Marcos-Martínez *et al. Journal of NeuroEngineering and Rehabilitation* (2026) 23:107
https://doi.org/10.1186/s12984-026-01912-z

Journal of NeuroEngineering
and Rehabilitation

RESEARCH **Open Access**

Motor imagery-based neurofeedback in older adults: neural signatures and feasibility in a randomized controlled trial targeting age-related cognitive decline

Diego Marcos-Martínez[1,2*], Eduardo Santamaría-Vázquez[1,2], Sergio Pérez-Velasco[1,2], C. Rubén Ruiz-Gálvez[1,2], Ana Martín-Fernández[1,2], Beatriz Pascual-Roa[1,2], Rebeca Martínez-Velasco[1], Víctor Martínez-Cagigal[1,2] and Roberto Hornero[1,2]

Abstract

Background Neurofeedback (NF) is a non-invasive endogenous stimulation technique that enables individuals to voluntarily modulate brain activity, which has shown potential to induce neuroplasticity. Among its promising applications is cognitive enhancement in healthy older adults to prevent age-related cognitive decline. However, its efficacy remains controversial due to methodological limitations and a high proportion of individuals unable to achieve effective self-regulation, known as non-responders. This study aimed (1) to evaluate the feasibility of motor imagery (MI)-based NF training in older adults and characterize associated brain activity patterns; and (2) to assess its potential cognitive benefits through a randomized, double-blind, controlled design.

Methods Ninety-two healthy participants aged 65–75 were randomly assigned to a training (TG), placebo (PG), or control group (CG). TG and PG completed ten electroencephalography (EEG)-based NF sessions over ten weeks, while CG engaged in ten classical cognitive stimulation sessions. All participants completed a comprehensive neuropsychological evaluation prior to and following the intervention. EEG data from the NF training sessions were analyzed using spectral and network metrics to characterize modulations in local activity and large-scale functional network patterns induced by the intervention.

Results Although a substantial proportion of TG participants achieved high MI accuracy values, statistical analyses revealed no cognitive improvements specific to TG, suggesting limited efficacy of the MI-based protocol compared to classical cognitive stimulation. Spectral and network analyses identified distinct modulation patterns during MI in responders, absent in non-responders. Moreover, specific resting-state features—namely increased β_1 (13–20 Hz) band relative power and reduced α (8–13 Hz) band node strength—were associated with better self-regulation performance.

---

*Correspondence:
Diego Marcos-Martínez
diego.marcos.martinez@uva.es

Full list of author information is available at the end of the article

Conclusions The present study did not provide conclusive evidence supporting the effectiveness of MI-based NF training for cognitive enhancement in older adults. Nonetheless, the results offer valuable insights that may inform the refinement of future NF-based cognitive training protocols. Moreover, our findings suggest that baseline functional network organization may play a key role in determining the capacity for successful self-regulation. Identifying additional neurophysiological biomarkers will be essential to advance our understanding of the non-responsiveness phenomenon and to enable the development of more personalized NF interventions.

Keywords Neurofeedback, Cognitive training, Brain-computer interfaces, Motor imagery, Graph theory

Introduction

Neurofeedback (NF) is a biofeedback technique that aims to enable voluntary control of brain activity, thereby modulating the activity of neural substrates associated with specific behaviors or clinical conditions [1, 2]. Through a brain-computer interface (BCI), NF establishes a closed-loop system that acquires, processes and analyzes real-time neural signals to provide feedback on the user's mental state [3]. This feedback enables the identification and refinement of effective cognitive strategies (e.g., mental imagery, relaxation) to achieve desired brain activity patterns [4]. Repeated application of NF leverages operant conditioning to enhance self-regulation of neural processes. This, in turn, potentially promotes plastic changes in the targeted neural networks and reinforces functional circuits that support adaptive behaviors [1]. In contrast to other brain modulation methodologies, such as pharmacotherapy or exogenous brain stimulation, NF is an endogenous approach. Rather than externally modulating neuronal excitability, it promotes self-regulation via the reinforcement of internally generated mental strategies. This volitional engagement recruits a broader spectrum of physiological mechanisms, including experience-dependent plasticity and potentially long-lasting functional and molecular adaptations [5]. Furthermore, NF relies on non-invasive neuroimaging methods for signal acquisition, with electroencephalography (EEG) being the most widely used due to its portability and relatively low cost [4].

The potential clinical benefits of NF, together with its advantages over other neuromodulation techniques, have led to numerous research studies investigating the efficacy of NF in different clinical conditions. In this regard, NF has shown promising results inducing changes in the functionality of brain networks associated with non-degenerative brain disorders, such as depression [6], post-traumatic stress disorder [7], attention deficit hyperactivity disorder [8], or epilepsy [9]. It is hypothesized that NF could contribute to alleviating the symptoms of these pathologies by modulating the associated brain rhythms toward non-pathological states [5, 10]. Besides, NF-based neural rehabilitation in stroke survivors has yielded encouraging outcomes, demonstrating its ability to promote restorative neurplasticity not only for motor [10–12], but also for cognitive recovery [10, 13, 14]. The results of these studies indicate that incorporating novel NF-based approaches, which focus rehabilitation on the specific affected area, yields superior outcomes compared to conventional therapies applied in isolation [15]. In addition to its clinical applications, NF has also been explored as a tool for enhancing cognitive performance in cognitively healthy individuals [4]. This approach has gained particular attention in studies targeting cognitively healthy older adults [16]. This population often experiences subtle declines in fluid cognitive abilities due to normal aging, without significant impairment in daily functioning [16]. NF-based cognitive training is considered a promising strategy to strengthen neural resilience and help mitigate age-related cognitive decline. Acordingly, numerous studies have investigated how different NF training protocols could enhance participants' cognitive abilities [16].

Although there are no inherent restrictions on the neural features targeted by NF training, most protocols rely on simple spectral-based designs. These typically aim to modulate the power of specific frequency bands at localized brain regions associated with particular cognitive functions. These typically aim to modulate the power of specific frequency bands at well-defined cortical sites associated with distinct cognitive functions. For instance, frontal midline theta (4–8 Hz, commonly assessed at Fz) and sensorimotor area activity (13–15 Hz, often evaluated at Cz) are among the most extensively investigated in NF-based cognitive training, with reported benefits in executive functions [17–19] and working memory, attention, short- and long-term memory indices [20–22], respectively. While promising, these approaches present a major limitation. The volitional modulation of targeted features is often unintuitive and demands users to explore abstract cognitive strategies to identify effective modulation approaches. In this regard, a promising yet underutilized paradigm in NF-based cognitive training research is motor imagery (MI). MI elicits sensorymotor rythms (SMR) desynchronization through the mental simulation of movement without actual execution, engaging more concrete and familiar sensorimotor representations [10]. While MI has been widely applied in motor rehabilitation for stroke patients [10], its application in cognitive training among cognitively healthy older adults remains largely unexplored. Notably, the conclusions of a previous study suggested its effectiveness, reporting improvements in visuospatial skills, memory, and language functions [23].

Despite its broad therapeutic potential, NF efficacy remains in question. Most studies use small population samples, which reduces the statistical power of the analyses and contributes to skepticism about the reported effects [16]. Although the many NF sessions required for neuroregulation may pose challenges for participant recruitment, large sample sizes remain essential for reliable results [24]. Another challenge in evaluating NF efficacy is to control the likely cognitive changes that are not specifically leaded by NF, but for other factors, such as placebo or test-retest effect. To address this, recent guidelines advocate for the inclusion of both placebo-control groups (receiving non-contingent feedback) and non-NF control conditions [25]. Importantly, when such groups are included, a double-blind design is considered essential to minimize expectancy biases and ensure the integrity of the findings [25]. However, implementing such rigorous designs is technically demanding. It requires large sample sizes and dedicated software capable of delivering sham feedback and blinding both participants and experimenters. Such a functionality remains limited in currently available NF platforms [25]. Furthermore, the neurophysiological mechanisms underlying successful self-regulation during NF remain poorly understood [1, 26]. This poses challenges for researchers in refining NF protocols and interpreting outcomes. For instance, some studies report that about 25% [18, 19] to even 50% [27] of users, known as “non-responders," cannot voluntarily modulate their brain activity. Non-responding condition is a major problem in NF research, as the underlying reasons that prevent users from successfully modulating their brain activity through NF remain poorly understood [26]. Despite its widespread occurrence, non-responsiveness is often overlooked in the literature. Many studies identifying non-responders exclude them from further analysis rather than investigating their neural activity in depth [18, 19]. This practice limits our understanding of the variability in NF learning and prevents the identification of potential predictors of successful neuroregulation. To advance the field, it is essential to incorporate comprehensive analyses of both responder and non-responder populations, enabling a more complete characterization of the mechanisms underpinning NF.

The goal of this study is twofold: (1) to investigate the feasibility and characterize brain patterns of MI-based NF cognitive training in the older adult population; and (2) to rigorously study whether this intervention could enhance cognitive performance in this population. Specifically, we aim to answer the following research questions: (**RQ1**) Is MI-based NF training an effective approach for cognitive enhancement in healthy older individuals?; and (**RQ2**) Are there brain activity patterns that influence responsiveness to NF training? To address these questions, we conducted a randomized, double-blind NF-based cognitive training study involving 92 cognitively healthy older adults, who were randomly assigned to a training group (TG), a placebo group (PG), or a passive control group (CG).

The main novelties of this study can be summarized as follows. First, it provides the first empirical validation of a previously proposed and promising MI-based NF protocol for cognitive training in older adults. This validation was conducted under a rigorous randomized, double-blind experimental design. Second, the study addresses a major limitation in prior NF research by including one of the largest samples reported to date ($N = 92$), which enables more robust statistical analyses and enhances the generalizability and reliability of the findings. Third, we performed an in-depth characterization of the neural mechanisms underlying NF learning, incorporating both spectral and graph theory analyses. Finally, this study contributes to a largely unexplored area in NF research by separately analyzing the neural activity of responders and non-responders. This allowed us to identify novel resting-state electrophysiological features that may serve as predictive biomarkers of NF non-responsiveness. Together, these contributions reinforce methodological rigor in NF research and offer new insights that could inform the development of more effective and individualized NF interventions.

Materials and methods

Participants

Ninety-two older adults (69 females and 23 males; mean age = 70.12 ± 2.92 years) without previous BCI experience participated in the study. All participants provided written informed consent, and the study protocol was approved by the Ethics Committee of “Hospital Clínico Universitario de Valladolid" (reference: PI 23-3325), Valladolid, Spain. The inclusion criteria were: (1) age between 65 and 75 years; (2) no history of significant neurological or psychiatric disorders (e.g., epilepsy, schizophrenia, dementia, traumatic brain injury, or stroke); (3) no current treatment with medications affecting the central nervous system; and (4) no history of alcohol or substance abuse.

Experimental protocol

In order to reliably assess the efficacy of a MI-based NF training for cognitive enhancement, we designed a randomized, double-blind experimental protocol in accordance with the recommendations of *Consensus on Reporting and Experimental Design of Clinical and Cognitive-Behavioral Neurofeedback Studies* (CRED-NF)

[25]. Participants were randomly divided into an NF TG (N = 31), PG (N = 31) and CG (N = 30). Group allocation was stratified by age, sex, and years of education to ensure homogeneity across groups. Participants in both the TG and PG groups completed ten NF sessions over a ten-week period. TG participants received contingent feedback based on their own brain activity during the NF trial. On the other hand, PG participants always received non-contingent feedback, which was generated by randomly selecting previously acquired EEG recordings from individuals who did not participate in the current study. The details of the NF-based cognitive training protocol are thoroughly described in sect. 2.2.1.

By contrast, CG participants took part in ten classical cognitive stimulation sessions over the same ten-week span. These session were composed of classical cognitive stimulation activities, which are structured interventions aimed at engaging and enhancing cognitive functions by promoting neural plasticity and maintaining or improving cognitive performance [28]. This traditional approach was considered in our experimental design to compare its efficacy with the NF-based cognitive training prposed. The details of the NF-based cognitive training protocol are thoroughly described in sect. 2.2.2.

In addition to cognitive training, a healthy lifestyle represents the second key component of active aging interventions. Specifically, regular aerobic exercise has been widely recognized as an effective non-pharmacological strategy to mitigate the risk of cognitive decline by improving cerebrovascular conditions [29]. To complement the two cognitive training interventions (i.e., NF and classical cognitive stimulation), all participants took part in a weekly guided group session of aerobic physical activity.

To evaluate the potential cognitive changes induced by the NF training, all participants underwent two cognitive assessment sessions: one before and one after the intervention.

The inclusion of the PG allowed for the control of potential placebo effects associated with NF, while the CG enabled comparison between NF-based cognitive training and widely used cognitive stimulation approaches aimed at mitigating age-related cognitive decline. Importantly, a double-blind design was implemented for the NF-related arms of the study: both the participants and the researchers involved in administering the NF sessions and conducting the cognitive assessments were blinded to group allocation (i.e., TG or PG). This approach minimized potential biases in the delivery of the intervention and in outcome evaluation. Blinding was not feasible for the CG due to the nature of the classical cognitive stimulation activities implemented

Neurofeedback training protocol

We implemented a NF protocol for cognitive enhacement based on MI building on our previous work [23]. The rationale for selecting MI as the NF strategy was as follows. MI involves voluntary modulation of SMR over sensorimotor cortices essential for movement planning and execution [3]. MI also engages brain areas linked to complex cognitive functions. Studies have shown that MI activates frontal regions involved in executive control and decision-making [30, 31], as well as the parietal cortex essential for sensory integration and spatial representation [30]. This suggests that MI-based training could strengthen the fronto-parietal network and enhance cognitive functions [23]. In addition, as previously mentioned, MI-based NF training represents a promising approach to facilitate self-regulation. In contrast to the more abstract strategies required in other NF paradigms, MI leverages the imagination of familiar sensations and movements to facilitate neuroregulation [10]. Finally, since the effectiveness of a MI-based NF protocol for cognitive enhancement in healthy older adults has been examined in only one study [23], additional evidence is required to assess its suitability. Consequently, our experimental design was aligned with that study to provide complementary findings. Specifically, this included the implementation of multiple gamified NF training scenarios with different levels of difficulty [23]. Importantly, despite age-related neurophysiological changes, healthy older adults have been shown to retain sufficient motor imagery ability: MI vividness remains largely preserved [32], and MI-related neural engagement is maintained through functional reorganization rather than loss of capacity [33]. Therefore, the MI paradigm is well suited for healthy older adults as a target task for self-regulating their brain rhythms through neurofeedback.

During the NF training sessions, participants were seated in a comfortable chair positioned in front of an LCD screen, which was used to deliver real-time feedback. EEG data were recorded using a g.Nautilus PRO system *(g.tec Medical Engineering GmbH*, Austria) equipped with 16 active hybrid g.SAHARA electrodes. Electrodes were positioned according to the 10–10 international system at the following scalp locations: Fp1, Fp2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P3, Pz, P4, and POz. An elastic cap was used to maintain electrode placement, and conductive gel was applied to ensure optimal signal quality. Ground electrode and common reference were placed in the left and right mastoid, respectively. Signals were sampled at 250 Hz.

