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Title: Mental strategies and resting state EEG: effect on high alpha amplitude modulation by neurofeedback in healthy young adults

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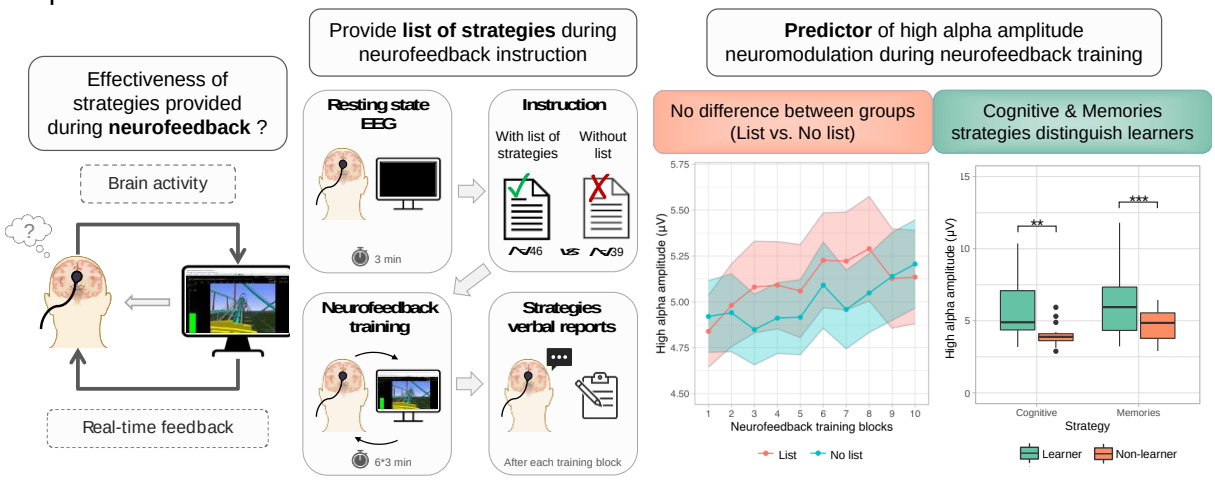
Abstract.
Neurofeedback (NFB) is a brain-computer interface which allows individuals to modulate their brain activity. Despite the self-regulatory nature of NFB, the effectiveness of strategies used during NFB training has been little investigated. In a single session of NFB training (6*3min training blocks) with healthy young participants, we experimentally tested if providing a list of mental strategies (list group, *N* = 46), compared with a group receiving no strategies (no list group, *N* = 39), affected participants' neuromodulation ability of high alpha (10-12 Hz) amplitude. We additionally asked participants to verbally report the mental strategies used to enhance high alpha amplitude. The verbatim was then classified in pre-established categories in order to examine the effect of type of mental strategy on high alpha amplitude. First, we found that giving a list to the participants did not promote the ability to neuromodulate high alpha activity. However, our analysis of the specific strategies reported by learners during training blocks revealed that cognitive effort and recalling memories were associated with higher high alpha amplitude. Furthermore, the resting amplitude of trained high alpha frequency predicted an amplitude increase during training, a factor that may optimize inclusion in NFB protocols. The present results also corroborate the interrelation with other frequency bands during NFB training. Although these findings are based on a single NFB session, our study represents a further step towards developing effective protocols for high alpha neuromodulation by NFB.

Graphical abstracts



Highlights.

- Providing a list of mental strategies did not promote the ability to neuromodulate high alpha activity
- Two strategies were associated with higher high alpha in learners compared to non-learners: cognitive effort and recalling past memories.
- Cognitive effort and recalling past memories were associated with higher high alpha amplitude in learners.
- High alpha amplitude during resting state predicted high alpha neuromodulation during training.
- Low and high alpha amplitudes increased while delta, beta, and gamma amplitudes decreased during training.
- Only the amplitudes of low and high alpha frequencies were affected by training during the resting-state measurement.

1. Introduction

From single neurons to large-scale brain activity, neural oscillations have been associated to distinct cognitive activities. These brain oscillations can be modulated by neuromodulation techniques to produce behavioral improvements. Neurofeedback (NFB) is a non-invasive method used to train people to regulate their brain activity. Among the frequencies targeted to drive behavioral improvements, the high alpha frequency is particularly used to improve cognitive performance (Yeh et al., 2021), probably because of its role in working memory involved in different cognitive tasks (Pavlov & Kotchoubey, 2022). However, the factors predicting the effectiveness of training are still poorly identified (Kadosh & Staunton, 2019; Weber et al., 2020). To date, there has been no consensus on the role of mental strategies in NFB training: some authors suggest that they may be a factor for success in the neuromodulation task (Autenrieth et al., 2020), whereas others consider them irrelevant because of the implicit learning that occurs during NFB training (Shibata et al., 2019). The primary aim of this study was to test if providing mental strategies during instruction of a single session of high alpha NFB training would support the neuromodulation process.

a. Principles of neurofeedback

NFB is a particular type of biofeedback that translates a signal from brain activity into an external signal, perceptible by the individual (Enriquez-Geppert et al., 2017). This method places the individual in a closed-loop feedback to help them learn to self-regulate their brain activity (Sitaram et al., 2017). NFB with electroencephalogram (EEG) measures the amplitude or coherence of the signal corresponding to the neural oscillations (Buzsáki & Draguhn, 2004). As these neural oscillations play a role in human cognition (Fries, 2015; Van Diepen et al., 2019) and are abnormal in many neuropsychiatric disorders (Uhlhaas et al., 2009), the interest of NFB is to enable the modulation of this brain activity in a non-invasive way, to enhance cognitive processes (Gruzelier, 2014) or to reduce symptoms, by normalizing a deviant neuroelectric signal (Marzbani et al., 2016). NFB with EEG is a brain imaging technique that has the advantage of being relatively inexpensive to acquire and maintain, easily manipulated and usable (Thibault et al., 2016). With the improvement of brain imaging techniques (Watanabe et al., 2017) and the expansion of the field of brain-computer interfaces (Chaudhary et al., 2016), NFB has seen a resurgence of interest in recent years.

b. Models of neurofeedback

Historically, the foundations of NFB are based on operant conditioning theory (Nowlis & Kamiya, 1970; Sterman et al., 1969), which posits that the frequency of a response can be reinforced or decreased by a contingent reward or punishment (Sherlin et al., 2011). In NFB, specific neural activity (e.g., amplitude of a specific frequency) is reinforced by positive stimuli when brain activity reaches a reward threshold (e.g., a circle displayed on a screen expands or changes color when the amplitude is greater than a predefined value). Through trial-and-error and repetition, the participant has to find a mental state that correlates with a neural state that activates positive feedback (Hammer et al., 2012; Sakurai & Song 2016). Several theoretical models coexist to explain the mechanism of NFB, without being mutually exclusive. The neural plasticity model considers that repeated production of the rewarded neural state leads to neuroplasticity by strengthening the synaptic connections of the neural

network (Niv, 2013; Ros et al., 2014), subsequently favoring its reactivation (Shibata et al., 2019). Hebbian plasticity is considered to be the mechanism underlying this neural reinforcement and studies such as those conducted by Ros et al. (2010, 2013) have shown that this plasticity can occur after only 30 min of NFB training. The model of skill learning (Birbaumer et al., 2013) postulates that individuals develop idiosyncratic response plans (e.g., mental imagery) which become progressively pruned of irrelevant response elements until a specific response reliably produces the desired effect. Like a procedural skill, these learned brain responses are stored and retrieved via cortical-basal ganglia loops (Koralek et al., 2012).

Both models (neural plasticity model and skill learning model) emphasize the automated and implicit aspect of learning during NFB. This assumption differs from the multi-stage model (Davelaar, 2018), which emphasizes the active participation of the individual during the initial phase of exploration of a brain response relevant to feedback. The multi-stage model (Davelaar, 2018) proposed to decompose NFB learning into three stages. The first stage is mainly the exploration by the individual of different mental states that are maintained depending on the feedback signal (reward or punishment). This exploration involves the maintenance of goal representations, the implementation of different mental strategies and the evaluation of their effectiveness. The second phase corresponds to the repeated activation of the mental representation that is most frequently associated with a positive feedback signal and to a reinforcement of the cerebral activity associated with this representation by neuroplasticity. The model argues that in the third stage the desired brain state is consolidated and forms a homeostatic set point that can serve as a secondary reinforcer, provided that the state is sufficiently discriminable. The exploration phase could be a critical period, during which individuals manage or fail to set up a mental state capable of modulating the trained frequency. Our study focuses on this first phase in order to distinguish the mental states favoring the increase in the high alpha amplitude.

c. High alpha neurofeedback training

Among the different frequencies targeted by NFB-EEG training to improve cognitive processes, the higher alpha frequency is particularly used to improve working memory. Since the series of experiments conducted by Kamiya in the 1960s demonstrated the ability of humans to discriminate and voluntarily modulate the alpha frequency (Kamiya, 1968), this frequency has been widely used in NFB to obtain various cognitive and clinical improvements (Vernon et al., 2009). At the neurophysiological level, alpha oscillations measured by EEG are known to be more prominent in posterior areas (Klimesch, 1999) and are produced by the synchronous activity of postsynaptic potentials of pyramidal neurons, thalamocortical and cortico-cortical loops and local interneurons (Bazanova & Vernon, 2014; Buzsáki et al., 2012; Cohen, 2017). Posterior alpha amplitude is generally inversely related to cognitive activity, but this result is not always observed (Pavlov & Kotchoubey, 2022). Initially seen as a form of "cortical idling" (Pfurtscheller et al., 1996), the alpha frequency is now considered to play a functional inhibitory role in sensory processing (Klimesch, 2012; Van Diepen et al., 2019). A decrease in the amplitude of the oscillation is typically observed when attention is focused on an external visual event, while an increase in the amplitude of the oscillation can be observed when attention is directed to internal representations (Wang et al., 2016).

The predominant frequency of the alpha band (i.e., frequency at which the alpha amplitude is largest) can vary inter- (Haegens et al., 2014; Klimesch, 1999) and intra-individually (e.g., over time; Benwell et al., 2019; Chiang et al., 2011). From this predominant frequency, an individual alpha frequency band (IAF) can be determined. While the use of the IAF could allow for the selection of a more biologically valid frequency band, there is no standardized method for determining it (Corcoran et al., 2018). The different methods used may thus introduce bias or render comparison between studies difficult (Chiang et al., 2008; Corcoran et al., 2018; Goljahani et al., 2012). In the field of NFB, studies target both the IAF (Alexeeva et al., 2012 ; Bazanova et al., 2013 ; Bobby & Prakash, 2017 ; Escolano et al., 2014 ; Grosselin et al., 2021 ; Hanslmayr et al., 2005 ; Nan et al., 2012 ; Wan et al., 2014 ; Zoefel et al., 2011) and the standard alpha frequency (Berger & Davelaar, 2018 ; Biswas & Ray, 2019 ; Bobby & Prakash, 2017 ; Brickwedde et al., 2019 ; Cho et al., 2008 ; Chow et al., 2017 ; Dekker et al., 2014 ; Guez et al., 2015 ; Hsueh et al., 2016 ; Lee et al., 2019 ; Nan et al., 2013 ; Nan et al., 2020 ; Naas et al., 2019 ; Nawaz et al., 2022 ; Peeters et al., 2014 ; Peng et al., 2020 ; Ros et al., 2010 ; Ros et al., 2013 ; Su et al., 2021 ; Takabatake et al., 2021 ; Wei et al., 2017). The advantage of IAF over standard alpha frequency, however, has still little empirical validation. To our knowledge, only one study has demonstrated neural and behavioral gains associated with NFB modulation of IAF (Bazanova & Aftanas, 2010). However, the level of evidence is quite low, the study being a case study with only one patient trained to increase upper alpha and decrease EMG activity (Bazanova & Aftanas, 2010).

