Hjärnvågor, andning och robotar: En omvärdering av feedback i meditationsträning

Brainwaves, Breath and Robots: Rethinking Feedback in Meditation Training

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Meditation has seen a surge in recent years among secular cultures as a tool to improve quality of life through improved emotional regulation, though novice practitioners tend to struggle attaining meditative states. Neurofeedback is a technology that can offer real-time data on meditative states and thus be integrated with artificial meditation guides, embodied and disembodied alike. This thesis sought to investigate whether an embodied meditation guide in the form of the socially assisted robot Epi, or a disembodied voice-only guide, both informed by real-time neurofeedback differ in efficacy as compared against each other or no feedback at all. Electroencephalogram (EEG) measures of the alpha/theta (α/θ) ratio and its stability throughout the meditation phase were analyzed alongside self-reports of focus and relaxation. Contrary to the primary hypotheses, no significant differences were observed between the conditions. Notably, the no-feedback group displayed more stable neural activity, suggesting that auditory prompts may interfere with the attentional demands of meditation. Epi's embodied presence conferred no measurable effect over the disembodied voice. These findings indicate that real-time auditory neurofeedback may not be a reliable aid for novice meditators and that the benefits of embodiment do not appear to extend to introspective tasks. This thesis contributes to clarifying the limits of neurofeedback and embodiment within the context of contemplative practice.

1 Introduction

The practice of meditation has seen a uprise in popularity, moving from a primarily spiritual discipline to a widespread secular tool for fostering good health and well-being (Engström et al., 2022). A body of research supports this trend by demonstrating measurable benefits across psychological and cognitive domains. In the psychological domain, meditation has been shown to successfully reduce stress (Pascoe et al., 2017) and promote general well-being (Evans et al., 2018). From a cognitive standpoint, research has highlighted enhancements in attention (Eberth & Sedlmeier, 2012) and other executive functions (Crescentini et al., 2017).

This connection between practice and psychological benefit is based on evidence that contemplative training can induce measurable changes in the central nervous system, including brain structure and function (Fox & Cahn, 2018; Young et al., 2018). In a randomized controlled trial, it was shown that mindfulness meditation training facilitated more effective emotion regulation and stress resilience by altering the brain's functional connectivity, specifically by coupling the default mode network with regulatory areas of the prefrontal cortex (Creswell et al., 2016). Such findings, establish that dedicated mental training can alter key neural networks, creating opportunities for inquiries into how this process might be supported and accelerated.

The Novice's Dilemma and the Feedback Gap

While these results promote the positive potential of a dedicated practice, the path from novice to expert is often challenging. For beginners, the foundational technique of Focused Attention (FA) meditation, which involves voluntarily focusing on a chosen object like the breath, presents a major hurdle (Lutz et al., 2008). The primary challenge is the mind's natural tendency toward mind-wandering and distraction. Consequently, the reduction of mind-wandering is often considered a key behavioral marker of successful practice (Crescentini et al., 2017). For those new to the practice, the constant cycle of focusing attention, realizing the mind has wandered, and gently returning focus to the breath requires significant mental effort. This difficulty often leads new practitioners to discontinue practice before experiencing long-term benefits (Brandmeyer & Delorme, 2018). One factor contributing to this difficulty might be the absence of feedback, a component central to the acquisition of most other skills. Feedback is one of the most impactful influences on learning and achievement, serving as the information that allows a learner to reduce the discrepancy between their current performance and a desired goal (Timperley & Hattie, 2007). In most domains, acquiring expertise involves a form of "deliberate practice", which requires not only effort but also immediate, informative feedback that provides knowledge of results. Without this information, learning is inefficient and improvement is minimal, even for highly motivated individuals (Ericsson et al., 1993). Meditation, being a purely internal and subjective process, inherently lacks this external feedback loop. A novice practitioner often cannot with certainty know if they are in a state of focused attention or lost in thought (Eberth & Sedlmeier, 2012). This "feedback gap" contributes directly to the frustration that leads to attrition, and it reveals an opportunity where technology might offer a unique form of guidance.

A Possible Solution

It is precisely this feedback gap that modern technology, specifically neurofeedback, aims to bridge. Neurofeedback is a psycho-physiological procedure where a person is provided with real-time feedback of their own neural activation for the purpose of learning self-regulation (Piron, 2022). By measuring brain activity and presenting it back to the individual, neurofeedback creates a closed-loop system that allows a person to learn control over specific brain states (Sitaram et al., 2017). For a novice meditator, this process can convert the invisible, internal state of "focus" or "distraction" into a tangible, external signal, providing knowledge of the meditator's state of mind and aiding in effective learning.

The potential of this approach has been amplified by the increasing availability of consumer-grade neurotechnology. Although the scientific precision of such devices is debated, with limitations noted outside laboratory conditions (Przegalinska et al., 2018), their accessibility allows guided practice to be studied in real-world contexts. Research has shown that with adequate filtering and under controlled conditions, such devices can be used effectively (Abujelala et al., 2016). This thesis employs such a technology, determining how it can be used within an empirical framework to provide meaningful insights. Additionally, the position taken here is that the medium through which feedback is delivered is not a trivial detail but a critical, and under-explored, variable. The central inquiry is grounded in principles from Socially Assistive Robotics (SAR), where the physical presence, or embodiment, of a robot has been shown to have a measurable effect on human perception and performance (Tapus et al., 2007; Wainer et al., 2006). This raises the question of whether these principles apply within a contemplative context. Therefore, the central question addressed is: can a physically present robotic guide enhance a meditator's ability to regulate their brain state more effectively than a disembodied voice?

To address this question, an experiment was designed to systematically examine the effects of different guidance modalities on meditation, employing a between-subjects design, evaluating differences in meditative states across three conditions: feedback from an embodied robotic guide, feedback from a disembodied auditory guide, and a no-feedback control condition. These differences were assessed using both neurophysiological and subjective measures. Neurophysiologically, states of focus and distraction were quantified using electroencephalography (EEG) data, specifically the ratio of alpha to theta brainwave power. Subjectively, participants' experiences of focus, relaxation, and overall session quality were collected via a post-session questionnaire. By comparing these conditions, this thesis aims to contribute to a better understanding of the role of embodiment in designing effective technological aids for contemplative practice.

2 Background

Meditation can be understood not as a single practice, but as a family of complex emotional and attentional regulatory training regimes designed to cultivate specific mental skills (Lutz et al., 2008; Tang et al., 2015). These practices are often categorized into two main styles. Focused Attention (FA), which entails voluntarily focusing on a chosen object like the breath, and Open Monitoring (OM), which involves non-reactive awareness of any experience that arises (Lutz et al., 2008). The two practices can also be seen as two different forms of cognitive control, FA having a top-down style, contrasting to the OM's bottom-up style (Crescentini et al., 2017). This distinction is supported by neuroimaging literature, which shows that different training styles can produce distinct neural signatures (Engström et al., 2022). For instance, long-term practitioners of compassion meditation can self-induce high-amplitude gamma-band oscillations, a state associated with integrative awareness (Lutz et al., 2004). Because this thesis investigates the foundational skill of maintaining focus amidst distraction, it concentrates on FA meditation. The practice of FA is defined by three core components: the cultivation of sustained, focused attention, the challenge of overcoming mind-wandering, and a non-judgmental attitude when returning focus to the breath (Engström et al., 2022).

This challenge calls attention to the need for effective guidance and support mechanisms to help individuals develop their meditative skills to overcome the initial barriers. EEG is often a preferred method of choice used to study the neural correlates of these attentional states. EEG is a noninvasive technique that records the electrical activity generated by the cerebral cortex by attaching electrodes to the scalp. This recorded activity is not the firing of single neurons, but rather the summed postsynaptic potentials of large populations of neurons, which create a potential field strong enough to be detected on the scalp (Marcuse et al., 2016). The resulting complex signal is typically analyzed by decomposing it into its constituent frequency bands each associated with different cognitive states (Marcuse et al., 2016). These frequencies, measured in Hertz (Hz), represent the speed of the rhythmic, oscillatory electrical activity, or 'brainwaves'; a frequency band is simply a standardized range of these speeds. While there are five principal bands (delta, theta, alpha, beta, and gamma) this thesis is primarily concerned with the alpha and theta bands. This focus is intentional, as their dynamic relationship serves as an established neural marker for the central challenge in FA meditation: maintaining focus amidst distraction (Engström et al., 2022; Katyal & Goldin, 2021; Marcuse et al., 2016). The strength of these brainwaves is quantified by measuring their 'power,' a calculation performed using Power Spectral Density (PSD) analysis, a method that calculates how the total power of the signal is distributed across different frequency bands (Phanikrishna, 2023).

The alpha rhythm (8 to <13 Hz) is historically one of the most significant, first identified by Hans Berger in 1929 (Marcuse et al., 2016). It is most prominent in the posterior regions of the head in relaxed, awake adults with their eyes closed, a state often referred to as the posterior dominant rhythm (PDR) (Sugimoto et al., 2024; Marcuse et al., 2016). In contrast, the theta rhythm (4 to <8 Hz) is also present in a normal waking adult but is particularly associated with states of drowsiness (Strijkstra et al., 2003). The opposing nature of these two frequency bands in the context of meditative practice makes them suitable for analysis.

The Alpha/Theta Ratio as a Marker for Meditative State

While analyzing bands independently is informative, their relationship is particularly revealing. A study by Katyal and Goldin (2021) investigated the roles of these oscillations by correlating them with self-reported levels of meditation depth, revealing a functional dissociation between the two. Their core finding was that alpha and theta activity were related to meditation progress in a precisely opposite manner. Theta activity was positively correlated with meditative 'hindrances' like distraction and was increasingly suppressed during deeper meditative states. Conversely, alpha activity was negatively correlated with these hindrances and increased as participants reported deeper levels of meditation. This inverse relationship suggests that increased alpha power reflects the suppression of distracting information, while decreased theta power reflects a reduced need for executive cognitive control (Sugimoto et al., 2024). The interpretation of theta activity as a marker for distraction or lack of focus is further supported by research on sleepiness. Further supporting this, a study by Strijkstra et al. (2003) on sleep-deprived individuals found a strong positive correlation between theta power and subjective ratings of sleepiness, particularly in the frontal and central areas of the scalp. Given this opposing dynamic, the ratio of alpha power to theta power emerges as a robust, single metric to quantify the quality of a meditative state (Katyal & Goldin, 2021; Rodriguez-Larios et al., 2020; Sugimoto et al., 2024). A higher alpha/theta (α/θ) ratio is therefore is signifies of a more desirable state of focused, internalized attention.