Each NF session lasted one hour and consisted of 12 blocks, each comprising 10 randomly ordered MI trials (left- or righ-hand). Figure 1 depicts the schematic structure of each block and MI trial. Each trial lasted 6 s, followed by a 4-second rest period, and was preceded by a

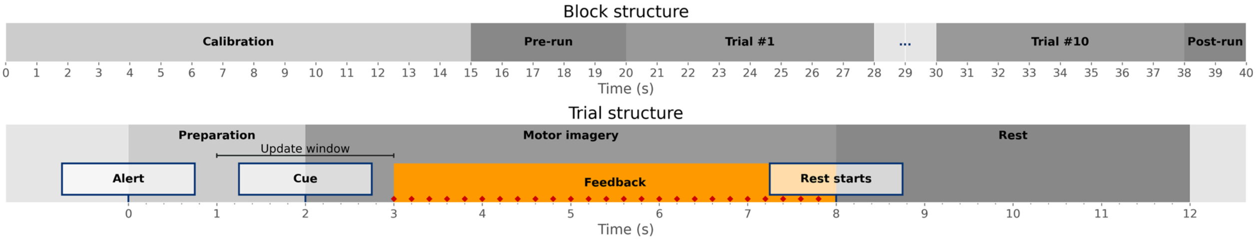

Fig. 1 Schematic representation of the structure of the training blocks comprising a NF session (top) and of the trial design (bottom). The time points at which the preparation alert and trial cue are presented, as well as when feedback updates are delivered, are indicated

2-second cue indicating the hand for the MI task. Prior to each block, a 15-second calibration recording was conducted with participants in a resting state with eyes closed to calculate baseline characteristics. Because the NF training relied on MI, the self-regulation target was to elicit the characteristic contralateral event-related desynchronization (ERD) over sensorimotor cortex. Rather than adapting the processing pipeline to each participant's individual MI features (as typically done in BCI systems to optimize discrimination) we employed a fixed pipeline specifically designed to capture these well-established ERD patterns. This approach ensured that participants adapted their brain rhythms to the predefined neural target, rather than the system adapting to their individual variability. The real-time processing pipeline used to compute the feedback was as follows: (1) a bidirectional 3-order bandpass IIR filter was applied between 0.5 and 40 Hz; (2) a short Laplacian spatial filter was applied on channels C3 and C4; (3) signal windows in which 2% of their samples exceed four times the standard deviation measured during the calibration period were discarded to minimize the influence of potential artifacts on feedback; (4) the power spectral density (PSD) was estimated using the Welch periodogram method [34] with a 2-second Hamming window with a 50% overlap; and (5) the signal power in the 8 to 30 Hz frequency band was computed for channels C3 and C4. This range includes the alpha (α; 8–13 Hz), β_1 (β_1; 13–20 Hz), and β_2 (β_2; 20–30 Hz) frequency bands, all of which are known to be modulated during MI tasks [3, 35]. Then, we calculated the feedback value as follows:

$$\text{NF Value} = \frac{P_{C4}/P^b_{C4}}{P_{C3}/P^b_{C3}}, \tag{1}$$

where P_{C4} and P_{C3} represent the power of the EEG signal in the 8–30 Hz frequency range at electrodes C4 and C3 during the MI trial, respectively. P^b_{C4} and P^b_{C3} denote the corresponding power values calculated during resting state recording following the same processing and analysis steps. These terms are used to normalize the EEG power relative to the individual baseline. This formulation, grounded in MI-related ERD principles [35], captures contralateral desynchronization during MI and reflects participants' self-regulation performance. According to Eq. 1, a *NF Value* < 1 indicates that the normalized power at electrode C4 is lower than at C3, a pattern typically observed during a left MI task [35]. Conversely, a *NF Value* > 1 indicates that the normalized power at electrode C3 is lower than at C4, which is commonly observed during a right MI task [35]. The feedback value was computed every 200 ms.

The NF system was implemented using MEDUSA© (https://medusabci.com/), a Python-based general-purpose software ecosystem to develop BCIs and neuroscience experiments [36]. Specifically, we implemented the signal-processing pipeline described above and designed three gamified NF training scenarios, which were developed using the Unity graphics engine. The workflow was structured as follows: the MEDUSA© Platform monitored the EEG signal via the lab streaming layer (LSL), processed and analyzed the data in real time, and provide real-time feedback throughout the training scenario. The communication between MEDUSA© and the training scenario was performed through a multi-client asynchronous TCP/IP-based protocol. The three NF training scenarios were developed to structure the training protocol according to two guiding assumptions: (1) alternating between scenarios would reduce the subjective sense of monotony and help sustain participants' engagement throughout the intervention [37] and (2) the progressive increase in task complexity would facilitate the consolidation of previously acquired self-regulation skills while promoting continued improvement in MI-based control [38]. In the following, we describe each of the scenarios used (Fig. 2):

- Sphere scenario: A sphere is displayed at the center of the screen. After the trial cue, the sphere continuously moves either to the left or right based on the user's MI performance. That is, this scenario provides a concurrent real-time feedback, every 200 ms, which is suggested to help establish a clearer association between the cognitive strategy and its outcome, thereby facilitating self-regulation learning in the early stages of training [38]. It should be

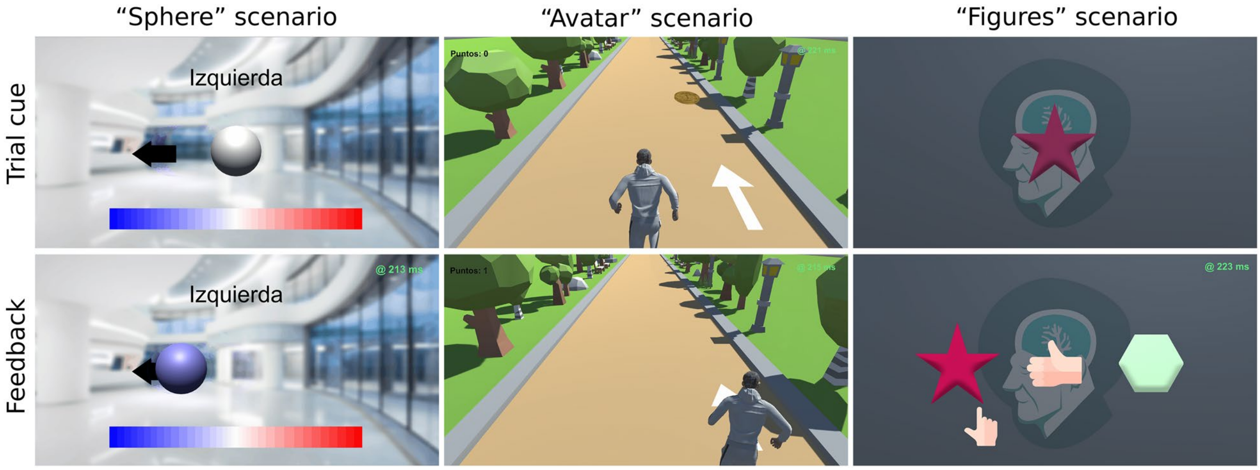

Fig. 2 Screenshots of the three NF training scenarios implemented in the study. The top row displays each scenario at the cue, while the bottom row illustrates the feedback phase. The left column corresponds to the "Sphere" scenario, the middle column to the "Avatar" scenario, and the right column to the "Figures" scenario

noted that the this scenario was implemented both with and without reinforcement feedback. In the reinforcement condition, the sphere was restricted to move only toward the target, preventing the movement from the center to the opposite direction. This design was intended to minimize the negative feedback and help preserve participant motivation.

- Avatar scenario: An avatar is presented walking through a park, centrally positioned on the screen. Although the avatar remains static, a walking animation is rendered while the environment moves forward toward the avatar. Each trial begins with a cue indicating the location (left or right), where a golden coin will appear at the horizon of the pathway. The participant is then instructed to perform a sustained MI task to move the avatar toward the coin. Notably, this scenario delivers terminal feedback, computed from the accumulation of NF values obtained every 200 ms during the trial. This type of feedback is preferred once participants have formed an internal representation of the task, as it may promote more stable learning outcomes [38]. While the task remains similar to that in Sphere scenario, the gamified design is intended to enhance motivation and engagement.
- Figures scenario: Unlike the previous scenarios, no directional cue is provided in this training scenario. Initially, a geometric figure (such as a triangle, square, or pentagon) is displayed in the center of the screen. After it disappears, two geometric figures appear on the left and right sides, with one matching the initial figure. Participants must perform the MI task to move the cursor toward the matching figure. As in the Avatar scenario, terminal feedback is provided, based on the participant's overall MI performance during that trial. This scenario is designed to engage both MI and short-term memory.

The distribution of use of the different training scenarios throughout the 10 NF sessions is depicted in S.Fig. 1, included in the supplementary material.

Classical cognitive stimulation activities

CG participants attended ten weekly group-based cognitive stimulation sessions, each lasting one hour and conducted by a professional neuropsychologist. These sessions involved a variety of individual tasks targeting different cognitive domains, such as problem-solving puzzles, word games for language, memory exercises, and attention tasks. The sessions took place in a classroom and the tasks were carried out using a classic design (i.e., paper and pencil).

Physical activities sessions

All participants took part in a weekly one-hour group session of guided physical activity. Conducted by a certified physical education professional, these sessions combined aerobic exercise with tasks aimed at enhancing balance, psychomotor coordination, reaction time, spatial orientation, muscular strength, and flexibility. The intervention was designed to target motor-related cognitive functions from a physical training perspective. The sessions were held both in a specialized sports center and outdoors.

Cognitive assessment

The cognitive assessment sessions were conducted by a professional neuropsychologist and lasted approximately 1 h and 45 min. These sessions were conducted during the week immediately preceding the start and the week immediately following the end of the intervention, respectively. Since the effects of the NF training protocol on cognitive domains were not well established, a comprehensive evaluation was conducted to cover a broad range of cognitive domains. The neuropsychological domains assessed, as well as the test used, are shown in Table 1.

Table 1 Neuropsychological domains considered in cognitive assessment sessions and the tests used to assess these domains

Neuropsychological domain	Test
Working memory	Digit span test from the WAIS-IV [40]
	Arithmetic test from the WAIS-IV [41]
Processing speed	Symbol search test from the WAIS-IV [42]
	Digit–Symbol coding test from WAIS-IV [41]
Abstract reasoning	Matrix Reasoning test from the WAIS-IV [41]
Language	Verbal fluency test [43]
	Boston naming test [44]
	Similarities test from the WAIS-IV [41]
Verbal episodic memory & Logical memory	Logical Memory I test from the WMS-IV [45]
	Logical Memory II test from the WMS-IV [45]
Spatial episodic memory	Immediate recall phase of the Rey-Osterrieth Complex Figure (ROCF) [46]
	Delayed recall phase of the Rey-Osterrieth Complex Figure (ROCF) [46]
Visuospatial abilities	Copy phase of the ROCF [46]
Executive functions	Modified Wisconsin card sorting test [47]
	Rings test [48]

Offline EEG analysis

To investigate the neuroregulation mechanisms, we conducted an offline analysis of the EEG signals recorded during NF trials from both TG and PG. In addition, prerun calibration recordings were also analyzed to characterize the baseline brain activity patterns during the resting state. In both cases, the signal pre-processing involved the following steps: (1) the EEG signals were re-referenced using a common average reference (CAR) to reduce spatially correlated noise and enhance the signal-to-noise ratio; (2) a bidirectional 3-order bandpass IIR filter was applied between 0.5 and 40 Hz; (3) the filtered signal was segmented into 2-second epochs with a 1-second overlap; and (4) epochs where discarded as noisy if 2% of their samples exceeded four times the standard deviation of the entire signal [19]. To provide a comprehensive view of neural activity patterns, both local activation and brain network analyses were considered. Local activation analysis provides insights into region-specific responses to task demands [39], such as contralateral ERD during MI. In contrast, network analysis show how different brain areas are functionally organized and communicate during complex cognitive processes, offering an integrated perspective on neural connectivity and function [39].

Local activation was evaluated via spectral analysis of the pre-processed EEG. The PSD was computed using the Welch method [34] with a Hamming window and 50% overlap. The spectral distributions were then normalized and the relative power (RP) calculated for the three canonical frequency bands that composed the NF training band (α, β_1 and β_2). RP values were then averaged across NF sessions, separately for left-hand and right-hand MI trials. Thus, general local activation patterns were obtained for each group both during MI task and in the resting state. Finally, the modulation of relative power (RP) was computed by subtracting the RP during eyes-closed resting-state from the RP during MI: $\mathrm{RP}_{\mathrm{modulation}} = \mathrm{RP}_{\mathrm{MI}} - \mathrm{RP}_{\mathrm{rest}}$. This allowed us to quantify task-induced variations in local oscillatory activity resulting from the NF training.

Brain network functional reorganization during NF was assessed using the node strength (NS) [49]. This metric is derived from graph theory and measures the sum of the connections of each node with the rest of the brain activity network [50]. NS allows to identify those nodes which hold a large part of the brain network communication [49]. To compute it, functional connectivity was estimated by means of amplitude envelope correlation (AEC) method [51]. This quantifies how the amplitude envelopes of neural oscillations are temporally correlated between different brain regions [51]. This metric has been proven to provide a robust index of neural activity synchronization that is less affected by volume conduction than other functional connectivity metrics [52]. Prior to applying AEC, pre-processed EEG signals were filtered in α, β_1 and β_2 frequency bands and orthogonalized [53]. Similarly to the RP analysis, was computed from eyes-closed resting-state EEG and during MI trials. NS modulation was then calculated as $\mathrm{NS}_{\mathrm{modulation}} = \mathrm{NS}_{\mathrm{MI}} - \mathrm{NS}_{\mathrm{rest}}$, allowing us to quantify task-induced changes in the organization of functional brain networks resulting from the NF training.

Analysis of participants' control over the NF system

To assess the ability of participants to control the NF system, we computed the averaged MI accuracy per session. For each trial, accuracy was determined by comparing the true label with the predicted intention, which was inferred from the summed feedback values (see Eq. 1). Specifically, trials with a *NF Value* < 1 were considered as left-hand, while *NF Value* > 1 were classified as right-hand. Session accuracy was then obtained by averaging trial accuracies across all runs. TG accuracies were directly obtained from the NF sessions, as participants received real-time contingent feedback. By contrast, PG accuracy was derived through offline analysis by applying the same processing pipeline to their recorded EEG. In this way, we estimated the feedback they would have received under contingent conditions.

Analysis of non-responding participants

We applied the K-means clustering method as proposed in out previous work [19] to identify non-responder participants. This unsupervised approach offers an objective alternative to heuristic, threshold-based criteria. The input data consisted of session-wise MI accuracy values from all TG and PG participants, yielding one accuracy vector per participant. Clustering was performed with $k = 2$, aiming to separate responders from non-responders. It was hypothesized that non-responders within the TG would display MI performance profiles more closely aligned with those of the PG group (who are not expected to successfully learn to self-regulate their brain activity), and would thus be classified within the cluster primarily comprising PG participants.

