

# Predicting Theta/Alpha Neurofeedback Success through Psychological and Personality Profiles: A Hybrid Approach Using Multilayer Perceptron and Elastic Net Models

## Abstract

**Background:** The present study aimed to identify and analyze the psychological, cognitive, and neurophysiological factors influencing success in theta/alpha neurofeedback training. The research focused on how personality dimensions (Myers–Briggs Type Indicator), impulsivity (UPPS), intelligence quotient (Raven's Progressive Matrices), and baseline EEG frequency bands relate to neural self-regulation performance. **Methods:** A quantitative descriptive–analytical design was employed. Data from six healthy participants who completed eight neurofeedback sessions were collected and analyzed using a multilayer perceptron (MLP) neural network and Elastic Net regression implemented in Python. **Results:** Findings revealed consistent increases across EEG frequency bands, with baseline neurophysiological measures sufficient for predicting training outcomes. The Elastic Net analysis identified the Judging personality trait, impulsivity, and baseline delta power as the most influential predictors of responsiveness. Furthermore, enhanced negative correlations between theta and alpha bands suggested improved cognitive differentiation during training. **Conclusion:** Neurofeedback responsiveness is a multifaceted phenomenon influenced by both neurophysiological indices and psychological–cognitive factors. These results underscore the importance of integrating psychological profiling with neural data to optimize individualized neurofeedback interventions.

**Keywords:** Electroencephalogram, Elastic Net regression, multilayer perceptron, neurofeedback training, relative power

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## Introduction

Neurofeedback training (NFT), also known as electroencephalogram (EEG)-biofeedback, is a noninvasive neurophysiological training technique that involves real-time monitoring of brain activity and the provision of contingent feedback to enable individuals to learn self-regulation of their neural function.<sup>[1]</sup> This method has demonstrated significant therapeutic potential across a wide range of clinical conditions, including learning disabilities, stroke, depression, autism, insomnia, tinnitus, epilepsy, attention-deficit/hyperactivity disorder (ADHD), anxiety, alcohol dependence, and posttraumatic stress disorder.<sup>[2]</sup> Beyond its clinical applications, NFT is increasingly employed to enhance cognitive performance, behavioral regulation, and skill acquisition in healthy

individuals, such as improving memory, attention, concentration, and developing athletic or artistic abilities.<sup>[3,4]</sup> Despite these promising benefits, empirical evidence indicates that a significant proportion of individuals fail to achieve successful self-regulation of brain activity, even after multiple training sessions.<sup>[5]</sup> For instance, approximately one-third of participants do not exhibit significant control over their EEG signals following repeated NFT.<sup>[3]</sup> In a study on children with ADHD, Doehner *et al.* found that 50% of participants were unable to modulate their brain activity despite undergoing slow cortical potential (SCP) neurofeedback.<sup>[6]</sup> Similarly, Lubar *et al.* reported that 40% of ADHD patients failed to achieve targeted EEG modifications after 40 training sessions.<sup>[7]</sup> These findings highlight a critical challenge in the field: the substantial interindividual variability in response to NFT, which can lead to inefficiencies in time, cost, and

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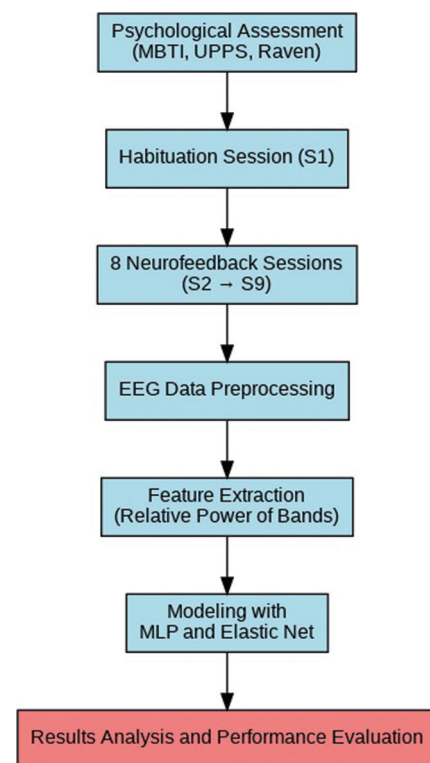
therapeutic outcomes. Given these limitations, identifying reliable predictors of NFT success and developing accurate predictive models have become essential for optimizing training protocols and personalizing interventions. Several studies have explored factors influencing neurofeedback efficacy. For example, Kober *et al.* demonstrated that participants who used no specific mental strategy during sensorimotor rhythm (SMR) neurofeedback showed greater linear improvement in SMR activity compared to those who employed concentration or relaxation techniques.<sup>[3]</sup> Witte *et al.* further found a negative correlation between control beliefs and SMR enhancement, suggesting that an overemphasis on feedback control may hinder learning.<sup>[8]</sup> Hardman *et al.* showed that participants who received no strategic guidance outperformed those instructed to use emotion-based strategies during SCP neurofeedback, indicating that implicit learning may be more effective than explicit control. Moreover, neurophysiological markers have shown predictive value.<sup>[9]</sup> Kotchoubey *et al.* found that the initial capacity of epilepsy patients to modulate SCPs predicted their response to neurofeedback therapy.<sup>[10]</sup> Weber *et al.* demonstrated that early changes in SMR power during initial sessions could reliably predict long-term NFT performance.<sup>[11]</sup> Sho'ouri showed that baseline low-beta power significantly influenced training outcomes and could be used to predict success in beta/theta ratio neurofeedback.<sup>[12]</sup> More recently, Nan *et al.* found that resting and initial beta amplitudes predicted learning ability in beta/theta ratio NFT,<sup>[13]</sup> and Jurewicz *et al.* demonstrated that alpha and beta frequency modulation can be effectively trained in healthy populations.<sup>[14]</sup> Despite these advances, research on the role of psychological and personality factors in NFT success remains limited. For instance, it has been hypothesized that extraverts may respond better to NFT due to their higher sensitivity to external rewards, which are central to the scoring and feedback mechanisms in neurofeedback.<sup>[15,16]</sup> Similarly, sensation seekers, who are drawn to novel and exciting experiences, may engage more enthusiastically in training and achieve better outcomes.<sup>[17,18]</sup> The Myers–Briggs Type Indicator (MBTI) dimensions – such as Judging/Perceiving, Thinking/Feeling, and Extraversion/Introversion – have been linked to cognitive processing styles and may influence an individual's ability to adapt to neurofeedback protocols.<sup>[15,19]</sup> Cognitive abilities, particularly general intelligence quotient (IQ), have also been associated with neurofeedback learning. Raven's Progressive Matrices (RPM) have been used to assess fluid intelligence, which may support the implicit learning processes involved in NFT.<sup>[20,21]</sup> Furthermore, baseline EEG features, such as resting alpha and beta power, have been shown to predict learning ability in frequency-specific neurofeedback protocols.<sup>[13,22]</sup> Against this background, the present study aims to systematically investigate the contributions of MBTI personality dimensions, impulsivity a model that identifies five distinct traits of impulsivity:

negative urgency, positive urgency, lack of premeditation, lack of perseverance, and sensation seeking cognitive ability (Raven's IQ), and baseline EEG frequency features to individual differences in theta/alpha neurofeedback success. Furthermore, two predictive models – a multilayer perceptron (MLP) neural network and Elastic Net regression – were developed to forecast participants' ability to self-regulate theta-band activity, providing an integrative framework that combines psychological, cognitive, and neurophysiological determinants of NFT outcomes.

## Methods

### Study design

This study was conducted using a combined approach of longitudinal experimental design and machine learning-based predictive modeling. The primary aim was to identify predictors of success in theta/alpha NFT. The focus was on determining the role of baseline neurophysiological, psychological, and cognitive features in shaping individual responses to the intervention. To model EEG changes, an MLP neural network was applied to predict the relative power (RP) of frequency bands, and Elastic Net regression was employed to identify key predictors. The overall experimental workflow is illustrated in Figure 1, which provides a schematic overview of the seven main stages: (A) Psychological and cognitive assessment, (B) Habituation session (S1), (C) Eight NFT



**Figure 1: Overview of the experimental and analytical workflow.** MLP – Multilayer perceptron; EEG – Electroencephalogram; MLP – Multilayer perceptron; MBTI – Myers–Briggs Type Indicator

sessions (S2–S9), (D) EEG data preprocessing, (E) Feature extraction (RP of frequency bands), (F) Predictive modeling using MLP and Elastic Net, and (G) Results analysis and performance evaluation.