Beyond the power of the ratio itself, the stability of brainwave patterns over time is a meaningful indicator of cognitive control. While a healthy, awake EEG is typically characterized by a high degree of variability, a controlled and temporary reduction in this variability can represent a state of heightened attentional stability (Lutz et al., 2008, 2009; Marcuse et al., 2016). During tasks requiring sustained focus, such as FA meditation, the brain must suppress distracting thoughts to maintain a stable mental state. It has been proposed that this cognitive stability should manifest as a more regular and less variable EEG signal, reflecting decreased neural "noise" (Brandmeyer & Delorme, 2018; Lutz et al., 2008). Thus, the variance of the α/θ ratio over time was also selected as a key secondary measure in this thesis, with lower variance suggesting a more stable meditative state.

Neurofeedback as a Meditative Aid

Given these markers of a focused meditative state, a natural question arises: can individuals be actively trained to modulate these neural signatures to improve their practice? One compelling paradigm for such training is neurofeedback. Neurofeedback is a psychophysiological procedure where a participant is provided with online feedback of their own neural activation for the purpose of self-regulation (Sitaram et al., 2017). By measuring neural activity and presenting a real-time representation back to the individual, neurofeedback creates a closed-loop system that allows a person to learn control over specific brain states, a skill that has been shown to successfully alter behavior (Sitaram et al., 2017). The practical benefits have been demonstrated in demanding cognitive tasks; for instance, a study by Kumar et al. (2025) found that participants receiving real-time neurofeedback in a simulation task not only improved their performance but also reported a lower perceived cognitive workload compared to a control group.

However, the efficacy of applying these principles to meditation with consumer-grade technology is not yet conclusive. A meta-analysis by Treves et al. (2025) found no definitive evidence that users could successfully modulate their target brain activity, indicating that observed benefits might stem from what they term a “neurosuggestion” placebo effect, where a user's enthusiasm for the technology enhances their motivation. A similar point is reinforced by the concept of the “seductive allure of neuroscience”, which shows that people judge explanations as more satisfying simply because they contain references to the brain, even when that information is irrelevant (Weisberg et al., 2015).

Therefore, the effectiveness of neurofeedback may depend less on the technology itself and more on how the feedback is scheduled and delivered. While continuous, high-frequency feedback can guide immediate performance, some research suggests it can become a “crutch” that hinders long-term skill development (Guadagnoli & Kohl, 2001). An intermittent feedback schedule, in contrast, may encourage a more robust form of learning by prompting the practitioner to rely on their own internal sensations between feedback periods (Guadagnoli & Kohl, 2001). This indicates that the medium and method of feedback delivery are critical variables to consider when designing a neurofeedback system for meditation.

The Medium of Feedback: The Case for an Embodied Guide

While the timing of neurofeedback is one critical design variable, the medium through which that feedback is delivered is arguably just as important, especially for a contemplative practice that requires a state of non-distraction. This thesis conceptualizes the feedback system within the framework of Socially Assistive Robotics (SAR), a field that focuses on helping users through social, rather than physical, interaction (Tapus et al., 2007; Urakami & Seaborn, 2023). Within a meditative context, the role of a guide is not to perform a physical task, but to act as a coach and motivator, providing support for the cognitive and attentional training central to meditation. To be effective, Tapus et al. (2007) and Lambert et al. (2020) suggest that assistive robots should be believable but not so human-like that they create unrealistic expectations of social intelligence, which can lead to user frustration.

Therefore, this thesis is built upon the principle of embodiment, which holds that a physical presence has a measurable effect on human perception and performance. Consistent results have shown that people perceive a co-located physical robot as more watchful, engaging, and enjoyable to interact with compared to non-embodied agents, such as a voice from an unseen source (Lambert et al., 2020; Wainer et al., 2006). This heightened sense of social presence is not merely a preference; it can be functional. The mere presence of a robot can elicit a social facilitation effect, where being observed by a physical entity improves performance on a focused task, an effect that may be diminished with a less salient, disembodied presence (Riether et al., 2012).

The Practicalities of Consumer-Grade EEG

The experimental procedure, as detailed in the following Method section, incorporated strict instructions such as asking participants to remain as still as possible with their eyes closed in a quiet environment, to minimize artifacts and maximize the quality and validity of the recorded EEG data. In order for EEG activity to be meaningful it must be processed. This processing step uses digital filters to remove signal drift and noise, and mathematical tools such as the Fast Fourier Transform (FFT) to decompose the signal and quantify the power within specific frequency bands like alpha and theta (Jiang et al., 2019; Phanikrishna, 2023). Therefore, by combining a theoretically grounded metric α/θ ratio with an adequate experimental design comparing different neurofeedback modalities, this thesis aimed to investigate the effect of an embodied guide on meditation in a variety of practitioners. The research was guided by the following primary and secondary hypotheses.

Primary Hypotheses

H1: Participants in the embodied feedback condition would demonstrate a significantly greater increase in their α/θ ratio from baseline to meditation phase compared to participants in the disembodied feedback condition.
H2: Participants in both neurofeedback conditions (embodied and disembodied) would show a significantly greater increase in their α/θ ratio from baseline compared to participants in the no-feedback condition.

Secondary Hypothesis

H3: Regarding the participants’ self-reported experience, it is expected that the participants in the embodied feedback condition would report significantly higher levels of focus, relaxation and overall session quality compared to participants in both the disembodied feedback and the no-feedback conditions.

3 Method

Participants

A total of thirty individuals (N = 30) consisting of 17 males and 13 females, participated in the study. Recruitment was open to participants of all experience levels; however, the resulting sample was composed predominantly of novice meditators. Specifically, 80% of participants reported having little to no prior meditation experience (50% with no experience and 30% having meditated only a few times), while the remaining 20% had experience ranging from occasional to regular practice. This predominantly novice sample characteristic provided a specific context for the analysis of the study's hypotheses. Participants were assigned in equal numbers to one of three experimental conditions, resulting in ten participants per group (n = 10). To ensure participant anonymity, demographic information such as age and gender was not collected.

Ethics

Prior to the experiment, each participant was provided with a detailed information sheet and gave written informed consent. The consent form outlined the study's purpose, the voluntary nature of participation, and the participant's right to withdraw at any point without providing a reason. Each participant was also verbally informed that they can withdraw at any moment. Confidentiality and anonymity were maintained throughout the study. All collected data, including EEG recordings and questionnaire responses, were stored securely and handled in a manner that prevented personal identification. Participants were also informed that the experiment was not designed to evoke negative emotions and that they could interrupt the session at any time if they felt any type of discomfort.

Apparatus

In this thesis, the embodied guide was the smaller, head-only version of the Epi humanoid robot (Figure 1). Epi is an open-source platform designed for developmental robotics. Its proportions are intended to give a childlike impression while remaining decidedly robotic (Johansson et al., 2020), a design choice intended to avoid unrealistic expectations of social intelligence, which may lead to user frustration with more human-like robots (Lambert et al., 2020; Tapus et al., 2007).

Epi's expressiveness is delivered from its mechanical and lighting capabilities. The head is controlled by six servos for pan and tilt motions, with additional servos for lateral eye movement and pupil size. Further expression is achieved through a grid of 12 RGB-LEDs that form an animated mouth and color-changing irises (Johansson et al., 2020). This non-verbal vocabulary was used to give Epi a sense of being “alive” and competent during the session (Löffler et al., 2018; Urakami & Seaborn, 2023).

Figure 1. The socially assistive robot Epi, which served as the embodied guide for the neurofeedback condition.

EEG and Audio Hardware

Brain activity was captured using the Muse 2 EEG headband (InteraXon, n.d.). The spoken audio for all three conditions was generated using the ElevenLabs text-to-speech tool with the 'Charlotte' voice, selected for its high intelligibility and neutral, calming tone suitable for a meditative context. Auditory instructions and feedback were delivered either through Epi's internal speaker, which is housed within its 3D-printed frame (Johansson et al., 2020), or in the disembodied conditions, through an external UE Boom 2 speaker.

Software and Data Streaming

The experimental procedure and real-time analysis were managed by a custom software system developed for this thesis in Python. The system was composed of several interconnected modules: a main controller managed the session flow, while a dedicated analysis module processed EEG data in 60-second blocks. This duration was chosen as a balance, ensuring each block was long enough to yield a stable Power Spectral Density (PSD) estimate while being short enough to provide relatively timely feedback. This module calculated the α/θ ratio and its variance, and triggered the appropriate feedback. Audio prompts were handled by a separate process to avoid resource conflicts. The underlying EEG data stream was made available over the network via the Lab Streaming Layer (LSL) protocol. The full source code for the experimental software is available on GitHub.[1]

Experimental Design

This thesis employed a between-subjects design to investigate the effects of different guidance modalities on meditation. Participants were randomly assigned to one of three experimental groups. The independent variable was the “type of guidance”, which had three levels: an embodied feedback condition featuring a physical robot and a voice, a disembodied feedback condition with a voice only, and an instruction-only (no-feedback) condition. The dependent variables consisted of both subjective and neurophysiological measures. Subjective measures were collected via the post-session questionnaire and included self-reported levels of focus, relaxation, overall meditation quality, and the perceptions of the guide. The neurophysiological measure was the participant’s EEG activity. This was used both as a real-time metric to generate feedback in the neurofeedback conditions and as a post-hoc measure of brain state across all conditions.

Procedure

Upon arrival, each participant was briefed on the study's general purpose and provided written informed consent. To minimize distractions and potential EEG artifacts, participants were instructed to silence their mobile phones, remain as still as possible, and keep their eyes closed during both the baseline and meditation phases. To ensure a successful data collection procedure, the researcher remained unobtrusively in the room throughout the session. This was a necessary precaution to secure that no technical interruption occurred since the custom software had shown occasional instability during its development.