Statistical analysis

To analyze the impact of the cognitive training on participants' cognitive abilities while accounting for both known experimental factors and unobserved sources of variability, we employed mixed-effects linear models. This approach estimates group and time effects while properly handling the non-independence of repeated measures and subject-level heterogeneity. For each cognitive test, the following model was fitted:

$$\begin{aligned} score_{i,t} = {} & \beta_0 + \beta_{group} G_i^{(g)} + \beta_{time}\, t + \beta_{int} \left(G_i^{(g)} \cdot t \right) \\ & + \beta_{age}\, age_i + \beta_{sex}\, sex_i + \beta_{edu}\, education_i + b_{0i} + b_{1i}\, t \\ & + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where $score_{i,t}$ denotes the cognitive score of subject i at time point t (pre and post). The term β_0 represents the grand mean at baseline, β_{group} the deviation of each group from this mean, β_{time} the overall pre–post change, and β_{int} the group-specific deviation from that change. Age, sex, and years of education were included as covariates. Subject-specific random intercepts and slopes (b_{0i}, b_{1i}) capture unobserved heterogeneity in baseline performance and individual trajectories of change. The residual error term is represented by $\varepsilon_{i,t}$. Within-group changes Δ_g were computed as:

$$\Delta_g = \beta_{time} + \beta_{int} G^{(g)}, \tag{3}$$

Furthermore, we analysed if TG participants exhibited a better improvement in cognitive performance than PG and CG. To this end, pairwise differences between groups were obtained as linear combinations of these quantities (i.e., $\Delta_{\mathrm{TG}} - \Delta_{\mathrm{PG}}$ and $\Delta_{\mathrm{TG}} - \Delta_{\mathrm{CG}}$). To obtain robust inference, all within- and between-group differences were estimated via subject-level bootstrap resampling. At each of 1000 iterations, subjects were resampled with replacement, the model was refitted, and the change estimates recomputed, preserving the within-subject dependency structure. Effect sizes were calculated using Cohen's d to quantify the magnitude of the observed effects.

For the analysis of neuroregulation mechanisms, within-group differences between resting-state and MI-related activity patterns were assessed using the Wilcoxon signed-rank test. In addition, we examined whether intrinsic neurophysiological characteristics were associated with participants' neuroregulation capacity. To this end, we computed Pearson correlation coefficients between resting-state EEG features and mean MI accuracy across sessions. In order to obtain a population-level view of these potential relationships in healthy older adults, the analysis was performed using the EEG features and MI accuracies of all participants in both the TG and PG. Finally, we analyzed whether the specific training scenario had any influence on participants' self-regulation performance. To this end, we fitted a mixed-effects linear model and evaluated the contribution of the scenario factor to MI accuracy. The full description of this analysis and its results has been included in Section S.II of the supplementary material.

In all our analyses, the statistical significance level was set at p-value < 0.05. To control for multiple comparisons and reduce the risk of false discoveries, all statistical tests were corrected using the Benjamini–Hochberg false discovery rate (FDR–BH) procedure.

Results

NF cognitive training outcomes

Eight participants dropped out of the study before its completion: 2 from the TG, 5 from the PG and 1 from the CG. Consequently, their data were excluded from all subsequent analyses. In the following subsections, we present the results addressing RQ1, focusing on participants' ability to self-regulate brain activity associated with the MI task and the potential cognitive effects of the proposed training protocol.

NF control of the participants

The k-means clustering analysis yielded the following subgroups: 15 TG responders (TG-R), 14 TG non-responders (TG-NR), 7 PG responders (PG-R) and 20 PG non-responders (PG-NR). For visualization purposes, Fig. 3a displays the clustering solution projected onto the first three principal components of a principal component analysis (PCA). Besides, Fig. 3b shows the averaged MI accuracy for each group (i.e., TG and PG), as well as for each subgroup (i.e., TG-R, TG-NR, PG-R and PG-NR). The clustering results mean that 48.3 $\%$ of the TG participants were unable to succesfully self-regulate

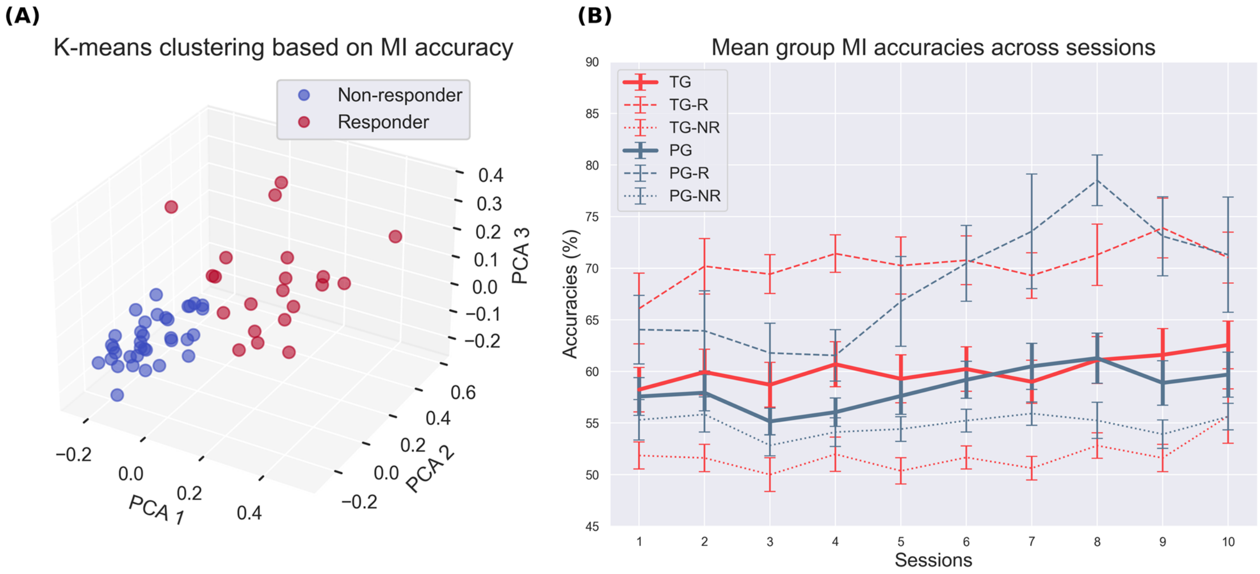

Fig. 3 **A** *K*-means clustering of participants based on their MI accuracy profiles. Principal component analysis (PCA) was applied to visualize the three components capturing most of the variance. Non-responder and responder participants are shown in blue and red, respectively; **B** MI accuracy averaged per session for NF training group (TG), placebo group (PG), TG responders (TG-R) and non-responders (TG-NR), and PG responders (PG-R) and non-responders (PG-NR)

their brain activity patterns during MI trails. In addition, 26 % of the PG participants exhibited successful overall control of the NF system, despite receiving non-contingent feedback. We performed a post hoc-analysis using the Mann–Whintey U-test to evaluate potential differences in age and years of formal education between responders (TG-R and PG-R) and non-responders (TG-NR and PG-NR). In addition, a chi-square test of independence was conducted to examine the relationship between sex and responding condition. No significant differences were found in age (p-value = 0.35), years of formal education (p-value = 0.27), or sex (p-value = 0.87).

Cognitive assessment analysis

Table 2 shows the within-group pre-post changes in cognitive performance. Statistically significant changes in scores are marked in bold. As shown, significant improvements in performance on different tests were found in the three experimental groups. Specifically, TG participants improved their performance in tests related to domains, such as processing speed, logical memory, spatial episodic memory, visuospatial ability and executive functions. However, only the improvements in visuospatial ability and executive functions reached medium effect sizes ($|d| > 0.5$), whereas the remaining changes corresponded to small effects. On the other hand, an improvement in the performance of the PG participants was observed in processing speed, language, logical memory, visuospatial abilities and executive functions. One of the logical memory measures showed a large effect size ($|d| > 0.8$), while the gains in language and visuospatial abilities reached medium effect sizes. The remaining improvements reflected small effects. Finally, CG participants improved their performance in processing speed, logical memory, spatial episodic memory, visuospatial abilities and executive functions, The gains in logical memory and spatial episodic memory showed medium-to-large effect sizes, whereas all other improvements were of small magnitude.

With respect to the comparison analysis between groups, no statistically significant differences were found between the scores of the groups (TG vs. PG and TG vs. CG) in the pre-training evaluation, post-training evaluation, nor in the pre vs. post changes (ΔTG vs. ΔPG and ΔTG vs. ΔCG). Detailed results of the between-group comparisons can be found in S.Tab. 2 of the supplementary material.

Brain activity patterns during MI

The results of spectral and network analyses of brain activity patterns during MI are presented below. These analyses have included both the original groups (TG and PG) and the identified subgroups of responders and non-responders. Thus, we aimed to answer RQ2 by identifying potential brain activity signatures that may underlie the non-responsiveness condition.

Spectral analysis

The spectral distributions of C3 and C4 during MI trials with the right and left hands, averaged across all subjects and sessions within TG and PG, are presented in Figure S.Fig. 3 S.Fig. 4 of the supplementary material,

Table 2 Within-group changes (Δ) in neuropsychological test scores for Training (TG), Placebo (PG) and Control (CG) groups (mean ± standard deviation, 95% confidence intervals and absolute value of Cohen's *d*)

Neuropsychological domain	**Test**	Δ_{TG}		Δ_{PG}		Δ_{CG}	
		mean±std [CI95%]	$\lvert\mathbf{d}\rvert$	**mean±std [CI95%]**	$\lvert\mathbf{d}\rvert$	**mean±std [CI95%]**	$\lvert\mathbf{d}\rvert$
Working memory	Digit span (↑)	0.31 ± 0.42 [−0.50, 1.14]	0.07	−0.63 ± 0.36 [−1.36, 0.07]	0.14	0.52 ± 0.45 [−0.35, 1.45]	0.11
	Arithmetic (↑)	0.59 ± 0.31 [−0.06, 1.19]	0.26	−0.04 ± 0.26 [−0.53, 0.50]	0.01	0.38 ± 0.26 [−0.14, 0.86]	0.11
Processing speed	Symbol search (↑)	**2.17** ± **0.65** [0.92, 3.45]	0.31	**1.89** ± **0.67** [0.60, 3.27]	0.26	**2.14** ± **0.72** [0.79, 3.60]	0.26
	Digit–Symbol coding (↑)	0.24 ± 0.77 [−1.27, 1.71]	0.02	**1.74** ± **0.75** [0.27, 3.23]	0.16	**3.72** ± **0.83** [2.20, 5.35]	0.30
Abstract reasoning	Matrix reasoning (↑)	0.48 ± 0.53 [−0.58, 1.53]	0.11	**1.15** ± **0.48** [0.19, 2.12]	0.27	1.31 ± 0.55 [0.24, 2.45]	0.24
Language	Verbal fluency (↑)	1.14 ± 0.67 [−0.28, 2.37]	0.23	0.78 ± 0.70 [−0.50, 2.10]	0.15	−0.28 ± 0.48 [−1.20, 0.57]	0.07
	Boston naming (↑)	0.28 ± 0.16 [−0.01, 0.60]	0.20	**1.22** ± **0.19** [0.85, 1.59]	0.76	0.34 ± 0.21 [−0.06, 0.78]	0.20
	Similarities (↑)	−0.76 ± 0.48 [−1.66, 0.18]	0.18	−0.30 ± 0.53 [−1.27, 0.77]	0.08	−0.10 ± 0.35 [−0.75, 0.60]	0.02
Verbal episodic memory & logical memory	Logical memory I (↑)	**2.24** ± **0.71** [0.70, 3.60]	0.40	**3.33** ± **0.77** [1.87, 4.83]	0.48	**3.10** ± **0.80** [1.61, 4.63]	0.52
	Logical memory II (↑)	**2.28** ± **0.71** [0.89, 3.64]	0.37	**4.89** ± **0.66** [3.57, 6.20]	0.83	**4.07** ± **0.65** [2.77, 5.13]	0.89
Spatial episodic memory	Immediate recall ROCF (↑)	**1.71** ± **0.57** [0.64, 2.76]	0.35	1.28 ± 0.77 [−0.13, 2.75]	0.20	**5.57** ± **0.89** [3.84, 7.29]	0.87
	Delayed recall ROCF (↑)	**1.69** ± **0.56** [0.62, 2.75]	0.35	**1.61** ± **0.62** [0.40, 2.86]	0.32	**5.38** ± **0.82** [3.80, 7.08]	0.83
Visuospatial abilities	Copy phase ROCF (elements) (↑)	−1.14 ± 0.35 [−1.83, −0.47]	0.46	−2.11 ± 0.37 [−2.82, −1.37]	1.00	−0.48 ± 0.64 [−1.85, 0.71]	0.09
	Copy phase ROCF (time in seconds) (↓)	**−44.00** ± **7.35** [−58.00, −29.33]	0.56	**−27.52** ± **4.75** [−36.50, −17.72]	0.50	**−27.38** ± **6.89** [−41.39, −12.99]	0.33
Executive functions	MWCST (completed categories) (↑)	0.00 ± 0.25 [−0.47, 0.50]	0.00	0.33 ± 0.27 [−0.19, 0.85]	0.15	0.34 ± 0.26 [−0.16, 0.83]	0.15
	MWCST (total errors) (↓)	−1.79 ± 1.49 [−4.65, 1.10]	0.14	−1.67 ± 1.50 [−3.95, 0.80]	0.14	−3.59 ± 1.34 [−5.94, −1.05]	0.30
	Rings (time in seconds) (↓)	**−29.92** ± **4.23** [−38.23, −21.59]	0.64	**−33.84** ± **6.77** [−46.67, −20.13]	0.45	**−22.57** ± **6.03** [−33.55, −10.20]	0.35
	Rings (movements) (↓)	−2.72 ± 1.34 [−5.35, −0.16]	0.28	−1.52 ± 1.04 [−3.44, 0.50]	0.15	−0.17 ± 0.78 [−1.74, 1.47]	0.03

Tests in which an improvement is reflected by an increase in the score are marked with an up arrow (↑); otherwise, they are marked with a down arrow (↓). Bold mean values indicate statistically significant effects (FDR-adjusted $p < 0.05$)

respectively. Figure 4 shows the RP modulation patterns (i.e., $\mathrm{RP}_{\mathrm{MI}} - \mathrm{RP}_{\mathrm{rest}}$) in the α band. It is observed that all participants presented a similar pattern of general desynchronization (i.e., decrease in power) of the RP α, being especially intense in the posterior region. Figure 5 displays the topographic patterns of β_1 RP modulation during MI trials. For this frequency band, a general desynchronization is observed, mainly centered in the central region. In TG-R participants, it was significantly stronger in the hemisphere contralateral to the imagined (target) hand. Noteworthly, the modulation also yielded significant differences in frontal and parietal regions. This phenomenon can also be partially observed for PG-R, although with a lower intensity. Despite TG-NR and PG-NR showing statistically significant central desynchronization, they lack the characteristic contralateral pattern typically elicited by MI. Finaly, Fig. 6 shows the topographic patterns of β_2 RP modulation. Topographic analyses across all groups revealed mild desynchronization at Cz accompanied by frontal synchronization within this frequency band, none of which reached statistical significance. On the other hand, the TG-R subgroup alone exhibited a lateralized β_2 band modulation: during left-hand MI, C3 showed an increased RP while C4 decreased, with the inverse pattern manifesting during right-hand MI.

