associated with improvements in memory and cognitive control, while beta-band training may enhance sustained attention and task engagement. Gamma-band training may show relationships with higher-order cognitive integration and working memory performance. These findings will help clarify how different frequency bands contribute to cognitive enhancement.

Potential Pitfalls and Alternative Strategies

Repeated cognitive testing may introduce practice effects that inflate performance gains. To minimize this, alternate task versions or baseline-normalized scores will be used. If cognitive effects overlap across frequency bands, multivariate analyses will be employed to isolate band-specific contributions.

Specific Aim #3: Develop a predictive model linking early neural responses to long-term cognitive improvement

The goal of this aim is to develop a predictive model that links early-session EEG features to long-term cognitive outcomes following neurofeedback training. Early neural responses, including baseline power and initial modulation ability, will be integrated with behavioral data to predict individual training success.

Justification and Feasibility

Recent reviews emphasize the need for predictive and personalized neurofeedback approaches but note that such models are rarely implemented (Weber et al., 2020). EEG and cognitive performance data are quantitative and well-suited for statistical and machine-learning modeling. With appropriate feature selection and validation, predictive models can be developed even with modest sample sizes.

Expected Outcomes

This aim is expected to produce a model capable of predicting which individuals will show the greatest cognitive benefit from neurofeedback and which frequency band is most effective for each participant. Successful prediction would provide evidence that early neural markers can guide individualized neurofeedback protocols.

Potential Pitfalls and Alternative Strategies

Limited sample size may reduce model generalizability or increase the risk of overfitting. To address this, simpler statistical models and cross-validation techniques will be used. If machine-learning approaches is seen as unstable, regression-based models will be used as an alternative strategy.

Section III: Resources/Equipment

OpenBCI Gelfree Electrode Cap (with electrodes), OpenBCI CytonDaisy 16-channel Biosensing Board, Faraday cage, saline conductive solution, cotton swabs, EEGLAB, MATLAB, cognitive tasks.

Section V: Ethical Considerations

This project involves human participants and therefore requires careful attention to ethical considerations. All participants will provide informed consent prior to participation, with parental consent obtained for any underage participants. Participation will be completely voluntary, and individuals may withdraw from the study at any time without penalty. EEG recording and neurofeedback training are non-invasive and pose minimal risk; however, participants will be monitored for discomfort, fatigue, or frustration, and sessions will be paused or stopped if needed. All collected EEG and cognitive performance data will be de-identified and securely stored to protect participant privacy and confidentiality. The study will follow institutional guidelines for research with human subjects and adhere to ethical standards for data handling, participant safety, and transparency.

Section VI: Timeline

November 5, 2025: Begin collecting preliminary data

December 15, 2025: December Fair

January, 2026: Start data collection from participants

Late January, 2026: Start data analysis

February 16, 2026: February Fair

Section VII: References

Egner, T., & Gruzelier, J. H. (2004). EEG biofeedback of low-beta band components: Frequency-specific effects on variables of attention and event-related brain potentials. *Clinical Neurophysiology*, *115(1), 131–139.* https://doi.org/10.1097/00001756-200112210-00058

Engel, A. K., & Fries, P. (2010). Beta-band oscillations—Signalling the status quo? *Current Opinion in Neurobiology*, *20(2), 156–165.* https://doi.org/10.1016/j.conb.2010.02.015

Gruzelier, J. (2009). A theory of alpha/theta neurofeedback, creative performance enhancement, long distance functional connectivity and psychological integration. *Cogn Process 10* (Suppl 1), 101–109. https://doi.org/10.1007/s10339-008-0248-5

Hanslmayr, S., Sauseng, P., Doppelmayr, M. et al. (2005). Increasing Individual Upper Alpha Power by Neurofeedback Improves Cognitive Performance in Human Subjects. *Appl Psychophysiol Biofeedback 30*, 1–10. https://doi.org/10.1007/s10484-005-2169-8

Jensen, O., Kaiser, J., & Lachaux, J.-P. (2007). Human gamma-frequency oscillations associated with attention and memory. *Trends in Neurosciences, 30(*7)*,* 317–324. https://doi.org/10.1016/j.tins.2007.05.001

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

Spitzer, B., & Haegens, S. (2017). Beyond the status quo: A role for beta oscillations in endogenous content (re)activation. *eNeuro, 4*(4), 1–15. https://doi.org/10.1523/ENEURO.0170-17.2017

Vernon, D. J., Egner, T., Cooper, N., Compton, T., Neilands, C., Sheri, A., & Gruzelier, J. (2003). The effect of training distinct neurofeedback protocols on aspects of cognitive performance. *International Journal of Psychophysiology*, *47*(1), 75–85. https://doi.org/10.1016/S0167-8760(02)00091-0

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

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

Zoefel, B., Huster, R. J., & Herrmann, C. S. (2011). Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance. *NeuroImage*, *54(*2), 1427–1431. https://doi.org/10.1016/j.neuroimage.2010.08.078