[1] https://github.com/danderstorm1/Epi_in_Serenity]

Following the initial briefing, the Muse 2 headband was fitted and adjusted. Using the MuseLSL visualization tool, the signal quality for each of the four electrodes was visually inspected until the waveforms appeared stable and free of major artifacts, indicating a reliable connection. The session began with spoken instructions delivered by the software, either through the Epi robot's speaker (for the embodied condition) or an external speaker (for the two disembodied conditions). During the instruction phase, Epi was not entirely static; it performed subtle, intermittent movements to convey a sense of presence (Löffler et al., 2018), without being distracting. Participants then underwent a baseline phase where they listened to a short, neutral audio clip. After further instructions, the main meditation phase commenced, lasting 15 minutes. During this period, participants experienced their randomly assigned condition.

Immediately following the meditation, the software provided a brief concluding message, and the participant was asked to complete the post-session questionnaire. The session concluded with a full verbal debriefing by the researcher, who explained the different conditions and the specific aims of the study, what was measured, and answered any questions the participant had.

Data Acquisition and Processing

To implement this neurofeedback system, this thesis utilized the Muse 2 headband, a consumer-grade neurotechnological device (Figure 2). The device was selected for its practical advantages, including rapid setup time and a high degree of user comfort compared to traditional, multi-electrode EEG caps. The Muse 2 is equipped with four primary recording electrodes positioned according to standard EEG conventions: two on the forehead at the Anterior Frontal region (AF7 and AF8) and two behind the ears at the Temporo-Parietal junction (TP9 and TP10) (InteraXon, n.d.).

While accessible, the use of such a consumer-grade product in a research context required a critical evaluation of its reliability and precision. The validity of using the Muse headband for scientific measurement is a subject of debate. An observational study by Przegalinska et al. (2018) concluded that its usefulness for measuring EEG signals is extremely limited in non-laboratory conditions. The researchers found that the data was often noisy, polluted with artifacts, and lacked proper temporal resolution due to inconsistencies in the sampling rate (Przegalinska et al., 2018).

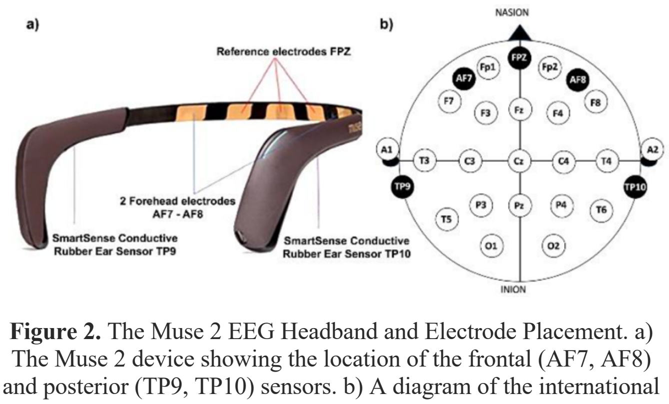

Figure 2. The Muse 2 EEG Headband and Electrode Placement. a) The Muse 2 device showing the location of the frontal (AF7, AF8) and posterior (TP9, TP10) sensors. b) A diagram of the international 10-20 system for EEG electrode placement, with the locations used by the Muse 2 headband highlighted in black.

These were significant challenges, as any recorded electrical signal that is not of cerebral origin was considered an artifact and could easily be mistaken for genuine neural data (Marcuse et al., 2016). Such artifacts can be physiological, originating from the user's own body, such as eye blinks (ocular artifacts) or jaw clenching (EMG), or external, such as 50/60 Hz interference from nearby electrical equipment (Marcuse et al., 2016; Phanikrishna, 2023).

However, other research has demonstrated that the Muse headband can be used effectively under the right circumstances. A study by Abujelala et al. (2016) successfully used the device to predict user enjoyment in a video game task by implementing adequate filtering and conducting the experiment in highly structured, controlled conditions. More directly, a validation study by Krigolson et al., (2017) demonstrated that the Muse system could be used to reliably measure and quantify well-established ERP components like the N200 and P300, with results comparable to a research-grade system Informed by these findings, the current study was designed specifically to mitigate the known limitations of the device.

Signal Processing Pipeline

Raw EEG data was acquired from the four channels of the Muse 2 headband (AF7, AF8, TP9, TP10) at a sampling rate of 256 Hz (InteraXon, n.d.). For the neurofeedback calculations, the signal from the two posterior channels (TP9 and TP10) was averaged to create a single data stream, as these locations were most sensitive to the PDR. The real-time processing pipeline began with preprocessing to remove noise.

The power within the alpha and theta frequency bands was then quantified by estimating the Power Spectral Density (PSD) from each 60-second block of data using Welch’s method (Welch, 1967). This procedure involved dividing the data block into shorter, 2-second overlapping segments and applying a Hann window function to each to minimize spectral leakage. After computing the Fast Fourier Transform (FFT) for each segment, the resulting periodograms were averaged. Finally, the mean power within the defined alpha (8-13 Hz) and theta (4-8 Hz) bands was extracted. These power values served as the basis for computing the neurofeedback metrics.

Neurofeedback Metrics and Logic

Two key metrics were computed from the extracted power values. The primary metric was the α/θ ratio, defined as the average power in the alpha band (P_α) divided by the average power in the theta band (P_θ). The secondary metric, the ratio variance, served as a stability metric and was calculated from the sample variance of α/θ ratios across smaller, overlapping 5-second sub-windows within each 60-second block (Guadagnoli & Kohl, 2001). The system used a 180-second baseline phase at the start of each session to establish personalized thresholds for these metrics. The average α/θ ratio and ratio variance from this baseline were used to set a meditative state threshold at 115% of the baseline ratio and a stability threshold at 85% of the baseline variance. These specific thresholds were established during pilot testing.

Feedback was delivered intermittently (Guadagnoli & Kohl, 2001), according to specific timing rules. After an initial positive prompt was delivered one minute into the first meditation block, the system categorized the participant's state in subsequent blocks by comparing the block's metrics against the personalized thresholds. The system used a sequential classification logic, evaluating the state in a specific priority order. First, it checked for instability; if the block's ratio variance was above the 85% stability threshold, the state was classified as 'High Variance', and no further checks were made. If the variance was stable (at or below the 85% threshold), the system then evaluated the α/θ ratio, classifying the state as 'Meditative' if the ratio was at or above the 115% meditative state threshold. If the state was not classified as 'High Variance' or 'Meditative', it was designated as 'Relaxed' when the α/θ ratio was above the participant's baseline average but still below the 115% meditative threshold. In the final check, the state was classified as 'Sleepy' if the variance was stable and the α/θ ratio fell below the baseline average. To provide variation and prevent auditory habituation, each of these four states was associated with a pool of six unique sound files. When feedback for a specific state was triggered, the system randomly selected and played one of the corresponding six files.

$$Ratio = \frac{P_\alpha}{P_\theta}$$

Equation 1. α/θ ratio

$$T_{Ratio} = \bar{R}_{Baseline} \times 1.15$$

Equation 2. Ratio threshold

$$T_{Variance} = \bar{V}_{Baseline} \times 0.85$$

Equation 3. Variance threshold

$$Var(R) = \frac{1}{n-1}\sum_{i=1}^{n}(R_i - \bar{R})^2$$

Equation 4. Variance of α/θ ratio

Measures

To evaluate the subjective experience of the participants, custom questionnaires were developed and administered immediately following each experimental session. The questionnaire began by background information regarding the participants' prior experience with meditation, including the duration, frequency, and primary type of their practice. All scaled responses were captured using a 5-point Likert format. The questionnaire included two sections that were identical across all conditions. The 'Perception of the Guide/agent' scale assessed the qualities of the guide, whether it was the embodied robot or the disembodied voice. This scale included items rating the guide on attributes such as being social, friendly, human-like, and trustworthy (Becker et al., 2025; Tapus et al., 2007). The 'Subjective Session Experience' section measured the participant's self-reported internal state during the meditation, including their perceived level of relaxation, focus, and the overall quality of the session (Becker et al., 2025).

To account for the different experimental manipulations, the questionnaire was specifically adapted for each condition. Participants in the two neurofeedback groups received a section titled 'Perception of the Guidance Received', where they rated the perceived helpfulness, clarity, timing, and distracting nature of the feedback. In contrast, participants in the no-feedback control condition answered a different set of questions under 'Perception of the Instructions'. This section evaluated the clarity and sufficiency of the spoken instructions, the balance between instruction and silence, and whether they found themselves wishing for feedback. Finally, all versions of the questionnaire concluded with an optional open-ended question allowing for the participants to provide any further comments on their experience.

Data Analysis

The collected data was analyzed to test the primary hypotheses and explore secondary relationships. The primary analyses involved three separate one-way ANOVAs to compare the experimental groups on: (1) subjective ratings from the post-session questionnaire, (2) the mean α/θ ratio and its variance during the meditation phase, and (3) the change in these EEG metrics from baseline. To account for the multiple comparisons across the seven ANOVAs, a Bonferroni correction was applied, adjusting the threshold for statistical significance to $p < .007$.

A Pearson correlation analysis was planned to test the convergence between participants' subjective experience and the EEG data. To facilitate this exploratory analysis, a composite subjective experience score was to be calculated for each participant by averaging their rating for session focus, relaxation, and overall quality. This score would then be correlated against the change in α/θ ratio and the change in the ratio's variance from baseline to the meditation phase. A supplementary analysis was also planned to determine if a direct relationship existed between the absolute alpha power during the meditation phase and the subjective experience score. A significant correlation would suggest that the EEG metrics in question are valid indicators of a participant's subjective internal state during meditation.

On top of that, a concordance analysis was planned to quantify the agreement between each participant's subjective experience ranking and their EEG metric rankings. Participants were to be ranked from 1st to 28th based on their composite subjective score. Two additional rankings were to be generated based on their average α/θ ratio and average ratio variance during the meditation phase. A concordance score would then be calculated for each metric as the absolute difference between the subjective rank and the EEG rank, where the lower score indicated a smaller difference between the two ranks.

Finally, a time-series analysis was conducted to visualize the development of the α/θ ratio throughout the 15-minute meditation session. This analysis served two purposes. First, it was intended to distinguish the dynamic cognitive effort of meditation from simple relaxation effects, such as the PDR that occurs when closing the eyes. A fluctuating, non-linear pattern would suggest active engagement in the meditative task rather than a simple linear increase in relaxation over time. Second, the analysis allowed for a visual comparison of the groups' performance over time to explore whether specific feedback events had a discernible immediate impact on the participants' neural state.