### Participants

Six healthy participants (2 females and 4 males; mean age =  $27.5 \pm 3.2$  years) were recruited. Inclusion criteria were: Absence of neurological or psychiatric disorders (e.g., epilepsy, severe anxiety, depression, and ADHD), no use of psychoactive medication, and no prior experience with neurofeedback. All participants provided informed written consent after being fully briefed. The study protocol was approved by the University Medical Ethics Committee.

### Neurofeedback training

Participants underwent eight training sessions (S2 to S9), conducted at 48–72-h intervals. Session 1 (S1) served as a habituation session and was excluded from the main analyses. Each session consisted of three 7-min trials, separated by 2-min rest intervals.

Training goal: enhancement of relative theta power (4–8 Hz) and simultaneous reduction of alpha power (8–12 Hz) at site T6 (according to the 10–20 EEG system). This protocol was designed to improve internal focus and reduce unwanted mental activity.

During each NFT trial, participants viewed a display containing various visual stimuli, including natural scenes, paintings in different artistic styles, fractal patterns, and short animated cartoons. These visual stimuli remained static unless participants successfully met both training criteria – i.e., increasing theta band amplitude while simultaneously decreasing alpha band amplitude for at least 0.25 s. Upon successful achievement of these criteria, the images and animations began to move or change, and the participant's cumulative score was updated on the screen. In addition to visual feedback, participants also received auditory feedback: A “ding” sound and a gradually increasing background tone were played when the training goal was achieved. If participants were unable to modulate their brain activity according to the protocol, the images remained static, and no auditory feedback was provided. This multimodal (visual and auditory) feedback system helped participants implicitly learn and reinforce desired brain activity patterns. The gamified interface maintained motivation and engagement throughout the prolonged training sessions.

### Electroencephalogram recording and preprocessing

EEG signals were recorded from site T6 using the FlexComp Infiti system (Thought Technology Ltd., Canada) at a sampling rate of 256 Hz. Before electrode placement, the scalp at site T6 was cleaned with Nuprep abrasive gel, and Ten20 conductive paste was applied. Electrode impedance was maintained below 5 k $\Omega$  throughout the recording.

Preprocessing was performed in MATLAB:

1. Bandpass filtering (1–30 Hz) using a 4<sup>th</sup>-order Butterworth filter
2. Manual artifact removal (eye blinks, muscle contractions, body movements) through visual inspection of the signals
3. Computation of RP for the following frequency bands using 20-s windows with 5-s overlap:
  - Delta: 2–4 Hz
  - Theta: 4–8 Hz
  - Alpha: 8–13 Hz
  - SMR: 13–15 Hz
  - Low Beta: 15–18 Hz.

The RP for each frequency band was calculated as the ratio of the absolute power within the band to the total power across the 2–20 Hz frequency range, using the following formula:

$$P_r = \frac{P_a}{P_T}$$

where  $P_a$  denotes the absolute power of each band and  $P_T$  the total power across the 2–20 Hz range.

### Psychological and cognitive measures

Before training, participants completed the following assessments:

- IQ: RPM<sup>[20]</sup>
- Impulsivity: UPPS-P Impulsive Behavior Scale, including dimensions:
  - Urgency: Tendency to act under intense emotional states
  - Lack of Premeditation: Failure to reflect before acting
  - Lack of Perseverance: Inability to maintain attention during tasks
  - Sensation Seeking: Pursuit of novel and exciting experiences.<sup>[17]</sup>
- Personality: MBTI, including:
  - Introversion/Extraversion (I/E): Perceptual orientation
  - Sensing/Intuition (S/I): Information processing style
  - Thinking/Feeling (T/F): Decision-making preference
  - Judging/Perceiving (J/P): Lifestyle orientation.<sup>[19]</sup>

### Statistical and machine learning analyses

#### *Modeling electroencephalogram dynamics with multilayer perceptron neural network*

An MLP with a 5 → 4 → 5 architecture was designed to predict changes in RP from session S2 to S9.

- Inputs: RP of delta, theta, alpha, SMR, and low beta bands at S2
- Outputs: RP of the same bands at S9
- Hidden Layer: 1 layer with 4 neurons, ReLU activation function
- Loss function: mean squared error (MSE)

- Optimizer: Adam (learning rate = 0.001)
- Training epochs: 200 – each epoch represents one full forward and backward pass over the training data
- Batch size: 32
- Data split: 80% training, 10% validation, 10% test
- Validation Method: Hold-out validation using the 10% validation set to monitor model performance during training and prevent overfitting; early stopping was applied when validation loss plateaued. The test set (10%) was used for the final unbiased evaluation of predictive accuracy
- Evaluation Metrics: MSE, Root mean squared error (RMSE), mean absolute error (MAE), and  $R^2$ .

### Predicting individual response with Elastic Net regression

To identify key predictors of neurofeedback success, Elastic Net regression was used.<sup>[23,24]</sup> The dependent variable was the slope of relative theta power change (slope\_theta\_pr) across the 8 sessions.

- Predictors:
  - Psychological: UPPS, judging, thinking, intuition, and extraversion
  - Cognitive: Raven IQ
  - Neurophysiological: Pr\_delta\_t1\_t3, pr\_theta\_t1\_t3, pr\_alpha\_t1\_t3, pr\_smr\_t1\_t3, pr\_low\_beta\_t1\_t3 (t1-t3 refers to trials 1-3 of NFT).

The model was configured with  $\alpha = 0.1$  and l1\_ratio = 0.5. To assess generalizability and prevent overfitting, 5-Fold and 10-Fold cross-validation (CV) were employed.

### Descriptive and inferential analyses

- Pearson's correlation matrix was computed to examine intervariable associations
- Paired-sample *t*-tests were applied to compare mean RP values between S2 and S9
- Variance inflation factor (VIF) was calculated to assess multicollinearity
- Statistical significance threshold:  $P < 0.05$ .

### Software

All statistical analyses and machine learning were implemented in Python (libraries: scikit-learn, pandas, numpy, matplotlib, TensorFlow/Keras). MATLAB and EEGLAB toolbox were used for initial EEG preprocessing and RP calculation. Figures were generated in Python and refined for publication using Adobe Illustrator.

## Results

### Electroencephalogram changes and prediction of neurofeedback response using the multilayer perceptron model

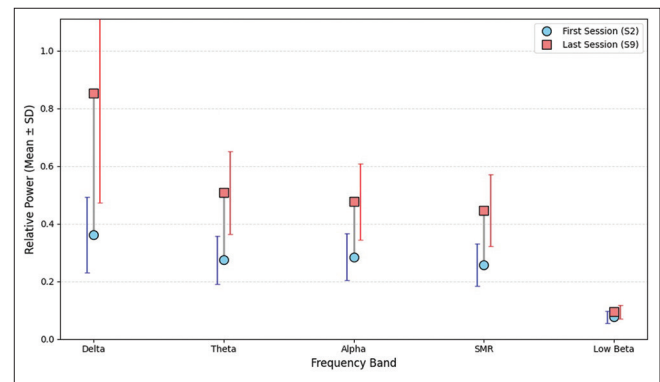
#### Systematic changes in electroencephalogram bands

The results presented in Table 1 and Figure 2 indicate that the EEG frequency bands underwent significant and directed changes throughout the NFT sessions. A consistent

**Table 1: Changes in relative power of electroencephalogram bands from S2 to S9**

Frequency band	First session (S2)	Last session (S9)	Change (S9–S2)
Delta	0.362±0.131	0.854±0.382	0.492
Theta	0.274±0.084	0.508±0.143	0.234
Alpha	0.285±0.081	0.477±0.132	0.192
SMR	0.258±0.073	0.446±0.124	0.188
Low Beta	0.077±0.021	0.094±0.023	0.017

SMR – Sensorimotor rhythm



**Figure 2: Changes in relative power of electroencephalogram bands from S2 to S9. SMR – Sensorimotor rhythm; SD – Standard deviation**

upward trend in RP was observed across most bands from the first session (S2) to the ninth session (S9). The most pronounced change was seen in the delta band, which increased by 0.492, reflecting a shift of brain activity toward deeper relaxation and enhanced regulation of baseline arousal. Subsequently, the theta band exhibited a 0.234 increase, indicating strengthened internal focus and emotional processing, while positive changes in the alpha band (0.192) reflected improved cortical relaxation and sustained attention. The SMR band also increased by 0.188, suggesting enhanced sensorimotor inhibition and stabilization of selective attention. In contrast, the low beta band showed only a minimal increase (0.017), signifying relative stability of executive functions and rapid cognitive processing throughout the protocol. Moreover, the higher standard deviations (SDs) observed in the final session – particularly in the delta (0.382) and theta (0.143) bands – highlight individual differences in responsiveness to training, indicating that some participants exhibited faster adaptation. Overall, these findings suggest that neurofeedback, by reorganizing brain activity – especially within low-frequency bands – can provide a foundation for meaningful cognitive and emotional improvements.

