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Decoding Depth of Meditation: Electroencephalography Insights From Expert Vipassana Practitioners

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ABSTRACT

BACKGROUND: Meditation practices have demonstrated numerous psychological and physiological benefits, but capturing the neural correlates of varying meditative depths remains challenging. In this study, we aimed to decode self-reported time-varying meditative depth in expert practitioners using electroencephalography (EEG).

METHODS: Expert Vipassana meditators (n = 34) participated in 2 separate sessions. Participants reported their meditative depth on a personally defined 1 to 5 scale using both traditional probing and a novel spontaneous emergence method. EEG activity and effective connectivity in theta, alpha, and gamma bands were used to predict meditative depth using machine/deep learning, including a novel method that fused source activity and connectivity information.

RESULTS: We achieved significant accuracy in decoding self-reported meditative depth across unseen sessions. The spontaneous emergence method yielded improved decoding performance compared with traditional probing and correlated more strongly with postsession outcome measures. Best performance was achieved by a novel machine learning method that fused spatial, spectral, and connectivity information. Conventional EEG channel-level methods and preselected default mode network regions fell short in capturing the complex neural dynamics associated with varying meditation depths.

CONCLUSIONS: This study demonstrates the feasibility of decoding personally defined meditative depth using EEG. The findings highlight the complex, multivariate nature of neural activity during meditation and introduce spontaneous emergence as an ecologically valid and less obtrusive experiential sampling method. These results have implications for advancing neurofeedback techniques and enhancing our understanding of meditative practices.

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Meditation, which is hard to define due in part to its wide spectrum of traditions and techniques (1), essentially involves the intentional shift of consciousness through observation, production, and awareness (2) to states that are more responsive and observant rather than reflexive and reactive. Extensive literature supports meditation's salutogenic outcomes across traditions (3), including psychological (4–8) and physical (9,10) well-being, metacognitive awareness (11,12), equanimity (13,14), and cognitive dispositions toward openness, acceptance, empathy, and positive affect (15–20), even in prisons (21). These outcomes have clinical relevance (22–25), enhance cognition (26,27), slow fluid intelligence decline in aging (28), and reduce substance use (25,29).

Beginners often grapple with questions like "what should it feel like?" or "am I doing it right?," which make the establishment of regular practice arduous (30,31). However, such ponderings are misguided; meditation transcends the pursuit of a specific phenomenological state. Just as developing a consistent practice involves progress and plateaus, meditation itself follows a nonlinear evolution in which advances and retreats cultivate present-moment awareness and equanimity. This process involves fostering awareness of mind wandering as integral to, rather than disruptive of, meditation (32), thereby offering opportunities to develop awareness of thought dynamics and transient experiences (33). Recognizing and addressing mind wandering strengthens meta-awareness, which is central to practices that emphasize nonjudgmental attention to a focal point such as breath (34,35).

Despite meditation's ambiguous end goal, prolonged practice can permit the cultivation of experiential states beyond the cyclic recognition of mind wandering (36–40). Such culminating meditative states may, at most, share characteristics of nondual awareness (41) and transcendence of time and space (42). Advanced stages can involve thought cessation—a pure consciousness of minimal phenomenology (43). These ephemeral states typically occur in brief bursts (44) [c.f. (45)], despite extensive practice. These reports suggest a conceptual framework that distinguishes between states of profound fulfillment and arduous, foundational practices in meditation. This delineation illuminates the progression from

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concerted cognitive effort to effortless consciousness, which is central to meditation's transformative ethos (46,47).

Historically, humans have used technology to extend these desired states, from monasteries harnessing geometry (48) to neurofeedback (49–51). Much like training wheels, these tools can promote the democratization of these states, but they must be employed with an aim of eventual obsolescence so that individuals can cultivate these states innately. Neurofeedback for meditation necessitates delineating its neural correlates. Research has mapped many signatures that distinguish meditation from other states like rest or mind wandering: elevated gamma power, reduced frontal theta/beta power, increased midline theta, and enhanced alpha:theta harmonics (36,44,52–57), all possibly stemming from reduced dimensional complexity (58). Like the idiom "keep making that face and it will stay that way," these transient state effects persist into sleep (59) and can lead to enduring neurobehavioral trait changes in long-term meditators. These changes include enhanced frontal alpha coherence; improved regulation; alterations in brain areas related to meta-awareness, memory, and self-regulation (18,28,29,54,60–67); increased gamma-band activity and phase synchrony (68); enhanced executive functions and emotional processing (69); and stable alpha activity under various stimuli (70–74).