4 Results

Primary Analyses

The following analyses were conducted to test the thesis' hypotheses on the collected sample. As detailed in the Method section, this group consisted overwhelmingly of participants with little to no prior meditation experience. Prior to the main analyses, the EEG data from two participants from specifically the no-feedback condition were excluded. Participant 8 was excluded due to self-reported physical discomfort (neck pain) that prevented them from maintaining focus during the experimental task. Participant 6 was excluded as a statistical outlier, as their α/θ ratio increased by over 260% from baseline to meditation, whereas the group average was an increase of just under 13%. This resulted in a final sample size of N=28 for the EEG analyses. The primary analyses involved three separate one-way ANOVAs to test the main hypotheses by comparing the experimental groups on: (1) subjective ratings from the post-session questionnaire, (2) the mean α/θ ratio and its variance during the meditation phase, and (3) the change in these EEG metrics from baseline. Although the primary analyses found no statistically significant differences between the guidance conditions, exploratory analyses indicated patterns worth further consideration.

Guidance Condition	Mean Focus (±SD)	Mean Relaxation (±SD)	Mean Overall Quality (±SD)
Embodied Feedback	3.2 ± 1.32	3.8 ± 1.14	3.4 ± 0.97
Disembodied Feedback	3.2 ± 1.14	4.2 ± 0.63	3.4 ± 0.84
No Feedback	2.8 ± 1.14	3.8 ± 1.14	3.1 ± 0.57

Table 1. Subjective Experience Ratings. Values are presented as mean ± standard deviation (SD) on a 5-point scale.

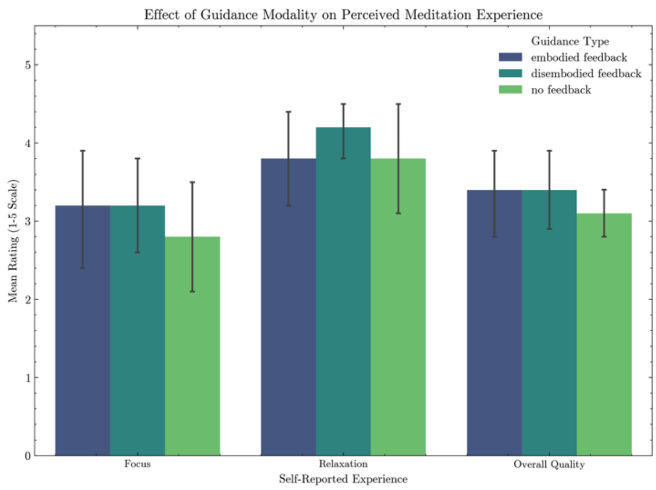

Figure 3. Mean Self-Reported Meditation Experience by Guidance Condition. Participants' ratings of Focus, Relaxation, and Overall Session Quality on a 5-point Likert scale. No statistically significant differences were found between the conditions. Error bars represent the standard error of the mean.

The initial analysis focused on the subjective questionnaire data (N=30) to determine if the guidance modality influenced the participants' self-reported experience (Table 1, Figure 3). A one-way ANOVA indicated no significant differences between the groups on measures of focus ($F(2,27) = 0.37$, $p =$ .693), relaxation ($F(2,27) = 0.54$, $p = .590$), or the overall quality of the session ($F(2,27) = 0.46$, $p = .638$). These findings suggest that the type of guidance provided did not have a measurable effect on the participants' subjective experience.

Guidance Condition	Mean α/θ Ratio (±SD)	α/θ Ratio Variance (±SD)	α/θ Baseline Change (±SD)
Embodied Feedback	0.88 ± 0.48	0.37 ± 0.53	1.00 ± 0.30
Disembodied Feedback	0.93 ± 0.48	0.26 ± 0.33	0.99 ± 0.16
No Feedback	0.95 ± 0.49	0.20 ± 0.18	1.13 ± 0.49

Table 2. Summary of EEG data. Values are presented as mean ± standard deviation (SD).

The second analysis examined the EEG data (N=28), comparing the average brainwave activity between the groups during the 15-minute meditation phase (Table 2, Figure 4). A one-way ANOVA was used to test for differences in both the mean α/θ ratio and the mean variance of this ratio. The analysis revealed no statistically significant differences between the groups for either the mean α/θ ratio ($F(2,25) = 0.44$, $p = .652$) or the mean ratio variance ($F(2,25) = 0.37$, $p =$ .695). This indicates that, when averaged over the entire session, the guidance modality did not lead to significant differences in the overall brainwave states of the participants.

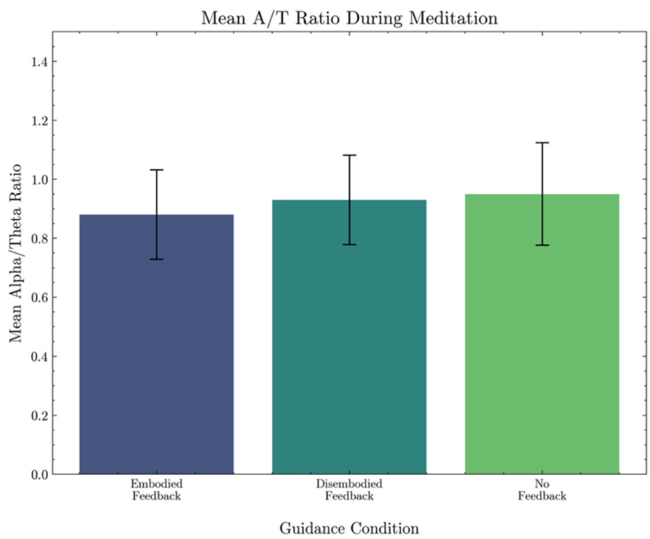

Figure 4. Mean α/θ Ratio During Meditation by Guidance Condition. The chart displays the average α/θ ratio for each group across the entire 15-minute meditation phase. No statistically significant differences were observed. Error bars represent the standard error of the mean.

The final and most primary analysis examined the change in EEG metrics from each participant's own baseline to their meditation state (Figure 5, Figure 6). This analysis controls for individual differences in resting brain activity. A one-way ANOVA performed on these changes between baseline and post-intervention found no statistically significant differences between the groups for the change in the α/θ ratio ($F(2,25) = 1.45$, $p = .258$) or for the change in the ratio variance ($F(2,25)$

= 1.10, p = .352). This result demonstrates that no guidance modality affected participant's brainwave state transitions from their baseline to their meditative states.

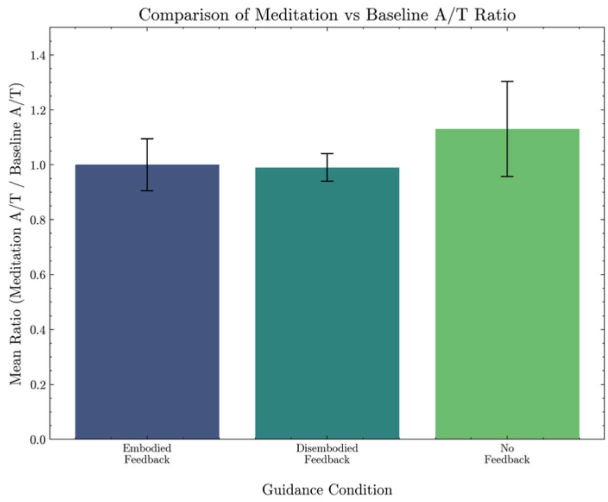

Figure 5. Change in Mean α/θ Ratio from Baseline to Meditation. The y-axis represents the ratio of the mean α/θ during meditation to the mean ratio at baseline. A value of 1.0 signifies no change. While the no-feedback group showed a larger average increase, the differences between the conditions were not statistically significant. Error bars represent the standard error of the mean.

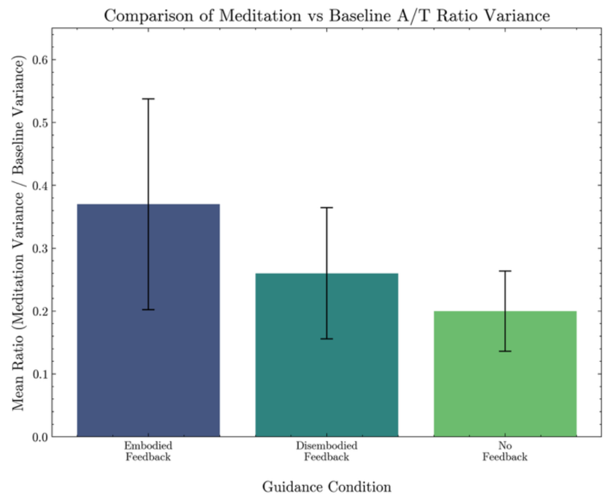

Figure 6. Change in the Variance of the α/θ Ratio from Baseline to Meditation. The y-axis represents the ratio of the mean variance during meditation to the mean variance at baseline. This metric assesses the stability of the brain state. No statistically significant differences between conditions were found. Error bars represent the standard error of the mean.

To put it concisely, three distinct analyses examining subjective reports, neurophysiological states, and the change in these states from baseline, yielded highly consistent results: no evidence was found to suggest that either embodied or disembodied neurofeedback produced any significant effect.

Concordance Analysis

An analysis was conducted to quantify the concordance between each participant's subjective experience ranking and their EEG metric rankings. Participants were ranked from 1st to 28th based on their composite subjective score. Two additional rankings were generated based on their average α/θ ratio and average ratio variance during the meditation phase.

A concordance score was calculated for each metric as the absolute difference between the subjective rank and the EEG rank (Figure 7, Figure 8). A lower score indicates a smaller difference between the two ranks.

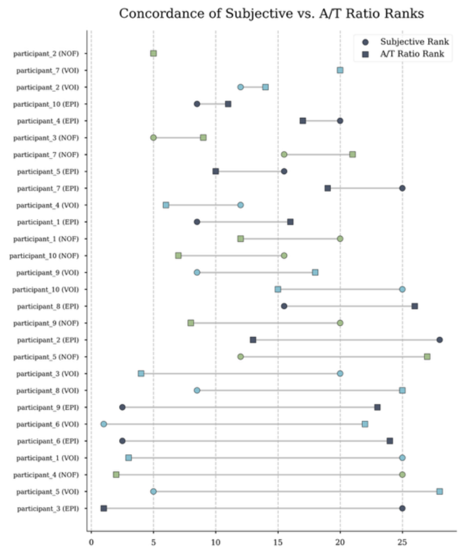

Figure 7. Concordance of Subjective Experience Ranks vs. Alpha/Theta (α/θ) Ratio Ranks. Each horizontal line represents a single meditation session. The circle (Subjective Rank) denotes the participant's rank based on self-report, while the square (α/θ Ratio Rank) denotes their rank based on the EEG metric. The length of the connecting line illustrates the concordance score, or the discrepancy between subjective feeling and EEG data.