The different modulations of the frequency in response to various cognitive tasks have led authors to consider the alpha frequency (8-12 Hz) to be composed of sub-bands, interacting distinctly depending on the cognitive task being performed: low (8-10 Hz) and high alpha frequencies (10-12 Hz; Klimesch, 1999). Although both sub-bands have been studied in the NFB field, it is the latter that has been used the most to drive cognitive improvements (Yeh et al., 2021). The high alpha frequency has been trained to improve performance on tasks involving short term memory (Bucho et al., 2019; Naas et al., 2019; Nan et al., 2012), working memory (Bobby & Prakash 2017; Dehghanpour et al., 2018; Domingos et al., 2021; Escolano et al., 2011, 2012, 2014; Esteves et al., 2021; Gorgon et al., 2020; Navarro Gil et al., 2018), episodic memory (Guez et al., 2015) or mental rotation (Hanslmayr et al., 2005; Zoefel et al., 2011). Although the number of sessions varies greatly between studies and can be as many as 20 sessions (Nan et al., 2012), some studies have demonstrated the possibility of modulating the alpha frequency, and in particular the high alpha, in only one session (Belinskaia et al., 2020; Bucho et al., 2019; Escolano et al., 2012, 2014; Hanslmayr et al., 2005). However, although promising, empirical results were not systematically consistent, and some studies showed mixed results regarding the modulation of high alpha activity and increased cognitive performance (Bucho et al., 2019; Gorgon et al., 2019; Naas et al., 2019; Navarro Gil et al., 2018; Gökşin et al., 2019). Debate persists in the NFB field about the mechanisms underlying this technique, with the call for consideration of non-specific effects on outcomes (Thibault et al., 2016, Thibault et al., 2018) and a better understanding of the factors distinguishing individuals who successfully modulate their brain activity ("learners") and those who do not ("non-learners", Alkoby et al., 2018). Much interest is now focused on the neuro/psychological factors that predict NFB training success (Haugg et al., 2020; Kadosh & Staunton, 2019; Weber et al., 2020), including the mental strategies used by individuals during NFB training (Sitaram et al., 2017; Ros et al., 2020; Autenrieth et al., 2020).

d. The use of strategies during alpha neurofeedback training

A fundamental aspect of NFB protocols that may explain the success of NFB over and above inter-individual differences is the implementation of strategies. Although this term is often mentioned in NFB studies, it is rarely explicitly defined. We draw on the definition of Utz (1994) who considered a strategy as the mental approaches or techniques used by the participant to learn the NFB task (i.e., to self-regulate the measured brain activity). The question of strategies has sometimes been neglected because of a dominance of implicit processes during NFB learning and inconsistency in verbal reports of the strategies employed (Muñoz-Moldes & Cleeremans, 2020). While learning to self-regulate one's brain activity is to a large extent an implicit process (Birbaumer et al., 2013), this is not sufficient to exhaust the issue of mental strategies, specifically during the beginning of training. Indeed, the main models of the NFB mechanism agree that at the beginning of training, individuals explore different mental or physiological strategies through trial and error to modulate the feedback signal (Birbaumer et al., 2013; Lacroix, 1986; Davelaar, 2018). Thus, it is possible that many problems of the so-called "non-learners" can be explained in part by individuals' inability to find or implement the correct strategy. Understanding which type of strategy is most effective in modulating brain activity would allow us to design NFB protocols that have a higher probability of being effective by reducing the number of "non-learners". Yet, the question of whether to recommend specific strategies to individuals to facilitate NFB learning has not been resolved in the field of NFB.

One of the first research studies that looked at the subjective state associated with the success of a NFB task was the study by Nowlis and Kamiya (1970), in which 26 participants had to try to modulate their alpha level (16 with eyes closed and 10 with eyes open). At the end of the single experimental session, the authors interviewed the participants to ask them about the strategy used to modulate their alpha level. Participants' verbatim was recorded and categorized by the experimenters. Although participants found it difficult to explain clearly what they did, the authors noted that some strategies were reported with higher frequency amplitude such as "Relaxation", "Awareness of inhalations and exhalations", "Not focusing (visual)" or "Letting go". More recently, one study trained students to modulate their alpha amplitude on Cz for 20 sessions over a 15-day period (Nan et al., 2012). After each session, participants were asked to write down the strategy used and its effects. Ranking the strategies according to the effects estimated by the participants, the authors observed that the best strategies were positive thinking such as "Friends", "Love", "Family" while the worst were "Anger" and 'Calculation". In another study, most participants reported "Evoking emotions" as the best strategy to increase posterior (P3, PZ, P4, O1 and O2) high alpha amplitude during 5 training sessions within 1 week (Zoefel et al., 2011).

Although these qualitative measures are interesting for exploring the mental strategies used by individuals, they did not report the neurophysiological effects of these strategies on brain activity. In a study that investigated this aspect, three elderly participants were trained to upregulate alpha frequency during approximately 35 sessions of NFB (Angelakis et al., 2007). After each session, they were asked to write down the strategy that they felt was most effective. Results showed a great diversity of strategies used, with a descriptive association of some strategies with higher alpha amplitude (e.g., "concentrated," "relaxed," "pleasant thoughts"). A recent study attempted to apply inferential statistical analyses to determine the relative effectiveness of the strategies on the trained frequency

(Naas et al., 2019). The authors trained 17 individuals to increase the amplitude of their individual high alpha band on P7, P8, O1 and O2 during 4 sessions over 4 consecutive days, each session consisting of 5 blocks of 3 min. In the first session, participants were asked to use 5 different strategies, one for each block, with the aim of determining the most effective one (to be used in subsequent sessions). For participants who had difficulty finding strategies, they proposed a list based on Nan et al. (2012): "Positive thinking", "Evoking emotions", "Visualizing activities", "Love" and "Physiological calm." Two raters independently classified the recorded strategies into different categories. The authors then evaluated the effectiveness of the strategies via the mean amplitude associated with their use. Descriptively, the "Visualizing activities" strategy was the most effective, followed successively by "Love", "Physiological calm", "Positive emotion", "Art" and finally "Negative emotion". However, the analysis of variance applied to these strategies did not show any significant difference, perhaps due to a lack of statistical power (*N* = 33 participants). Despite the several attempts to identify effective strategies during NFB training, the methods used have suffered from several problems previously mentioned (e.g., qualitative measure without examining the neurophysiological effects). The study of the strategies used by individuals during an NFB task deserves to be more systematized, with a larger sample size, as it is possible that these investigations will help us to design trainings with a larger proportion of learners. In addition to the strategies used during NFB, studies have also explored factors (e.g., psychological, cognitive, electrophysiological) that predict the effectiveness of a NFB protocol.

e. Predictors of neurofeedback success

The question of predictors in task success is central to NFB/BCI protocols (Jeunet et al., 2018; Weber et al., 2020). Identifying the psychological or neurophysiological variables that promote success in this type of task would provide a better understanding of what distinguishes learners from non-learners. This type of variable is of crucial importance in the clinic, where allocation of the type of therapeutic intervention could depend on variables measured during an initial assessment, or to help the therapist decide whether or not to continue the training protocol. This would also allow for the optimization of training by tailoring it to the individual, or by promoting a certain state in the participants. Variables that are empirically shown to be relevant could also contribute to and extend the mechanistic models of NFB learning.

Two systematic reviews have recently examined this issue (Kadosh & Staunton, 2019; Weber et al., 2020). Overall, “the most promising predictor seems to be the (neurophysiological) baseline activity, derived from the parameter targeted by the training” (Weber et al., 2020). Indeed, the amplitude of the signal measured during the resting state EEG or the first session seems to be a reliable predictor of an individual's ability to modulate this signal, in that the higher the level of baseline activity, the greater the modulation. This has been observed for the alpha (Su et al., 2021; Wan et al., 2014), sensorimotor rhythm (SMR, Blankertz et al., 2010; Li et al., 2021; Reichert et al., 2015; Weber et al., 2011) and low beta bands (12-15 Hz, Nan et al., 2015; Sho'ouri, 2021). Interestingly, although most of the cited studies aimed to increase the amplitude of the target signal during the resting state, one study (Nan et al., 2018) showed that a lower amplitude of the trained alpha frequency also predicted the ability to decrease it during NFB training. Apart from the effect of strategies and electrophysiological activity on neuromodulation, a systematic review pointed

out that working memory, mood, and motivation were variables that should be examined during NFB training (Kadosh & Staunton, 2019). However, the majority of studies concern other brain frequencies (e.g., slow cortical potentials, SMR), and the factors predicting the ability to modulate high alpha frequency have received little attention.

f. The present study

By focusing on the exploration phase of NFB learning, our primary goal was to study the impact of a list of strategies inspired by the literature on the ability to modulate high alpha activity. For this purpose, we compared the brain modulation of a group helped by a list of strategies to that of a group that did not receive any advice on strategies during NFB task instruction. Our hypothesis was that both groups would succeed in modulating their high alpha frequency (main effect of NFB training) during this first stage of NFB, and that providing a list of strategies would facilitate the modulation of individuals' brain activity (i.e., participants receiving the list would increase their high alpha amplitude more than participants who did not receive the list, interaction hypothesis). We also analyzed the impact of the strategies reported by learners and non-learners on the modulation of the high alpha amplitude (interaction hypothesis). Lastly, we investigated the effects of inter-individual factors in predicting success in high alpha NFB training. These predictors were cognitive (working memory performance), psychological (emotional state at the beginning of the session) and neurophysiological (brain activity at rest).

2. Method

a. Participants

We used G-Power (Faul et al., 2007) for the a-priori estimation of the sample size. The required sample size was calculated with the following parameters: Effect size f = .10, power level = .80, number of groups = 2, number of measures = 10, correlation between repeated measures = .50. This gave a total sample size estimate of 80 participants. Because we expected dropouts in our analysis (e.g., a poor EEG signal), 106 healthy participants (mainly students) were recruited at the University of [Blinded for review] through its learning platform and flyers. They were all naïve about the NFB technique. They were randomly assigned to one of two instruction formats: the group receiving a list of strategies (N = 53) or the group without a list (N = 53). Some participant data had to be discarded (15%) because of poor quality EEG data (e.g., more than 20% of the signal was removed after artifact rejection, N = 16), or incomplete data (e.g., technical problem, N = 5). The remaining 85 participants were thus divided into the Strategy List Group (N = 46, M_{age} = 22.33, SD = 5.62, 78% female) and the No List Group (N = 39, M_{age} = 23.28, SD = 5.96, 82% female). Each participant was tested in a single experimental session lasting approximately 120 minutes and received course credits for participation. Because of the SARS-CoV-2 pandemic, all experiments were conducted following a health protocol (e.g., use of masks, physical distancing except during electrode placement, cleaning and disinfecting of material). The study was carried out in accordance with the recommendations of local ethics guidelines and approved by the Ethics Committee of [Blinded for review] (N°IRB = 00012019-41). All participants gave written informed consent before their enrollment.

b. Procedure

Throughout the whole experiment the participants were seated comfortably in front of a computer screen. At the beginning of the experiment, they were informed of the main points of the study and gave their written consent to participate.

Before and after NFB training participants performed computerized working memory tasks (numerical span, N-Back, Corsi block) from the Psychology Experiment Building Language (PEBL, Mueller & Piper, 2014) and completed a short version of the Neurofeedback Evaluation & Training questionnaire (NExT; Bismuth et al., 2020; Jaumard-Hakoun et al., 2017; Pillette et al., 2021) which evaluates the participant's subjective state during the NFB protocol.

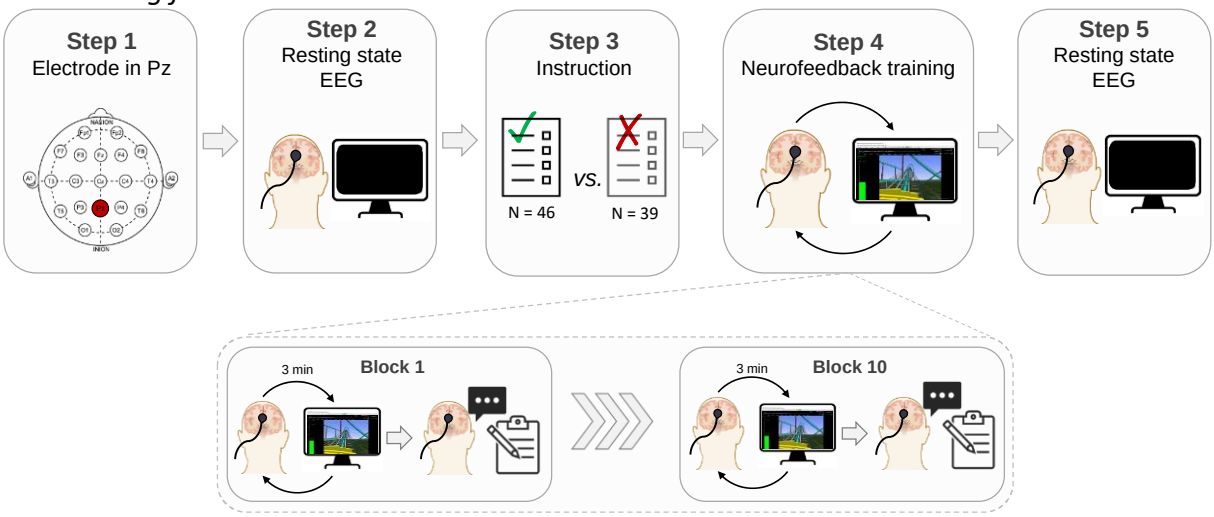
Because we did not have an active control group to distinguish between specific and nonspecific effects of training on changes in behavioral test performance, these analyses are not presented here. Only pre-training working memory task scores were used as a predictor of changes in high alpha amplitude during training.