Leveraging correlates that distinguish meditation from other states has informed initial neurofeedback protocols (30,75–77). However, these observations often overlap significantly with neural activities associated with other states [e.g., posterior cingulate cortex downregulation following itch relief (78,79)] and traits [e.g., increased theta band power in patients with sickle cell disease (80)], diluting specificity for meditation neurofeedback (51).

Responding to calls for phenomenological approaches in meditation research (81–83), we propose studying gradations within meditation, using real-time, online reporting [vs. post-session questionnaires (84)] to demarcate neuroimaging epochs and standardize cross-participant data (83,85,86). This approach, while risking an observer effect and potentially disturbing meditation, is consistent with the veridical and ecological tenets of cognitive neuroscience (87–89), embraces meditation's inherent complexity and subjectivity (90), and provides sensitivity to detect neural correlates of subjective microfluctuations. Previous experiential sampling approaches have probed meditation stages, distinguishing mind wandering from practice engagement (91). Hasenkamp *et al.* (92) identified neural correlates of meditation stages: activation of default mode network (DMN) during mind wandering, salience network during mind-wandering awareness, and executive network when refocusing. Similar efforts have demarcated meditative phenomenologies: cessation (44), effortless awareness (76), transcendence (93), bliss (54), interoceptive accentuation (94), altered time perception (95), self-boundary dissolution (96,97), and light percepts (98).

While measures exist to assess postmeditation outcomes (99), characterizing the moment-to-moment "what it is like to meditate" experience remains challenging (100). To our knowledge, no studies have identified an online marker tracking the continuum from foundational to culminative meditative states, a scientific metric analogous to assessing meditation depth. Thus, it is unclear whether neural correlates of meditation depth follow an amplifying pattern like task networks under increased difficulty (101) or transgress metastable states as seen in consciousness recovery (102).

In the current study, distinct from basic neuroimaging and as a first foray into predicting online meditative depth, we aimed to determine the feasibility of accurately decoding personally defined, but standardized, meditation depth across participants. By using a between-subjects approach, we aimed to establish a universal foundational model that has immediate (zero training) practical applicability while laying the groundwork for future personalization. This approach also sidestepped the issue of otherwise insufficient model training/testing data per individual if we had aimed for a purely within-subjects approach. Recognizing varied neural correlates and implementation flexibility across and within meditation practices (63,103,104), we investigated Vipassana meditation for its systematic nature and large expert practitioner pool. Participants engaged in their practice as usual, reporting perceived meditative depth as personal closeness to the culminating state. We employed depth as a comprehensible handle (83), asking participants to report their online meditative state on a relative scale from 1 (shallow) to 5 (deepest, culminative state). This approach captures meditation's inherent subjectivity while addressing the challenge of articulating advanced experiences while also ensuring uniformity across practitioners. Reports were gathered during meditation both through probing and a novel ecological method that we termed "spontaneous emergence."