#### Effect of neurofeedback on coupled brain networks

The results presented in Table 2 and Figure 3, which examine the correlation matrix of EEG frequency bands during the first session (S2), provide a multilayered depiction of the dynamic interactions among different brain rhythms, reflecting the baseline state of cognitive

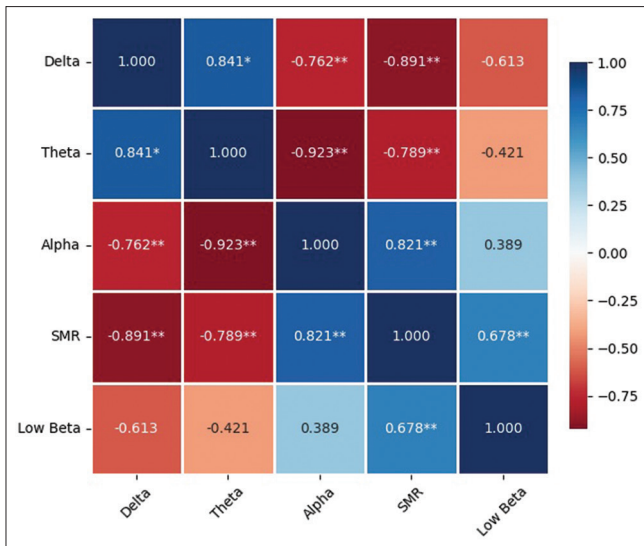


Figure 3: Band correlations in Session S2. SMR – Sensorimotor rhythm. \* $P < 0.05$ , \*\* $P < 0.01$  (two-tailed)

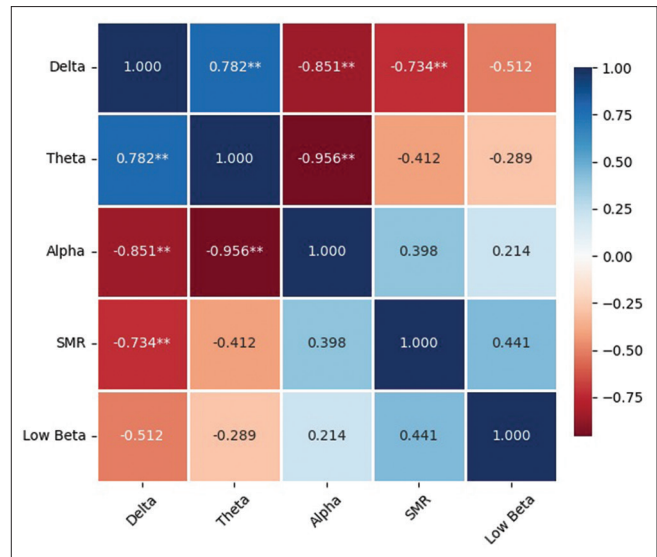


Figure 4: Band correlations in S9. SMR – Sensorimotor rhythm. \* $P < 0.05$ , \*\* $P < 0.01$  (two-tailed)

Table 2: Band correlations in session S2

	Delta	Theta	Alpha	SMR	Low beta
Delta	1	0.841*	-0.762**	-0.891**	-0.613*
Theta	0.841*	1	-0.923**	-0.789**	-0.421
Alpha	-0.762**	-0.923**	1	0.821**	0.389
SMR	-0.891**	-0.789**	0.821**	1	0.678**
Low beta	-0.613*	-0.421	0.389	0.678**	1

\* $P < 0.05$ , \*\* $P < 0.01$  (two-tailed). SMR – Sensorimotor rhythm

and emotional processing before the effects of NFT. At this stage, a strong positive correlation between the delta and theta bands ( $r = 0.841$ ) indicates that increases in the activity of these two bands occurred simultaneously. Conversely, a very strong negative correlation between the theta and alpha bands ( $r = -0.923$ ) reflects a balancing relationship in which increases in alpha power are accompanied by decreases in theta activity, and vice versa. A strong negative correlation between delta and SMR ( $r = -0.891$ ) demonstrates that dominance of slower rhythms coincides with a reduction in SMR activity. At the same time, a significant positive correlation was seen between SMR and low beta ( $r = 0.678$ ). Finally, weaker correlations between low beta and the theta and alpha bands ( $r = -0.421$  and  $r = 0.389$ , respectively) indicate a relative independence of low beta from the slower rhythms. Collectively, these findings reveal that during the first session, the brain network was predominantly governed by interactions between slower rhythms (delta and theta) and mid-range rhythms (alpha and SMR), while low beta occupied a more independent, peripheral role.

The results presented in Table 3 and Figure 4, which analyze the correlation matrix of EEG frequency bands in the final session (S9), reveal a markedly different and significant pattern compared to the initial session, clearly reflecting the neuroplastic effects of NFT on neural network

interactions. At this stage, the positive correlation between delta and theta, although remaining high ( $r = 0.782$ ), has decreased relative to the initial session, indicating that these two bands no longer operate fully in phase and have developed a degree of relative independence. In contrast, the negative correlation between theta and alpha has strengthened, increasing from  $-0.923$  to  $-0.956$ . Meanwhile, the negative correlation between delta and SMR has weakened (from  $-0.891$  to  $-0.734$ ). The positive correlation between SMR and low beta, though still significant ( $r = 0.441$ ), has decreased relative to the first session, reflecting a reduced interdependence between these rhythms. One of the most striking changes is the sharp reduction in the correlation between alpha and SMR, which dropped from a very strong relationship ( $r = 0.821$ ) to a weaker level ( $r = 0.398$ ), signaling increased flexibility of neural networks. Overall, the findings from the final session indicate that following the neurofeedback intervention, EEG bands are less co-activated in pairs and exhibit greater functional independence. This emerging pattern of interactions among EEG bands can be considered a clear marker of neuroplastic changes induced by the intervention.

#### Efficiency of the multilayer perceptron model in predicting electroencephalogram band changes

The results presented in Table 4 provide a comprehensive overview of the architecture and performance of the MLP model in predicting changes across EEG frequency bands. The model, with a  $5 \rightarrow 4 \rightarrow 5$  structure, consisted of five input neurons (representing the RP of delta, theta, alpha, SMR, and low beta bands in the initial session), one hidden layer with four neurons and a ReLU activation function, and five output neurons predicting the same bands in the final session. Data from 331 samples were carefully divided into training (80%), validation (10%), and test (10%) sets to ensure generalizability. The

**Table 3: Band correlations in S9**

	Delta	Theta	Alpha	SMR	Low beta
Delta	1	0.782**	-0.851**	-0.734**	-0.512
Theta	0.782**	1	-0.956**	-0.412	-0.289
Alpha	-0.851**	-0.956**	1	0.398	0.214
SMR	-0.734**	-0.412	0.398	1	0.441*
Low beta	-0.512	-0.289	0.214	0.441*	1

\* $P < 0.05$ , \*\* $P < 0.01$  (two-tailed). SMR – Sensorimotor rhythm

**Table 4: Specifications of the multilayer perceptron model**

Metrics	Values
Inputs	Delta, Theta, Alpha, SMR, Low Beta (S2)
Outputs	Delta, Theta, Alpha, SMR, Low Beta (S9)
Number of samples	331
Network architecture	5 → 4 → 5 (Input → Hidden → Output)
Hidden layer activation	ReLU
Optimizer	Adam
Epochs	200
Batch size	32
MSE	$8.02 \times 10^{-3}$
RMSE	$8.96 \times 10^{-2}$
MAE	$6.73 \times 10^{-2}$
$R^2$ (coefficient of determination)	0.851

MSE – Mean squared error; RMSE – Root mean squared error; MAE – Mean absolute error; SMR – Sensorimotor rhythm

training process employed the Adam optimizer over 200 epochs with a batch size of 32. Quantitative results demonstrated the strong predictive capability of the model: The (MSE =  $8.02 \times 10^{-3}$ ), (RMSE =  $8.96 \times 10^{-2}$ ), and (MAE =  $6.73 \times 10^{-2}$ ) all remained at low levels, while the coefficient of determination ( $R^2 = 0.851$ ) indicated that the model successfully explained more than 85% of the variance in EEG band changes. This high level of accuracy suggests that the initial neural activity pattern in session S2 contains sufficient and well-structured information to reliably predict the final state (S9) following neurofeedback, reflecting a robust and coherent neuroplastic response to the intervention.