The NFB training (see Figure 1) started by the experimenter measuring the dimensions of the participants' heads. Then a gel and a paste were applied to prepare the skin and amplify the signal obtained at each electrode. Once the correct impedance was obtained at each electrode, a first baseline was performed by recording the resting EEG for 3 minutes: participants were asked to stare at a black screen in front of them, to relax while keeping their eyes open and to avoid blinking, moving their body or contracting their jaw. Once the baseline was recorded and the high alpha amplitude was extracted, the threshold for receiving positive feedback was implemented for each individual. Participants were then

given the task instructions according to their assigned experimental group. They were all informed that the gauge displayed on the left side of the screen represented the amplitude of a specific brain frequency in real time. When the gauge exceeded the threshold (indicated by an orange bar), the animation on the screen (roller-coaster) was played, accompanied by pleasant music. Their goal was to maintain the level of this gauge as long and as often as possible. To achieve this, they could use the audio-visual information provided by the feedback to find a mental state that would allow them to move the car forward (both No list group and List group). In addition to these instructions, the List group was given a sheet of paper with 8 strategies from the literature that could help them to increase their high alpha amplitude (see 2.3.2 List of strategies during instruction). In the first few blocks, they were asked to try different strategies until they found one that worked for them. If a strategy seemed to work, they were advised to keep it and use it again in the following sessions. They were also allowed to try a different type of strategy than the ones listed on the sheet. It was recommended that they limit themselves to one type of strategy per session. Participants in both groups were informed that the training would consist of 10 blocks of 3 minutes, spaced by short breaks. At the end of each block, they were asked to verbally report the strategies they used to move the car forward and the experimenter recorded the verbatim. After the 10 blocks, the resting EEG was recorded again in front of a black screen. The electrodes were then removed, the participants' head was cleaned, and the participants completed the NExT questionnaire and the working memory tasks again.

Figure 1

NFB training flow chart



c. Materials

i. EEG recording and processing

The NFB system consisted of a ProComp T740M encoder connected to a laptop via a fiber optic cable and USB interface. The BioGraph Infiniti software (version 6.1, Thought Technology Ltd., Montreal, QC, Canada) was used to analyze and convert the signal into the audio-visual feedback. Because alpha is most stable in the parieto-occipital region (Alexeeva et al., 2012), a scalp electrode was placed at Pz in accordance with the International 10–20 system with the reference and ground electrode on the right and left earlobe, respectively. The signal was sampled at 256 Hz, band-pass filtered (from 0.1 to 60 Hz) and notch filtered

(50 Hz) to eliminate electrical interference. High alpha (10-12 Hz) amplitude was extracted online by the software and converted into audio-visual feedback. Other main frequency bands were recorded for offline analysis: delta (1-3 Hz), theta (4–7 Hz), low alpha (8–10 Hz), beta (13–35 Hz), and gamma (36-64 Hz) using Fast Fourier Transform (FFT). A gel (Nuprep Skin Prep Gel, Weaver and Company, Aurora, USA) was used to clean the skin before fixing the electrodes via a conductive paste (Ten20 Conductive Paste, Weaver and Company, Aurora, USA). Impedance was checked with an EEG-Z sensor and maintained below 10 kΩ. An automatic artefact rejection threshold was set to 100 µV before visual inspection of raw data and manual rejection of artifacts. Additional pre-processing or artefact correcting (e.g., ICA) were not made possible by the software. Feedback was provided audio-visually in the form of an animated car in a roller coaster, accompanied by a pleasant sound (Wang & Hsieh, 2013). The participant received positive visual (i.e., screen animation) and auditory (i.e., pleasant music) feedback when the amplitude of the high alpha exceeded a threshold that corresponded to 80% of the mean high alpha amplitude recorded during the first resting EEG (baseline 1).

ii. List of strategies during instruction

During the instructions given to participants at the beginning of NFB training, a list of strategies based on studies that previously trained SMR and alpha was proposed to one group of participants (Autenrieth et al., 2020; Esteves et al., 2021; Nan et al., 2012). As the systematic study of strategies used during an NFB task remains rare, we drew on strategies used in previous studies to test their effectiveness in the context of high alpha NFB training. The strategies proposed (*N* = 8) were the following: “Focus on the animation on the screen”, “Invent stories in your mind”, “Recall past experiences”, “Imagine yourself performing physical activities”, “Relax with breathing exercises”, “Think of natural environments”, “Think of entertainment (music, singing, movies)”, “Think about loved ones (friends, family)”.

iii. Strategy verbal report categorization

At the end of each training block, participants were asked to verbally report the strategy(ies) implemented to modulate their brain activity. These reported strategies were then categorized by two raters who worked blindly and independently of each other. All categories were pre-specified except for the category "Future thinking" which was added post hoc to consider the different types of mental time travel and distinguish between memories, imagination and future thinking (Schacter et al., 2012). The categories (*N* = 10) were as follows: Feedback (related to visual and auditory feedback), Imagination (imagines unreal events, scenes, situations), Memories (remembers past events), Future thinking (imagines future events), Cognitive (performs a task requiring cognitive effort such as mental calculation, course recall), Motor (imagines performing motor actions such as running, swimming), Relaxation (seeks to relax body and mind), Other (any type of strategy that does not fit into the above categories), Multiple (several strategies were used during the block), and No strategy (reports not using a specific strategy).

iv. Working memory tasks

All working memory tasks were implemented in the PEBL software (v.2.1; Mueller & Piper, 2014). PEBL is an open-source tool widely used to design and run behavioral tests. Three working memory tasks were presented in the following order: backward digit span (Wechsler, 1955), N-back with 1, 2 and 3-back condition (Owen et al., 2005) and backward Corsi block tapping task (Corsi, 1972). See Supplementary material for further information.

v. Psychological state

Participants completed a short version of the NExT questionnaire (Bismuth et al., 2020; Jaumard-Hakoun et al., 2017; Pillette et al., 2021) which evaluates a participant's subjective state during the biofeedback protocol with 5-point Likert scale items on five dimensions: mood ("calm", "energetic", "happy", "relaxed", "satisfied"), mindfulness ("receptive", "focused"), cognitive load, motivation, and agency ("feeling of control of feedback signal" and "predictability of feedback signal"). See Supplementary material for further information.

d. Statistical analyses

All statistical analyses were performed using R studio (v.4.0.2; R Core Team, 2020), with the lme4 (v.1.1-27.1; Bates et al., 2015) and *lmer* package (v. 3.1-3; Kuznetsova et al., 2017) for classic and mixed linear regression, the multcomp (v. 1.4-17; Hothorn et al., 2016) and modelbased (v. 0.8.0; Makowski et al., 2020a) package for post hoc contrasts, and report (v. 0.5.1; Makowski et al., 2020b) and ggplot2 (v. 3.3.6; Wickham, 2016) for formatting and visualizing results. A linear mixed-effect model was estimated using the Restricted Maximum Likelihood (RML) method and a classic linear regression model was estimated with the Ordinary Least Squares (OLS) method. We reported *p* values for the F test of type III ANOVA with degrees of freedom based on the Kenward-Roger approximation (Kenward & Roger, 1997; Luke, 2016) and partial eta-square (η_p^2) as effect size. When appropriate, Tukey contrasts for multiple comparisons with the Holm correction were applied (Bender & Lange, 2001) as post hoc comparisons. The significance level for all analyses was $\alpha = .05$. Analysis of the R script and raw data can be found online (https://osf.io/ebyqc/?view_only=de1a1837004749859eda4f86ff9313c7).

i. Training effect on high alpha amplitude

To evaluate the impact of the training on high alpha amplitude (in µV), we applied a linear mixed-effects regression on the interaction between two fixed effects: Instruction (between-subject fixed effect with two levels: List vs. No list) and NFB training (within-subject fixed effect with ten levels: Blocks 1 to 10). As we expected variance from intra-individual variations in brain frequency amplitude between blocks (which can neither be predicted nor controlled), we fitted a random intercept (1| participant) in the model.

ii. Training effect on high alpha amplitude at rest

To evaluate the impact of the training on high alpha amplitude at rest, we applied a linear mixed-effects regression on the interaction between two fixed effects: Instruction (between-subject fixed effect with two levels: List vs. No list) and Resting state (within-subject fixed effect with two levels: Pre- and Post-training). As we expected variance from

intra-individual variations in brain frequency amplitude between resting state recordings, we fitted a random intercept (1| participant).

iii. Effect of experimental manipulation on reported strategies

In order to evaluate the effect of our experimental manipulation on the strategies implemented by the participants, we applied a linear model on the interaction between two fixed effects: Instruction and Strategy (10 levels: Feedback, Imagination, Memories, Future thinking, Cognitive, Motor, Relaxation, Other, Multiple, No strategy).

iv. Effect of strategies used by learners on high alpha amplitude

To explore the effectiveness of the strategies employed during high alpha NFB training, we distinguished learners from non-learners. This distinction is used in the field of NFB to explore inter-individual differences in NFB training success (i.e., effective neuromodulation) during an NFB protocol. A common method used to discriminate learners from non-learners is to categorize them according to the slope of their evolution of the amplitude of the high alpha amplitude during the 10 blocks of training (e.g., Autenrieth et al., 2020; Domingos et al., 2021; Kober et al., 2017; Zoefel et al., 2011). A participant with a slope greater than 0 was categorized as a "learner", while a slope equal to or less than 0 was considered "non-learner". To test the effect of the strategies used during training on high alpha amplitude, we first applied classic linear regression to predict the frequency use of Strategy (10 levels: Feedback, Imagination, Memories, Future thinking, Cognitive, Motor, Relaxation, Other, Multiple, No strategy) by Learner (between-subject factor with two levels: Learner vs. Non-learner). We then applied classic linear regression to predict high alpha amplitude with Strategy and Learner as predictors.

v. Predictors of neurofeedback success

Individual performance in the NFB task was determined by computing the high alpha slope for each participant. To identify the predictors of NFB success we fitted a multiple linear regression with high alpha slope as the predicted variable and pre-training Working memory performance, pre-training Subjective state, High alpha amplitude during the first Resting-State and Instruction as predictor variables.

vi. Specificity of the training

To evaluate the specificity of the NFB training on the high alpha amplitude, we fitted multiple linear mixed-effects regression with delta, theta, low alpha, beta, and gamma amplitude during training blocks and resting state as outcome variables with two fixed effects (Instruction and NFB training blocks or Resting state) and participant as random effect (1| participant).

G*Power was used to calculate the power achieved by our study (post hoc analysis) given α, sample size and effect size. Using the software parameter estimate we converted the effect size obtained at our within-between interaction ($\eta_p^2 = 0.02$) to Cohen's f ($f = 0.14$). With an $\alpha = .05$, groups = 2, sample size = 85, number of measurements = 10, correlation between repeated measurements = .50, we obtained a power ($1 - \beta$) of 0.99.

3. Results

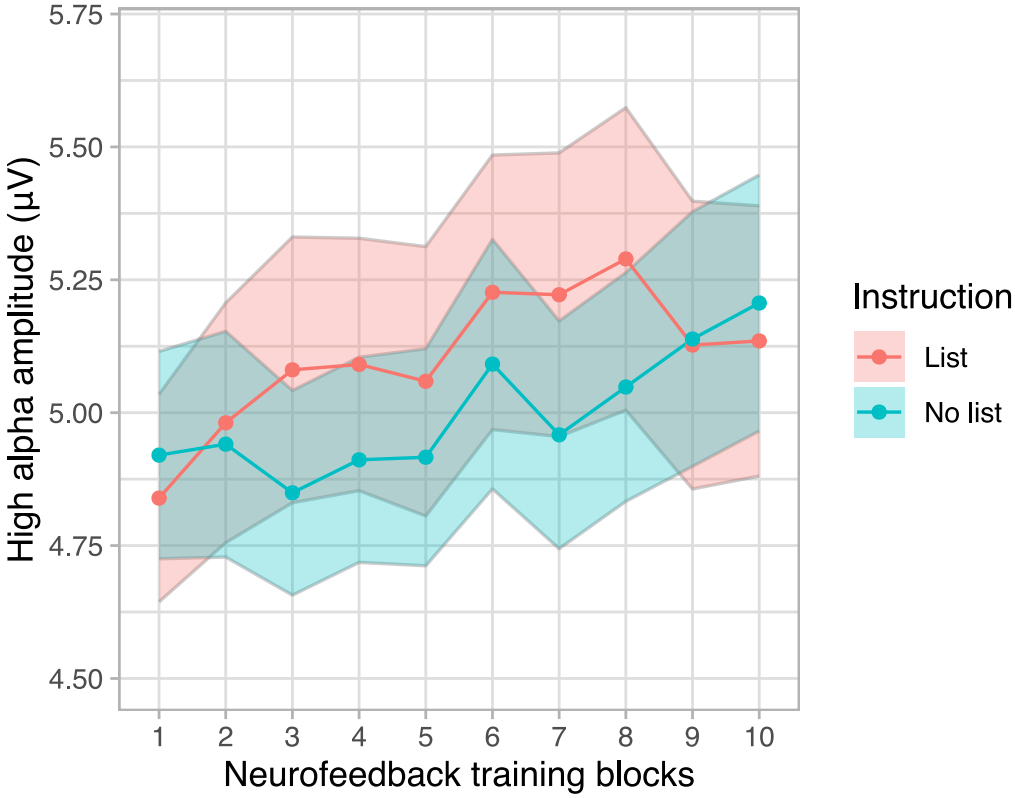
a. Neurofeedback performance

i. Effect of NFB training block on high alpha amplitude (Figure 2)

We fitted a linear mixed model to predict high alpha amplitude with Instruction and NFB training block as fixed effects and Participant as random effect. The ANOVA showed that the main effect of NFB training block was statistically significant and small ($F(9,747) = 3.36$, $p < .001$; $\eta_p^2 = 0.04$, 95% *CI* [0.01, 1.00]). The main effect of Instruction and the interaction between Instruction and NFB training block were statistically not significant ($p = .74$ and $p = .24$, respectively). Providing a list of strategies could accelerate learning to modulate high alpha activity. To test this hypothesis, an additional analysis was conducted to compare the evolution of high alpha over the first 5 blocks of training. No significant effects were observed (see Supplementary material, Section 2, page 4 for results of the analysis).