METHODS AND MATERIALS

Experimental Methods

Participants. The study enrolled expert Vipassana practitioners (N = 41; 29 female; age mean [SD] = 46.34 [12.4] years, age range 27–70) who passed a screening that required at least 5 years of experience, with practice sessions of at least 10 minutes 5 days a week. All participants confirmed proficiency in Vipassana as instructed by S.N. Goenka: a combination breath-focused awareness (anāpānasati) with body scanning (directing attention along consecutive bodily loci to observe localized sensations). Participants declared no history of hypotension, neurological/psychiatric disorders, or central nervous system medication or dreadlocks or nonremovable scalp/ear metal for electroencephalography (EEG) collection. Participants who completed both sessions (n = 37) averaged 15.78 years' experience (SD = 11.88), practiced 6.59 days/week (SD = 0.71), and had 78.88 cumulative retreat days (SD = 162.57). Of these, 34 (26 female, 8 male; ages 27–70, mean [SD] = 46.53 [13.09] years) provided sufficient depth ratings and EEG data for analysis, averaging 16.15 years' experience (SD = 12.74), 6.53 practice days/week (SD = 0.75), and 82.38 cumulative retreat days (SD = 177.83). Reported session durations varied: 10 to 30 minutes (n = 9), 30 to 60 minutes (n = 16), 1 to 2 hours (n = 14), and >2 hours (n = 2).

Participants were remunerated $30/hour, rounded up to the nearest 15 minutes from arrival to departure across 2 sessions. Payment was made via cash or Venmo, and parking fees were fully covered.

Materials: Hardware/Software/Audio. Participants completed questionnaires via Castor ePRo: pre/post on laptop/iMac and intra-experimental on laptop/iPad. Bioperipherals were recorded using the Aim II (CGX, Inc.): electromyography (left/right sternocleidomastoid muscle), bioimpedance-based respiration rate (left/right pectoralis major), heart rate, and galvanic skin response (nondominant palm). Isopropyl alcohol was used to clean the skin prior to attaching electrocardiogram electrodes (Skintact Inc.). EEG signal (500 Hz) was acquired using a dual-amp 64-channel cap system (BrainVision, LLC). Nuprep (Weaver and Co.) was used to exfoliate the scalp before applying high-chloride abrasive electrolyte gel (Neurospec; EasyCap, Inc.).

Participants wore in-ear headphones connected to a laptop to present the gong, auditory oddball task, and audio prompts of: depth ("Please rate the depth of your meditation since your last response on a scale from 1–5") and confidence ("On a scale from 1–5, how confident are you in your response?"). During the experimental session, participants chose to sit on an office chair, recliner, zafu/zabuton, or their own materials and wore a Bluetooth Finger Ring Presentation Clicker on their dominant pointer finger (see Figure S1).

The NeuroPype Experiment Recorder (Intheon) using Lab Streaming Layer was used for protocol timing and temporal synchronization of all data streams. All analyses were realized in NeuroPype (Intheon).

Materials: Behavioral Questionnaires. Questionnaires administered before the first experimental session included: the Five Facet Mindfulness Questionnaire (105), Freiburg Mindfulness Inventory (106), Cognitive and Affective Mindfulness Scale-Revised (107), Mindfulness Attention Awareness Scale (108), and Profile of Mood States-Brief (109). Questionnaires administered after each experimental session included the Meditation Depth Index (110) and Toronto Mindfulness Scale (99). We also probed participants' thoughts on task design elements (Supplemental Methods).

Procedure. Before arrival, participants received experiment details to orient them to the task (Supplemental Methods). Consistent with COVID-19 regulations, all participants were temperature screened upon arrival, and all research assistants and participants wore N-95 masks (which participants could remove during solitary meditation) and silenced their phones.

Participants completed questionnaires before being outfitted with EEG caps (54–60 cm), positioned with FPz at 10% nasion-inion distance. During setup, participants reviewed instructions, confirmed their understanding of depth as a personal relative metric, practiced with the clicker, and adjusted volume. Afterward, participants transitioned to their meditation seating. Powered devices were unplugged to reduce EEG line noise. Following the experimental session, EEG and bioperipherals were removed, and questionnaires were completed before participant compensation/parking validation.

Procedure: Experimental Sessions. Each session ($\geq$1 week apart) comprised 6 blocks (Figure S2): 1) resting state (5 minutes, eyes closed, instructed not to meditate); 2) warm-up meditation (5 minutes, no stimuli/interruptions); 3) meditation with sustained attention passive oddball (SAPO) (Figure S4), with online depth ratings (35 minutes); 4) active oddball task (5 minutes, button press for oddball tones); 5) meditation without SAPO with online depth ratings (35 minutes); and 6) cool-down meditation (5 minutes, repeat of block 2). Eyes remained closed throughout. Questionnaires were completed following 35-minute meditations (Supplemental Methods). The total session duration was $\sim$100 minutes for data collection/tasks and 80 minutes for prep/questionnaires.