#### Reproduction accuracy of the multilayer perceptron in predicting relative electroencephalogram power

Table 5 and Figure 5 provide a precise and convincing depiction of the MLP model's ability to reproduce the actual RP values of frequency bands in the final session (S9), demonstrating that the model maintains stable performance not only at the global level but also at the finest scales. A comparison of three representative samples (initial, middle, and final) reveals that the differences between actual and predicted values across all bands were remarkably minimal, with none of the absolute errors exceeding the threshold of 0.0003. For instance, in the delta band of the first sample, the actual value of

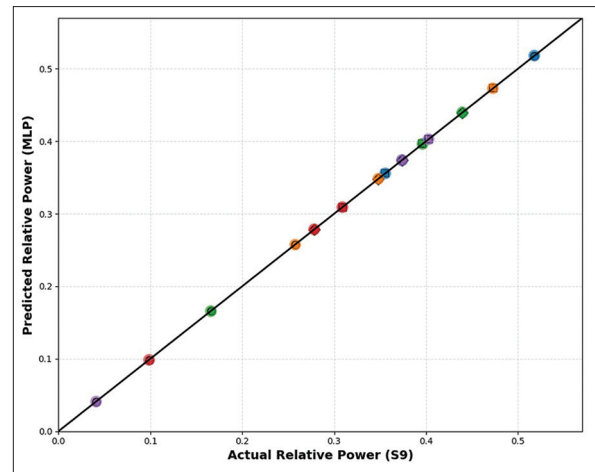


Figure 5: Comparison of actual and predicted values (representative samples). MLP – Multilayer perceptron

0.5178 deviated by only 0.0003 from the predicted value of 0.5181, reflecting prediction accuracy down to the fourth decimal place. A similar pattern was consistently observed across other bands, including theta, alpha, SMR, and even the low-amplitude low beta band. For example, in the last sample of the low beta band, the actual value of 0.3739 matched almost perfectly with the predicted value of 0.374. This consistency across both low-and higher-frequency bands not only validates the model's robustness but also indicates that the neural patterns recorded in the initial session (S2) are systematically and predictably associated with the final state following neurofeedback intervention.

#### Statistical impact of theta/alpha neurofeedback on electroencephalogram band power

Table 6 and Figure 6 provide a rigorous statistical demonstration of the effectiveness of the theta/alpha neurofeedback protocol in modulating neurophysiological brain activity, showing that the intervention exerted effects not only on a single band but across a broad spectrum of EEG frequency bands. Data derived from 331 samples across six participants revealed that the mean RP of all bands increased significantly from the initial session (S2) to the final session (S9). Statistically, these changes were confirmed by high  $t$ -values and extremely low  $P$  values (below 0.001 for four bands and 0.001 for low beta). The most prominent finding was observed in the delta band, which exhibited a 136% increase (from 0.362 to 0.854) along with a striking  $t$ -statistic of 15.34. Similarly, theta (85% increase,  $t = 12.11$ ), alpha (67% increase,  $t = 10.88$ ), and SMR (73% increase,  $t = 11.45$ ) all showed substantial growth. Although the low beta band demonstrated only a modest rise (from 0.077 to 0.094), the statistical significance of this change ( $P = 0.001$ ) indicates that even small increases in low-power bands may reflect genuine intervention effects. Moreover, the elevated SD in S9, particularly in delta and theta, likely reflects individual differences in the magnitude and trajectory of responses

to training. Taken together, these findings provide strong evidence of systematic and enduring changes in neural networks, demonstrating that neurofeedback not only has the capacity to modulate brain activity but also induces

effects sufficiently robust to be clearly captured by classical statistical tests.

### Predicting neurofeedback response via psychological profiles using Elastic Net

#### Descriptive statistics

The descriptive findings of the present study [Table 7 and Figure 7] indicate that the participants' brainwave patterns and psychological characteristics formed a diverse and multidimensional profile. In terms of neural signals, the alpha band accounted for the largest proportion of total power, with an average of approximately 34% of the total signal energy. This was followed by the delta and theta bands, contributing roughly 23% and 21% of the total power, respectively, while the low-beta and SMR bands exhibited lower contributions, ranging between 7% and 9%. This pattern suggests that participants were predominantly in a relaxed and restful baseline state, providing an appropriate starting point for the neurofeedback protocol targeting "theta enhancement and alpha reduction." The theta-to-alpha power ratio was observed to be <1, indicating a relative predominance of the alpha band over theta at baseline. Accordingly, an increase in theta power across sessions can serve as a suitable index for evaluating learning progression within the protocol. However, examination of the theta-band slope revealed that the mean change was minimal and close to zero, implying no significant group-level trend. Nevertheless, the wide range of individual changes highlights considerable heterogeneity among participants, with some showing increases and others decreases in theta power. This variability underscores the critical role of individual differences in neurofeedback learning success. Regarding psychological variables, the mean IQ (assessed via the RPM) was relatively high and homogeneous, indicating that most participants possessed satisfactory cognitive abilities. In contrast, impulsivity (UPPS) exhibited greater variability, ranging from moderate to high levels. Such differences may influence individual responsiveness to NFT. Analysis

**Table 5: Comparison of actual and predicted values (representative samples)**

Frequency band	Sample	Actual (S9)	Predicted (MLP)	Absolute error
Delta	First	0.5178	0.5181	0.0003
	Middle	0.3556	0.3557	0.0001
	Last	0.3739	0.3737	0.0002
Theta	First	0.2576	0.2574	0.0002
	Middle	0.4727	0.473	0.0003
	Last	0.3481	0.3483	0.0002
Alpha	First	0.1659	0.1657	0.0002
	Middle	0.3962	0.3963	0.0001
	Last	0.4395	0.4397	0.0002
SMR	First	0.0987	0.0985	0.0002
	Middle	0.309	0.3091	0.0001
	Last	0.2783	0.2785	0.0002
Low beta	First	0.041	0.0409	0.0001
	Middle	0.4027	0.4028	0.0001
	Last	0.3739	0.374	0.0001