Figure 2

High alpha amplitude evolution during NFB training



Note. Line plot of mean high alpha amplitude (µV) by group List and No list during the 10 NFB training blocks. The shaded areas indicate standard error of the mean (SEM) of the mean.

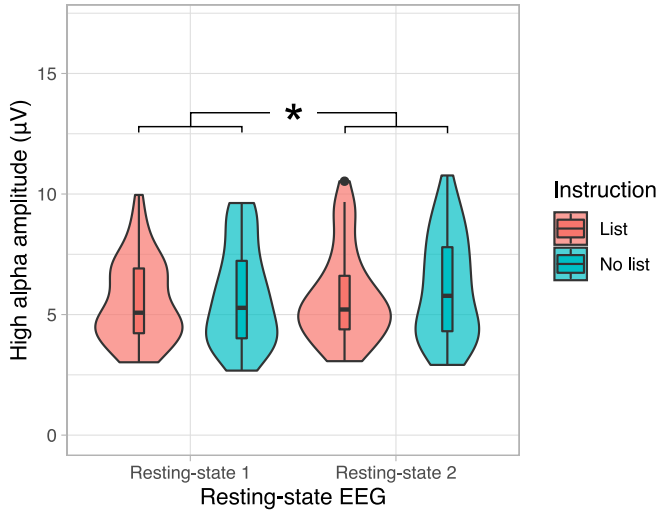
ii. Effect of NF training on high alpha amplitude at rest (Figure 3)

We fitted a linear mixed model to predict high alpha amplitude measured during post-training resting state EEG with Instruction and Resting state as fixed effects and Participant as random effect. The ANOVA indicated that the main effect of Resting state was

statistically significant and medium ($F(1, 83) = 10.88$, $p = .001$; $\eta_p^2 = 0.12$, 95% *CI* [0.03 - 1.00]), with a higher amplitude after training ($M = 5.88 \pm 2.00$) compared to before ($M = 5.63 \pm 1.84$). The main effect of Instruction and the interaction between Instruction and Resting state were statistically not significant ($p = .45$ and $p = .25$, respectively).

Figure 3

High alpha amplitude during resting-state EEG before and after NFB training



Note. Violin plot with integrated boxplot of high alpha amplitude (µV) by group List and No list during the pre- and post- NFB training resting state. Significant differences between the two resting states are depicted with $*p < .05$.

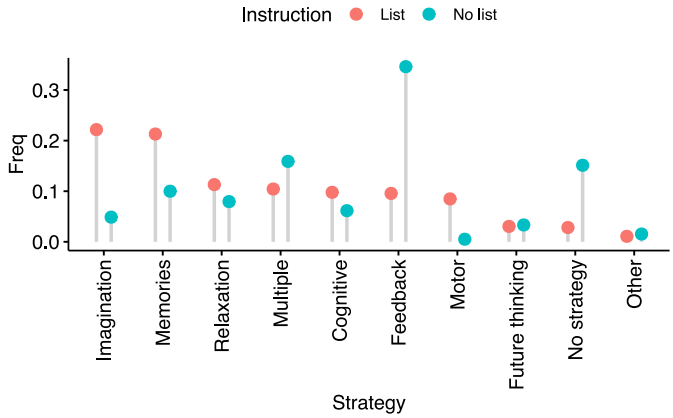
b. Strategies used during neurofeedback training

i. Effect of experimental manipulation on reported strategies (Figure 4)

We fitted a linear model to predict the frequency use of strategies with Instruction and Strategy as fixed effect. The ANOVA indicated that the main effect of Strategy was statistically significant and large ($F(9, 153) = 27.83$, $p < .001$; $\eta_p^2 = 0.62$, 95% *CI* [0.54, 1.00]), and the interaction between Strategy and Instruction was statistically significant and large ($F(9, 153) = 28.98$, $p < .001$; $\eta_p^2 = 0.63$, 95% *CI* [0.55, 1.00]). Post-hoc tests with the Holm correction applied on the interaction effect indicated that Imagination and Memories strategies type were more frequently used by participants of the List group ($\beta = 0.17$, $SEM = 0.02$, $p < .001$ and $\beta = 0.11$, $SEM = 0.02$, $p < .001$, respectively) whereas Feedback and No strategy were more used by participants from the No list group ($\beta = -0.24$, $SEM = 0.02$, $p < .001$ and $\beta = -0.12$, $SEM = 0.02$, $p < .001$). The main effect of Instruction was not significant ($p = .58$).

Figure 4

Frequency use of categories of strategies by participants of the experimental groups

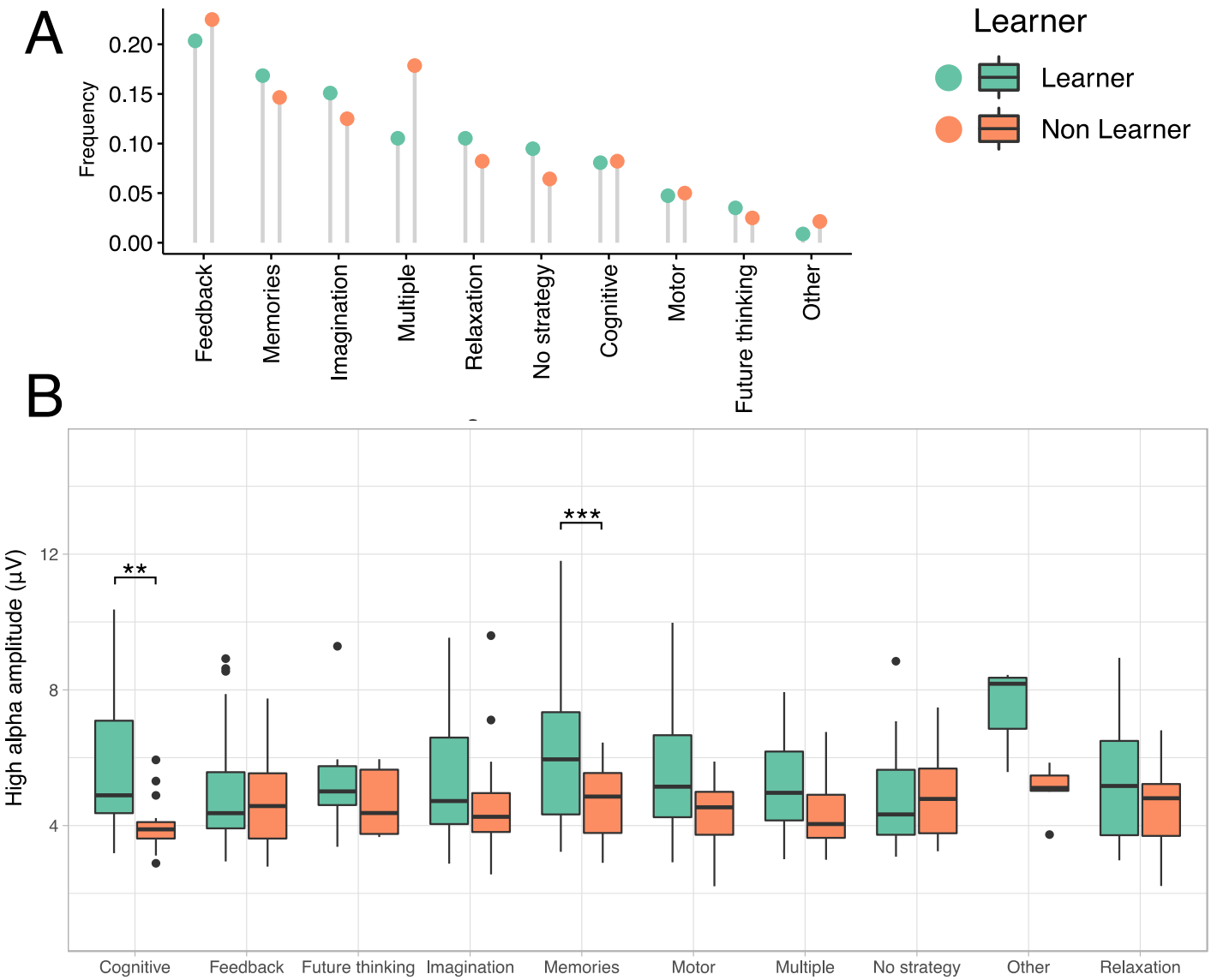


ii. Effect of strategies used by learners on high alpha amplitude

We classified the individuals as learners or non-learners according to their high alpha slope. The proportion of learners was not significantly different according to the experimental group (group List: 63% [N = 29/46]; group No list: 71% [N = 28/39], χ^2 [1, N = 85] = 0.73, p = .392). We fitted a linear model to predict the frequency use of strategies with Learner as fixed effect (Figure 5.A). The ANOVA suggested that the main effect of Strategy was statistically significant and large (F(9, 158) = 27.08, p < .001; η_p^2 = 0.61, 95% *CI* [0.52, 1.00]), and the interaction between Strategy and Learner was statistically significant and medium (F(9, 158) = 2.05, p = .038; η_p^2 = 0.10, 95% *CI* [0.003, 1.00]). Post-hoc tests with the Holm correction applied on the interaction effect indicated that there was no strategy used proportionally more in the Learner group than in the Non-learner group ("Multiple" strategy: p = .054). The main effect of Learner was statistically not significant (p = .30).
We then fitted a linear model to predict high alpha amplitude with Strategy and Learner as fixed effects (Figure 5.B). The ANOVA suggested that the main effect of Strategy was statistically significant and small (F(9, 830) = 4.54, p < .001; η_p^2 = 0.05, 95% *CI* [0.02, 1.00]), the main effect of Learner was statistically significant and small (F(1, 830) = 50.04, p < .001; η_p^2 = 0.06, 95% *CI* [0.03, 1.00]), and the interaction between Strategy and Learner was statistically significant and small (F(9, 830) = 3.38, p < .001; η_p^2 = 0.04, 95% *CI* [9.77e-03, 1.00]). Post-hoc tests with the Holm correction applied on the interaction effect indicated that the high alpha amplitudes associated with the strategies “Cognitive” and “Memories” were statistically higher in the Learner group than in the Non-learner group (“Cognitive” [β = 1.63, *SEM* = 0.37, p = .002] and “Memories” [β = 1.29, *SEM* = 0.27, p < .001]).

Figure 5

Strategies used by learners and non-learners



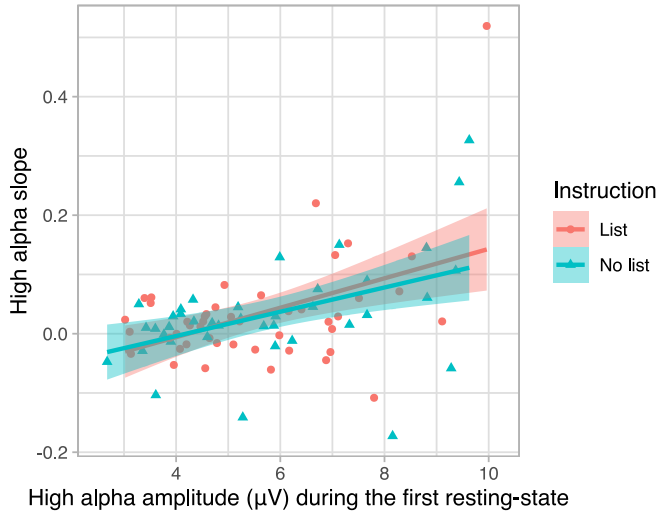
Note. A. Frequency use of categories of strategies by learners and non-learners. B. Box plot of high alpha amplitude (µV) associated with categories of strategies used by learners and non-learners during NFB training blocks. Significant differences between the two groups are depicted with $^{**}p < .01$ and $^{***}p < .001$.

c. Predictors of neurofeedback success

We fitted a multiple linear model to predict high alpha slope with Working memory tasks performance, Subjective state, High alpha amplitude during pre-training resting state EEG and Instruction. Result of the multiple linear regression indicated that the model explained a statistically significant proportion of variance ($R^2 = 0.30$, $F(14, 70) = 3.208$, $p = .023$, adjusted $R^2 = 0.16$). Only high alpha amplitude during the first resting-state was a significant predictor of high alpha slope during training ($\beta = 0.02$, $SEM = 0.01$, $t = 4.10$, $p < .001$ CI [0.01, 0.03], see Figure 6). Results for non-statistically significant predictors are presented in the Supplementary material (Section 2, table A1).