Figure 7 illustrate the correlation between participants' resting-state eyes-closed RP in the α, β_1 and β_2 bands and their NF control performance. Each of the three panels comprises a left side depicting the topographic distribution of RP for each of the four identified subgroups, and a right side presenting the Pearson correlation between resting-state RP and MI accuracy (averaged across all sessions) for both TG and PG participants. In Fig. 7a, the α band topographies for all four subgroups are characterized by a greater activity over parieto-occipital region with modest frontal involvement. Although the Pearson correlation between resting-state α RP and MI accuracy was positive across EEG channels, none of these associations reached statistical significance. In the β_1 band (Fig. 7b), the four subgroups exhibit a pronounced power maximum at C3 and C4, with responders showing higher values than non-responders. Moreover, Pearson correlation analysis revealed a statistically significant positive

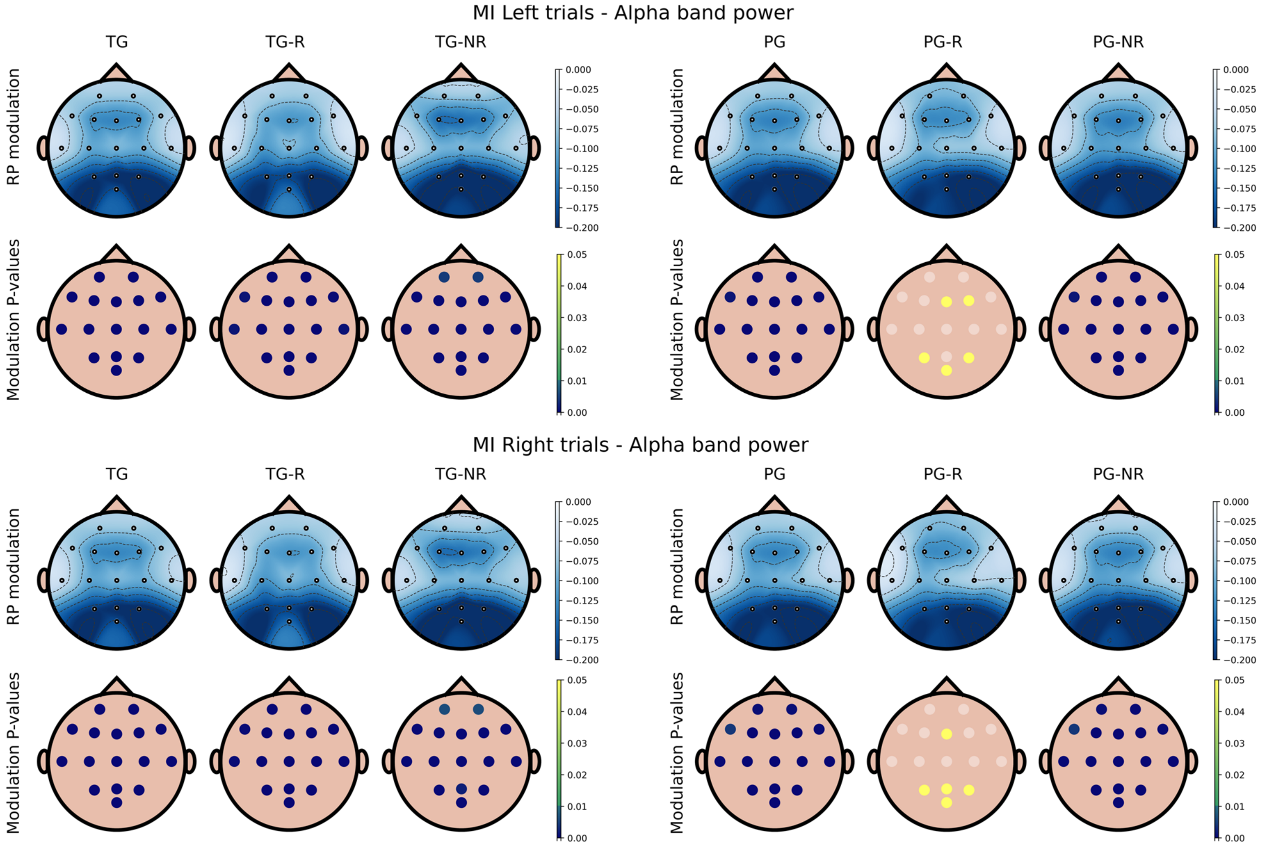

Fig. 4 Topographic distribution and statistical significance of α band RP modulation during MI tasks. Modulation was computed as the difference between RP during MI and RP at eyes-closed resting-state. The top two rows correspond to left-hand MI trials, and the bottom two to right-hand MI trials. Each column represents a different subgroup. Each pair of rows shows scalp topographies of α RP modulation (top) and corresponding *p*-values(bottom; FDR–BH corrected)

association between resting-state eyes-closed β_1 RP and MI accuracy across all EEG channels. Lastly, Fig. 7c illustrates that β_2 RP is concentrated at electrodes F3, F4, C3 and C4 across all subgroups, with TG-R and PG-R exhibiting the highest values. Pearson correlation analysis found no statistically significant association between resting-state β_2 RP and MI accuracy.

Network analysis

The results of the NS analysis of the brain network derived for alpha band activity are shown in Fig. 8. Positive modulation of NS (i.e., $\mathrm{NS}_{\mathrm{MI}} - \mathrm{NS}_{\mathrm{rest}}$) in prefrontal channels (Fp1 and Fp2) is observed across all subgroups. However, disctinct NS modulation patterns differentiated responders from non-responders, indicating subgroup-specific reorganization of the functional α band network during MI. Heterogeneous increases in NS were observed in both TG-R and PG-R, while TG-NR and PG-NR exhibited a more consistent and widespread reduction in NS values across the cortex. Specifically, statistically significant decreases were found in frontal and parietal electrodes for these non-responders subgroups. With respect to the β_1 band, different NS modulation maps are observed among the different subgroups (Fig. 9). Non-responders exhibited minimal positive NS modulation within this frequency band, whereas responders showed pronounced increases. Specifically, TG-R participants demonstrated statistically significant NS increases across frontal, central, parietal, and occipital electrodes during both MI conditions. In PG-R, marked NS increases were localized primarily to prefrontal and parietal channels. Figure 10 shows the NS modulation of the β_2 functional network during the MI. Distinct patterns of functional reorganization in this frequency band are observed across subgroups. Both TG-R and PG-R exhibited consistent changes in NS, albeit with distinct topographic profiles. However, only TG-R yielded statistically significant increases. TG-NR showed a marginal, non-significant positive NS modulation, whereas PG-NR displayed a slight, non-significant decrease overall, accompanied by modest NS increases in prefrontal and several frontal channels.

Figure 11a shows the correlation between resting-state eyes-closed α band functional network NS distribution and participants' MI accuracy. Responders exhibited α band NS distributions concentrated in central region,

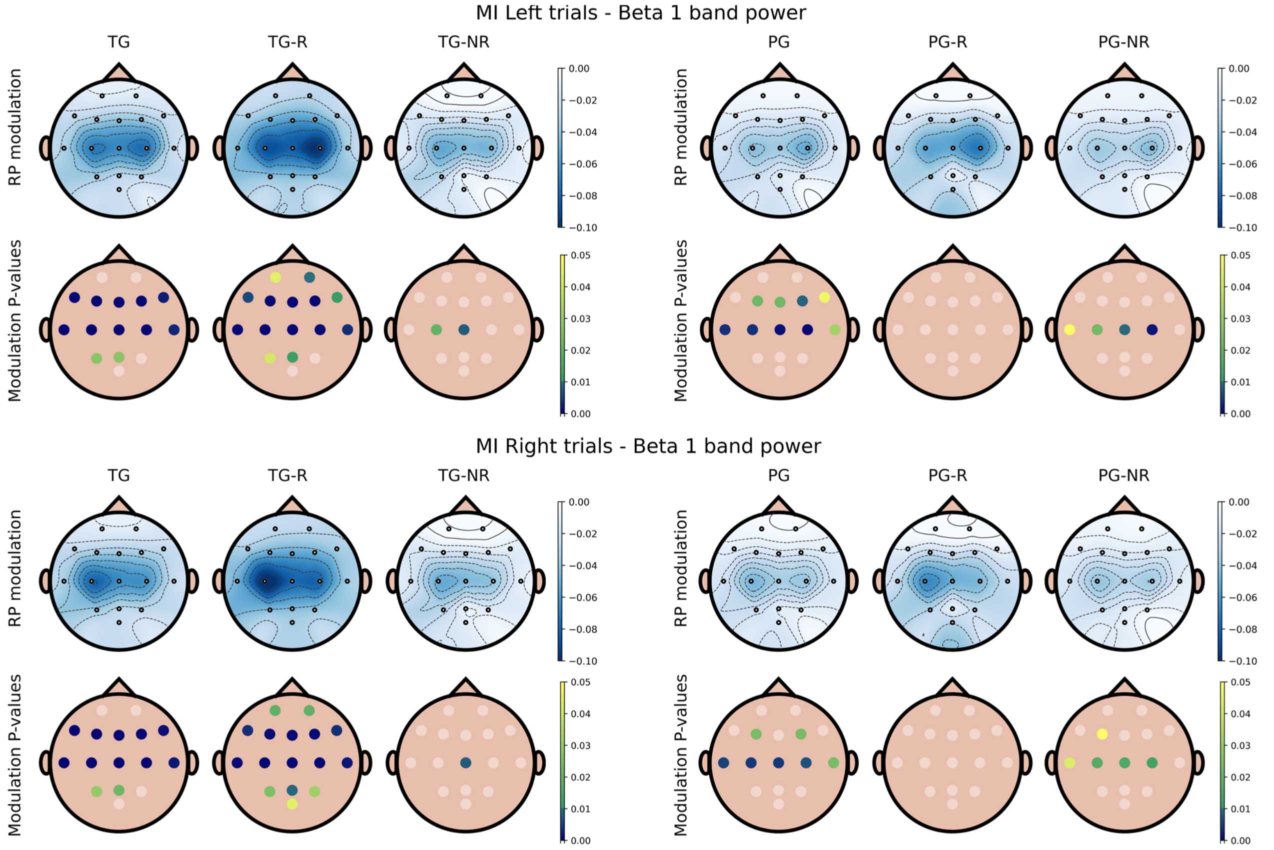

Fig. 5 Topographic distribution and statistical significance of β_1 band RP modulation during MI tasks. Modulation was computed as the difference between RP during MI and RP at eyes-closed resting-state. The top two rows correspond to left-hand MI trials, and the bottom two to right-hand MI trials. Each column represents a different subgroup. Each pair of rows shows scalp topographies of β_1 RP modulation (top) and corresponding *p*-values (bottom; FDR–BH corrected)

whereas non-responders presented higher overall NS extending into both central and parietal channels. In addition, a global negative correlation was observed between resting-state eyes-closed NS and MI performance, with statistically significant associations identified at frontal, parietal, and occipital electrodes. Regarding the β_1 (Fig. 11b) and β_2 (Fig. 11c) bands, both exhibited similar resting-state eyes-closed NS topographies across participant subgroups, predominantly centered over central region channels. Interestingly, resting-state eyes-closed NS in the β_2 band was higher in PG-NR participants compared to all other subgroups. In both bands, a negative correlation was observed between resting-state NS and MI performance. However, these correlations did not reach statistical significance in any of the frequency bands.

Discussion

In this study, we designed, conducted and evaluated an MI-based NF training protocol aimed at enhancing cognitive functions in healthy older adults. A total of 92 participants were enrolled, representing one of the largest cohorts reported in NF research to date. To evaluate the effectiveness of the training protocol, a comprehensive cognitive assessment was performed across two evaluation sessions. Additionally, spectral and functional network analyses of brain activity were considered to explore the neuroregulatory mechanisms engaged during the NF training.

Suitability of MI-based NF for cognitive training of older adults

The 51.7% of the TG participants were able to self-regulate the neural oscilation patterns related to MI task. In this regard, TG-R participants achieved an average session accuracy near to 70% from second session onwards. Despite this, the results of the pre- vs. post-training analysis (Table 2) indicated that the improvements observed in the cognitive assessment tests were not exclusive to the TG. While participants in this group showed enhancements across five cognitive domains, similar gains were also observed in the PG and CG groups. Indeed, the significant improvements observed in the PG and CG were accompanied by effect sizes that were generally larger than those found for the TG. Importantly, these conclusions are supported by a mixed-effects modeling

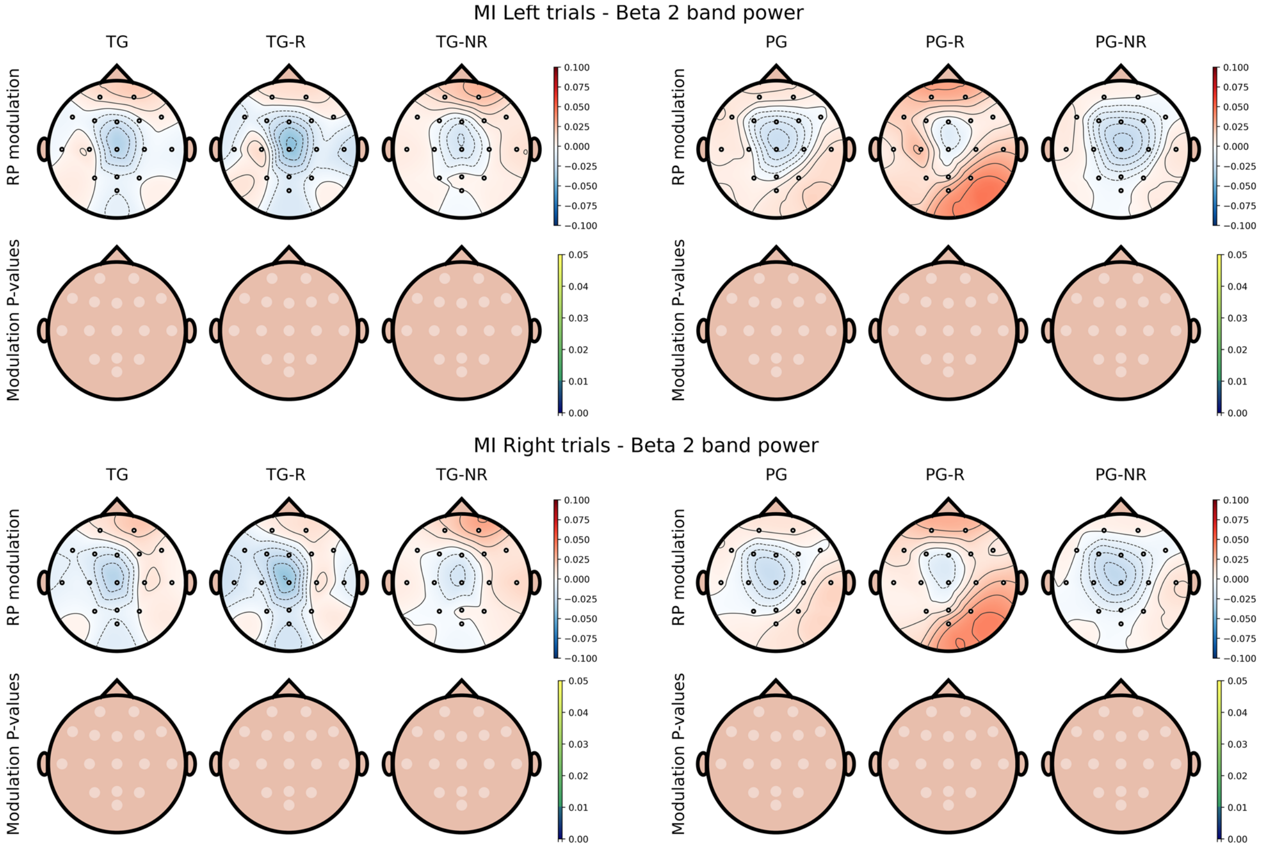

Fig. 6 Topographic distribution and statistical significance of β_2 band RP modulation during MI tasks. Modulation was computed as the difference between RP during MI and RP at eyes-closed resting-state. The top two rows correspond to left-hand MI trials, and the bottom two to right-hand MI trials. Each column represents a different subgroup. Each pair of rows shows scalp topographies of β_2 RP modulation (top) and corresponding *p*-values (bottom; FDR–BH corrected)

approach that incorporated demographic covariates, experimental factors, and subject-specific variability. This framework also allowed us to account for potential unobserved influences, providing a rigorous estimation of the cognitive changes observed across groups. Therefore, it cannot be conclusively attributed that the cognitive enhancement observed in the TG was specifically driven by the NF training protocol. Furthermore, the absence of significant baseline differences among groups discards the possibility that TG could not have a greater improvement due to a higher baseline values. The comparable improvements observed in the CG also reduce the likelihood that placebo effects account for the changes seen in the TG and PG.