MLP – Multilayer perceptron; SMR – Sensorimotor rhythm

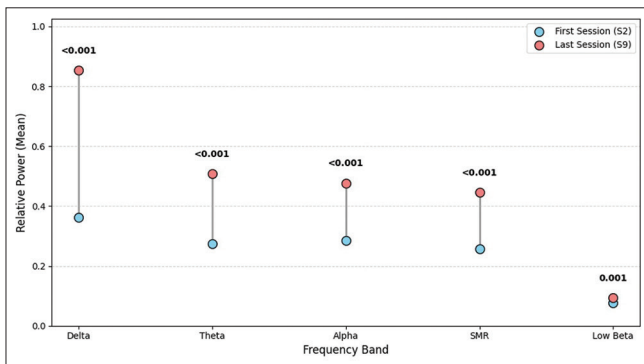


Figure 6: T-test and P value. SMR – Sensorimotor rhythm

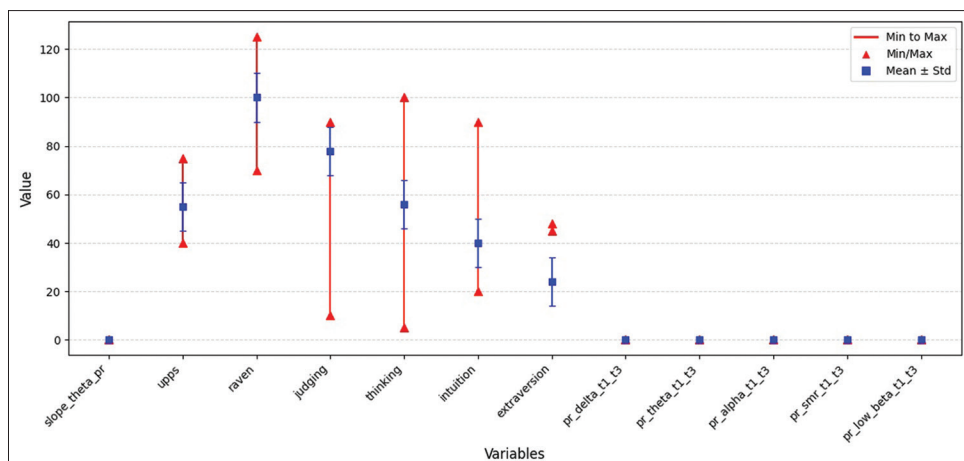


Figure 7: Descriptive statistics

of personality traits (MBTI) further demonstrated significant heterogeneity within the group. On average, the “Judging” and “Thinking” dimensions scored relatively high, while “Intuition” was lower and “Extraversion” was at a moderate level. Score ranges across all dimensions were extensive, spanning from the minimum to maximum possible values, indicating that some participants were at the lowest and others at the highest levels. This broad heterogeneity suggests that personality differences may constitute key factors in explaining individual success or failure in neurofeedback learning. Overall, the review of descriptive statistics indicates that, although the general

pattern of brainwave power across the group is relatively coherent, individual differences in personality traits, impulsivity, and theta-band changes are crucial variables that can explain variability in learning outcomes and the effectiveness of neurofeedback among participants.

*Autocorrelation matrix*

The findings from the correlation matrix [Table 8 and Figure 8] indicated that there are significant and relatively strong relationships among certain neurocognitive and psychological variables. Notably, the variable *slope\_theta\_pr* exhibited a high positive correlation with the MBTI components Judging ( $r = 0.75$ ) and Thinking ( $r = 0.68$ ). This relationship suggests that changes in theta band power are significantly aligned with cognitive tendencies based on logical and judgmental processing. Furthermore, a moderate-to-strong positive association of this variable with changes in delta ( $r = 0.62$ ) and theta power over time ( $r = 0.38$ ) reflects overlapping neurophysiological mechanisms related to learning and cognitive processing in these frequency bands. Conversely, *slope\_theta\_pr* showed a notable negative correlation with alpha power ( $r = -0.45$ ) and impulsivity (UPPS;  $r = -0.42$ ). This pattern indicates that increases or stability in theta activity were accompanied by reductions in impulsivity and relative alpha power; in other words, participants exhibiting greater baseline cognitive control and self-regulation experienced a decrease in alpha and a gradual increase in theta. At the inter-band level, changes in theta were strongly positively correlated with SMR ( $r = 0.51$ ) and delta ( $r = 0.58$ ), while showing very strong negative correlations with alpha ( $r = -0.72$ ) and low-beta ( $r = -0.53$ ). These findings suggest that neurofeedback learning likely occurs concomitantly with increased activity in slower bands (theta and delta) and decreased activity in faster bands (alpha and low-beta). In addition, the very strong negative correlation between SMR and low-beta ( $r = -0.82$ ) underscores that these two bands may play opposing or competitive roles in

**Table 6: *t*-test and *P* value**

Frequency band	First session (mean±SD)	Last session (mean±SD)	<i>t</i> -test	<i>P</i>
Delta	0.362±0.131	0.854±0.382	15.34	<0.001
Theta	0.274±0.084	0.508±0.143	12.11	<0.001
Alpha	0.285±0.081	0.477±0.132	10.88	<0.001
SMR	0.258±0.073	0.446±0.124	11.45	<0.001
Low beta	0.077±0.021	0.094±0.023	4.23	0.001

SD – Standard deviation; SMR – Sensorimotor rhythm

**Table 7: Descriptive statistics**

Variables	Mean±SD	Minimum	Maximum
Slope_theta_pr	2.22×10 <sup>-6</sup> ±3.08×10 <sup>-6</sup>	-1.73×10 <sup>-6</sup>	5.71×10 <sup>-6</sup>
Upps	54.83±12.94	41	75
Raven	121.5±8.16	104	131
Judging	77.5±33.41	13	93
Thinking	55.83±35.64	7	100
Intuition	41.5±24.15	27	93
Extraversion	23.5±18.2	0	47
pr_delta_t1_t3	0.228±0.055	0.108	0.339
pr_theta_t1_t3	0.215±0.048	0.11	0.326
pr_alpha_t1_t3	0.338±0.087	0.231	0.538
pr_smr_t1_t3	0.074±0.022	0.05	0.117
pr_low_beta_t1_t3	0.088±0.018	0.063	0.117

SD – Standard deviation

**Table 8: Autocorrelation matrix**

Variable	Slope_theta_pr	Upps	Raven	Judging	Thinking	Intuition	Extraversion	pr_delta_t1_t3	pr_theta_t1_t3	pr_alpha_t1_t3	pr_smr_t1_t3	pr_low_beta_t1_t3
Slope_theta_pr	1	-0.42	0.18	0.75	0.68	-0.31	-0.22	0.62	0.38	-0.45	0.29	-0.33
Upps	-0.42	1	-0.11	-0.38	-0.41	0.29	0.15	-0.27	-0.33	0.21	-0.18	0.25
Raven	0.18	-0.11	1	0.22	0.35	-0.18	0.09	0.19	0.27	-0.26	0.14	-0.11
Judging	0.75	-0.38	0.22	1	0.72	-0.24	-0.18	0.41	0.39	-0.44	0.28	-0.31
Thinking	0.68	-0.41	0.35	0.72	1	-0.31	-0.21	0.44	0.42	-0.47	0.31	-0.35
Intuition	-0.31	0.29	-0.18	-0.24	-0.31	1	0.27	-0.33	-0.28	0.25	-0.19	0.23
Extraversion	-0.22	0.15	0.09	-0.18	-0.21	0.27	1	-0.14	-0.11	0.12	-0.08	0.1
pr_delta_t1_t3	0.62	-0.27	0.19	0.41	0.44	-0.33	-0.14	1	0.58	-0.61	0.42	-0.45
pr_theta_t1_t3	0.38	-0.33	0.27	0.39	0.42	-0.28	-0.11	0.58	1	-0.72	0.51	-0.53
pr_alpha_t1_t3	-0.45	0.21	-0.26	-0.44	-0.47	0.25	0.12	-0.61	-0.72	1	-0.58	0.59
pr_smr_t1_t3	0.29	-0.18	0.14	0.28	0.31	-0.19	-0.08	0.42	0.51	-0.58	1	-0.82
pr_low_beta_t1_t3	-0.33	0.25	-0.11	-0.31	-0.35	0.23	0.1	-0.45	-0.53	0.59	-0.82	1