Figure 6

High alpha amplitude during the first resting-state predicts high alpha slope during NFB training



Note. High alpha slope corresponds to the slope of the evolution of the frequency amplitude across the 10 training blocks.

d. Effect of training on the amplitude of other frequencies.

i. Effect of training on the amplitude of other frequencies during training

We fitted multiple linear mixed models to predict delta, theta, low alpha, beta and gamma amplitude during training with Instruction and NFB training as fixed effects and Participant as random effect. The ANOVAs suggested that the main effect of NFB training was statistically significant for multiple frequencies: delta ($F(9, 747) = 2.15$, $p = .024$; $\eta_p^2 = 0.03$, 95% *CI* [1.69e-03, 1.00]); low alpha ($F(9, 747) = 2.74$, $p = .004$; $\eta_p^2 = 0.03$, 95% *CI* [5.93e-03, 1.00]); beta ($F(9, 747) = 2.60$, $p = .006$; $\eta_p^2 = 0.03$, 95% *CI* [4.86e-03, 1.00]) and gamma ($F(9, 747) = 10.37$, $p < .001$; $\eta_p^2 = 0.11$, 95% *CI* [0.07, 1.00]). Except for the low alpha frequency, NFB training resulted in a reduction in the mean amplitude of these frequencies during the training blocks. Other main effects and interactions were statistically not significant (see Supplementary material for exact *p*-values).

ii. Effect of training on the amplitude of other frequencies during resting EEG

We fitted a linear mixed model to predict delta, theta, low alpha, beta and gamma amplitude during resting EEG with Instruction and Resting state as fixed effects and Participant as random effect. The ANOVAs indicated that the main effect of NFB training was statistically significant and small on the low alpha frequency ($F(1) = 5.04$, $p = .027$; $\eta_p^2 = 0.06$, 95% *CI* [3.47e-03, 1.00]), with a higher amplitude after training ($M = 6.74 \pm 3.14$) compared to before ($M = 6.47 \pm 2.84$). Other main effects and interactions were statistically not significant (see Supplementary material for exact *p*-values).

4. Discussion

The main objective of this study was to better understand the factors that promote success in NFB training. As the high alpha amplitude is one of the most widely trained frequencies to improve cognitive processes in healthy individuals, we were interested in the factors predicting a high alpha neuromodulation ability. In this study, we investigated whether giving individuals strategies would help them to modulate their high alpha amplitude during a single NFB training session (i.e., during the exploration phase of NFB training). Some studies have investigated the types of strategies used by participants during NFB training, but none have experimentally tested the effect of strategies given during instruction on neuromodulation ability. To evaluate the effect of this training, we analyzed the evolution of the amplitude of the whole frequency spectrum during training and during resting state before and after training. We also analyzed the effect of the strategies reported by learners and non-learners on their brain activity and tried to identify factors (psychological, cognitive, or electrophysiological) able to predict the success of the NFB task (i.e., the increase in the amplitude of the frequency targeted by the training). We observed that globally giving a list of different strategies did not improve the capacity to neuromodulate high alpha activity. However, according to our examination of the specific strategies reported by learners throughout training blocks, cognitive effort and recalling memories were associated with higher high alpha amplitude, suggesting that these two strategies may be the most effective. Our results also replicated the statistical relationship between electrophysiological activity during the resting state and changes in high alpha amplitude during training. Finally, an analysis of the entire EEG spectrum indicated that the training resulted in an increase in low and high alpha amplitude and a decrease in the amplitude of delta, beta and gamma frequencies. These different results will be discussed below.

a. Effects of strategies on neuromodulation

We analyzed the effect of the strategies in two parts. First, we compared the neuromodulation of the high alpha amplitude according to the experimental group (i.e., according to whether the individual received a list of strategies during the instructions or not). Second, we examined the differences in strategy use between learners and non-learners and compared the mean amplitude of the high alpha amplitude associated with the type of strategy reported by the learners and non-learners during training.

The first question in this research was to evaluate the interest of giving a list of strategies in high alpha NFB training. It was hypothesized that participants with a list of strategies would be helped to modulate their high alpha amplitude compared to a group without such a list. Contrary to expectations, the list provided to the participants did not promote the ability to neuromodulate high alpha activity. This lack of difference could be due to the strategies suggested on the list, which were perhaps too numerous or not relevant. As numerous strategies were proposed, participants were inclined to try several of them. The use of multiple strategies during training may have reduced the implementation of an efficient strategy in favor of less relevant strategies. For example, focusing on the display of visual feedback may have desynchronized the high alpha amplitude. Ros et al. (2013) found that in order to decrease their alpha frequency amplitude, the majority of individuals reported focusing their visual attention. Among the strategies proposed on the list, focusing on the feedback display may have been counterproductive. As participants in the "No-List" group

received a single instruction, their high alpha amplitude may have been reduced by the fact that they were in a more stable and focused mental state than participants in the "List" group. Indeed, participants in the No-List group reported a narrower range of strategies than those in the List group. However, additional analysis focusing on the first five blocks (1-5) did not indicate a significant difference between the two groups (included in Supplementary Material, Section 2, page 4).

On the other hand, we observed a distinct effect of the strategies on high alpha amplitude, indicating that strategies may play a role in neuromodulation and that this process is not totally implicit (Muñoz-Moldes & Cleeremans, 2020). Specifically, although our analyses found that learners and non-learners did not differ in frequency of strategy use, the high alpha amplitude associated with the different categories of strategies indicated that some strategies had a different impact on electrophysiological activity. Our analyses revealed a difference between learners and non-learners in the mean high alpha amplitude associated with the "Cognitive" and "Memories" strategies. A possible explanation could be that learners mobilize different cognitive processes from those mobilized by non-learners during these two strategies. What cognitive processes distinguish them, however, remains difficult to determine because of the multiple associations between alpha frequency and cognition. Alpha frequency is involved in perceptual decision making (Samaha et al., 2020), in working memory (de Vries et al., 2020; Riddle et al., 2020; van Ede, 2018; Wianda & Ross, 2019), in spatial (Foster & Awh, 2019) and visual attention (Clayton et al., 2018; Peylo et al., 2021) and in mind-wadering (Compton et al., 2019). These multiple implications represent a "many-to-many" relation, where one neurophysiological phenomenon is associated with several distinct cognitive processes (Cacioppo & Tassinary, 1990). In this situation, the psychophysiological inference (i.e., the association between a mental state and a neural state) can be very complex (Cacioppo et al., 2007; Fairclough, 2009). High alpha frequency has shown divergent associations with cognitive processes, with decreases (Chikhi et al., 2022) or increases (Pavlov & Kotchoubey, 2022) in amplitude associated with cognitive load. It is generally observed that alpha amplitude decreases when attention is turned outward, especially via visual attention, whereas amplitude increases when attention is turned inward (Cooper et al., 2003; Magosso et al., 2019; Wang et al., 2016). Recent work has suggested that memory recall corresponds to the latter case (Logan et al., 2021). Posterior high alpha may provide protection of memory representations against interference via cortical inhibition of the region involved in processing external stimuli (Wianda & Ross, 2019). What distinguished learners from non-learners in the present study could be the implementation of a more vivid reinstatement of information during memory recall, with a more inward attention. A potential confound in our results is that in the “Cognitive” strategy classification, we included tasks that require cognitive resources. This may include the strategy of recalling academic courses. This task, which may be cognitively demanding, can also be assimilated to the category “Memories”, or at least involve similar processes of inhibition of external stimuli. Our results suggest that there is not a quantitative difference in the frequency of the strategy used but a qualitative difference in its implementation. However, classifying strategies into 10 categories may lack the sensitivity to understand the different cognitive processes involved in NFB training.

To better understand the relevance of the strategies in high alpha training, several methods could help to better understand the mental state of learners in the application of their strategies. At the methodological level, we could refine the analysis of the strategies by creating sub-categories. For example, we distinguished between different types of mental

time travel using 3 distinct categories during classification (i.e., “Memory, Imagination and Future thinking” categories), but we did not evaluate the valence and emotional intensity associated with these mental representations. The study by Nan et al. (2012) observed that participants found strategies involving positive emotions to be more effective than those involving negative emotions such as anger. Thus, it may be important to study the content of this type of strategy, by examining the valence and emotional intensity of activated memories (Kensinger & Ford, 2020).

Another difficulty in studying the strategies used during NFB is that this procedure relies on the introspective ability of participants. The latter are faced with what the field of reinforcement learning calls the credit assignment problem: they must determine the degree to which a particular mental state contributes to the magnitude of the feedback signal (Minski, 1961). This ability to discriminate one's internal states during the NFB task may rely on meta-cognitive processes that we did not evaluate here (Craig et al., 2020). Further research to better understand the involvement of meta-cognitive processes in the learning process of NFB could be valuable. This could be done, for example, by applying an alpha level discrimination task at the beginning of training (Frederick, 2012) to study whether good discrimination performance predicts neuromodulation ability.

Although it seems impossible to have real-time information about the particular mental state of individuals, a phenomenological analysis would allow for a more in-depth study of the content of participants’ mental states during NFB training (Varela, 2006). Inspired by the explicitation interview (Vermersch, 2009), micro-phenomenology aims to enable the identification and description of the microdynamics of participants' singular subjective experience (Petitmengin et al., 2019). In this kind of interview, non-suggestive questions are asked to draw the participant's attention to the different moments of his experience and the “mental actions” he took during the training (Petitmengin et al., 2019). The aim of this interview, which is much more in-depth than our qualitative analysis, could provide a better understanding of the course of the mental phenomena that took place during the NFB training. Although it has not yet been widely used in the field of NFB (Bagdasaryan & Quyen, 2013), this methodological tool could be relevant for a better understanding of the role of strategies in NFB training.

An arguable weakness of our study is the arbitrariness in our classification of mental strategies. Although we based the classification on existing studies (Autenrieth et al., 2020; Naas et al., 2019), the choice of these categories and the way those reported mental activities were categorized may have been influenced by cultural biases, limiting the relevance of our study to a WEIRD context (Western, Educated, Industrialized, Rich, and Democratic cultures, Henrich et al., 2010.

b. Predictor variables of neuromodulation

Beyond strategies, we also analyzed the ability of pre-training measures to predict task success. For this purpose, we attempted to predict the capacity of neuromodulation (i.e., slope of high alpha amplitude evolution) by different variables measured before training: cognitive (working memory performance), psychological (mental state measured by questionnaire) and electrophysiological (resting state EEG). Of all the predictors examined, high alpha amplitude at rest seems to be particularly important in accounting for neuromodulation capacity. Specifically, we found that individuals with higher high alpha amplitude during the pre-training resting state increased their amplitude the most. This

finding supports the work of other alpha NFB training studies linking resting state EEG with neuromodulation success and extends it to the high alpha frequency (Su et al., 2021; Nan et al., 2018; Wan et al., 2014). As discussed by previous authors (Su et al., 2021; Wan et al., 2014), this association could be explained by the cortical inhibitory role of the alpha frequency (Klimesch et al., 2007). A high level of alpha amplitude may lead to better inhibition of task-irrelevant information, thereby facilitating neuromodulation. However, a note of caution is due here since this explanation is unable to explain how lower alpha amplitude at rest could predict the neuromodulation success of alpha down-regulation training (Nan et al., 2018). Nor does this neurocognitive explanation apply to other frequencies where a similar relationship between resting state amplitude and neuromodulation success has been observed (e.g., SMR, Reichert et al., 2015; beta, Sho'ouri, 2021). Further work is required to establish the validity of resting state EEG as a decisive criterion for the inclusion of individuals in NFB training. In future investigations, it may be possible to better understand the relationship between resting state EEG and neuromodulation capacity by using a neurostimulation technique such as transcranial alternating current stimulation (tACS) on the trained frequency just before NFB training (Orendáčová & Kvašňák, 2021). The application of tACS allows the increase of endogenous neurophysiological activity by rhythmic stimulation (Liu et al., 2018; Zaghi et al., 2010). For instance, an increase in alpha amplitude was observed following the application of tACS compared to pre-stimulation (Herrmann et al., 2013), and this immediately (Zaehle et al., 2010; Neuling et al., 2012), 30 minutes (Neuling et al., 2013) or 70 minutes (Kasten et al., 2016) after tACS application. By modulating the alpha activity at rest, one could evaluate the causal role of the resting amplitude in the ability to neuromodulate this frequency by NFB.

c. Effect of the training on the amplitude of EEG frequencies.