Taken together, these findings suggest that the observed cognitive gains may stem from a combination of factors rather than from the NF intervention alone. Notably, both the cognitive and physical components of the protocol may have contributed to these improvements. The NF task itself, regardless of successful self-regulation, requires substantial cognitive engagement. Participants were asked to explore and apply diverse mental strategies, simulate sensorimotor experiences, and interpret performance-based feedback. This cognitively demanding activity places sustained demands on executive functions and attentional control, and its repeated practice over the 10 training sessions. Therefore, it may have contributed to general cognitive benefits, comparable to those resulting from classical cognitive stimulation. Additionally, all groups participated in weekly physical activity sessions, which are known to promote cognitive health. The contribution of this component to the observed improvements cannot be dismissed. However, it is important to note that the participants in the three group underwent the same exercise intervention, and therefore, the effects attributable to physical exercise are expected to be comparable across groups. Accordingly, the cognitive improvements observed across groups are more likely attributable to the combined influence of the study's multimodal interventions, rather than being exclusively driven by the proposed NF training protocol.

These results make it pertinent to discuss whether the MI paradigm is a suitable NF protocol for the goal of improving cognitive abilities in healthy older adults. To frame this issue, we draw upon Wolpaw et al. [2] concept of the "heksor", defined as a distributed network of

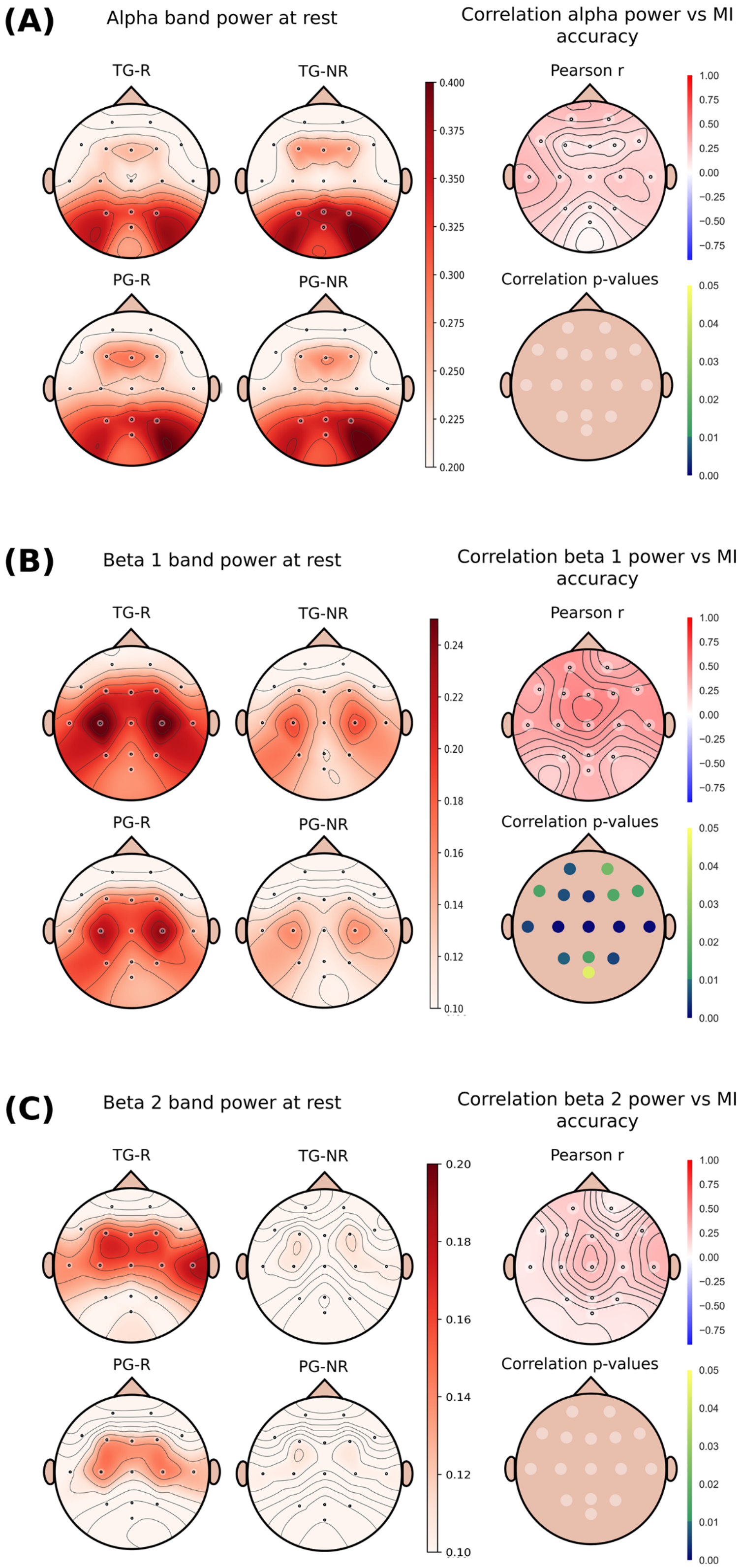

Fig. 7 Topographic distribution of resting-state eyes-closed RP α (A), β_1 (B), and β_2 (C) for different subgroups (left side) and Pearson correlation (with statistical significance) between resting-state RP of all participants and MI accuracy (right side). All *p*-values have been corrected with FDR-BH

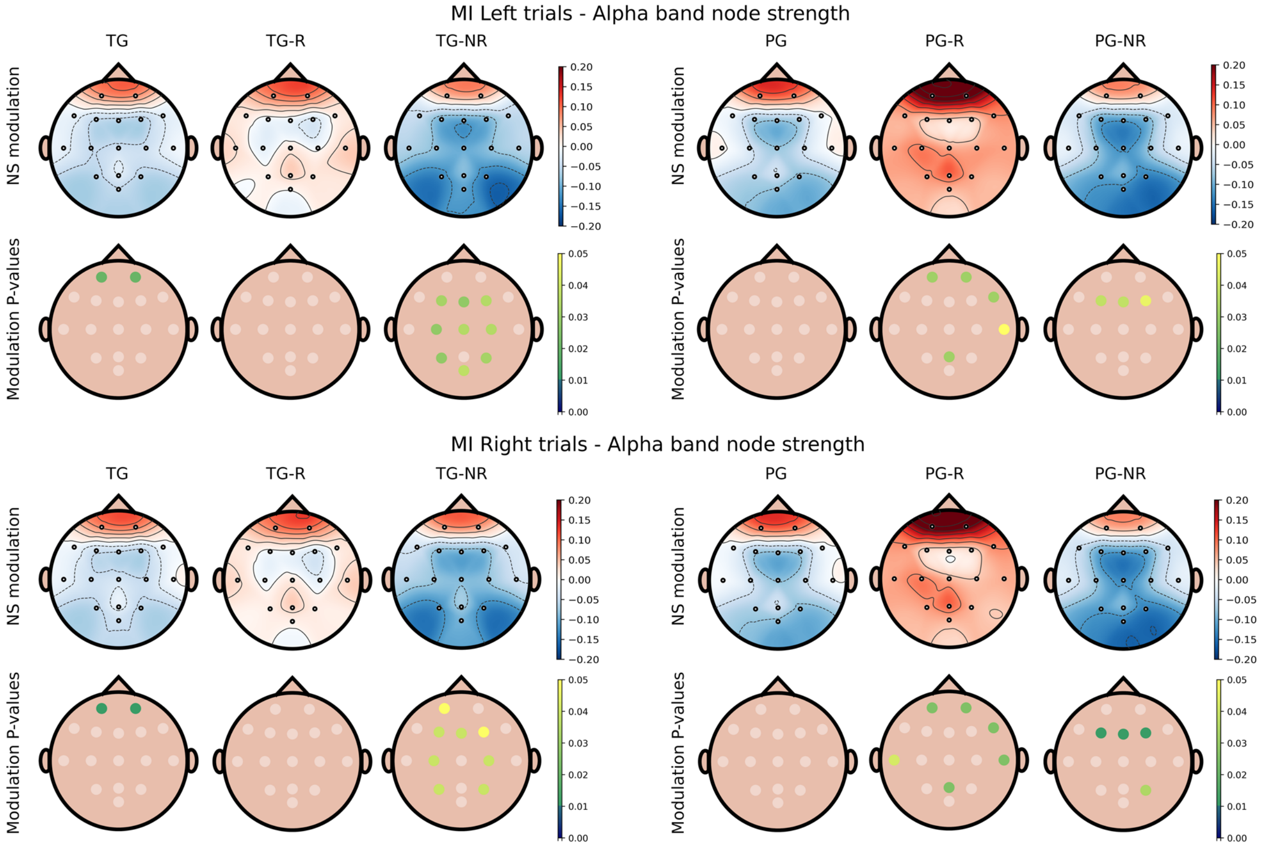

Fig. 8 Topographic distribution and statistical significance of α band NS modulation during MI tasks. Modulation was computed as the difference between NS during MI and NS at eyes-closed resting-state. The top two rows correspond to left-hand MI trials, and the bottom two to right-hand MI trials. Each column represents a different subgroup. Each pair of rows shows scalp topographies of α NS modulation (top) and corresponding *p*-values (bottom; FDR-corrected)

neurons and synapses that generates a particular adaptive behavior and continually reshapes itself to preserve that behavior's essential features. Multiple heksor coexist in the central nervous system and share common neural resources. Thus, they must adjust to one another. This creates what the authors call a "negotiated equilibrium". It means that each heksor adapts so it can function without disrupting the others. We therefore hypothesized that an MI-based NF protocol could give rise to a new heksor dedicated to voluntary modulation of sensorimotor cortex activity. For it to work, it would need to integrate into the existing equilibrium without interfering with other behaviors. Our spectral and network analyses have shown that the self-regulation behaviour, accquired by TG-R participants, recruited regions beyond the focus of the task. Specifically, β_1 band RP modulation revealed that, although the primary desynchronization occured over sensorimotor cortex, a widespread significant desynchronization across all regions was also occuring. Furthermore, NS analysis revealed distinct patterns of functional network reorganization between responders and non-responders across all three frequency bands considered. Statistically significant NS increases in β_1 and β_2 bands imply that optimal MI performance depended on engaging distributed frontal and parietal networks. These findings are aligned with prior reports of MI-induced network reconfiguration [54–56] and highlight the critical role of fronto-parietal connectivity in supporting complex cognitive processes, such as planning, selective attention and efficient sensory processing. These processes are essential for successful MI control [54, 57, 58]. Therefore, our results suggest that the potential new heksor accquired by TG-R participants shares neural substrates with existing heksors supporting key cognitive functions. However, this emergence did not elicit measurable adaptations in those preexisting heksors via negotiated equilibrium. By contrast, MI-based interventions in stroke rehabilitation have yielded such cross-network effects. For instance, MI training enhanced attentional capacity [59, 60] and overall cognitive function [60] of stroke survivors.

Furthermore, the original MI-based NF protocol designed for cognitive enhancement in healthy older adults also reported broad cognitive gains in its TG [23]. Consequently, it is pertinent to try to clarify the hypothetical causes that may have limited the possible

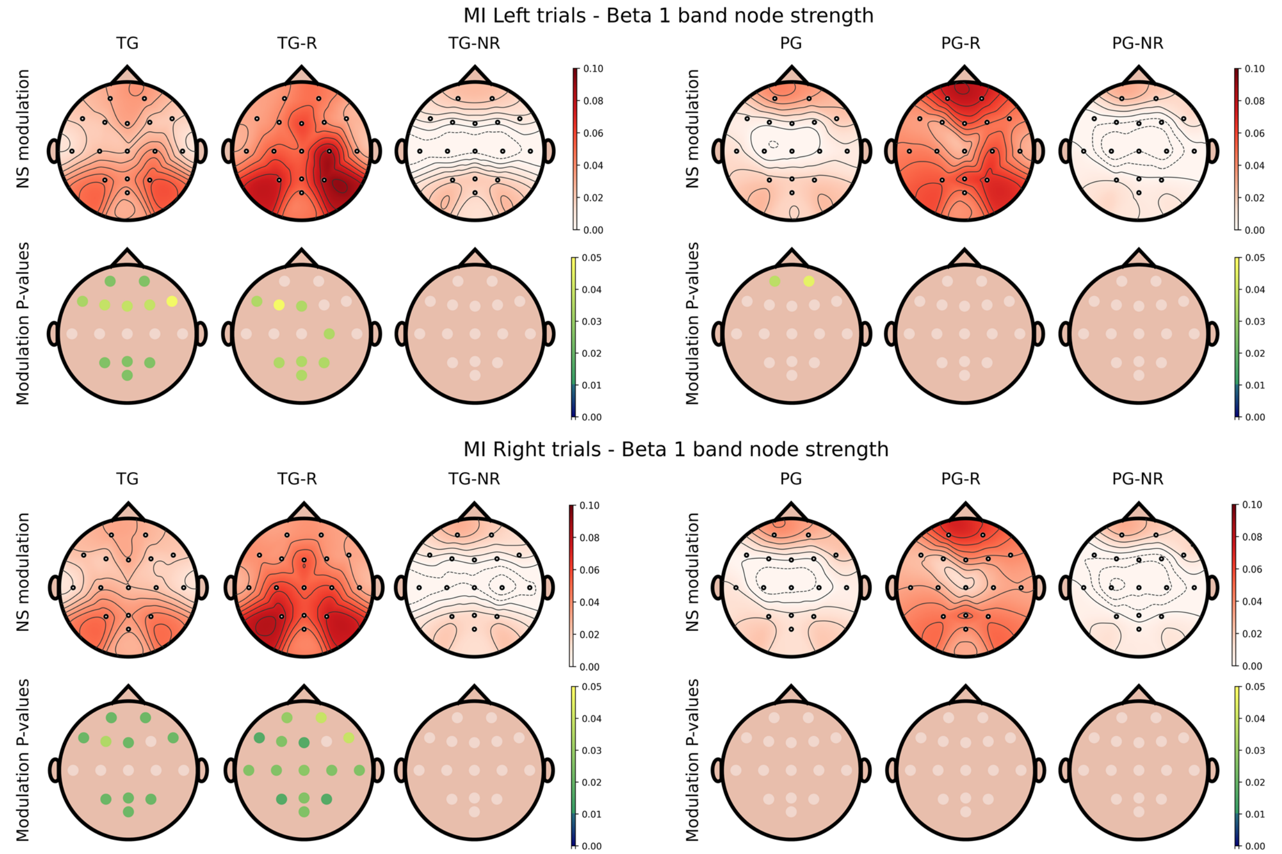

Fig. 9 Topographic distribution and statistical significance of β_1 band NS modulation during MI tasks. Modulation was computed as the difference between NS during MI and NS at eyes-closed resting-state. The top two rows correspond to left-hand MI trials, and the bottom two to right-hand MI trials. Each column represents a different subgroup. Each pair of rows shows scalp topographies of β_1 NS modulation (top) and corresponding *p*-values (bottom; FDR-corrected)

cognitive improvement of our participants. First, we can point out a possible suboptimal training protocol. Gómez-Pilar et al. [23] based their feedback on the power of three narrow bands concentrated in the β_1 range, whereas we used ERD in the canonical bands involved in MI [3]. Our spectral analyses indicate that this wider bandwidth may have attenuated task-specific effects: α band modulation during MI was homogeneous across subgroups (Fig. 4), likely reflecting the eyes-closed resting baseline's strong posterior α synchronization [61], and yielded no C3–C4 differences (see S.Fig. 3 from supplementary material). In contrast, β_1 band ERD (Fig. 5) exhibited the expected contralateral desynchronization in TG-R [50], and β_2 band patterns (Fig. 7c) appeared only in TG-R, albeit non-significantly [3]. By including α activity in our feedback metric, we likely masked the real C3–C4 differences, mainly present in β_1 band, as also reported by Corsi et al. [50]. Thus, although TG-R participants achieved voluntary self-regulation, our protocol may be suboptimal for driving the desired cognitive-heksor adaptations. A further factor that may underlie the limited transfer of the newly acquired heksor in our healthy older adults cohort is the inherently stable equilibrium of existing cognitive heksors. In the context of stroke, lesions disrupt the negotiated equilibrium, triggering endogenous reparative and plasticity mechanisms that enhance network plasticity [62, 63]. During this adaptive window, introducing a new conditioned behavior such as MI can exert a pronounced influence on both motor and cognitive heksors. By contrast, in cognitively healthy older adults, preexisting heksors responsible for various sensorimotor and higher-order cognitive behaviors coexist in a well-balanced state. This homeostatic stability means that the central nervous system migh have little room for further plastic reorganization without a substantial perturbation of existing network dynamics. This limited capacity for additional adaptation could be interpreted as a ceiling effect, where the system operates near its optimal level and further improvements are difficult to achieve. Consequently, the acquisition of a novel NF-induced heksor may not suffice to disrupt the equilibrium of entrenched cognitive heksors and thereby induce measurable functional adaptations. Under such conditions, only highly optimized NF protocols (e.g., a