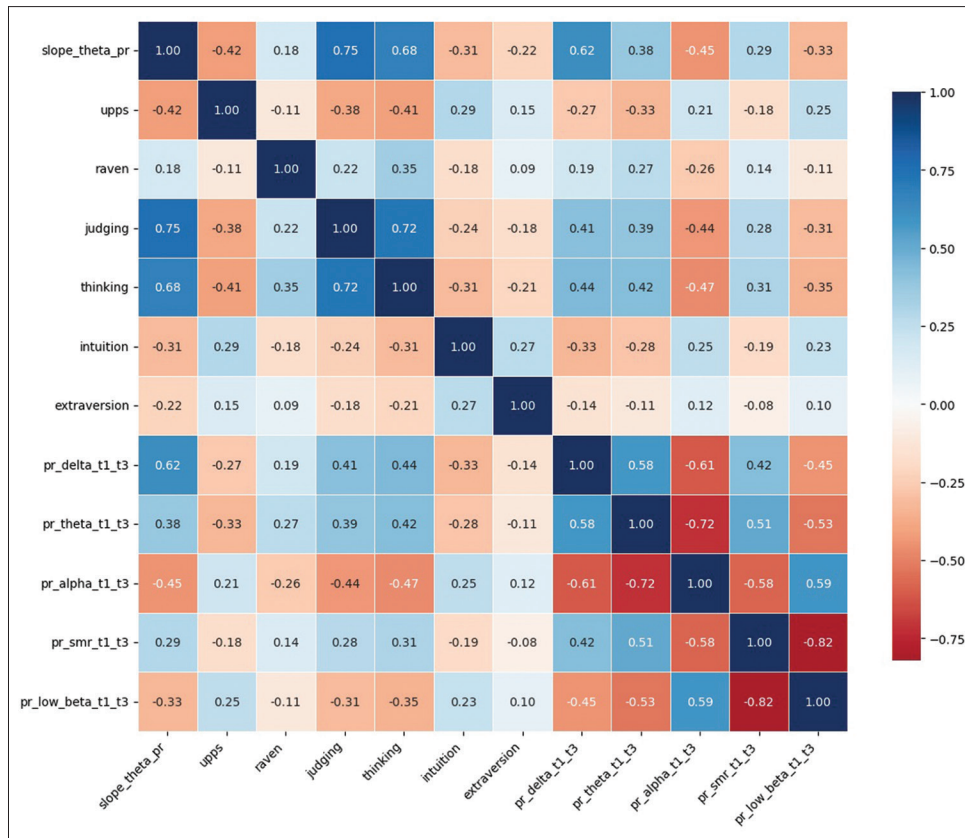


Figure 8: Autocorrelation matrix

cognitive-attentional regulation. In the psychological dimension, impulsivity showed moderate negative correlations with Judging ( $r = -0.38$ ) and Thinking ( $r = -0.41$ ), indicating that individuals with a stronger tendency toward logical decision-making display lower levels of impulsivity. Although the RPM scores did not show high correlations with other variables, their positive association with Thinking ( $r = 0.35$ ) and Judging ( $r = 0.22$ ) aligns with theoretical expectations in psychometrics. Overall, the correlation pattern indicates that changes in theta and delta bands are most closely associated with cognitive and personality indices, whereas increases in alpha and low-beta are often linked to reduced cognitive performance or higher impulsivity.

*Multicollinearity*

Based on the results presented in Table 9 and Figure 9, the VIF for the predictors included in the model indicates that there is no severe multicollinearity among them. In other words, each variable provides unique information to the model and does not exhibit excessive dependency on other variables. At first glance, the highest VIF value corresponds to the variable *judging*, with a value of 4.32. Although this value is higher relative to the other predictors, it remains below the conventional threshold of 10, indicating that multicollinearity is not a serious issue in the model. The next highest value is observed for thinking at 3.91, which

Table 9: Multicollinearity among variables

Feature	VIF
Upps	2.14
Raven	1.87
Judging	4.32
Thinking	3.91
Intuition	2.05
Extraversion	2.67
pr_delta_t1_t3	1.98
pr_theta_t1_t3	1.76
pr_alpha_t1_t3	2.45
pr_smr_t1_t3	1.89
pr_low_beta_t1_t3	2.01

VIF – Variance inflation factor

suggests a moderate correlation with some other variables but still falls within an acceptable range. The remaining predictors, including UPPS, Raven, intuition, and the EEG-related indices (delta, theta, alpha, SMR, and low beta), all have VIF values between 1.7 and 2.6, reflecting low multicollinearity and overall model stability. Overall, the results suggest that the predictors do not exhibit dangerous statistical overlap, and the model estimates can be considered reliable. The only point warranting attention is the relatively higher VIF values of Judging and Thinking, which, while still within permissible limits, may require careful consideration in supplementary analyses.

*Model estimation results*

The results from the Elastic Net model estimation indicate that only a limited subset of variables played a significant role in predicting the dependent variable, while the remaining variables were eliminated from the model. As observed in the Table 10 and Figure 10, the three variables –Judging, UPPS, and pr\_delta\_t1\_t3 – exhibited the highest importance and remained as key indicators in the model. The Judging variable, with a positive coefficient of  $+3.42 \times 10^{-8}$ , had the most substantial impact in the model. This suggests that an increase in the Judging index directly enhances the prediction of the target variable, playing a decisive role in shaping the outcomes. In contrast, the UPPS variable, which measures impulsivity, appeared

in the model with a negative coefficient of  $-2.15 \times 10^{-8}$ . This finding indicates that higher impulsivity may lead to a reduction in the dependent variable, reflecting an inverse relationship between the two. On the other hand, pr\_delta\_t1\_t3, with a relatively larger coefficient of  $+1.88 \times 10^{-6}$ , demonstrates that delta waves within the specified time interval exert a strong positive effect on the model’s prediction. The high importance of this variable underscores that neurophysiological indicators, alongside cognitive factors, can significantly enhance the explanatory power of the model. The Thinking variable, with a coefficient of  $+1.03 \times 10^{-8}$ , although less influential than the three aforementioned variables, remained in the model and acted as a supporting factor in improving model fit. Finally, other variables were excluded by the Elastic Net algorithm due to their lack of meaningful weight. This indicates that the model automatically retained only the truly impactful predictors, preventing the inclusion of low-importance or overlapping factors. Overall, the findings suggest that a combination of cognitive features (Judging and Thinking), personality traits (UPPS), and neurophysiological indicators (pr\_delta\_t1\_t3) played the most significant roles in explaining and predicting the target variable.

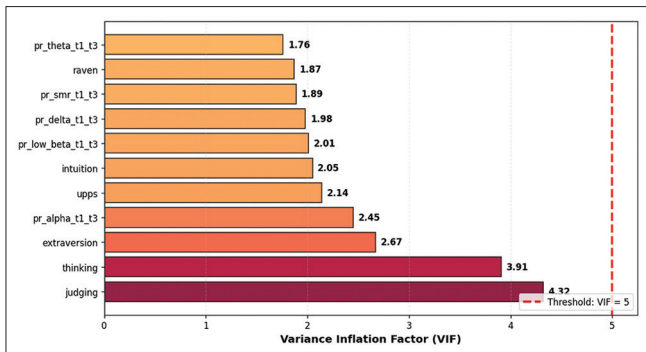


Figure 9: Multicollinearity among variables. VIF – Variance inflation factor

*Error metrics (mean squared error; root mean squared error; R<sup>2</sup>) and model comparison*

As illustrated in Figure 11 and Table 11, the results related to the model’s error metrics indicate that the model has

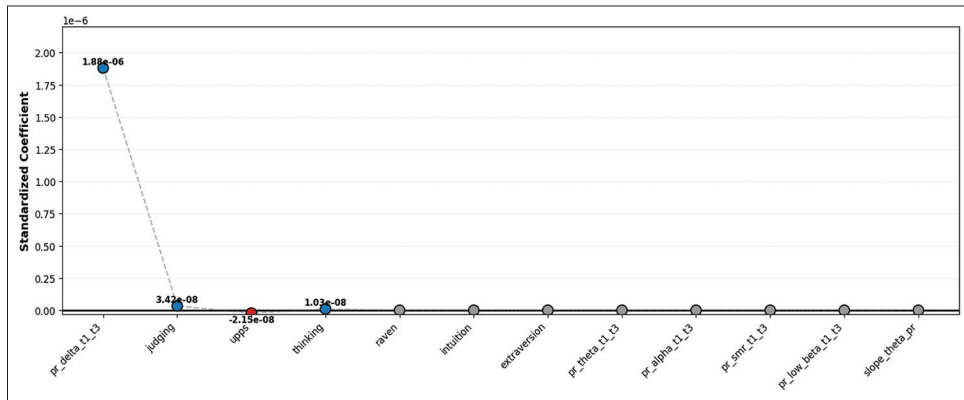


Figure 10: Elastic Net Model Results

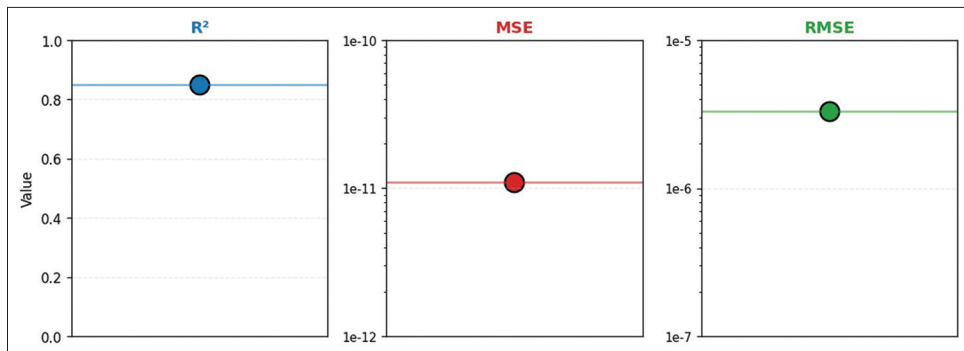


Figure 11: Performance evaluation metrics of the Elastic Net model. MSE – Mean squared error; RMSE – Root mean squared error