The 35-minute meditation blocks included 2 depth rating variants, both of which required participants to report their deepest meditation level since their last report using 1 to 5 clicker presses (1, shallow/foundational; 5, deepest/culminative) followed by a 1 to 5 confidence rating. In the emerge variant, intended to capture a more ecological representation of depth trajectories, participants spontaneously reported when they noticed their awareness wandering. After each spontaneous emergence depth rating, an auditory probe triggered a confidence rating. In the more operationalized probe variant, participants were prompted at random 3:00- to 3:50-minute intervals for depth and confidence ratings.

Each participant experienced all 4 block types (emerge/probe $\times$ SAPO/no SAPO) once across 2 sessions, with the starting block randomly assigned and counterbalanced across participants and sessions (Figure S3). The current study focused exclusively on classifying depth in the silent no-SAPO blocks, which more closely approximate naturalistic meditation practices uninterrupted by experimental auditory stimuli. SAPO data were reserved for future event-related potential analyses of intrameditative depth variability. Meditation blocks were divided into 100- to 120-second subblocks. Each ended with a gong (used as a tool to reorient attention) except during reporting or if $<$10 seconds remained. Depth ratings initiated new subblocks. Three successive gongs signaled block completion, which prompted a final rating unless reported within 60 seconds.

Recruitment, Confidentiality, Ethics, Institutional Review Board. Participants were recruited through paid advertising (Facebook, Tricycle: The Buddhist Review), email campaigns (Lion's Roar Foundation), fliers at Los Angeles Vipassana meditation sanghas, and referrals from previous participants ($100 award).

The Advarra Institutional Review Board approved all study materials prior to initiating enrollment (Pro00063946). Participants provided informed consent via Castor eConsent, which includes the Research Subject's Bill of Rights (CA Health & Safety Code 24172).

EEG Methods

Data Curation and Ground Truthing. Continuous EEG data between reports were labeled by self-reported meditation depth (1–5), and only high-confidence ($>$3/5) reports were used. We assumed 1) constant depth within time segments and 2) 10-second descent and 5-second emergence periods, which were excluded from analysis (Figure S5). Resting-state periods were labeled as depth 0, enabling 1) model robustness during brief meditation interruptions and 2) quantification of mental states across the full spectrum from nonmeditation to ideal deep meditation. While these assumptions and self-report uncertainty introduce some labeling error, this can only reduce observed model accuracy, making eventual classification results conservative estimates. After preprocessing, labeled time segments were partitioned into 5-second EEG windows (epochs) for decoding analysis (see Supplemental Methods for more detail).

Decoding Approach. Our decoding approach constructs a time-varying measure of meditation depth from EEG data using both a continuous scale (0–5) and a 2-level scale (low: 0–2, high: 4–5). Models operate on 5-second sliding windows within epochs of interest.

To decode meditation depth, we compared 2 sets of EEG measures:

1) spectral power variance in theta (4–7 Hz), alpha (8–12 Hz), and gamma (31–42 Hz) bands and
2) Granger-causal effective connectivity (e.g., 111) in the same frequency bands.

We extracted measures from estimated EEG source signals rather than raw scalp signals to improve signal-to-noise ratio. Three source estimation approaches were compared:

A) a traditional standardized low resolution brain electromagnetic tomography (sLORETA) (112) approach using a 6 region of interest model of the DMN;
B) a data-driven generalized eigendecomposition of the EEG signal [following Dähne *et al.* (113) for the continuous scale and Ramoser *et al.* (114) for the 2-condition scale]; and
C) a deep learning model similar to that of Schirrmeister *et al.* (115), one of the earliest and simplest deep learning-based EEG decoders with an emphasis on interpretability.