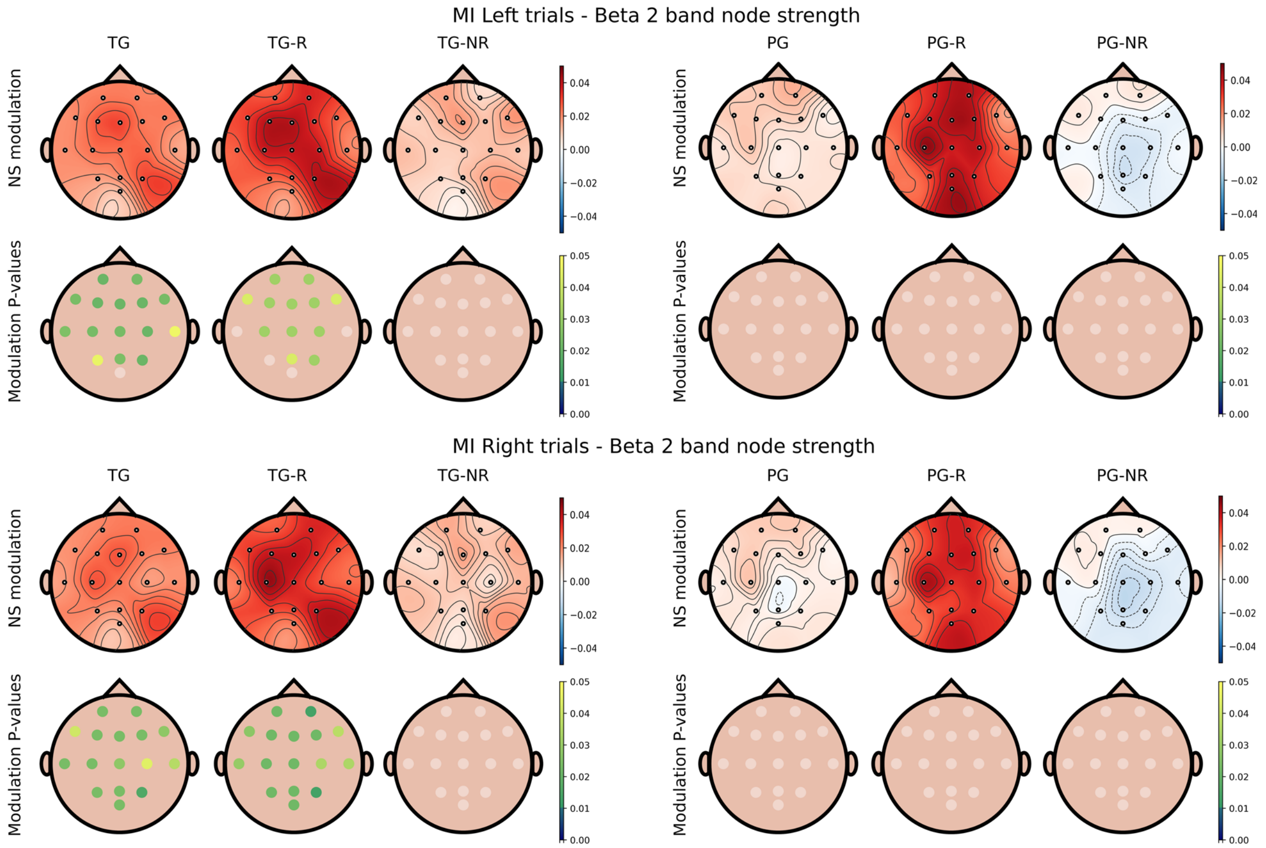

Fig. 10 Topographic distribution and statistical significance of β_2 band NS modulation during MI tasks. Modulation was computed as the difference between NS during MI and NS at eyes-closed resting-state. The top two rows correspond to left-hand MI trials, and the bottom two to right-hand MI trials. Each column represents a different subgroup. Each pair of rows shows scalp topographies of β_2 NS modulation (top) and corresponding *p*-values (bottom; FDR-corrected)

training protocol tailored to the specific characteristics of the participant) could potentially yield the desired cognitive enhancements [15].

In conclusion, in view of the results we cannot establish with certainty that the MI-based NF protocol is a suitable option for cognitive training of healthy older adults. Although the protocol aimed to induce neuroplastic changes in specific neural networks associated with high-level cognitive functions, it did not lead to cognitive improvements beyond those observed with a less targeted intervention, such as classical cognitive stimulation. However, as discussed above, our study presented certain methodological features that may have limited the final outcomes. Therefore, we consider it pertinent for future studies to further investigate the effectiveness of this NF protocol by systematically varying potentially suboptimal parameters, such as the frequency range used to compute the MI-related feedback signal.

Brain activity patterns influencing responsiveness

The inability of some individuals to volitionally modulate their brain activity poses a major challenge in NF research, particularly in defining and identifying non-responders [27]. Previous approaches have included subjective inspection of training curves [18], comparisons of spectral power between early and late recordings [27, 64], and threshold-based measures of feature increase during NF [65]. By contrast, we adopted a data-driven clustering strategy, grouping participants by their average MI accuracy across ten NF sessions. This unsupervised approach only requires specifying the number of clusters (k) and offers an objective framework to differentiate responders from non-responders. As a result, we obtained a compact cluster of non-responders, positioned in the negative range of the three PCA components, while responder features were more widely distributed across the PCA space. This pattern reflects that non-responders exhibited a consistently low level of NF control throughout the training, whereas responders show greater variability across sessions, consistent with the dynamics typically associated with learning and adaptation. These findings indicate that our approach successfully achieved an unsupervised and interpretable separation between responder and non-responder participants.

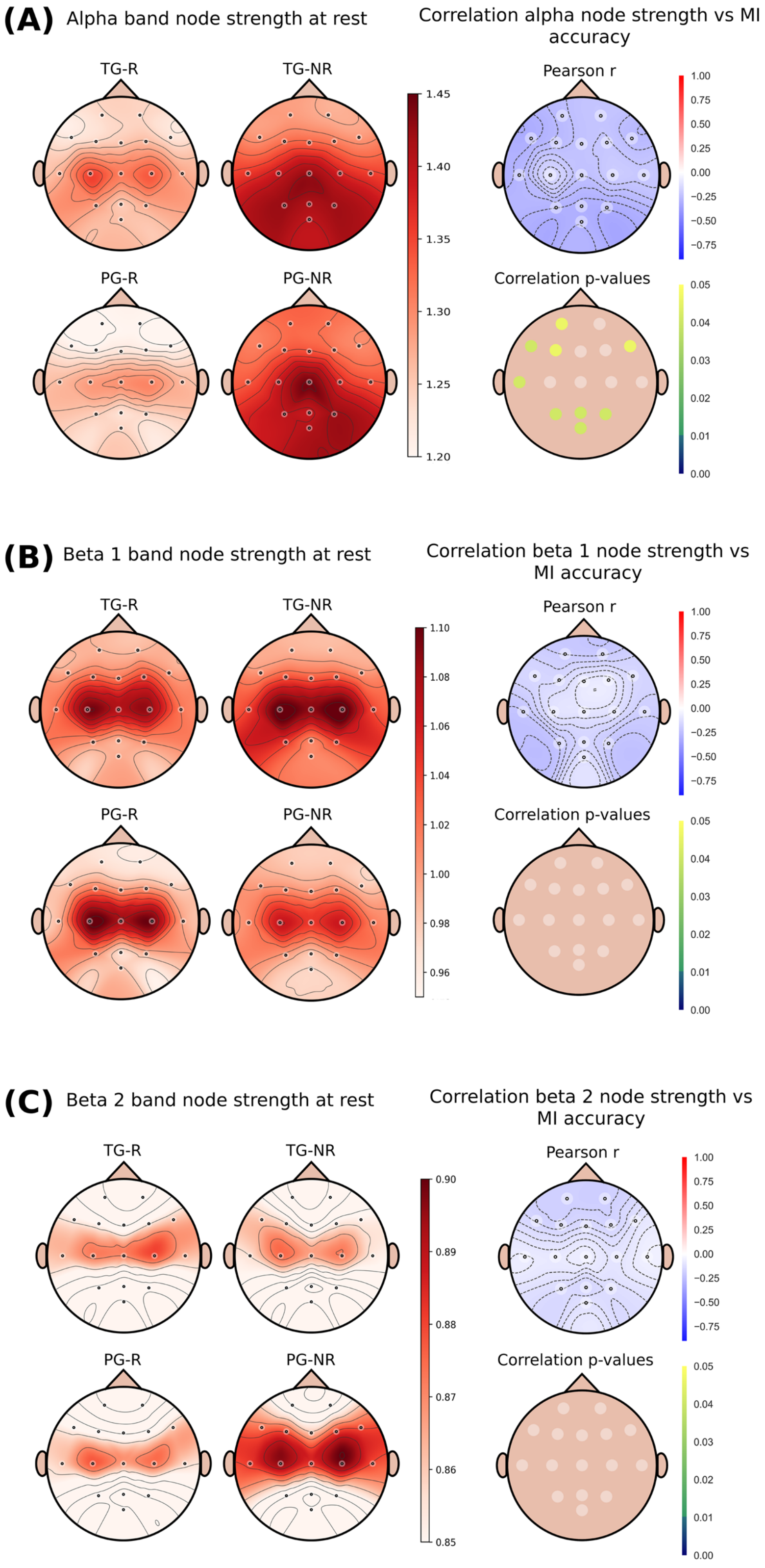

Fig. 11 Topographic distribution of resting-state eyes-closed NS α (**A**), β_1 (**B**), and β_2 (**C**) for different subgroups (left side) and Pearson correlation (with statistical significance) between resting-state NS of all participants and MI accuracy (right side). All *p*-values have been corrected with FDR-BH

Functional imaging studies have provided neurophysiological evidence that may help to explain poor NF performance in certain individuals [66, 67]. These studies identified a frontal network responsible for monitoring internal states and adjusting them in response to external feedback. Notably, this network is recruited regardless of feedback contingency, even under sham conditions. Therefore, non-responsiveness may reflect a diminished capacity to engage this core neuroregulatory system, rather than being solely attributable to the use of suboptimal cognitive strategies [26, 68, 69]. Several findings from our study further support this interpretation. In resting-state eyes-closed condition, β_1 band RP (Fig. 7b) correlated positively and significantly with participants' ability to self-regulate during MI. Moreover, responders exhibited markedly higher baseline β_1 RP over sensorimotor area than non-responders. This baseline–performance relationship has been documented as a potential NF predictor [26, 27, 70] and has been proposed as indicator of a higher neural adaptability [27]. Complementing these findings, α band NS analysis during resting-state revealed a distinct functional network distribution between responders and non-responders (Fig. 11a). Notably, baseline α NS values were negatively correlated with NF performance in frontal and parietal regions. These distinct resting-state NS patterns may underlie the statistically significant α band network downregulation observed during MI tasks only in non-responders (Fig. 8). Together, these findings may reflect a baseline network organization in non-responders that may limit the successful recruitment of neural resources required for effective self-regulation. This could explain why only TG-R exhibited significant patterns of NS increase in β_1 and β_2 bands (Figs. 9 and 10), which could reflect the network-level adaptations required for a successful NF control. Previous studies have suggested a potential link between resting-state network properties and MI performance. Lee et al. [71] identified effective connectivity between the supplementary motor area and the dorsolateral prefrontal cortex as a potential biomarker for predicting individual MI performance. Similarly, Zhang et al. [72] examined resting-state functional networks in the 4–14 Hz range and reported a positive correlation between higher NS and greater MI accuracy. However, both studies evaluated this relationship using only two NF sessions, providing a limited view of the learning trajectory. In this regard, our findings are based on a more extended training period, allowing us to assess how resting-state NS relates to MI accuracy after users have gained sufficient experience to effectively control the BCI system.

Our findings underscore the importance of conducting in-depth analyses of brain activity in users undergoing NF-based cognitive training. The approach implemented in this study, which combines multiple analytical methods, proves essential for gaining a more comprehensive understanding of the neuroregulatory mechanisms engaged during NF and the resulting effects on users' brain activity.

Reevaluating placebo groups in NF research

K-means clustering not only revealed a substantial subset of non-responders within the TG, but also identified PG individuals who achieved high MI accuracy values. Despite receiving non-contingent feedback, these individuals generated MI-typical neural patterns. This phenomenon has been documented in several studies. Reichert et al. [27] reported that 58% of participants who received non-contingent SMR feedback were able to increase SMR during NF sessions. More recently, Stefano Filho et al. [69] examined MI ERD and BCI control under three conditions: no feedback, sham feedback, and contingent feedback. The authors found that, although contingent feedback produced the largest gains, four (two statistically significant) out of ten sham-feedback participants increased their ERD production in β_1 band at the contralateral hemisphere to the imagined hand. Notably, three of ten participants with no feedback also improved BCI classification. In addition, our results are in line with the previous mentioned neural network inteded for the self-regulation mechanism, which can be recluted regardless the feedback contingency [66].

In light of these findings, we raise a fundamental question for the NF research community: Are placebo groups a valid control strategy in NF studies? In NF research, the term "placebo" typically refers to the use of non-contingent feedback. However, the results of this and previous studies suggest that the absence of feedback contingency does not necessarily prevent participants from engaging the neural networks involved in the self-regulation of brain oscillations [66, 67]. From this perspective, participants receiving non-contingent feedback should not be regarded as placebo controls in the traditional sense, as they actively engage in the same tasks and rely on the same neuroregulatory mechanisms. Rather than representing a true placebo condition, sham-feedback protocols may constitute highly challenging training environments that significantly hinder learning. The observation that individuals in a placebo group can volitionally modulate their brain activity patterns implies that they might be capable of benefiting from NF training. Therefore, we argue that the current definition of placebo in NF warrants reconsideration. Specifically, is the inclusion of non-contingent feedback conditions appropriate for controlling placebo effects, or does it risk misinterpreting study outcomes by comparing fundamentally different protocols? We believe these questions should be carefully addressed by the NF research community in order

Table 3 Comparison of the experimental designs of published NF-based cognitive training studies in cognitively healthy older adults

Author	No. participants	PG included	CG included	Double-blind design
Andrade et al. [73]	37	✓		✓
Becerra et al. [74]	40	✓		
Campos et al. [75]	17	✓	✓	
Gómez-Pilar et al. [23]	63		✓	
Jirayu et al. [76]	54		✓	
Lee et al. [77]	39		✓	
Marlats et al. [22]	33			
Reis et al. [78]	30	✓	✓	
Staufenbiel et al. [79][a]	20			✓
Wang et al. [17]	16	✓		
Our study	92	✓	✓	✓

[a] The double-blind condition indicated in Staufenbiel et al. [79] refers to the fact that two different NF training protocols were used, and both participants and researchers were blinded to the specific protocol assignment

to refine training designs and ultimately enhance NF effectiveness.