achieved a high level of fit to the observed data. The coefficient of determination,  $R^2 = 0.85$ , demonstrates that the model explains 85% of the variance in the dependent variable, meaning that a substantial portion of the observed variability can be predicted by the selected features. This high  $R^2$  value confirms the model’s strong explanatory power and indicates an appropriate fit to the data. The MSE, equal to  $1.10 \times 10^{-11}$ , shows that the average squared prediction errors are extremely low; in other words, the model is able to reconstruct the actual values of the dependent variable with very high accuracy. This low MSE minimizes the prediction error and indicates the high precision of the estimates. The RMSE, which is the square root of MSE and expressed in the same units as the dependent variable, was reported as  $3.32 \times 10^{-6}$ . The extremely small RMSE value indicates minimal deviation between the predicted and actual values, showing that the model successfully captures the precise variations in the dependent variable. Overall, the combination of these metrics (high  $R^2$  and low MSE/RMSE) demonstrates that the Elastic Net model provides an excellent fit and is capable of accurately predicting individual differences in neurofeedback learning even with a limited sample size. These findings confirm the superior performance of the model compared to other potential approaches and validate the reliability of its results for subsequent analyses.

**Cross-validation results**

To evaluate the generalizability of the model and ensure that it has not overfitted the training data, two CV methods

**Table 10: Standardized coefficients of the Elastic Net model**

Feature	Coefficient	Importance
Judging	$+3.42 \times 10^{-8}$	✔ Very important
Upps	$-2.15 \times 10^{-8}$	✔ Very important
pr_delta_t1_t3	$+1.88 \times 10^{-6}$	✔ Very important
Thinking	$+1.03 \times 10^{-8}$	✔ Important
Other variables	0	✘ Removed

**Table 11: Performance evaluation metrics of the Elastic Net model**

Metric	Value
$R^2$	0.85
MSE	$1.10 \times 10^{-11}$
RMSE	$3.32 \times 10^{-6}$

MSE – Mean squared error; RMSE – Root mean squared error

**Table 12: Cross-validation results of the Elastic Net model**

Validation type	$R^2$ (mean±SD)
5-fold CV	$0.82 \pm 0.18$
10-fold CV	$0.79 \pm 0.20$

CV – Cross-validation; SD – Standard deviation

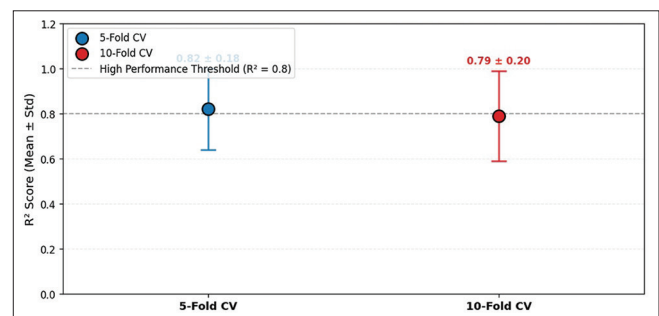
were employed: 5-Fold CV and 10-Fold CV [Table 12 and Figure 12]. In the 5-Fold CV, the mean coefficient of determination (Mean  $R^2 = 0.82$ ) indicates that, on average, the model was able to predict 82% of the variance in the dependent variable on unseen data. The SD ( $SD R^2 = 0.18$ ) reflects moderate variability across the five data splits, suggesting that model performance was slightly better in some folds and slightly lower in others; however, all values remain within an acceptable range. In the 10-Fold CV, the mean  $R^2$  slightly decreased to 0.79, while the SD increased to 0.20. This minor reduction in predictive power may be due to the increased number of data splits, which reduces the sample size in each fold. Nevertheless,  $R^2$  values remained above 0.75, indicating that the model maintains strong generalization to new data and is robust against variations in data partitioning. Overall, the CV results presented in Table 12 and Figure 12 demonstrate that the model predicting neurofeedback success exhibits high stability and generalizability, and its predictions are reliable. These findings reinforce the model’s validity beyond the initial training dataset, confirming that the selected features have the capacity to explain and predict the dependent variable in new samples.

**Discussion**

The present study provides compelling evidence that individual differences in NFT success are determined by a complex interplay of neurophysiological, psychological, and cognitive factors. By integrating machine learning models – specifically a MLP and Elastic Net regression – this research establishes a robust and interpretable framework for predicting neural self-regulation during theta/alpha NFT. The findings demonstrate that not only do EEG dynamics undergo systematic reorganization across training sessions, but these changes are profoundly shaped by baseline personality traits, impulsivity, and initial brain states, underscoring the necessity of a personalized approach to neurofeedback.

**Neurophysiological changes and neural plasticity**

A central finding of this study is the significant and directed increase in the RP of low-frequency EEG bands – particularly delta, theta, and alpha – from the second



**Figure 12: Cross-validation results of the Elastic Net model. CV – Cross-validation**

session (S2) to the ninth session (S9). The most pronounced change was observed in the delta band (+0.492), followed by theta (+0.234), alpha (+0.192), and SMR (+0.188). This pattern of change suggests a progressive shift toward deeper relaxation, enhanced internal focus, and improved cortical inhibition, all of which are associated with successful NFT outcomes.<sup>[3,4]</sup> The substantial increase in delta power is particularly noteworthy, as it reflects a transition toward a more relaxed and introspective brain state, often linked to reduced arousal and improved emotional regulation.<sup>[25]</sup> This aligns with clinical observations that NFT can reduce anxiety and improve sleep quality, both of which are associated with elevated delta activity. The concurrent rise in theta and alpha power further supports enhanced attentional control, sensorimotor inhibition, and cognitive stability – key markers of successful neurofeedback learning.<sup>[14,13]</sup> Moreover, the reorganization of functional connectivity between EEG bands, as revealed by correlation matrix analyses, provides strong evidence of neuroplastic changes induced by NFT. In the initial session (S2), strong positive correlations were observed between delta and theta ( $r = 0.841$ ), and between SMR and low beta ( $r = 0.678$ ), indicating a tightly coupled neural network. However, in the final session (S9), these correlations weakened, while the negative correlation between theta and alpha intensified (from  $-0.923$  to  $-0.956$ ). This increasing segregation between theta and alpha suggests that participants developed a greater ability to switch flexibly between states of focused attention (theta) and relaxed idling (alpha) – a hallmark of improved cognitive flexibility and self-regulatory capacity.<sup>[26]</sup> This finding is consistent with prior research showing that effective neurofeedback leads to desynchronization of initially coupled brain rhythms.<sup>[10,11]</sup> Our results extend these findings by showing that dynamic reorganization of interband correlations, not just changes in individual band power, is a critical indicator of neuroplastic adaptation.

### Psychological predictors of neurofeedback training success

One of the most significant contributions of this study is the identification of psychological traits as powerful predictors of NFT success. Elastic Net regression revealed that Judging (MBTI), UPPS impulsivity, and baseline delta power ( $pr\_delta\_t1\_t3$ ) were the strongest predictors of the slope of theta power change, with Judging emerging as the most influential psychological factor. The positive association between Judging and learning efficacy suggests that individuals who are more organized, goal-oriented, and comfortable with decision-making are better able to engage with the structured nature of NFT. This aligns with the findings of Kober *et al.*, who reported that participants who used no specific mental strategy during SMR NFT showed better learning, possibly because they adopted a more flexible, process-oriented approach.<sup>[3]</sup> However, our results suggest that a structured

cognitive style – rather than the absence of strategy – may be more beneficial in theta/alpha protocols, which require sustained attention and goal-directed effort. Conversely, higher levels of impulsivity (UPPS) were associated with poorer learning, highlighting the critical role of inhibitory control and sustained attention in successful self-regulation. This is consistent with research showing that impulsive individuals struggle with tasks requiring delayed gratification and internal focus.<sup>[18]</sup> The fact that impulsivity outperformed several EEG features in predictive power underscores the importance of cognitive control mechanisms in NFT.