The concordance score for the α/θ ratio which quantifies the discrepancy between subjective assessment and EEG metrics, ranged from 0 to 26. A lower score signifies greater agreement, with a score of 0 representing perfect concordance. This was achieved by participant 2 (no-feedback condition) and participant 7 (voice). The largest divergence was observed in participant 3 (epi), who ranked 28th subjectively but 2nd on the EEG metric, resulting in a concordance score of 26.

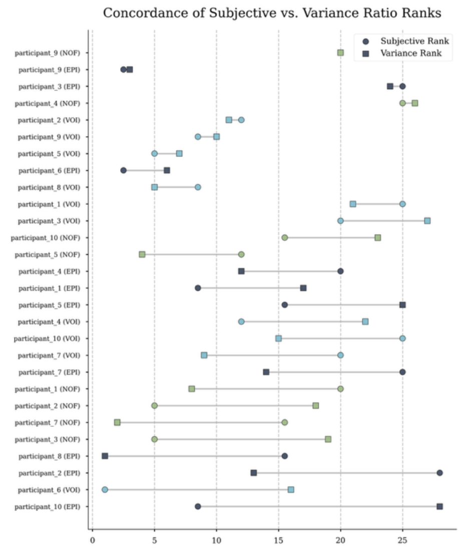

Figure 8. Concordance of Subjective Experience Ranks vs. A/T Ratio Variance Ranks. This chart compares the participant's subjective rank (circle) with their rank based on the variance of the α/θ ratio (square), a measure of neural stability. The connecting line visualizes the concordance score, with longer lines indicating greater divergence between self-perception and overall stability.

Exploratory Analyses

An analysis of the relationship between subjective experience and the change in the α/θ ratio revealed no statistically significant correlation for all participants combined (r(26)=.12,p=.542) (Appendix, B, Figure 9). When examined by individual condition, the results also remained non-significant for the embodied feedback (r(8)=.43,p=.210), disembodied feedback (r(8)=−.11,p=.769), and no-feedback groups (r(6)=−.14,p=.734).

Similarly, the relationship between subjective experience and the change in the α/θ ratio variance was examined (Appendix C, Figure 10). The overall correlation was not statistically significant (r(26)=−.11,p=.569). While the per-condition analyses for the embodied feedback (r(8)=.27,p=.446) and no-feedback groups (r(6)=−.34,p=.403) were also non-significant, the disembodied feedback group showed a moderate negative correlation (r(8)=−.63,p=.052). This suggests a possible link between higher subjective ratings and greater brainwave stability for that group, though the finding did not meet the threshold for statistical significance.

Finally, a time-series analysis of the α/θ ratio was also conducted (Figure 11). The no-feedback group consistently maintained a higher average α/θ ratio throughout the entire 15-minute meditation session compared to both the embodied feedback and disembodied feedback groups. The standard error band for the no-feedback group shows little to no overlap with the other conditions, suggesting a sustained difference in brain state. In contrast, the embodied feedback and disembodied feedback groups were visually indistinct from one another. Their average ratios and extensive overlapping error bands indicate that they performed similarly throughout the session, fluctuating at a lower α/θ ratio than the no-feedback group.

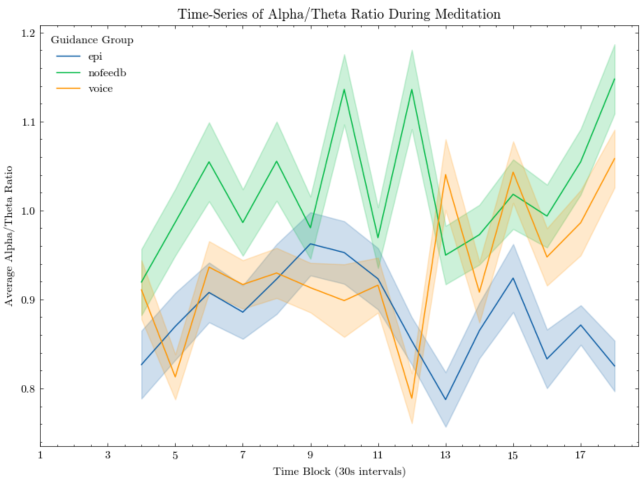

Figure 11. Time-Series of the Average α/θ Ratio During Meditation. The plot shows the evolution of the mean α/θ ratio for each condition across the 15-minute session. Shaded areas represent the standard error. The no-feedback group consistently maintained a higher mean ratio than both feedback conditions, whose error bands largely overlap.

5 Discussion

The primary aim of this thesis was to investigate whether neurofeedback, delivered by an embodied robot or a disembodied voice, could enhance meditation more effectively than instructions alone. However, the findings must be understood with considerable caution. The study's small sample size resulted in low statistical power, meaning it may not have been able to detect certain effects with certainty. Consequently, the results should be viewed as preliminary, highlighting potential trends that require further research rather than providing conclusive evidence.

With this limitation in mind, the analyses did not find statistically significant benefits of neurofeedback, contrary to the initial hypotheses. These non-significant results, while not conclusive, align with other findings suggesting that the mental health and behavioral benefits of mindfulness-based neurofeedback have not yet been firmly established (Treves et al., 2024). Given that the participant sample was predominantly composed of novices, these findings may offer specific insights into the potential challenges of applying current neurofeedback paradigms to beginners. In the end, neither the EEG data nor the subjective data provided statistical support for the primary (H1, H2) or secondary (H3) hypotheses, indicating that the guidance modality did not have a measurable effect on this practitioner group within the statistical limitations of this study.

The Effects of Neurofeedback on Attention

A central finding of this thesis is that providing neurofeedback, regardless of modality, did not confer any benefit over instructions alone. In fact, the data suggests it may have actively hindered the development of a focused meditative state, as the no-feedback group consistently demonstrated the most positive change from their baseline to α/θ ratio throughout the meditation phase. Importantly, the fluctuating, non-linear pattern observed in the time-series analysis across all groups suggests that this difference was not due to simple relaxation or an enhancement of the PDR. Instead, the dynamic nature of the signal likely reflects the ongoing cognitive effort involved in the meditative task, including the cycle of focusing, mind-wandering, and refocusing (Lutz et al., 2008; Rodriguez-Larios et al., 2020). This implies that all participants were actively engaged in the practice, which makes the superior performance of the no-feedback group particularly significant.

Given this context of active engagement, a plausible explanation for the result is that the auditory feedback, intended as a support, instead imposed a cognitive load that was fundamentally at odds with the primary goal of Focused Attention (FA) meditation. The practice of FA meditation is an exercise in endogenous attentional control; it requires the practitioner to voluntarily sustain focus on an internal sensation, most commonly the breath, while monitoring for internal distractions like mind-wandering, and gently returning focus when they arise (Brandmeyer & Delorme, 2013; Lutz et al., 2008). The intermittent auditory prompts, however, introduced a recurring exogenous attentional demand. Participants were required to disengage from their internal focus, orient towards the external sound, process its meaning, and then attempt to re-establish their meditative state. This repeated cycle of interruption may have actively fragmented their efforts to achieve the sustained, stable focus that is the hallmark of the practice (Brandmeyer & Delorme, 2018).

This aligns with research in motor learning, which suggests that while frequent feedback can guide immediate performance, it can become a "crutch" that hinders the long-term development of robust, internal error-detection skills (Guadagnoli & Kohl, 2001). In the context of meditation, where the goal is precisely to cultivate an internal sensitivity to one's own mental state, the neurofeedback may have inadvertently outsourced this crucial function. Instead of learning to recognize their own moments of distraction, participants may have become passively reliant on an external cue, thereby compromising the foundational skill of the practice. Therefore, the neurofeedback may have interfered with the practice, functioning less as a support and more as a source of attentional disruption. The cognitive load of processing an external signal can interfere with the internal focus required for the task, as the most benefit is seen when participants are only passively aware of the feedback (Biswas & Ray, 2019).

Subjective and Neural Measures: Diverging Results

This interpretation presents an apparent discrepancy when viewed alongside the subjective questionnaire data. While the EEG metrics suggest a neural hindrance, the subjective ratings for session focus, relaxation, and overall quality were statistically indistinguishable across all three groups. This apparent contradiction can be resolved by considering two distinct, simultaneous factors at play. At the neural level, the feedback likely acted as a cognitive disruption, as established in the previous section. It introduced an exogenous attentional demand that fragmented the internal focus essential for the meditative task, effectively dividing the participant's cognitive resources between the primary goal of meditation and the secondary task of processing the feedback.

Simultaneously, at the subjective, psychological level, it is proposed that participants were influenced by a placebo-like effect driven by the context of the experiment itself. The very presence of advanced technology (a socially assistive robot and a brainwave-monitoring EEG device) can create strong expectations of efficacy. The phenomenon neurosuggestion, which posits that a user's enthusiasm for and belief in a technology's promising self-improvement can create a strong predisposition to perceive positive results, regardless of the actual outcome (Treves et al., 2025). This effect is amplified by the well-documented seductive allure of neuroscience (Weisberg et al., 2015), a cognitive bias where the mere presence of neuroscientific equipment and terminology causes an experience to be perceived as more scientifically valid, influencing how it is reported. The combination of the Muse 2 headband and the physically present Epi robot likely created a setting that amplified these expectations. for these expectations to flourish, leading participants to believe the session was effective.

It is therefore possible that while the neurofeedback was disrupting the participants' neural stability, their positive expectations, reinforced by the perceived scientific legitimacy of the setup, led them to report a favorable experience. This "two effects" model explains the data more fully than either hypothesis alone and points to a critical challenge in the field: separating the genuine neural impact of neurofeedback from its significant and potentially confounding psychological effects.

Embodiment and Its Limited Role in Introspective Tasks

A central hypothesis of this thesis, that an embodied robotic guide would be more effective than a disembodied voice, was not supported by the data. A plausible explanation for this null finding likely lies not in the specific design of the robot, but in the introspective nature of the meditative task itself. The proposed benefits of embodiment, such as social facilitation and increased engagement, typically rely on the participant actively processing and attending to a social agent in their external environment (Riether et al., 2012; Wainer et al., 2006). The core instruction of FA meditation, however, is to do the opposite: to disengage from the external world and cultivate an 'isolated' internal state focused on the breath (Lutz et al., 2008).