Finally, in accordance with previous studies (Escolano et al., 2012, 2014; Hanslmayr et al., 2005), our results confirmed the trainability of high alpha amplitude in the parietal area during only one training session. However, analysis of other frequencies showed that training also increased the amplitude of the low alpha frequency while decreasing the amplitudes of delta, beta, and gamma frequencies. An interesting point of this non-specificity is that the only amplitude that increases is the alpha frequency. This increase in amplitude during training could have impacted the amplitude of other frequencies due to the "cross-frequency coupling" mechanism (Canolty & Knight, 2010; Klimesch, 2018). This mechanism of inter-relation between brain frequencies has been well documented for alpha and gamma frequencies, with a decrease in alpha amplitude leading to an increase in gamma amplitude (Osipova et al., 2008; Hinault et al., 2020). According to the “gating by inhibition” hypothesis (Jensen & Mazaheri, 2010), functional activation of a brain region could occur in part through a top-down mechanism of cortical disinhibition caused by a decrease in alpha frequency leading to an increase in gamma frequency. The increase in the amplitude of the alpha frequency during training could thus explain the decrease in amplitude of the other main frequencies (i.e., delta, beta and gamma). However, our data do not enable us to evaluate this explanation, which remains speculative and must be thoroughly tested in future research.

Surprisingly, although the amplitude of other frequencies decreased during training (delta, beta and gamma), only the amplitude of alpha frequencies (low and high) changed significantly during the post-training resting state. These results corroborate the findings of

previous studies that have demonstrated that alpha NFB training has an impact on resting state EEG (Alexeeva et al., 2012; Dekker et al., 2014; Dempster & Vernon, 2009; Escolano et al., 2011) and confirm the effect of NFB on brain activity after only one session (Ros et al., 2010; Ros et al., 2013). However, because the low alpha frequency was also significantly increased, we cannot state that our training had a completely specific effect on resting EEG activity. Although the use of individualized frequencies (i.e., an adapted alpha frequency range using alpha peak frequency, Bazanova & Vernon, 2014) is not necessary to observe alpha modulation by NFB (Belinskaia et al., 2020), it is possible that the lack of specificity between low and high alpha is due to the use of the standard frequency range (i.e., 10-12 Hz) in our training. However, the lack of specificity between lower and higher alpha frequency was also observed after individualized high alpha frequency training (Escolano et al., 2011). This lack of specificity was present in the passive baseline, but disappeared in the active baseline (i.e., counting the color change of a displayed square). Thus, it is possible that this specificity can only be observed during a cognitive task.

Our results highlight the importance of considering other frequencies when analyzing the effects of NFB training on brain activity and cognitive performance. For example, among the studies that evaluated modulation during a session, some did not report any analysis of changes in other frequency bands (Hanslmayr et al., 2005), so the specificity of the training is uncertain. The cognitive improvement observed after training should therefore be interpreted with caution as it may be partly attributed to modulation of other frequency bands (Hanslmayr et al., 2005). Some studies evaluating high alpha NFB training effects on other frequencies did observe a specificity of the training with an increase in high alpha amplitude without significant modulation of the low alpha and beta1 frequencies (Escolano et al., 2012; Escolano et al., 2014; Zoefel et al., 2011). However, those studies only looked at adjacent frequencies (i.e., low alpha and beta1). Our results suggest that non-adjacent frequencies can be modulated too (e.g., delta, gamma) and confirm that it is therefore important to consider the entire EEG spectrum in analyses of the electrophysiological and behavioral effects of NFB training (Ros et al., 2020). As proposed by Pimenta and colleagues (2018), training might become specific only after several training sessions. According to the multistage model (Davelaard, 2018), it may be necessary to wait until the exploration phase transitions to the consolidation process to specifically modulate the target frequency. This could explain the specificity observed by Zoefel et al., 2011, who compared the amplitude of low alpha, high alpha, and beta1 frequencies between the first baseline and the last training block of the fifth and final session. Longer term protocols studying the whole frequency spectrum should make it possible to study more precisely if this specification phenomenon occurs progressively.

5. Conclusion

This study contributes to recent investigations concerning the factors favoring success in a NFB task. The aim of the present research was to determine whether providing a list of strategies during instruction would facilitate neuromodulation during NF training. The study has shown that high alpha amplitude can be enhanced during a single session of NFB training, but that the proposed list of strategies did not improve neuromodulation ability. “Cognitive” and “Memory” strategies seem to distinguish learners and non-learners in the implementation of these strategies. This difference could arise from how learners implemented these strategies. For example, the amplitude of alpha appeared to be

modulated by whether attention was external or internal, which decreased or increased its amplitude, respectively (Magosso et al., 2019). Thus, non-learners would have maintained external attention while implementing the "Cognitive" or "Recall of Memory" strategies, whereas learners would have implemented these strategies with greater internal attention and inhibition of irrelevant external information (Klimesch, 2007). Thus, a successful strategy for modulating alpha frequency might be to learn to inhibit information from the external world. However, further investigation of the content of these mental strategies is needed to understand where this difference in effect comes from. More research will be needed to study the effect of this type of strategy over several sessions and whether these strategies allow greater brain plasticity. Also, experimental studies manipulating the resting state EEG amplitude prior to NFB training could provide insight into the relationship between resting activity and neuromodulation ability. Finally, these findings illustrated the need for analyzing the whole EEG spectrum when evaluating NFB training.

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References

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

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

Angelakis, E., Stathopoulou, S., Frymiare, J. L., Green, D. L., Lubar, J. F., & Kounios, J. (2007). EEG neurofeedback: a brief overview and an example of peak alpha frequency training for cognitive enhancement in the elderly. *The clinical neuropsychologist*, *21*(1), 110-129.

Autenrieth, M., Kober, S. E., Neuper, C., & Wood, G. (2020). How much do strategy reports tell about the outcomes of neurofeedback training? A study on the voluntary up-regulation of the sensorimotor rhythm. *Frontiers in Human Neuroscience*, *14*, 218.

Bagdasaryan, J., & Le Van Quyen, M. (2013). Experiencing your brain: neurofeedback as a new bridge between neuroscience and phenomenology. *Frontiers in human neuroscience*, *7*, 680.

Bates, D., Kliegl, R., Vasishth, S., & Baayen, H. (2015). Parsimonious mixed models. *arXiv preprint arXiv:1506.04967*.

Bazanova, O. M., & Aftanas, L. I. (2010). Individual EEG alpha activity analysis for enhancement neurofeedback efficiency: two case studies. *Journal of Neurotherapy*, *14*(3), 244-253.

Bazanova, O. M., Balioz, N. V., Muravleva, K. B., & Skoraya, M. V. (2013). Effect of voluntary EEG α power increase training on heart rate variability. *Human Physiology*, *39*(1), 86-97.

Bazanova, O. M., & Vernon, D. (2014). Interpreting EEG alpha activity. *Neuroscience & Biobehavioral Reviews*, *44*, 94-110.

Belinskaia, A., Smetanin, N., Lebedev, M., & Ossadtchi, A. (2020). Short-delay neurofeedback facilitates training of the parietal alpha rhythm. *Journal of Neural Engineering*, *17*(6), 066012.

Bender, R., & Lange, S. (2001). Adjusting for multiple testing—when and how?. *Journal of clinical epidemiology*, *54*(4), 343-349.

Benwell, C. S., London, R. E., Tagliabue, C. F., Veniero, D., Gross, J., Keitel, C., & Thut, G. (2019). Frequency and power of human alpha oscillations drift systematically with time-on-task. *Neuroimage*, *192*, 101-114.

Berger, A. M., & Davelaar, E. J. (2018). Frontal alpha oscillations and attentional control: a virtual reality neurofeedback study. *Neuroscience*, *378*, 189-197.

Birbaumer, N., Ruiz, S., & Sitaram, R. (2013). Learned regulation of brain metabolism. *Trends in cognitive sciences*, *17*(6), 295-302.

Bismuth, J., Vialatte, F., & Lefaucheur, J. P. (2020). Relieving peripheral neuropathic pain by increasing the power-ratio of low-β over high-β activities in the central cortical region with EEG-based neurofeedback: Study protocol for a controlled pilot trial (SMRPain study). *Neurophysiologie Clinique*, *50*(1), 5-20.

Biswas, A., & Ray, S. (2019). Alpha neurofeedback has a positive effect for participants who are unable to sustain their alpha activity. *ENeuro*, *6*(4).

Blankertz, B., Sannelli, C., Halder, S., Hammer, E. M., Kübler, A., Müller, K. R., ... & Dickhaus, T. (2010). Neurophysiological predictor of SMR-based BCI performance. *Neuroimage*, *51*(4), 1303-1309.

Bobby, J. S., & Prakash, S. (2017). Upper alpha neurofeedback training enhances working memory performance using LabVIEW. *International Journal of Biomedical Engineering and Technology*, *25*(2-4), 120-132.

Brickwedde, M., Krüger, M. C., & Dinse, H. R. (2019). Somatosensory alpha oscillations gate perceptual learning efficiency. *Nature communications*, *10*(1), 1-9.

Bucho, T., Caetano, G., Vourvopoulos, A., Accoto, F., Esteves, I., i Badia, S. B., ... & Figueiredo, P. (2019, July). Comparison of Visual and Auditory Modalities for Upper-Alpha EEG-Neurofeedback. In *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 5960-5966). IEEE.

Buzsaki, G., & Draguhn, A. (2004). Neuronal oscillations in cortical networks. *Science*, *304*(5679), 1926-1929.

Buzsáki, G., Anastassiou, C. A., & Koch, C. (2012). The origin of extracellular fields and currents—EEG, ECoG, LFP and spikes. *Nature reviews neuroscience*, *13*(6), 407-420.

Cacioppo, J. T., & Tassinary, L. G. (1990). Inferring psychological significance from physiological signals. *American psychologist*, *45*(1), 16.

Cacioppo, J. T., Tassinary, L. G., & Berntson, G. (Eds.). (2007). *Handbook of psychophysiology*. Cambridge university press.

Canolty, R. T., & Knight, R. T. (2010). The functional role of cross-frequency coupling. *Trends in cognitive sciences*, *14*(11), 506-515.

Chaudhary, U., Birbaumer, N., & Ramos-Murguialday, A. (2016). Brain–computer interfaces for communication and rehabilitation. *Nature Reviews Neurology*, *12*(9), 513-525.

Chiang, A. K. I., Rennie, C. J., Robinson, P. A., Roberts, J. A., Rigozzi, M. K., Whitehouse, R. W., ... & Gordon, E. (2008). Automated characterization of multiple alpha peaks in multi-site electroencephalograms. *Journal of Neuroscience Methods*, *168*(2), 396-411.

Chiang, A. K. I., Rennie, C. J., Robinson, P. A., Van Albada, S. J., & Kerr, C. C. (2011). Age trends and sex differences of alpha rhythms including split alpha peaks. *Clinical Neurophysiology*, *122*(8), 1505-1517.

Chikhi, S., Matton, N., & Blanchet, S. (2022). EEG power spectral measures of cognitive workload: A meta-analysis. *Psychophysiology*, *59*(6), e14009.

Cho, M. K., Jang, H. S., Jeong, S. H., Jang, I. S., Choi, B. J., & Lee, M. G. T. (2008). Alpha neurofeedback improves the maintaining ability of alpha activity. *Neuroreport*, *19*(3), 315-317.

Chow, T., Javan, T., Ros, T., & Frewen, P. (2017). EEG dynamics of mindfulness meditation versus alpha neurofeedback: a sham-controlled study. *Mindfulness*, *8*(3), 572-584.

Clayton, M. S., Yeung, N., & Cohen Kadosh, R. (2018). The many characters of visual alpha oscillations. *European Journal of Neuroscience*, *48*(7), 2498-2508.

Cohen, M. X. (2017). Where does EEG come from and what does it mean?. *Trends in neurosciences*, *40*(4), 208-218.

Compton, R. J., Gearinger, D., & Wild, H. (2019). The wandering mind oscillates: EEG alpha power is enhanced during moments of mind-wandering. *Cognitive, Affective, & Behavioral Neuroscience*, *19*(5), 1184-1191.

Cooper, N. R., Croft, R. J., Dominey, S. J., Burgess, A. P., & Gruzelier, J. H. (2003). Paradox lost? Exploring the role of alpha oscillations during externally vs. internally directed attention and the implications for idling and inhibition hypotheses. *International journal of psychophysiology*, *47*(1), 65-74.

Corcoran, A. W., Alday, P. M., Schlesewsky, M., & Bornkessel-Schlesewsky, I. (2018). Toward a reliable, automated method of individual alpha frequency (IAF) quantification. *Psychophysiology*, *55*(7), e13064.