### Neurophysiological predictors and the role of baseline delta

The results of MLP model ( $R^2 = 0.851$ ,  $MSE = 8.02 \times 10^{-3}$ ) suggest that baseline neural activity contained sufficient information to reliably predict posttraining states, indicating a consistent neuroplastic response to neurofeedback. According to the results of the Elastic Net model among neurophysiological features, only baseline delta power ( $pr\_delta\_t1\_t3$ ) remained a significant predictor in the Elastic Net model. Its positive coefficient indicates that individuals with higher initial delta activity may possess a neurophysiological state conducive to learning theta regulation, potentially reflecting greater cortical inhibition, thalamocortical stability, and readiness for internal focus. In previous studies, the role of baseline EEG in determining individuals' responsiveness to neurofeedback has been demonstrated. Indicating that the initial RP or the amplitude of the frequency bands may influence NFT outcomes within the same bands. For example, Wan *et al.* found that resting alpha power predicted learning ability in alpha neurofeedback,<sup>[22]</sup> Nan *et al.*, showed that baseline beta power predicted success in beta/theta ratio training,<sup>[13]</sup> and Sho'ouri established that the average low beta waves in the first session had the maximum effects on it in the last training session.<sup>[12]</sup> Our results extend this line of research by demonstrating that low-frequency baseline states (delta) can also serve as strong predictors, particularly in protocols targeting theta modulation. The elimination of other EEG bands (theta, alpha, SMR, and low beta) from the final model underscores a crucial point: baseline band power alone is insufficient for predicting NFT success. Instead, integrating psychological and neurophysiological features significantly enhances predictive accuracy, as demonstrated by the high performance of the Elastic Net model ( $R^2 = 0.851$ ,  $MSE = 1.10 \times 10^{-11}$ ).

### Model performance and clinical implications

The MLP model demonstrated exceptional predictive accuracy, confirming that the initial neural state contains information to forecast the final brain state after training. This high level of prediction is not merely a statistical artifact; it reflects a robust and coherent neuroplastic

response to the intervention. The success of the model in capturing complex, nonlinear dynamics highlights the potential of machine learning in advancing personalized neuromodulation. The Elastic Net model, with its built-in feature selection, provided an interpretable framework, identifying only three key predictors out of eleven. This sparsity enhances model generalizability and reduces overfitting, reinforcing the reliability of the identified predictors.

## Conclusion

This study demonstrates that NFT success is a multifaceted phenomenon shaped by the interaction of neurophysiological plasticity, personality traits, and cognitive control. The successful application of machine learning models to predict training outcomes opens new avenues for the development of personalized and adaptive neurofeedback systems. By identifying “good learners” in advance, clinicians and researchers can optimize training protocols, improve efficacy, and reduce resource waste. These findings contribute significantly to the growing body of literature on the mechanisms of neurofeedback learning and pave the way for more intelligent and individualized applications.

## Ethical approval

This study was approved by the Ethics Committee of Islamic Azad University, Tehran Central Branch (Approval Code: IR.IAU.CTB.REC.1400.010). All procedures involving human participants were conducted in accordance with the ethical standards of the institutional and national research committees, and with the 1975 Helsinki Declaration and its later amendments. Written informed consent was obtained from all participants prior to their enrollment in the study.

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## Availability of data and materials

The datasets generated and/or analysed during the current study are not publicly available due to ethical restrictions and to protect participant confidentiality. However, anonymized data may be made available from the corresponding author upon reasonable request and subject to approval by the institutional ethics committee.

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## Conflicts of interest

There are no conflicts of interest.

## References

1. Hammond DC. What is neurofeedback: An update. *J Neurother* 2011;15:305-36.
2. Hammond DC. What is neurofeedback? *J Neurother* 2007;10:25-36.
3. Kober SE, Witte M, Ninaus M, Neuper C, Wood G. Learning to modulate one's own brain activity: The effect of spontaneous mental strategies. *Front Hum Neurosci* 2013;7:695.
4. Gruzelier J, Egner T, Vernon D. Validating the efficacy of neurofeedback for optimising performance. *Prog Brain Res* 2006;159:421-31.
5. Alkoby O, Abu-Rmileh A, Shriki O, Todder D. Can we predict who will respond to neurofeedback? A review of the inefficacy problem and existing predictors for successful EEG neurofeedback learning. *Neuroscience* 2018;378:155-64.
6. Doehnert M, Brandeis D, Straub M, Steinhausen HC, Drechsler R. Slow cortical potential neurofeedback in attention deficit hyperactivity disorder: Is there neurophysiological evidence for specific effects? *J Neural Transm (Vienna)* 2008;115:1445-56.
7. Lubar JF, Swartwood MO, Swartwood JN, O'Donnell PH. Evaluation of the effectiveness of EEG neurofeedback training for ADHD in a clinical setting as measured by changes in TOVA scores, behavioral ratings, and WISC-R performance. *Biofeedback Self Regul* 1995;20:83-99.
8. Witte M, Kober SE, Ninaus M, Neuper C, Wood G. Control beliefs can predict the ability to up-regulate sensorimotor rhythm during neurofeedback training. *Front Hum Neurosci* 2013;7:478.
9. Hardman E, Gruzelier J, Cheesman K, Jones C, Liddiard D, Schleichert H, *et al.* Frontal interhemispheric asymmetry: Self regulation and individual differences in humans. *Neurosci Lett* 1997;221:117-20.
10. Kotchoubey B, Strehl U, Holzapfel S, Blankenhorn V, Fröscher W, Birbaumer N. Negative potential shifts and the prediction of the outcome of neurofeedback therapy in epilepsy. *Clin Neurophysiol* 1999;110:683-6.
11. Weber E, Köberl A, Frank S, Doppelmayr M. Predicting successful learning of SMR neurofeedback in healthy participants: Methodological considerations. *Appl Psychophysiol Biofeedback* 2011;36:37-45.
12. Sho'ouri N. Predicting the success rate of healthy participants in beta neurofeedback: Determining the factors affecting the success rate of individuals. *Biomed Sign Process Control* 2021;69:102753.
13. Nan W, Wan F, Vai MI, Da Rosa AC. Resting and initial beta amplitudes predict learning ability in beta/theta ratio neurofeedback training in healthy young adults. *Front Hum Neurosci* 2015;9:677.
14. Jurewicz K, Paluch K, Kublik E, Rogala J, Mikicin M, Wróbel A. EEG-neurofeedback training of beta band (12–22 Hz) affects alpha and beta frequencies-A controlled study of a healthy population. *Neuropsychologia* 2018;108:13-24.
15. Gram PC, Dunn BR, Ellis D. Relationship between EEG and psychological type. *J Psychol Type* 2005:33-46.
16. Shourie N, Firoozabadi M, Badie K. Neurofeedback training protocols based on spectral EEG feature subset and channel selection for performance enhancement of novice visual artists. *Biomed Signal Process Control* 2018;43:117-29.

17. Gagnon J, Daelman S, McDuff P, Kocka A. UPPS dimensions of impulsivity. *J Individ Diff* 2013;34:48-55.
18. Whiteside SP, Lynam DR. The five factor model and impulsivity: Using a structural model of personality to understand impulsivity. *Pers Individ Diff* 2001;30:669-89.
19. Myers IB, Myers PB. *Gifts Differing: Understanding Personality Type*. Mountain View, CA, USA: Nicholas Brealey; 2010.
20. John RJ. Raven progressive matrices. In: *Handbook of Nonverbal Assessment*. London, UK: Springer; 2003. p. 223-37.
21. Kaufman SB, DeYoung CG, Gray JR, Jiménez L, Brown J, Mackintosh N. Implicit learning as an ability. *Cognition* 2010;116:321-40.
22. Wan F, Nan W, Vai MI, Rosa A. Resting alpha activity predicts learning ability in alpha neurofeedback. *Front Hum Neurosci* 2014;8:500.
23. Zou H, Hastie T. Regularization and variable selection via the elastic net. *J R Stat Soc Ser B Stat Methodol* 2005;67:301-20.
24. Hou R, Wang X, Xia Y. Sparse damage detection via the elastic net method using modal data. *Structural Health Monitoring* 2022;21:1076-92.
25. Steriade M. Grouping of brain rhythms in corticothalamic systems. *Neuroscience* 2006;137:1087-106.
26. Klimesch W. EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Res Brain Res Rev* 1999;29:169-95.