The meditation depth estimator is a joint linear model of log-transformed source measures (log-power or log-connectivity) within the 3 EEG frequency bands for all source processes of interest. The model's output is limited within the 0 to 5 continuous depth scale's bounds using hard thresholding (variants A and B) or soft thresholded with a scaled sigmoid transform for deep learning (variant C). The full model that underlies all variants in this family of methods is described in full in the Supplemental Methods.

We compared all methods using the same automated preprocessing pipeline, which largely follows the approach proposed in Mullen *et al.* (116), with details tailored to the dataset at hand: removing non-EEG channels, resampling to 125 Hz, applying a high-pass finite impulse response filter (0.5–1 Hz transition band), removing low-contact and high-noise EEG channels, removing transient high-amplitude artifacts using artifact subspace reconstruction (116), removal of residual high-noise time windows, lowpass finite impulse response filtering (45–50 Hz transition band), spherical spline interpolation of removed channels, and common average rereferencing. Spatial whitening using a robust zero-phase component analysis (117) was then applied per session to align signals across sessions, which aids cross-session transferability of decoding models.

Models were evaluated using leave-one-participant-out cross-validation. Accuracy was measured using mean absolute error (MAE) (0–5 scale) and area under the curve (AUC) (2-level scale).

Exploratory EEG Analysis

Spectral Analyses. EEG power spectra were analyzed to assess neural correlates of meditation depth using both (pooled) emerge and probed periods. Data curation and preprocessing matched machine learning methods. We computed 1/f normalized, dB-converted power spectra using the Thomson multitaper method (0.5-Hz bins).

Statistics. For group-level statistics, a 1-way mass-univariate analysis of variance with meditation depth level as a factor was conducted on subject means, followed by post hoc pairwise analyses for each depth level combination. For the simplified 2-level depths (low vs. high), a paired t test was used. Connectivity analysis was only run on the 2-level depths using t tests to allow for plotting both positive and negative t scores (increased vs. decreased connectivity) thresholded by significance because analysis of variance F statistic values are only positive and cannot differentiate between significant increases and decreases in region of interest–to–region of interest connections.

RESULTS

Behavioral

Participants provided an average of 22.5 (SD = 6.4) depth and confidence ratings per session (Figure 1). Analysis focused on high-confidence (>4) depth ratings, which comprised 74% of all ratings. This resulted in a slightly flatter distribution with more depth 4 to 5 ratings, particularly in session 2. Emerge blocks produced 45.6% more ratings than probe blocks (μ = 20.1 vs. 13.8) and showed significantly higher confidence (Figure 2). We also found that online mean depth ratings correlated with postblock overall depth ratings in both sessions (session 1: emerge r = 0.58, probe r = 0.735; session 2: emerge r = 0.79, probe r = 0.731; all ps $<$ .0001). Session 2 mean emerge ratings correlated with all Meditation Depth Index subscales (r = -0.464 to 0.44, p $<$ .025), while probe ratings correlated only with the Meditation Depth Index-Personal Self scale (r = 0.426, p = .013) (see Supplemental Results).

EEG Results: Neural Characterizations of Depth

Mass-univariate analyses revealed no significant effects of depth rating on spectral frequencies, frequency band powers, or connectivity. However, higher frequency (beta and gamma) power showed nonsignificant increases at lower than at higher depths (Figure 3). This pattern was also observed when grouping depths into high (4–5) and low (1–2), with decreased high-frequency power at higher depths primarily in centroparietal regions (Figure S6). Source-level analyses using sLORETA showed similar nonsignificant spectral patterns and no significant connectivity differences between high and low depths.

EEG Results: Predicting Depth

Multivariate decoding strategies successfully decoded meditative depth from EEG data with significant accuracy in unseen sessions. Our analysis predicted depths on a 0 to 5 scale for both emerge and probe trials. We also distinguished lower (1–2) from higher (4–5) depths with notable precision.