Corsi, P.M. (1972). Human memory and the medial temporal region of the brain. *Dissertation Abstracts International*, 34 (02), 891B. (University Microfilms No. AAI05-77717).

Craig, K., Hale, D., Grainger, C., & Stewart, M. E. (2020). Evaluating metacognitive self-reports: systematic reviews of the value of self-report in metacognitive research. *Metacognition and Learning*, *15*(2), 155-213.

Davelaar, E. J. (2018). Mechanisms of neurofeedback: a computation-theoretic approach. *Neuroscience*, *378*, 175-188.

Dehghanpour, P., Farokhi, F., & Rostami, R. (2018). Improvement of working memory performance by parietal upper alpha neurofeedback training. *International Journal of Smart Electrical Engineering*, *7*(02), 77-81.

Dekker, M. K., Sitskoorn, M. M., Denissen, A. J., & van Boxtel, G. J. (2014). The time-course of alpha neurofeedback training effects in healthy participants. *Biological psychology*, *95*, 70-73.

Dempster, T., & Vernon, D. (2009). Identifying indices of learning for alpha neurofeedback training. *Applied psychophysiology and biofeedback*, *34*(4), 309-318.

de Vries, I. E., Slagter, H. A., & Olivers, C. N. (2020). Oscillatory control over representational states in working memory. *Trends in cognitive sciences*, *24*(2), 150-162.

Domingos, C., Peralta, M., Prazeres, P., Nan, W., Rosa, A., & Pereira, J. G. (2021). Session Frequency Matters in Neurofeedback Training of Athletes. *Applied Psychophysiology and Biofeedback*, *46*(2), 195-204.

Dunn, T. G., Gillig, S. E., Ponsor, S. E., Weil, N., & Utz, S. W. (1986). The learning process in biofeedback: is it feed-forward or feedback?. *Biofeedback and self-regulation*, *11*(2), 143-156.

Enriquez-Geppert, S., Huster, R. J., & Herrmann, C. S. (2017). EEG-neurofeedback as a tool to modulate cognition and behavior: a review tutorial. *Frontiers in human neuroscience*, *11*, 51.

Escolano, C., Aguilar, M., & Minguez, J. (2011, August). EEG-based upper alpha neurofeedback training improves working memory performance. In *2011 annual international conference of the IEEE engineering in medicine and biology society* (pp. 2327-2330). IEEE.

Escolano, C., Oliván, B., Lopez-del-Hoyo, Y., Garcia-Campayo, J., & Minguez, J. (2012, January). Double-blind single-session neurofeedback training in upper-alpha for cognitive enhancement of healthy subjects. In *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 4643-4647). IEEE.

Escolano, C., Navarro-Gil, M., Garcia-Campayo, J., & Minguez, J. (2014). The effects of a single session of upper alpha neurofeedback for cognitive enhancement: a sham-controlled study. *Applied psychophysiology and biofeedback*, *39*(3), 227-236.

Esteves, I., Nan, W., Alves, C., Calapez, A., Melício, F., & Rosa, A. (2021). An exploratory study of training intensity in EEG neurofeedback. *Neural plasticity*, *2021*.

Fairclough, S. H. (2009). Fundamentals of physiological computing. Interacting with computers, 21(1-2), 133-145.

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, *39*(2), 175-191.

Foster, J. J., & Awh, E. (2019). The role of alpha oscillations in spatial attention: limited evidence for a suppression account. *Current opinion in psychology*, *29*, 34-40.

Frederick, J. A. (2012). Psychophysics of EEG alpha state discrimination. *Consciousness and cognition*, *21*(3), 1345-1354.

Fries, P. (2015). Rhythms for cognition: communication through coherence. *Neuron*, *88*(1), 220-235.

Gökşin, B., Yılmaz, B., & İçöz, K. (2019). Improving short-term memory performance of healthy young males using alpha band neurofeedback. *NeuroRegulation*, *6*(1), 15-15.

Goljahani, A., D'Avanzo, C., Schiff, S., Amodio, P., Bisiacchi, P., & Sparacino, G. (2012). A novel method for the determination of the EEG individual alpha frequency. *NeuroImage*, *60*(1), 774-786.

Gordon, S., Todder, D., Deutsch, I., Garbi, D., Alkobi, O., Shriki, O., ... & Meiran, N. (2020). Effects of neurofeedback and working memory-combined training on executive functions in healthy young adults. *Psychological Research*, *84*(6), 1586-1609.

Grosselin, F., Breton, A., Yahia-Cherif, L., Wang, X., Spinelli, G., Hugueville, L., ... & George, N. (2021). Alpha activity neuromodulation induced by individual alpha-based neurofeedback learning in ecological context: a double-blind randomized study. *Scientific reports*, *11*(1), 1-15.

Gruzelier, J. H. (2014). EEG-neurofeedback for optimising performance. I: A review of cognitive and affective outcome in healthy participants. *Neuroscience & Biobehavioral Reviews*, *44*, 124-141.

Guez, J., Rogel, A., Getter, N., Keha, E., Cohen, T., Amor, T., ... & Todder, D. (2015). Influence of electroencephalography neurofeedback training on episodic memory: A randomized, sham-controlled, double-blind study. *Memory*, *23*(5), 683-694.

Haegens, S., Cousijn, H., Wallis, G., Harrison, P. J., & Nobre, A. C. (2014). Inter-and intra-individual variability in alpha peak frequency. *Neuroimage*, *92*, 46-55.

Hammer, E. M., Halder, S., Blankertz, B., Sannelli, C., Dickhaus, T., Kleih, S., ... & Kübler, A. (2012). Psychological predictors of SMR-BCI performance. *Biological psychology*, *89*(1), 80-86.

Hanslmayr, S., Sauseng, P., Doppelmayr, M., Schabus, M., & Klimesch, W. (2005). Increasing individual upper alpha power by neurofeedback improves cognitive performance in human subjects. *Applied psychophysiology and biofeedback*, *30*(1), 1-10.

Haugg, A., Sladky, R., Skouras, S., McDonald, A., Craddock, C., Kirschner, M., ... & Scharnowski, F. (2020). Can we predict real-time fMRI neurofeedback learning success from pretraining brain activity?. *Human brain mapping*, *41*(14), 3839-3854.

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world?. *Behavioral and brain sciences*, *33*(2-3), 61-83.

Herrmann, C. S., Rach, S., Neuling, T., & Strüber, D. (2013). Transcranial alternating current stimulation: a review of the underlying mechanisms and modulation of cognitive processes. *Frontiers in human neuroscience*, *7*, 279.

Hinault, T., Kraut, M., Bakker, A., Dagher, A., & Courtney, S. M. (2020). Disrupted neural synchrony mediates the relationship between white matter integrity and cognitive performance in older adults. *Cerebral Cortex*, *30*(10), 5570-5582.

Hothorn, T., Bretz, F., Westfall, P., Heiberger, R. M., Schuetzenmeister, A., Scheibe, S., & Hothorn, M. T. (2016). Package 'multcomp'. *Simultaneous inference in general parametric models. Project for Statistical Computing, Vienna, Austria*.

Hsueh, J. J., Chen, T. S., Chen, J. J., & Shaw, F. Z. (2016). Neurofeedback training of EEG alpha rhythm enhances episodic and working memory. *Human brain mapping*, *37*(7), 2662-2675.

Jaumard-Hakoun, A., Chikhi, S., Medani, T., Nair, A., Dreyfus, G., & Vialatte, F. B. (2017). An apparatus to investigate western opera singing skill learning using performance and result biofeedback, and measuring its neural correlates. *Psychology*, *55*, 102-111.

Jensen, O., & Mazaheri, A. (2010). Shaping functional architecture by oscillatory alpha activity: gating by inhibition. *Frontiers in human neuroscience*, *4*, 186.

Jeunet, C., Lotte, F., Batail, J. M., Philip, P., & Franchi, J. A. M. (2018). Using recent BCI literature to deepen our understanding of clinical neurofeedback: a short review. *Neuroscience*, *378*, 225-233.

Kadosh, K. C., & Staunton, G. (2019). A systematic review of the psychological factors that influence neurofeedback learning outcomes. *Neuroimage*, *185*, 545-555.

Kamiya, J. (1968). Conscious control of brain waves. *Psychology Today* 1, 56–60.

Kasten, F. H., Dowsett, J., & Herrmann, C. S. (2016). Sustained aftereffect of α-tACS lasts up to 70 min after stimulation. *Frontiers in human neuroscience*, *10*, 245.

Kensinger, E. A., & Ford, J. H. (2020). Retrieval of Emotional Events from Memory. *Annual Review of Psychology*, *71*, 251-272.

Kenward, M. G., & Roger, J. H. (1997). Small sample inference for fixed effects from restricted maximum likelihood. *Biometrics*, 983-997.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain research reviews*, *29*(2-3), 169-195.

Klimesch, W., Sauseng, P., & Hanslmayr, S. (2007). EEG alpha oscillations: the inhibition–timing hypothesis. *Brain research reviews*, *53*(1), 63-88.

Klimesch, W. (2018). The frequency architecture of brain and brain body oscillations: an analysis. *European Journal of Neuroscience*, *48*(7), 2431-2453.

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in cognitive sciences*, *16*(12), 606-617.

Kober, S. E., Witte, M., Neuper, C., & Wood, G. (2017). Specific or nonspecific? Evaluation of band, baseline, and cognitive specificity of sensorimotor rhythm-and gamma-based neurofeedback. *International Journal of Psychophysiology*, *120*, 1-13.

Koralek, A. C., Jin, X., Long II, J. D., Costa, R. M., & Carmena, J. M. (2012). Corticostriatal plasticity is necessary for learning intentional neuroprosthetic skills. *Nature*, *483*(7389), 331-335.

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. (2017). lmerTest package: tests in linear mixed effects models. *Journal of statistical software*, *82*, 1-26.

Lacroix, J. M. (1986). Mechanisms of biofeedback control. In *Consciousness and Self-regulation* (pp. 137-162). Springer, Boston, MA.

Lee, Y. J., Kim, H. G., Cheon, E. J., Kim, K., Choi, J. H., Kim, J. Y., ... & Koo, B. H. (2019). The analysis of electroencephalography changes before and after a single neurofeedback alpha/theta training session in university students. *Applied Psychophysiology and Biofeedback*, *44*(3), 173-184.

Li, L., Wang, Y., Zeng, Y., Hou, S., Huang, G., Zhang, L., ... & Zhang, Z. (2021). Multimodal Neuroimaging Predictors of Learning Performance of Sensorimotor Rhythm Up-Regulation Neurofeedback. *Frontiers in neuroscience*, 896.

Liu, A., Vöröslakos, M., Kronberg, G., Henin, S., Krause, M. R., Huang, Y., ... & Buzsáki, G. (2018). Immediate neurophysiological effects of transcranial electrical stimulation. *Nature communications*, *9*(1), 1-12.

Logan, G. D., Cox, G. E., Annis, J., & Lindsey, D. R. (2021). The episodic flanker effect: Memory retrieval as attention turned inward. *Psychological Review*, *128*(3), 397.

Luke, S. G. (2017). Evaluating significance in linear mixed-effects models in R. *Behavior research methods*, *49*(4), 1494-1502.

Magosso, E., De Crescenzio, F., Ricci, G., Piastra, S., & Ursino, M. (2019). EEG alpha power is modulated by attentional changes during cognitive tasks and virtual reality immersion. *Computational intelligence and neuroscience*, *2019*.

Makowski, D., Lüdecke, D., & Ben-Shachar, M. S. (2020a). Modelbased: Estimation of model-based predictions, contrasts and means. *R package version 0.3.0*. CRAN. Available from https://github.com/easystats/modelbased.

Makowski, D., Ben-Shachar, M.S., Patil, I. & Lüdecke, D. (2020b). Automated Results Reporting as a Practical Tool to Improve Reproducibility and Methodological Best Practices Adoption. CRAN. Available from https://github.com/easystats/report.

Marzbani, H., Marateb, H. R., & Mansourian, M. (2016). Neurofeedback: a comprehensive review on system design, methodology and clinical applications. *Basic and clinical neuroscience*, *7*(2), 143.

Minsky, M. (1961). Steps toward artificial intelligence. *Proceedings of the IRE*, *49*(1), 8-30.

Mueller, S. T., & Piper, B. J. (2014). The psychology experiment building language (PEBL) and PEBL test battery. *Journal of neuroscience methods*, *222*, 250-259.

Mulholland, T. (1977). Biofeedback as scientific method. *Biofeedback: Theory and research*, 9-28.

Muñoz-Moldes, S., & Cleeremans, A. (2020). Delineating implicit and explicit processes in neurofeedback learning. *Neuroscience & Biobehavioral Reviews*, *118*, 681-688.

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

Nan, W., Rodrigues, J. P., Ma, J., Qu, X., Wan, F., Mak, P. I., ... & Rosa, A. (2012). Individual alpha neurofeedback training effect on short term memory. *International journal of psychophysiology*, *86*(1), 83-87.