Contributions

In the following, we briefly review the main contributions of this work to the field of NF research. First, as previously discussed, doubts persist regarding the effectiveness of NF for cognitive training. This lack of consensus is largely attributable to methodological limitations in previous studies, including small sample sizes, inadequate control of efects unrelated to the NF, and the absence of randomized double-blind experimental designs. The omission of these essential experimental considerations undermines the reliability and generalizability of the reported outcomes. In response to these limitations, the present study follows the recommendations of the CRED-NF guidelines [25], implementing a robust experimental protocol that enhances the internal validity and interpretability of the results. Table 3 provides a comparative summary of the experimental designs employed in NF-based cognitive training studies involving cognitively healthy older adults, as compiled in a recent systematic review [16]. In light of this comparison, our study distinguishes itself among NF-based cognitive training state-of-the-art: we have included the largest participant sample to date and features the most rigorous experimental design, incorporating different condition groups under a double-blind protocol. We argue that these methodological features are essential to ensure the reliability, reproducibility, and scientific value of NF research. Moreover, although the previously promising MI-based NF protocol for cognitive training in older adults was proposed in [23], to the best of our knowledge, no prior validation study has assessed its efficacy. In this work, we provide novel empirical evidence evaluating the effectiveness of the MI-based NF protocol. Although a subset of participants in the TG successfully achieved self-regulation of their brain activity patterns, no specific cognitive improvements were observed in this group. These findings raise important concerns about the effectiveness of the approach and point to the need for refining MI-based NF paradigms aimed at cognitive enhancement in aging populations. In this context, our spectral analysis results offer valuable insights that may help shape the design of future MI-based NF training protocols.

It is also worth highlighting the comprehensive analysis of participants' brain activity conducted in this study. As previously noted, NF research has typically neglected the analysis of brain activity in non-responders, who are often excluded from further examination once their inability to self-regulate is identified [18, 19]. This study systematically examined the neurophysiological patterns of both responders and non-responders to NF. This approach enabled us to identify distinct spectral modulations and functional network reorganizations during MI tasks that differentiate the two groups. Additionally, we observed specific resting-state electrophysiological signatures in non-responders, which may reflect a limited capacity to engage the neural substrates necessary for successful self-regulation. These findings represent a relevant step toward uncovering the mechanisms underlying the non-responsiveness phenomenon. Lastly, the resting-state metrics identified, such as β_1 RP and α band NS, may serve as potential biomarkers for identifying individuals with limited capacity to achieve effective NF-induced neuroregulation [1]. However, further research is required to assess the robustness of these markers as predictors of NF responsiveness and to determine whether their predictive value depends on specific factors, such as the type of NF training protocol or characteristics of the population studied.

Limitations and future work

As previously noted, the absence of expected effects in our MI-based NF protocol may reflect aspects of the protocol that need optimization. In addition to adjusting the training to the β_1 band, we have identified several further aspects of improvement of our design that future studies should address when validating MI-based cognitive training. First, our protocol followed an approach that encourage the users to fit their neural oscillations to the target brain pattern, instead of adapting the BCI system to the user brain activity. In this regard, we did not follow the typicall signal-processing pipeline applied in

MI-based BCI studies (i.e., applying common spatial patterns followed by linear discriminant analysis or support vector machines to infer user intentions) [80]. We believe that the user-adaptation approach, as opposed to system-adaptation, may foster stronger neuroplastic effects by placing greater demands on the user and relying entirely on their capacity for self-regulation. However, this strategy did not account for inter-individual variability in brain activity. For example, the training frequency band was not personalized to each participant's neurophysiological characteristics. We therefore propose that tailoring the training protocol to individual's brain signal features may enhance NF control and potentially produce more robust cognitive outcomes. In this regard, we also propose exploring the potential of algorithms for automatically adjusting the threshold of the trained feature in NF according to each participant's individual progress [16, 81]. Another factor that may have influenced the outcomes of the training protocol is the overall intensity of the NF intervention, specifically in terms of the total number of sessions and their frequency. In our study, participants completed one session per week over a ten-week period. However, this may have been insufficient to elicit significant neuroplastic changes in the networks underlying the targeted cognitive functions. In comparison, previous studies have employed more intensive protocols. For instance, Andrade et al. [73] conducted 20 NF sessions, Becerra et al. [74] implemented 30 sessions, and Marlats et al. [22] delivered 20 sessions, all with a frequency of two to three sessions per week. These differences highlight the need for future research to examine the influence of session frequency and total training volume on the efficacy of NF interventions. Another relevant factor that may have influenced the outcomes is group-assignment expectancy. Even under a double-blind design, participants or experimenters might form beliefs about the assigned condition, potentially affecting engagement and performance during NF sessions. Because no post-intervention assessment of group beliefs was collected, this factor could not be incorporated into the statistical analyses. Finally, we acknowledge that our cohort was imbalanced with respect to participant sex, with 75 % of participants being females. Although this disparity was accounted for in group assignment, future studies should ensure equal representation of men and women to prevent potential sex-related biases.

Conclusion

This paper presents one of the largest cohort studies to date on NF-based cognitive training in healthy older adults. Specifically, our analyses addressed two research questions. First, although a large proportion of participants were able to voluntarily modulate their brain activity using a MI-based protocol, this did not translate into cognitive improvements specific to the TG. Accordingly, we cannot confirm the efficacy of this protocol for cognitive training in older adults, and future studies should refine the design by addressing the limitations identified here. Second, our comprehensive EEG analysis during NF sessions revealed neurophysiological patterns that distinguish responders from non-responders. Notably, we identified specific resting-state activity features that were associated with participants' ability to control the NF system. These findings suggest that a suboptimal organization of resting-state networks may hinder non-responders from recruiting the resources necessary for effective neural self-regulation.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12984-026-01912-z.

Supplementary file 1 (pdf 1166 KB)

Acknowledgements
Not applicable

Author contributions
All authors contributed to the manuscript. D.M.-M. drafted the original version and contributed to software, conceptualization, methodology, data acquisition, data analysis, and funding acquisition. E.S.-V. contributed to supervision, methodology, conceptualization, data acquisition, and funding acquisition. S.P.-V. contributed to methodology, conceptualization, data acquisition, and funding acquisition. A.M.-F., B.P.-R., and C.R.R.-G. contributed to data acquisition. R.M.-V. contributed to methodology, and data acquisition. V.M.-C. contributed to supervision, methodology, conceptualization, and funding acquisition. R.H. contributed to supervision, funding acquisition, and project administration. All authors reviewed and approved the final manuscript.

Funding
This work was supported by 0124_EUROAGE_MAS_4_E proyect, co-financed by the EU through the Interreg VI-A Spain-Portugal Programme (POCTEP) 2021-2027, and by the VA140P24 project, funded by the Regional Government of Castilla y León (Consejería de Educación) and EU-ERDF. Support has also been provided by the Centre for Biomedical Research in Bioengineering, Biomaterials and Nanomedicine (CIBER-BBN, CB19/01/00012) through the Carlos III Health Institute, co-financed with ERDF funds. C.R. R-G was in a receipt of a PIF grant from the 'Consejería de Educación de la Junta de Castilla y León'; A. M-F was in receipt of a PIF grant from the 'University of Valladolid', Spain.

Data availability
Pseudonymized data supporting the findings of this study are available from the corresponding author, Diego Marcos-Martínez, upon reasonable request, subject to Institutional Review Board approval and completion of a legal data-sharing agreement.

Declarations

Ethics approval and consent to participate
This study was approved by the Ethics Committee of "Hospital Clínico Universitario de Valladolid" (reference: PI 23-3325), Valladolid, Spain. Written informed consent was obtained from all participants.

Consent for publication
All participants provided written informed consent for the publication of findings derived from their participation in the study.

Competing interests

The authors declare no Conflict of interest.

Author details

[1]Biomedical Engineering Group (GIB), E.T.S Ingenieros de Telecomunicación, University of Valladolid, Valladolid, Spain
[2]Centro de Investigación Biomédica en Red en Bioingenieríа, Biomateriales y Nanomedicina (CIBER-BBN), Madrid, Spain

Received: 18 July 2025 / Accepted: 9 February 2026

References

1. Sitaram R, Ros T, Stoeckel L, Haller S, Scharnowski F, Lewis-Peacock J, et al. Closed-loop brain training: the science of neurofeedback. Nat Rev Neurosci. 2017;18(2):86–100. https://doi.org/10.1038/nrn.2016.164.
2. Wolpaw JR, Kamesar A. Heksor: the central nervous system substrate of an adaptive behaviour. J Physiol. 2022;600(15):3423–52. https://doi.org/10.1113/JP283291.
3. Wolpaw J, Wolpaw EW. Brain-computer interfaces: principles and practice. Oxford University Press; 2012. https://doi.org/10.1093/acprof:oso/9780195388855.001.0001.
4. Enriquez-Geppert S, Huster RJ, Herrmann CS. EEG-neurofeedback as a tool to modulate cognition and behavior: A review tutorial. Front Hum Neurosci. 2017;11(February):1–19. https://doi.org/10.3389/fnhum.2017.00051.
5. Ros T, Baars BJ, Lanius RA, Vuilleumier P. Tuning pathological brain oscillations with neurofeedback: A systems neuroscience framework. Front Hum Neurosci. 2014;8:1–22. https://doi.org/10.3389/fnhum.2014.01008.
6. Barreiros AR, Breukelaar IB, Harris AWF, Korgaonkar MS. fmri neurofeedback for the modulation of the neural networks associated with depression. Clin Neurophysiol. 2024;168:34–42. https://doi.org/10.1016/j.clinph.2024.10.003.
7. Fruchter E, Goldenthal N, Adler LA, Gross R, Harel EV, Deutsch L, et al. Amygdala-derived-eeg-fmri-pattern neurofeedback for the treatment of chronic post-traumatic stress disorder. a prospective, multicenter, multinational study evaluating clinical efficacy. Psychiatry Res. 2024;333:115711. https://doi.org/10.1016/j.psychres.2023.115711.
8. Wu G, He Q, Li D, Zhang Z, Miao J, Shu Y. Comparative efficacy of neurofeedback interventions for attention-deficit/hyperactivity disorder in children: a network meta-analysis. Brain Behav. 2024;14(12):e70194.
9. Fumuro T, Matsuhashi M, Kinoshita M, Matsumoto R, Takahashi R, Ikeda A. Self-regulation of slow cortical potential and seizure suppression by scalp electroencephalography: early prediction of therapeutic efficacy. Clin Neurophysiol. 2025;170:182–91. https://doi.org/10.1016/j.clinph.2024.11.018.
10. Mane R, Chouhan T, Guan C. BCI for stroke rehabilitation: motor and beyond. J Neural Eng. 2020;17(4):041001. https://doi.org/10.1088/1741-2552/aba162.
11. Sebastián-Romagosa M, Cho W, Ortner R, Murovec N, Von Oertzen T, Kamada K, et al. Brain computer interface treatment for motor rehabilitation of upper extremity of stroke patients-a feasibility study. Front Neurosci. 2020;14:591435. https://doi.org/10.3389/fnins.2020.591435.
12. Sebastián-Romagosa M, Cho WH, Ortner R, Sieghartsleitner S, Von Oertzen TJ, Kamada K, et al. Brain–computer interface treatment for gait rehabilitation in stroke patients. Front Neurosci. 2023;17:1256077. https://doi.org/10.3389/fnins.2023.1256077.
13. Musso M, Hübner D, Schwarzkopf S, Bernodusson M, LeVan P, Weiller C, et al. Aphasia recovery by language training using a brain–computer interface: a proof-of-concept study. Brain Commun. 2022;4(1):008. https://doi.org/10.1093/braincomms/fcac008.
14. Shutting down sensorimotor interferences after stroke. A proof-of-principle SMR neurofeedback study. Front Hum Neurosci. 2016;10(July):1–14. https://doi.org/10.3389/fnhum.2016.00348.
15. Norman SL, Wolpaw JR, Reinkensmeyer DJ. Targeting neuroplasticity to improve motor recovery after stroke: an artificial neural network model. Brain Commun. 2022;4(6):1–14. https://doi.org/10.1093/braincomms/fcac264.
16. Tsai PC, Akpan A, Tang KT, Lakany H. Brain computer interfaces for cognitive enhancement in older people—challenges and applications: a systematic review. BMC Geriatr. 2025;25(1):36. https://doi.org/10.1186/s12877-025-05676-4.
17. Wang JR, Hsieh S. Neurofeedback training improves attention and working memory performance. Clin Neurophysiol. 2013;124(12):2406–20. https://doi.org/10.1016/j.clinph.2013.05.020.
18. Enriquez-Geppert S, Huster RJ, Scharfenort R, Mokom ZN, Zimmermann J, Herrmann CS. Modulation of frontal-midline theta by neurofeedback. Biol Psychol. 2014;95(1):59–69. https://doi.org/10.1016/j.biopsycho.2013.02.019.
19. Marcos-Martínez D, Santamaría-Vázquez E, Martínez-Cagigal V, Pérez-Velasco S, Rodríguez-González V, Martín-Fernández A, et al. ITACA: an open-source framework for neurofeedback based on brain-computer interfaces. Comput Bio Med. 2023. https://doi.org/10.1016/j.compbiomed.2023.107011.
20. Paz VK, Garcia A, Paz Neto A, Tomaz C. SMR neurofeedback training facilitates working memory performance in healthy older adults: a behavioral and EEG study. Front Behav Neurosci. 2018;12:321. https://doi.org/10.3389/fnbeh.2018.00321.
21. Kober SE, Witte M, Stangl M, Väljamäe A, Neuper C, Wood G. Shutting down sensorimotor interference unblocks the networks for stimulus processing: An SMR neurofeedback training study. Clin Neurophysiol. 2015;126(1):82–95. https://doi.org/10.1016/j.clinph.2014.03.031.
22. Marlats F, Bao G, Chevallier S, Boubaya M, Djabelkhir-Jemmi L, Wu YH, et al. SMR/theta neurofeedback training improves cognitive performance and EEG activity in elderly with mild cognitive impairment: a pilot study. Front Aging Neurosci. 2020;12(June):1–11. https://doi.org/10.3389/fnagi.2020.00147.
23. Gomez-Pilar J, Corralejo R, Nicolas-Alonso LF, Álvarez D, Hornero R. Neurofeedback training with a motor imagery-based BCI: neurocognitive improvements and EEG changes in the elderly. Med Biol Eng Comput. 2016;54(11):1655–66. https://doi.org/10.1007/s11517-016-1454-4.
24. Marcos-Martínez D, Martínez-Cagigal V, Santamaría-Vázquez E, Pérez-Velasco S, Hornero R. Neurofeedback training based on motor imagery strategies increases EEG complexity in elderly population. Entropy. 2021;23(12):1–19. https://doi.org/10.3390/e23121574.
25. Ros T, Enriquez-Geppert S, Zotev V, Young KD, Wood G, Whitfield-Gabrieli S, et al. Consensus on the reporting and experimental design of clinical and cognitive-behavioural neurofeedback studies (CRED-nf checklist). Brain. 2020;143(6):1674–85. https://doi.org/10.1093/brain/awaa009.
26. Weber LA, Ethofer T, Ehlis AC. Predictors of neurofeedback training outcome: a systematic review. NeuroImage Clin. 2020;27:102301. https://doi.org/10.1016/j.nicl.2020.102301.
27. Reichert JL, Kober SE, Neuper C, Wood G. Resting-state sensorimotor rhythm (SMR) power predicts the ability to up-regulate SMR in an EEG-instrumental conditioning paradigm. Clin Neurophysiol. 2015;126(11):2068–77. https://doi.org/10.1016/j.clinph.2014.09.032.
28. Yuill N, Hollis V. A systematic review of cognitive stimulation therapy for older adults with mild to moderate dementia: an occupational therapy perspective. Occup Ther Int. 2011;18(4):163–86. https://doi.org/10.1002/oti.315. (**Epub 2011 Mar 21**).
29. Zhang M, Jia J, Yang Y, Zhang L, Wang X. Effects of exercise interventions on cognitive functions in healthy populations: a systematic review and meta-analysis. Ageing Res Rev. 2023;92:102116. https://doi.org/10.1016/j.arr.2023.102116. (**Epub 2023 Nov 3**).
30. Hétu S, Grégoire M, Saimpont A, Coll M-P, Eugène F, Michon P-E, et al. The neural network of motor imagery: an ale meta-analysis. Neurosci Biobehav Rev. 2013;37(5):930–49. https://doi.org/10.1016/j.neubiorev.2013.03.017.
31. Pérez-Velasco S, Marcos-Martínez D, Santamaría-Vázquez E, Martínez-Cagigal V, Moreno-Calderón S, Hornero R. Unraveling motor imagery brain patterns using explainable artificial intelligence based on shapley values. Comput Methods Programs Biomed. 2024;246:108048. https://doi.org/10.1016/j.cmpb.2024.108048.
32. Malouin F, Richards CL, Durand A. Normal aging and motor imagery vividness: implications for mental practice training in rehabilitation. Arch Phys Med Rehabil. 2010;91(7):1122–7. https://doi.org/10.1016/j.apmr.2010.03.007.
33. Heuninckx S, Wenderoth N, Swinnen SP. Systems neuroplasticity in the aging brain: recruiting additional neural resources for successful motor performance in elderly persons. J Neurosci. 2008;28(1):91–9. https://doi.org/10.1523/JNEUROSCI.3300-07.2008.
34. Welch PD. The use of fast Fourier transform for the estimation of power spectra. IEEE Trans Audio Electroacoust. 1976;15(2):70–3.
35. Pfurtscheller G, Neuper C, Flotzinger D, Pregenzer M. Eeg-based discrimination between imagination of right and left hand movement. Electroencephalogr Clin Neurophysiol. 1997;103(6):642–51. https://doi.org/10.1016/S0013-4694(97)00080-1.
36. Santamaría-vázquez E, Martínez-cagigal V, Marcos-martínez D, Rodríguez-gonzález V, Pérez-velasco S, Moreno-calderón S, et al. MEDUSA A novel Python-based software ecosystem to accelerate brain-computer interface and cognitive neuroscience research. 2023;230:107357. https://doi.org/10.1016/j.cmpb.2023.107357.