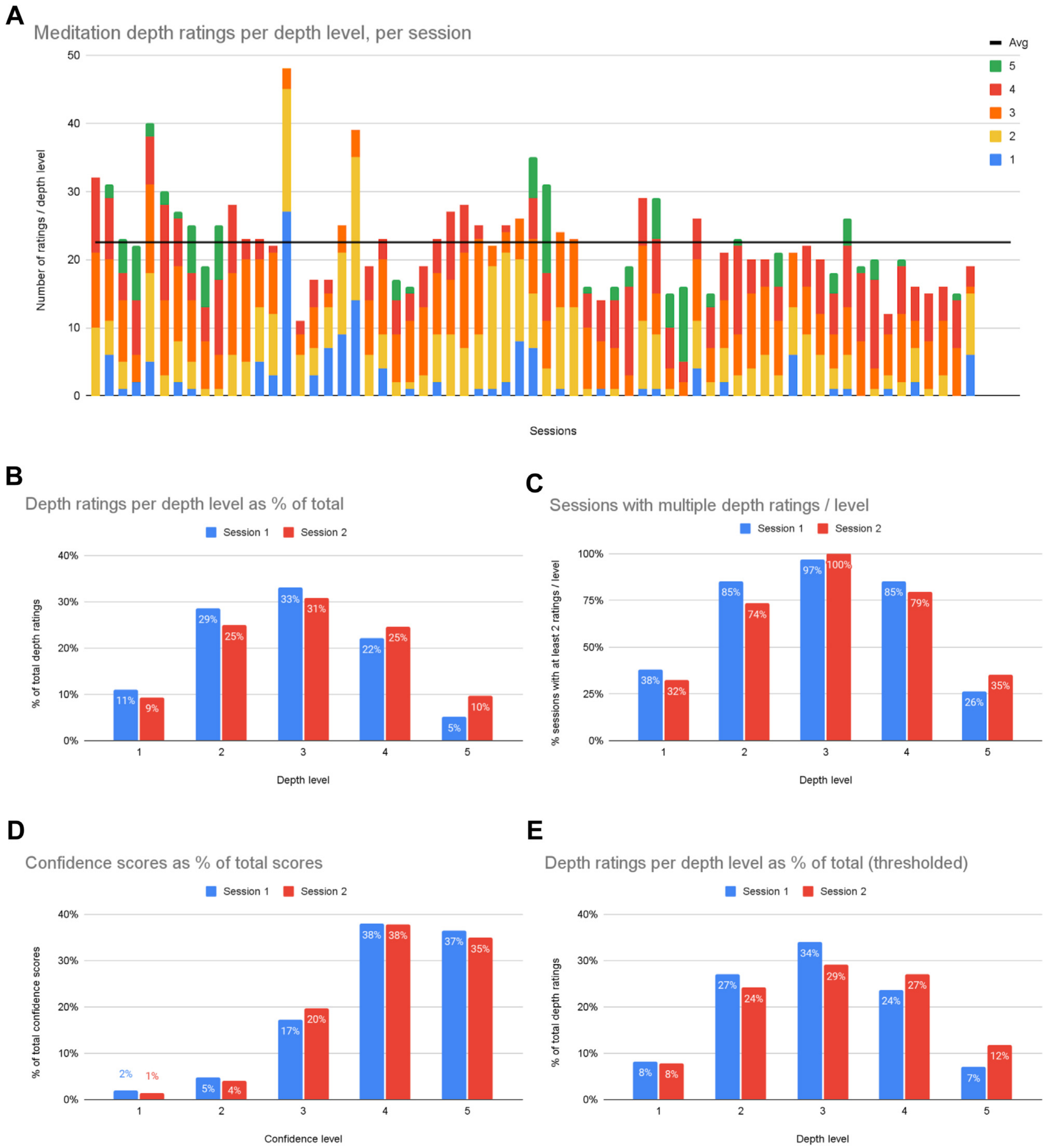

Figure 1. **(A)** Number of meditation depth ratings, per depth level, per session, with each vertical bar representing 1 session. Session 1s make up the leftmost half of bars, while session 2s make up the rightmost half. Levels 2 to 4 are shown in orange-to-red scale. The black line indicates the average (Avg) total ratings per session. **(B)** Share of meditation depth ratings for each depth level as a percentage of all depth ratings. Averages for all session 1s and session 2s shown separately. **(C)** Percentage of sessions containing more than 1 depth rating of a given depth level. **(D)** Confidence scores, given for each meditation depth rating, as a percentage of total scores for that session number, across all sessions; session 1s and session 2s shown separately. **(E)** Depth ratings per depth level as a percentage of total depth ratings; session 1 and session 2 shown separately. Only ratings with a corresponding confidence score of 4 or 5 were included.