Nan, W., Wan, F., Lou, C. I., Vai, M. I., & Rosa, A. (2013). Peripheral visual performance enhancement by neurofeedback training. *Applied psychophysiology and biofeedback*, *38*(4), 285-291.

Nan, W., Wan, F., Tang, Q., Wong, C. M., Wang, B., & Rosa, A. (2018). Eyes-closed resting EEG predicts the learning of alpha down-regulation in neurofeedback training. *Frontiers in psychology*, *9*, 1607.

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

Nan, W., Yang, L., Wan, F., Zhu, F., & Hu, Y. (2020). Alpha down-regulation neurofeedback training effects on implicit motor learning and consolidation. *Journal of neural engineering*, *17*(2), 026014.

Navarro Gil, M., Escolano Marco, C., Montero-Marín, J., Minguez Zafra, J., Shonin, E., & García Campayo, J. (2018). Efficacy of neurofeedback on the increase of mindfulness-related capacities in healthy individuals: a controlled trial. *Mindfulness*, *9*(1), 303-311.

Nawaz, R., Nisar, H., Yap, V. V., & Tsai, C. Y. (2022). The Effect of Alpha Neurofeedback Training on Cognitive Performance in Healthy Adults. *Mathematics*, *10*(7), 1095.

Neuling, T., Rach, S., & Herrmann, C. S. (2013). Orchestrating neuronal networks: sustained after-effects of transcranial alternating current stimulation depend upon brain states. *Frontiers in human neuroscience*, *7*, 161.

Neuling, T., Rach, S., Wagner, S., Wolters, C. H., & Herrmann, C. S. (2012). Good vibrations: oscillatory phase shapes perception. *Neuroimage*, *63*(2), 771-778.

Niv, S. (2013). Clinical efficacy and potential mechanisms of neurofeedback. *Personality and Individual Differences*, *54*(6), 676-686.

Nowlis, D. P., & Kamiya, J. (1970). The control of electroencephalographic alpha rhythms through auditory feedback and the associated mental activity. *Psychophysiology*, *6*(4), 476-484.

Orendáčová, M., & Kvašňák, E. (2021). Effects of transcranial alternating current stimulation and neurofeedback on alpha (EEG) dynamics: a review. *Frontiers in Human Neuroscience*, *15*.

Osipova, D., Hermes, D., & Jensen, O. (2008). Gamma power is phase-locked to posterior alpha activity. *PloS one*, *3*(12), e3990.

Owen, A. M., McMillan, K. M., Laird, A. R., & Bullmore, E. (2005). N-back working memory paradigm: A meta-analysis of normative functional neuroimaging studies. *Human brain mapping*, *25*(1), 46-59.

Pavlov, Y. G., & Kotchoubey, B. (2022). Oscillatory brain activity and maintenance of verbal and visual working memory: A systematic review. *Psychophysiology*, *59*(5), e13735.

Peeters, F., Ronner, J., Bodar, L., van Os, J., & Lousberg, R. (2014). Validation of a neurofeedback paradigm: manipulating frontal EEG alpha-activity and its impact on mood. *International Journal of Psychophysiology*, *93*(1), 116-120.

Peng, W., Zhan, Y., Jiang, Y., Nan, W., Kadosh, R. C., & Wan, F. (2020). Individual variation in alpha neurofeedback training efficacy predicts pain modulation. *NeuroImage: Clinical*, *28*, 102454.

Petitmengin, C., Van Beek, M., Bitbol, M., Nissou, J. M., & Roepstorff, A. (2019). Studying the experience of meditation through micro-phenomenology. *Current opinion in psychology*, *28*, 54-59.

Peylo, C., Hilla, Y., & Sauseng, P. (2021). Cause or consequence? Alpha oscillations in visuospatial attention. *Trends in Neurosciences*, *44*(9), 705-713.

Pfurtscheller, G., Stancak Jr, A., & Neuper, C. (1996). Event-related synchronization (ERS) in the alpha band—an electrophysiological correlate of cortical idling: a review. *International journal of psychophysiology*, *24*(1-2), 39-46.

Pillette, L., Roc, A., N'Kaoua, B., & Lotte, F. (2021). Experimenters' influence on mental-imagery based brain-computer interface user training. *International Journal of Human-Computer Studies*, *149*, 102603.

Pimenta, M. G., van Run, C., de Fockert, J. W., & Gruzelier, J. H. (2018). Neurofeedback of SMR and beta1 frequencies: an investigation of learning indices and frequency-specific effects. *Neuroscience*, *378*, 211-224.

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

Riddle, J., Scimeca, J. M., Cellier, D., Dhanani, S., & D'Esposito, M. (2020). Causal evidence for a role of theta and alpha oscillations in the control of working memory. *Current Biology*, *30*(9), 1748-1754.

Ros, T., J. Baars, B., Lanius, R. A., & Vuilleumier, P. (2014). Tuning pathological brain oscillations with neurofeedback: a systems neuroscience framework. *Frontiers in human neuroscience*, *8*, 1008.

Ros, T., Enriquez-Geppert, S., Zotev, V., Young, K. D., Wood, G., Whitfield-Gabrieli, S., ... & Thibault, R. T. (2020). Consensus on the reporting and experimental design of clinical and cognitive-behavioural neurofeedback studies (CRED-nf checklist).

Ros, T., Munneke, M. A., Ruge, D., Gruzelier, J. H., & Rothwell, J. C. (2010). Endogenous control of waking brain rhythms induces neuroplasticity in humans. *European Journal of Neuroscience*, *31*(4), 770-778.

Ros, T., Théberge, J., Frewen, P. A., Kluetsch, R., Densmore, M., Calhoun, V. D., & Lanius, R. A. (2013). Mind over chatter: plastic up-regulation of the fMRI salience network directly after EEG neurofeedback. *Neuroimage*, *65*, 324-335.

Sakurai, Y., & Song, K. (2016). Neural operant conditioning as a core mechanism of brain-machine interface control. *Technologies*, *4*(3), 26.

Samaha, J., Iemi, L., Haegens, S., & Busch, N. A. (2020). Spontaneous brain oscillations and perceptual decision-making. *Trends in cognitive sciences*, *24*(8), 639-653.

Schacter, D. L., Addis, D. R., Hassabis, D., Martin, V. C., Spreng, R. N., & Szpunar, K. K. (2012). The future of memory: remembering, imagining, and the brain. *Neuron*, *76*(4), 677-694.

Schad, D. J., Vasishth, S., Hohenstein, S., & Kliegl, R. (2020). How to capitalize on a priori contrasts in linear (mixed) models: A tutorial. *Journal of Memory and Language*, *110*, 104038.

Sherlin, L. H., Arns, M., Lubar, J., Heinrich, H., Kerson, C., Strehl, U., & Sterman, M. B. (2011). Neurofeedback and basic learning theory: implications for research and practice. *Journal of Neurotherapy*, *15*(4), 292-304.

Shibata, K., Lisi, G., Cortese, A., Watanabe, T., Sasaki, Y., & Kawato, M. (2019). Toward a comprehensive understanding of the neural mechanisms of decoded neurofeedback. *NeuroImage*, *188*, 539-556.

Sho'ouri, N. (2021). Predicting the success rate of healthy participants in beta neurofeedback: Determining the factors affecting the success rate of individuals. *Biomedical Signal Processing and Control*, *69*, 102753.

Sitaram, R., Ros, T., Stoeckel, L., Haller, S., Scharnowski, F., Lewis-Peacock, J., ... & Sulzer, J. (2017). Closed-loop brain training: the science of neurofeedback. *Nature Reviews Neuroscience*, *18*(2), 86-100.

Sterman, M. B., Wyrwicka, W., & Roth, S. (1969). Electrophysiological correlates and neural substrates of alimentary behavior in the cat. *Annals of the New York Academy of Sciences*.

Su, K. H., Hsueh, J. J., Chen, T., & Shaw, F. Z. (2021). Validation of eyes-closed resting alpha amplitude predicting neurofeedback learning of upregulation alpha activity. *Scientific reports*, *11*(1), 1-9.

Takabatake, K., Kunii, N., Nakatomi, H., Shimada, S., Yanai, K., Takasago, M., & Saito, N. (2021). Musical Auditory Alpha Wave Neurofeedback: Validation and Cognitive Perspectives. *Applied Psychophysiology and Biofeedback*, *46*(4), 323-334.

Team, R. C. (2020). R: A language and environment for statistical computing (Version 4.0. 2). *R Foundation for Statistical Computing*.

Thibault, R. T., Lifshitz, M., & Raz, A. (2016). The self-regulating brain and neurofeedback: experimental science and clinical promise. *Cortex*, *74*, 247-261.

Thibault, R. T., MacPherson, A., Lifshitz, M., Roth, R. R., & Raz, A. (2018). Neurofeedback with fMRI: A critical systematic review. *Neuroimage*, *172*, 786-807.

Uhlhaas, P., Pipa, G., Lima, B., Melloni, L., Neuenschwander, S., Nikolić, D., & Singer, W. (2009). Neural synchrony in cortical networks: history, concept and current status. *Frontiers in integrative neuroscience*, *3*, 17.

Utz, S. W. (1994). The effect of instructions on cognitive strategies and performance in biofeedback. *Journal of behavioral medicine*, *17*(3), 291-308.

Van Diepen, R. M., Foxe, J. J., & Mazaheri, A. (2019). The functional role of alpha-band activity in attentional processing: the current zeitgeist and future outlook. *Current opinion in psychology*, *29*, 229-238.

van Ede, F. (2018). Mnemonic and attentional roles for states of attenuated alpha oscillations in perceptual working memory: a review. *European Journal of Neuroscience*, *48*(7), 2509-2515.

Varela, F. J. (1996). Neurophenomenology: A methodological remedy for the hard problem. *Journal of consciousness studies*, *3*(4), 330-349.

Vermersch, P. (2009). Describing the practice of introspection. *Journal of consciousness studies*, *16*(10-11), 20-57.

Vernon, D., Dempster, T., Bazanova, O., Rutterford, N., Pasqualini, M., & Andersen, S. (2009). Alpha neurofeedback training for performance enhancement: reviewing the methodology. *Journal of neurotherapy*, *13*(4), 214-227.

Wan, F., Nan, W., Vai, M. I., & Rosa, A. (2014). Resting alpha activity predicts learning ability in alpha neurofeedback. *Frontiers in human neuroscience*, *8*, 500.

Wang, C., Rajagovindan, R., Han, S. M., & Ding, M. (2016). Top-down control of visual alpha oscillations: sources of control signals and their mechanisms of action. *Frontiers in human neuroscience*, *10*, 15.

Wang, J. R., & Hsieh, S. (2013). Neurofeedback training improves attention and working memory performance. *Clinical Neurophysiology*, *124*(12), 2406-2420.

Watanabe, T., Sasaki, Y., Shibata, K., & Kawato, M. (2017). Advances in fMRI real-time neurofeedback. *Trends in cognitive sciences*, *21*(12), 997-1010.

Weber, E., Köberl, A., Frank, S., & Doppelmayr, M. (2011). Predicting successful learning of SMR neurofeedback in healthy participants: methodological considerations. *Applied Psychophysiology and Biofeedback*, *36*(1), 37-45.

Weber, L. A., Ethofer, T., & Ehlis, A. C. (2020). Predictors of neurofeedback training outcome: A systematic review. *NeuroImage: Clinical*, *27*, 102301.

Wechsler, D. (1955). Wechsler adult intelligence scale. *Archives of Clinical Neuropsychology*.

Wei, T. Y., Chang, D. W., Liu, Y. D., Liu, C. W., Young, C. P., Liang, S. F., & Shaw, F. Z. (2017). Portable wireless neurofeedback system of EEG alpha rhythm enhances memory. *Biomedical engineering online*, *16*(1), 1-18.

Wianda, E., & Ross, B. (2019). The roles of alpha oscillation in working memory retention. *Brain and behavior*, *9*(4), e01263.

Wickham, H. (2016). Data analysis. In *ggplot2* (pp. 189-201). Springer, Cham.

Yeh, W. H., Hsueh, J. J., & Shaw, F. Z. (2021). Neurofeedback of alpha activity on memory in healthy participants: a systematic review and meta-analysis. *Frontiers in Human Neuroscience*, *14*, 562360.

Zaehle, T., Rach, S., & Herrmann, C. S. (2010). Transcranial alternating current stimulation enhances individual alpha activity in human EEG. *PloS one*, *5*(11), e13766.

Zaghi, S., Acar, M., Hultgren, B., Boggio, P. S., & Fregni, F. (2010). Noninvasive brain stimulation with low-intensity electrical currents: putative mechanisms of action for direct and alternating current stimulation. *The Neuroscientist*, *16*(3), 285-307.

Zoefel, B., Huster, R. J., & Herrmann, C. S. (2011). Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance. *Neuroimage*, *54*(2), 1427-1431.