This behavioral instruction has a clear neural correlate. Advanced meditation practice is associated with the decreased activation of the brain's Default Mode Network, a network strongly implicated in self-referential thought and the monitoring of one's external social environment (Dennison, 2019; Kaur & Singh, 2015). It is possible that even for the novices in this study, the act of closing their eyes and deliberately directing attention inward began to suppress this network's activity. If the very neural systems required to process social presence are being actively quieted by the task, it follows that the physical presence of a guide would have a diminished or negligible effect compared to a disembodied one. Furthermore, it is possible that the chosen auditory feedback modality was such a salient and cognitively demanding stimulus that it overshadowed any subtler, secondary effects of the robot's physical form. In essence, the cognitive context of the task appears to be a critical moderating variable, suggesting that the well-documented effects of embodiment are not universal and can be nullified when a task requires profound disengagement from one's physical and social surroundings.

Subjective Experience & Brain State

Another important finding emerged from both the concordance analysis and the Pearson correlation, which revealed a wide and inconsistent relationship between participants' subjective experience of their meditation and the EEG metrics. While a few individuals showed strong agreement between their self-reported focus and their α/θ ratio, many others demonstrated a major divergence. For example, some participants ranked near the top subjectively while ranking at the bottom in the EEG recording, or vice-versa. While one interpretation could be to question the validity of consumer-grade EEG, a more insightful conclusion points toward the unreliability of self-report in novice meditators (Sugimoto et al., 2024). The ability to accurately assess one's own internal state is a form of metacognitive or interoceptive awareness and can be seen as a skill of its own that is cultivated through contemplative practice (Brandmeyer & Delorme, 2018; Piron, 2022). It is therefore plausible that beginners lack a stable framework for interpreting their internal experiences; for instance, they might conflate drowsiness with deep relaxation, or a mind that is merely quiet with one that is actively focused. This finding adds nuance to studies that have successfully correlated self-reported depth with EEG signatures (Katyal & Goldin, 2021), suggesting that this relationship may be significantly weaker or more variable at the earliest stages of practice. This finding validates the core premise of neurofeedback, which is to provide neural data on a subjective state that novices often struggle to evaluate, even if the implementation of such feedback requires further refinement.

Limitations and Methodological Considerations

The findings of this study should be interpreted in light of several methodological limitations. The small sample size for the final EEG analysis (N=28) restricts the statistical power to detect more subtle effects. The absence of significant findings cannot be taken as conclusive proof of no effect; rather, it suggests that any potential effects were not strong enough to be detected with the current sample. This is a challenge compounded by the high degree of inter-subject variability commonly observed in studies with novice meditators (Eberth & Sedlmeier, 2012). Beyond that, the effectiveness of neurofeedback can be inconsistent, as a substantial portion of participants (up to 30%) fail to learn self-regulation (Sitaram et al., 2017). The use of a between-subjects design, while necessary to avoid carry-over effects between conditions, may have been less effective at handling this variability than a future study employing a within-subjects design would be.

Furthermore, the study did not control for potential confounding variables such as caffeine intake, sleep quality, or the time of day the session was conducted, all of which could influence baseline neural activity. While the use of a consumer-grade EEG device like the Muse 2 enhances the thesis's real-world relevance, such devices inherently lack the signal fidelity and spatial resolution of research-grade equipment, potentially obscuring more nuanced neural changes (Przegalinska et al., 2018; I. Treves et al., 2025). A more sensitive approach in future work could also involve tailoring the analysis to each participant's Individual Alpha Frequency, rather than using standardized frequency bands, which may have further clarified the results (Rodriguez-Larios et al., 2021).

A further methodological consideration is the focus on posterior EEG channels for analysis. While the selection of channels TP9 and TP10 was based on their sensitivity to the well-known PDR, this may have inadvertently obscured relaxation-specific effects occurring elsewhere. A recent and comprehensive meta-analysis on the topic found that the positive correlation between alpha power and relaxation is significant in central and frontal regions, but not in posterior ones (Sugimoto et al., 2024). It is therefore plausible that the null results of the present study are not due to an absence of a neural effect from meditation, but rather a consequence of measuring from scalp locations that are not the primary correlates of this specific introspective state.

Finally, a key consideration in interpreting these findings is the composition of the sample. Because the participants were predominantly novices, the conclusions, particularly regarding the potentially disruptive nature of auditory neurofeedback, may not be generalizable to experienced practitioners, who might interact with and benefit from such guidance differently.

Future Directions: Designing for a Quiet Mind

The results and limitations of this research open several promising avenues for future inquiry into neuro-assistive technology for meditation. Most importantly, given that auditory feedback may be inherently distracting, a critical next step is to systematically compare different feedback modalities. Exploring less cognitively intrusive forms of feedback, such as gentle haptic vibration or changes in ambient light, could reveal methods that successfully guide a user without disrupting their internal focus (Brandmeyer & Delorme, 2013). Additionally, the trend observed between subjective experience and brainwave stability suggests this may be a more meaningful metric than the α/θ ratio alone. Future neurofeedback systems could be designed to reward sustained, stable brain states over several minutes, rather than momentary ratio peaks. The timing of feedback also warrants investigation; providing a summary report after a session, instead of during, might be a more effective way to promote learning without fragmenting the practice itself. Finally, to understand how these dynamics might change with experience, a longitudinal study tracking novice users over multiple sessions would be necessary to determine if the utility of an embodied guide or real-time neurofeedback evolves as a practitioner's skill develops.

Conclusion

This thesis set out to determine if an embodied, socially assistive robot could more effectively guide meditation than a disembodied voice or instructions alone. For the novice meditators who comprised the majority of the sample, the thesis did not find statistically significant evidence to support the greater effectiveness of either neurofeedback condition. Instead, the results pointed toward a trend where the guidance may have hindered the attainment of desired neural states compared to the no-feedback control. While not statistically conclusive, the primary contribution of this thesis is twofold. First, the findings suggest that for internal cognitive tasks like FA meditation, the cognitive load of processing real-time feedback may outweigh its intended benefits. Secondly, it raises questions about the universality of embodiment effects, suggesting they may be nullified when a task requires complete disengagement from one's physical and social surroundings. Ultimately, the design of neurofeedback technologies should be informed by the specific cognitive context of the task, with particular attention to how feedback interacts with attentional demands.

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References

Abujelala, M., Abellanoza, C., Sharma, A., & Makedon, F. (2016). Brain-EE: Brain Enjoyment Evaluation using Commercial EEG Headband. *Proceedings of the 9th ACM International Conference on Pervasive Technologies Related to Assistive Environments*, 1–5. https://doi.org/10.1145/2910674.2910691

Aggarwal, P., Dutt, V., Kumar, A., & Rao, A. (2025). Neurofeedback training for cognitive optimization: Effects on performance and workload in a simulation task.

Proceedings of the 69th Human Factors and Ergonomics Society Annual Meeting, 69, 112-116.

Becker, D., Braach, L., Clasmeier, L., Kaufmann, T., Ong, O., Ahrens, K., Gäde, C., Strahl, E., Fu, D., & Wermter, S. (2025). Influence of Robots' Voice Naturalness on Trust and Compliance. *ACM Transactions on Human-Robot Interaction*, *14*(2), 1–25. https://doi.org/10.1145/3706066

Biswas, A., & Ray, S. (2019). Alpha Neurofeedback Has a Positive Effect for Participants Who Are Unable to Sustain Their Alpha Activity. *Eneuro*, *6*(4). https://doi.org/10.1523/ENEURO.0498-18.2019

Brandmeyer, T., & Delorme, A. (2013). Meditation and neurofeedback. *Frontiers in Psychology*, *4*. https://doi.org/10.3389/fpsyg.2013.00688

Brandmeyer, T., & Delorme, A. (2018). Reduced mind wandering in experienced meditators and associated EEG correlates. *Experimental Brain Research*, *236*(9), 2519–2528. https://doi.org/10.1007/s00221-016-4811-5

Crescentini, C., Fabbro, F., & Tomasino, B. (2017). Editorial Special Topic: Enhancing Brain and Cognition Through Meditation. *Journal of Cognitive Enhancement*, *1*(2), 81–83. https://doi.org/10.1007/s41465-017-0033-4

Creswell, J. D., Taren, A. A., Lindsay, E. K., Greco, C. M., Gianaros, P. J., Fairgrieve, A., Marsland, A. L., Brown, K. W., Way, B. M., Rosen, R. K., & Ferris, J. L. (2016). Alterations in Resting-State Functional Connectivity Link Mindfulness Meditation With Reduced Interleukin-6: A Randomized Controlled Trial. *Biological Psychiatry*, *80*(1), 53–61. https://doi.org/10.1016/j.biopsych.2016.01.008

Dennison, P. (2019). The Human Default Consciousness and Its Disruption: Insights From an EEG Study of Buddhist Jhāna Meditation. *Frontiers in Human Neuroscience*, *13*, 178. https://doi.org/10.3389/fnhum.2019.00178

Eberth, J., & Sedlmeier, P. (2012). The Effects of Mindfulness Meditation: A Meta-Analysis. *Mindfulness*, *3*(3), 174–189. https://doi.org/10.1007/s12671-012-0101-x

Engström, M., Willander, J., & Simon, R. (2022). A Review of the Methodology, Taxonomy, and Definitions in Recent fMRI Research on Meditation. *Mindfulness*, *13*(3), 541–555. https://doi.org/10.1007/s12671-021-01782-7

Ericsson, K. A., Krampe, R. T., & Tesch-Romer, C. (1993). The Role of Deliberate Practice in the Acquisition of Expert Performance. *Psychological Review, 100*(3), 363-406

Evans, S., Wyka, K., Thorpe Blaha, K., & Allen, E. S. (2018). Self compassion mediates improvement in well-being in a mindfulness-based stress reduction program in a community-based sample. *Mindfulness*, *9*, 1280–1287. https://doi.org/10.1007/s12671-017-0872-1

Fox, K. C. R., & Cahn, B. R. (2020). Meditation and the Brain in Health and Disease. In M. Farias, D. Brazier, & M. Lalljee (Eds.), *The Oxford Handbook of Meditation* (1st ed.). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780198808640.013.23

Institute for the Future of Education. (2022). *Muse 2 Headband Specifications (Neuronal Tracking)*. Tecnológico de Monterrey.