37. Jeunet C, Lotte F, Batail JM, Philip P, Micoulaud Franchi JA. Using recent BCI literature to deepen our understanding of clinical neurofeedback: a short review. Neuroscience. 2018;378:225–33.
38. Sigrist R, Rauter G, Riener R, Wolf P. Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review. Psychon Bull Rev. 2013;20(1):21–53. https://doi.org/10.3758/s13423-012-0333-8.
39. Gutiérrez-de Pablo V, Poza J, Maturana-Candelas A, Rodríguez-González V, Tola-Arribas M, Cano M, et al. Exploring the disruptions of the neurophysiological organization in Alzheimer's disease: an integrative approach. Comput Methods Programs Biomed. 2024;250:108197. https://doi.org/10.1016/j.cmpb.2024.108197.
40. Cullum CM. 4.11 - neuropsychological assessment of adults. In: Bellack AS, Hersen M, editors. Comprehensive Clinical Psychology. Oxford: Pergamon; 1998;303–47. https://doi.org/10.1016/B0080-4270(73)00227-3.
41. Abdelhamid G, Bassiouni M, Gómez-Benito J. Assessing cognitive abilities using the wais-iv: an item response theory approach. Int J Environ Res Public Health. 2021;18(13):6835. https://doi.org/10.3390/ijerph18136835.
42. Ito S, Sumiyoshi C, Matsumoto J, Miura K, Yasuda Y, Hasegawa N, et al. Usefulness of the wais-iv short form for measuring cognitive function in patients with schizophrenia. Neuropsychopharmacol Rep. 2025;45(1):1–6. https://doi.org/10.1002/npr2.70000.
43. Friesen DC, Luo L, Luk G, Bialystok E. Proficiency and control in verbal fluency performance across the lifespan for monolinguals and bilinguals. Lang Cogn Neurosci. 2015;30(3):238–50. https://doi.org/10.1080/23273798.2014.918630.
44. Sheppard C, Kousaie S, Monetta L, Taler V. Performance on the boston naming test in bilinguals. J Int Neuropsychol Soc. 2016;22(3):350–63. https://doi.org/10.1017/S135561771500123X.
45. Ahn YD, Yi D, Joung H, Seo EH, Lee YH, Byun MS, et al. Normative data for the logical memory subtest of the Wechsler memory scale-iv in middle-aged and elderly Korean people. Psychiatry Investig. 2019;16(11):793–9. https://doi.org/10.30773/pi.2019.0061.
46. Temple RO, Davis JD, Silverman I, Tremont G. Differential impact of executive function on visual memory tasks. Clin Neuropsychol. 2006;20(3):480–90. https://doi.org/10.1080/13854040590967540.
47. Pino R, Peña J, Ibarretxe-Bilbao N, Schretlen DJ, Ojeda N. Modified Wisconsin card sorting test: standardization and norms of the test for a population sample in Spain. Revista de Neurología. 2016;62(5):193–202.
48. Lezak MD, Howieson DB, Bigler ED, Tranel D. Neuropsychological assessment. 5th ed. New York: Oxford University Press; 2012.
49. Gonzalez-Astudillo J, Cattai T, Bassignana G, Corsi M-C, De Vico Fallani F. Network-based brain–computer interfaces: principles and applications. J Neural Eng. 2021;18(4):041002. https://doi.org/10.1088/1741-2552/abc760.
50. Corsi MC, Chavez M, Schwartz D, George N, Hugueville L, Kahn AE, et al. Functional disconnection of associative cortical areas predicts performance during BCI training. Neuroimage. 2020;209:116500. https://doi.org/10.1016/j.neuroimage.2019.116500.
51. Liu Z, Fukunaga M, de Zwart JA, Duyn JH. Large-scale spontaneous fluctuations and correlations in brain electrical activity observed with magnetoencephalography. Neuroimage. 2010;51(1):102–11. https://doi.org/10.1016/j.neuroimage.2010.01.092.
52. Hipp JF, Hawellek DJ, Corbetta M, Siegel M, Engel AK. Large-scale cortical correlation structure of spontaneous oscillatory activity. Nat Neurosci. 2012;15(6):884–90. https://doi.org/10.1038/nn.3101.
53. Rodríguez-González V, Núñez P, Gómez C, Shigihara Y, Hoshi H, Tola-Arribas M, et al. Connectivity-based meta-bands: a new approach for automatic frequency band identification in connectivity analyses. Neuroimage. 2023;280:120332. https://doi.org/10.1016/j.neuroimage.2023.120332.
54. Pilgramm S, Haas B, Helm F, Zentgraf K, Stark R, Munzert J, et al. Motor imagery of hand actions: decoding the content of motor imagery from brain activity in frontal and parietal motor areas. Hum Brain Mapp. 2016;37(1):81–93. https://doi.org/10.1002/hbm.23015.
55. Bauer R, Fels M, Vukelić M, Ziemann U, Gharabaghi A. Bridging the gap between motor imagery and motor execution with a brain–robot interface. Neuroimage. 2015;108:319–27. https://doi.org/10.1016/j.neuroimage.2014.12.026.
56. Koch G, Cercignani M, Pecchioli C, Versace V, Oliveri M, Caltagirone C, et al. In vivo definition of parieto-motor connections involved in planning of grasping movements. Neuroimage. 2010;51(1):300–12. https://doi.org/10.1016/j.neuroimage.2010.02.022.
57. De Lange FP, Jensen O, Bauer M, Toni I. Interactions between posterior gamma and frontal alpha/beta oscillations during imagined actions. Front Hum Neurosci. 2008;2:269. https://doi.org/10.3389/neuro.09.007.2008.
58. Zhang T, Liu T, Li F, Li M, Liu D, Zhang R, et al. Structural and functional correlates of motor imagery bci performance: insights from the patterns of fronto-parietal attention network. Neuroimage. 2016;134:475–85. https://doi.org/10.1016/j.neuroimage.2016.04.030.
59. Liu X, Zhang W, Li W, Zhang S, Lv P, Yin Y, et al. Effects of motor imagery based brain-computer interface on upper limb function and attention in stroke patients with hemiplegia: a randomized controlled trial. BMC Neurol. 2023;23(1):136. https://doi.org/10.1186/s12883-023-03150-5.
60. Wan C, Zhang W, Nie Y, Qian Y, Wang J, Xu H, Li Z, Su B, Zhang Y, Li Y. Impact of motor imagery-based brain-computer interface combined with virtual reality on enhancing attention, executive function, and lower-limb function in stroke: a pilot study. PM&R https://doi.org/10.1002/pmrj.13324
61. Barry RJ, De Blasio FM. EEG differences between eyes-closed and eyes-open resting remain in healthy ageing. Biol Psychol. 2017;129:293–304. https://doi.org/10.1016/j.biopsycho.2017.09.010.
62. Murphy TH, Corbett D. Plasticity during stroke recovery: from synapse to behaviour. Nat Rev Neurosci. 2009;10(12):861–72. https://doi.org/10.1038/nrn2735.
63. Berger D, Varriale E, Kessenich L, Herrmann HJ, Arcangelis L, et al. Three cooperative mechanisms required for recovery after brain damage. Sci Rep. 2019;9(1):15858. https://doi.org/10.1038/s41598-019-50946-y.
64. Zoefel B, Huster RJ, Herrmann CS. Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance. Neuroimage. 2011;54(2):1427–31. https://doi.org/10.1016/j.neuroimage.2010.08.078.
65. Angelakis E, Stathopoulou S, Frymiare JL, Green DL, Lubar JF, Kounios J. EEG neurofeedback: a brief overview and an example of peak alpha frequency training for cognitive enhancement in the elderly. Clin Neuropsychol. 2007;21(1):110–29. https://doi.org/10.1080/13854040600744839.
66. Ninaus M, Kober SE, Witte M, Koschutnig K, Stangl M, Neuper C, et al. Neural substrates of cognitive control under the belief of getting neurofeedback training. Front Hum Neurosci. 2013;7:1–10. https://doi.org/10.3389/fnhum.2013.00914.
67. Ninaus M, Kober SE, Witte M, Koschutnig K, Neuper C, Wood G. Brain volumetry and self-regulation of brain activity relevant for neurofeedback. Biol Psychol. 2015;110:126–33. https://doi.org/10.1016/j.biopsycho.2015.07.009.
68. 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;7:1–12. https://doi.org/10.3389/fnhum.2013.00695.
69. Stefano Filho CA, Attux R, Castellano G. Actual, sham and no-feedback effects in motor imagery practice. Biomed Signal Process Control. 2022;71(PB):103262. https://doi.org/10.1016/j.bspc.2021.103262.
70. Li L, Wang Y, Zeng Y, Hou S, Huang G, Zhang L, et al. Multimodal neuroimaging predictors of learning performance of sensorimotor rhythm up-regulation neurofeedback. Front Neurosci. 2021;15:699999. https://doi.org/10.3389/fnins.2021.699999.
71. Lee M, Yoon J-G, Lee S-W. Predicting motor imagery performance from resting-state eeg using dynamic causal modeling. Front Hum Neurosci. 2020;14:321. https://doi.org/10.3389/fnhum.2020.00321.
72. Zhang R, Yao D, Valdés-Sosa PA, Li F, Li P, Zhang T, et al. Efficient resting-state eeg network facilitates motor imagery performance. J Neural Eng. 2015;12(6):066024. https://doi.org/10.1088/1741-2560/12/6/066024.
73. Andrade K, Houmani N, Guieysse T, Razafimahatratra S, Klarsfeld A, Dreyfus G, et al. Self-modulation of gamma-band synchronization through eeg-neurofeedback training in the elderly. J Integr Neurosci. 2024;23(3):67. https://doi.org/10.31083/j.jin2303067.
74. Becerra J, Fernandez T, Roca-Stappung M, Diaz-Comas L, Galan L, Bosch J, et al. Neurofeedback in healthy elderly human subjects with electroencephalographic risk for cognitive disorder. J Alzheimers Dis. 2012;28(2):357–67. https://doi.org/10.3233/JAD-2011-111055.
75. Campos VKPV, Garcia A, Paz Neto A, Tomaz C. Smr neurofeedback training facilitates working memory performance in healthy older adults: A behavioral and eeg study. Front Behav Neurosci. 2018;12:321. https://doi.org/10.3389/fnbeh.2018.00321.
76. Chandarasart J, Israsena P, Pan-Ngum S, Hemrungrojn S, Maes M. A game-based neurofeedback training system to enhance cognitive performance in healthy elderly subjects and in patients with amnestic mild cognitive impairment. Clin Interv Aging. 2019;14:347–60. https://doi.org/10.2147/CIA.S189047.
77. Lee T-S, Quek S-Y, Goh SJA, Phillips R, Guan C, Cheung YB, et al. A pilot randomized controlled trial using eeg-based brain-computer interface training for a Chinese-speaking group of healthy elderly. Clin Interv Aging. 2015;10:217–27. https://doi.org/10.2147/CIA.S73955.

78. Reis J, Portugal AM, Fernandes L, Afonso N, Pereira M, Sousa N, et al. An alpha and theta intensive and short neurofeedback protocol for healthy aging working?memory training. Front Aging Neurosci. 2016;8:157. https://doi.org/10.3389/fnagi.2016.00157.
79. Staufenbiel SM, Brouwer A-M, Keizer AW, Wouwe NC. Effect of beta and gamma neurofeedback on memory and intelligence in the elderly. Biol Psychol. 2014;95:74–85. https://doi.org/10.1016/j.biopsycho.2013.05.020.
80. Pérez-Velasco S, Santamaría-Vázquez E, Martínez-Cagigal V, Marcos-Martínez D, Hornero R. EEGSym: overcoming inter-subject variability in motor imagery based BCIs with deep learning. IEEE Trans Neural Syst Rehabil Eng. 2022;30:1766–75. https://doi.org/10.1109/TNSRE.2022.3186442.
81. Dhindsa K, Gauder KD, Marszalek KA, Terpou B, Becker S. Progressive thresholding: shaping and specificity in automated neurofeedback training. IEEE Trans Neural Syst Rehabil Eng. 2018;26(12):2297–305. https://doi.org/10.1109/TNSRE.2018.2878328.

Publisher's Note