Guadagnoli, M. A., & Kohl, R. M. (2001). Knowledge of Results for Motor Learning: Relationship Between Error Estimation and Knowledge of Results Frequency. *Journal of Motor Behavior*, *33*(2), 217–224. https://doi.org/10.1080/00222890109603152

Jiang, X., Bian, G.-B., & Tian, Z. (2019). Removal of Artifacts from EEG Signals: A Review. *Sensors*, *19*(5), 987. https://doi.org/10.3390/s19050987

Johansson, B., Tjøstheim, T. A., & Balkenius, C. (2020). Epi: An open humanoid platform for developmental robotics. *International Journal of Advanced Robotic Systems*, *17*(2). https://doi.org/10.1177/1729881420911498

Katyal, S., & Goldin, P. (2021). Alpha and theta oscillations are inversely related to progressive levels of meditation depth. *Neuroscience of Consciousness*, *2021*(1). https://doi.org/10.1093/nc/niab042

Kaur, C., & Singh, P. (2015). EEG Derived Neuronal Dynamics during Meditation: Progress and Challenges. *Advances in Preventive Medicine*, *2015*, 1–10. https://doi.org/10.1155/2015/614723

Timperley, H., & Hattie, J. (2007). The power of feedback. *Review of educational research, 77*(1), 81-112. https://doi.org/10.3102/003465430298487

Krigolson, O. E., Williams, C. C., Norton, A., Hassall, C. D., & Colino, F. L. (2017). Choosing MUSE: Validation of a Low-Cost, Portable EEG System for ERP Research. *Frontiers in Neuroscience*, *11*. https://doi.org/10.3389/fnins.2017.00109

Lambert, A., Norouzi, N., Bruder, G., & Welch, G. (2020). A Systematic Review of Ten Years of Research on Human Interaction with Social Robots. *International Journal of Human–Computer Interaction*, *36*(19), 1804–1817. https://doi.org/10.1080/10447318.2020.1801172

Leyland, A., Rowse, G., & Emerson, L.-M. (2019). Experimental effects of mindfulness inductions on self-regulation: Systematic review and meta-analysis. *Emotion*, *19*(1), 108–122. https://doi.org/10.1037/emo0000425

Löffler, D., Schmidt, N., & Tscharn, R. (2018). Multimodal Expression of Artificial Emotion in Social Robots Using Color, Motion and Sound. *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*, 334–343. https://doi.org/10.1145/3171221.3171261

Lutz, A., Greischar, L. L., Perlman, D. M., & Davidson, R. J. (2009). BOLD signal in insula is differentially related to cardiac function during compassion meditation in experts vs. Novices. *NeuroImage*, *47*(3), 1038–1046. https://doi.org/10.1016/j.neuroimage.2009.04.081

Lutz, A., Greischar, L. L., Rawlings, N. B., Ricard, M., & Davidson, R. J. (2004). Long-term meditators self-induce high-amplitude gamma synchrony during mental practice. *Proceedings of the National Academy of Sciences*, *101*(46), 16369–16373. https://doi.org/10.1073/pnas.0407401101

Lutz, A., Slagter, H. A., Dunne, J. D., & Davidson, R. J. (2008). Attention regulation and monitoring in meditation. *Trends in Cognitive Sciences*, *12*(4), 163–169. https://doi.org/10.1016/j.tics.2008.01.005

Marcuse, L. V., Fields, M. C., Yoo, J., French, J. A., & Rowan, A. J. (2016). *Rowan's primer of EEG* (2nd ed.). Elsevier.

Pascoe, M. C., Thompson, D. R., Jenkins, Z. M., & Ski, C. F. (2017). Mindfulness mediates the physiological markers of stress: Systematic review and meta-analysis. Journal of Psychiatric Research, 95, 156–178. https://doi.org/10.1016/j.jpsychires.2017.08.004.

Phanikrishna, B. V. (2023). *A Brief Review on EEG Signal Pre-processing Techniques for Real-Time Brain-Computer Interface Applications*. Preprints. https://doi.org/10.36227/techrxiv.16691605.v1

Piron, H. (2022). Meditation Depth Questionnaire (MEDEQ) and Meditation Depth Index (MEDI). In O. N. Medvedev, C. U. Krägeloh, R. J. Siegert, & N. N. Singh (Eds.), *Handbook of Assessment in Mindfulness Research* (pp. 1–16). https://doi.org/10.1007/978-3-030-77644-2_41-1

Przegalinska, A., Ciechanowski, L., Magnuski, M., & Gloor, P. (2018). Muse Headband: Measuring Tool or a Collaborative Gadget? In F. Grippa, J. Leitão, J. Gluesing, K. Riopelle, & P. Gloor (Eds.), *Collaborative Innovation Networks* (pp. 93–101). Springer International Publishing. https://doi.org/10.1007/978-3-319-74295-3_8

Riether, N., Hegel, F., Wrede, B., & Horstmann, G. (2012). Social facilitation with social robots? *Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction*, 41–48. https://doi.org/10.1145/2157689.2157697

Rodriguez-Larios, J., Bracho Montes De Oca, E. A., & Alaerts, K. (2021). The EEG spectral fingerprints of meditation and mind wandering differ between experienced meditators and novices. *Neuroscience*. https://doi.org/10.1101/2021.07.06.451305

Rodriguez-Larios, J., Faber, P., Achermann, P., Tei, S., & Alaerts, K. (2020). From thoughtless awareness to effortful cognition: Alpha - theta cross-frequency dynamics in experienced meditators during meditation, rest and arithmetic. *Scientific Reports*, *10*(1), 5419. https://doi.org/10.1038/s41598-020-62392-2

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

Strijkstra, A. M., Beersma, D. G. M., Drayer, B., Halbesma, N., & Daan, S. (2003). Subjective sleepiness correlates negatively with global alpha (8–12 Hz) and positively with central frontal theta (4–8 Hz) frequencies in the human resting awake electroencephalogram. *Neuroscience Letters*, *340*(1), 17–20. https://doi.org/10.1016/S0304-3940(03)00033-8

Sugimoto, K., Kurashiki, H., Xu, Y., Takemi, M., & Amano, K. (2024). Electroencephalographic Biomarkers of Relaxation: A Systematic Review and Meta-analysis. *Neuroscience*. https://doi.org/10.1101/2024.03.27.586444

Tang, Y.-Y., Hölzel, B. K., & Posner, M. I. (2015). The neuroscience of mindfulness meditation. *Nature Reviews Neuroscience*, *16*(4), 213–225. https://doi.org/10.1038/nrn3916

Tapus, A., Matarić, M., & Scassellatti, B. (2007). The Grand Challenges in Socially Assistive Robotics. *IEEE Robotics & Automation Magazine, 14*(1), 35-45. https://doi.org/10.1109/MRA.2007.339605

Treves, I., Bajwa, Z., Greene, K. D., Bloom, P. A., Kim, N., Wool, E., Goldberg, S. B., Whitfield-Gabrieli, S., & Auerbach, R. P. (2025). Consumer-Grade Neurofeedback With Mindfulness Meditation: Meta-Analysis. *Journal of Medical Internet Research*, *27*, e68204. https://doi.org/10.2196/68204

Treves, I. N., Greene, K. D., Bajwa, Z., Wool, E., Kim, N., Bauer, C. C. C., Bloom, P. A., Pagliaccio, D., Zhang, J., Whitfield-Gabrieli, S., & Auerbach, R. P. (2024). Mindfulness-based neurofeedback: A systematic review of EEG and fMRI studies. *Imaging Neuroscience*, *2*. https://doi.org/10.1162/imag_a_00396

Urakami, J., & Seaborn, K. (2023). Nonverbal Cues in Human–Robot Interaction: A Communication Studies Perspective. *ACM Transactions on Human-Robot Interaction*, *12*(2), 1–21. https://doi.org/10.1145/3570169

Wainer, J., Feil-seifer, D., Shell, D., & Mataric, M. (2006). The role of physical embodiment in human-robot interaction. *ROMAN 2006 - The 15th IEEE International Symposium on Robot and Human Interactive Communication*, 117–122. https://doi.org/10.1109/ROMAN.2006.314404

Weisberg, D. S., Taylor, J. C. V., & Hopkins, E. J. (2015). Deconstructing the seductive allure of neuroscience explanations. *Judgment and Decision Making*, *10*(5), 429–441. https://doi.org/10.1017/S193029750000557X

Welch, P. (1967). The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. *IEEE Transactions on Audio and Electroacoustics*, *15*(2), 70–73. https://doi.org/10.1109/TAU.1967.1161901

Young, K. S., Van Der Velden, A. M., Craske, M. G., Pallesen, K. J., Fjorback, L., Roepstorff, A., & Parsons, C. E. (2018). The impact of mindfulness-based interventions on brain activity: A systematic review of functional magnetic resonance imaging studies. *Neuroscience & Biobehavioral Reviews*, *84*, 424–433. https://doi.org/10.1016/j.neubiorev.2017.08.003

Appendix A

Post-Session Questionnaire (Feedback Conditions)

Part 1: Background Information

- How much experience do you have with meditation? (None, A little, Some, A lot)
- How often do you meditate? (Daily, Weekly, Monthly, Rarely, Never)
- What type of meditation do you primarily practice? (e.g., Mindfulness, Vipassana, Zazen, etc.)

Part 2: Perception of the Guide/Agent *(Using a 5-point scale from Strongly Disagree to Strongly Agree)*

- The guide was social.
- The guide was friendly.
- The guide was human-like.
- The guide was trustworthy.

Part 3: Perception of the Guidance Received *(Using a 5-point scale from Strongly Disagree to Strongly Agree)*

- The feedback was helpful.
- The feedback was clear.
- The timing of the feedback was appropriate.
- The feedback was distracting.

Part 4: Subjective Session Experience *(Using a 5-point scale from Not at all to Very)*

- How relaxed did you feel during the session?
- How focused were you during the session?
- What was the overall quality of the session?

Part 5: Open-Ended Comments

- Do you have any other comments about your experience?

Post-Session Questionnaire (No-Feedback Condition)

(Parts 1, 2, 4, and 5 are identical to the Feedback Condition questionnaire)

Part 3: Perception of the Instructions *(Using a 5-point scale from Strongly Disagree to Strongly Agree)*

- The instructions were clear.
- The instructions were sufficient.
- The balance between instruction and silence was good.
- I found myself wishing for feedback during the session.

Appendix B

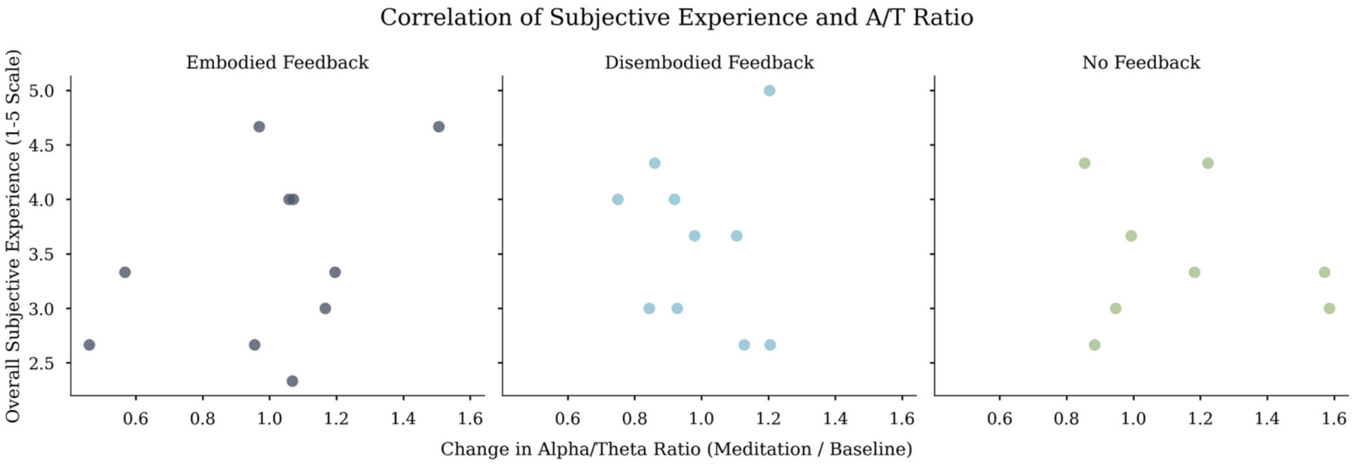

Figure 9. Correlation between subjective experience and Change in α/θ ratio. Each point represents a single participant, plotting their composite subjective score (y-axis) against the change in their α/θ ratio from baseline to meditation (x-axis). The data is separated by guidance condition. The plots visually demonstrate a lack of a clear linear relationship between participants' self-reported experience and their brainwave metrics, a finding supported by the non-significant correlation statistics.

Appendix C

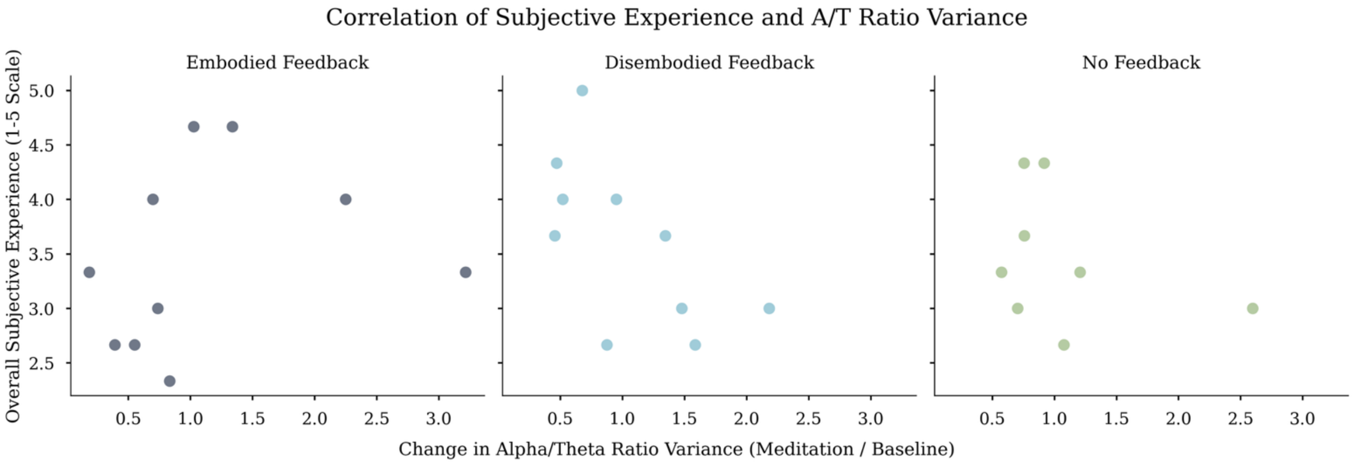

Figure 10. Correlation between Subjective Experience and Change in A/T Ratio Variance. Each point plots a participant's subjective score (y-axis) against the change in their A/T (α/θ) ratio variance (x-axis), a measure of neural stability. While no overall significant correlation was found, the plot for the disembodied feedback group visually suggests a negative trend, where higher-rated experiences are associated with a greater reduction in variance (increased stability).

Appendix D

Concordance Between Subjective Rank and Mean α/θ Ratio Rank

Participant ID	Condition	Subjective Rank	α/θ Ratio Rank	Concordance Score
participant_2 (NOF)	nofeedb	1	1	0
participant_7 (VOI)	voice	2	2	0
participant_2 (VOI)	voice	3	12	9
participant_10 (EPI)	epi	4	10	6
participant_4 (EPI)	epi	5	18	13
participant_3 (NOF)	nofeedb	6	4	2
participant_7 (NOF)	nofeedb	7	17	10
participant_5 (EPI)	epi	8	15	7
participant_7 (EPI)	epi	9	19	10
participant_4 (VOI)	voice	10	25	15
participant_1 (EPI)	epi	11	1	10
participant_1 (NOF)	nofeedb	12	13	1
participant_10 (NOF)	nofeedb	13	20	7
participant_9 (VOI)	voice	14	9	5
participant_10 (VOI)	voice	15	24	9
participant_8 (EPI)	epi	16	23	7
participant_9 (NOF)	nofeedb	17	14	3
participant_2 (EPI)	epi	18	28	10
participant_5 (NOF)	nofeedb	19	12	7
participant_3 (VOI)	voice	20	4	16
participant_8 (VOI)	voice	21	10	11
participant_9 (EPI)	epi	22	22	0
participant_6 (VOI)	voice	23	8	15
participant_6 (EPI)	epi	24	20	4
participant_1 (VOI)	voice	25	5	20
participant_4 (NOF)	nofeedb	26	3	23
participant_5 (VOI)	voice	27	6	21
participant_3 (EPI)	epi	28	2	26

Table 3. Concordance Between Subjective Rank and Mean α/θ Ratio Rank. This table quantifies the agreement between each participant's self-reported experience and their corresponding EEG-measured α/θ ratio. A lower concordance score indicates a smaller discrepancy between the subjective and neurophysiological measures.

Appendix E

Concordance Between Subjective Rank and Mean α/θ Ratio Variance Rank

Participant ID	Condition	Subjective Rank	Variance Rank	Concordance Score
participant_9 (NOF)	nofeedb	1	21	20
participant_9 (EPI)	epi	2	2	0
participant_3 (EPI)	epi	3	24	21
participant_4 (NOF)	nofeedb	4	25	21
participant_2 (VOI)	voice	5	12	7
participant_9 (VOI)	voice	6	10	4
participant_5 (VOI)	voice	7	6	1
participant_6 (EPI)	epi	8	3	5
participant_8 (VOI)	voice	9	5	4
participant_1 (VOI)	voice	10	22	12
participant_3 (VOI)	voice	11	26	15
participant_10 (NOF)	nofeedb	12	16	4
participant_5 (NOF)	nofeedb	13	4	9
participant_4 (EPI)	epi	14	20	6
participant_1 (EPI)	epi	15	9	6
participant_5 (EPI)	epi	16	15	1
participant_4 (VOI)	voice	17	12	5
participant_10 (VOI)	voice	18	13	5
participant_7 (VOI)	voice	19	10	9
participant_7 (EPI)	epi	20	25	5
participant_1 (NOF)	nofeedb	21	8	13
participant_2 (NOF)	nofeedb	22	17	5
participant_7 (NOF)	nofeedb	23	19	4
participant_3 (NOF)	nofeedb	24	6	18
participant_8 (EPI)	epi	25	16	9
participant_2 (EPI)	epi	26	28	2
participant_6 (VOI)	voice	27	1	26
participant_10 (EPI)	epi	28	27	1

Table 4. Concordance Between Subjective Rank and Mean Ratio Variance Rank. This table quantifies the agreement between each participant's self-reported experience and their corresponding EEG-measured ratio variance. A lower concordance score indicates a smaller discrepancy between the subjective feeling and the measure of brainwave stability.

Appendix F

Three ANOVA Measurments

Dependent Variable	df	F	p-value
Focus	(2,27)	0.37	.693
Relaxation	(2,27)	0.54	.590
Overall Session Quality	(2,27)	0.46	.638

Table 5. ANOVA Summary for Subjective Experience Ratings. This table summarizes the comparison of the three guidance groups on the self-reported questionnaire data. The results show no statistically significant differences between the groups.

Dependent Variable	df	F	p-value
Mean α/θ Ratio	(2, 25)	0.44	.652
Mean Ratio Variance	(2, 25)	0.37	.695

Table 6. ANOVA Summary for Mean EEG Metrics During Meditation. This table compares the average brainwave activity between the groups over the entire 15-minute meditation session. The results show no statistically significant differences.

Dependent Variable	df	F	p-value
Change in α/θ Ratio	(2, 25)	1.45	.258
Change in Ratio Variance	(2, 25)	1.10	.352

Table 7. ANOVA Summary for Change in EEG Metrics from Baseline. This table compares the change in brainwave activity from each participant's baseline to their meditation state. This is often the most critical analysis, and it also showed no statistically significant differences between the groups.

Appendix G

AI – Usage

Generative AI was utilized in three primary areas: (1) generating code for the experimental software on a function-by-function basis, (2) acting as a discussion partner to refine implementation strategies and sharpen ideas, and (3) proofreading the final thesis to enhance its clarity and structure.