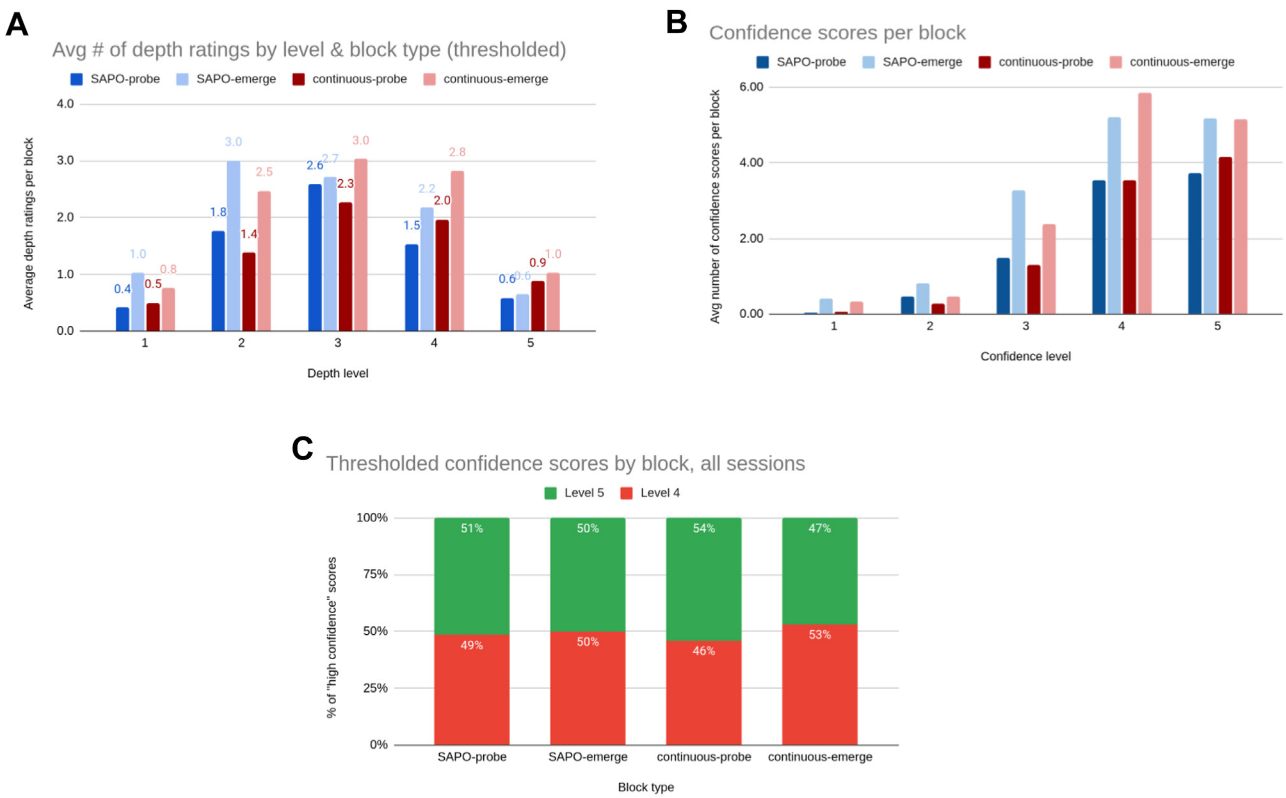

Figure 2. **(A)** Average (Avg) number of meditation depth ratings per block by block type. Sustained attention passive oddball (SAPO) and non-SAPO (continuous) blocks have blue and red hues, respectively, while probe and emerge blocks use dark and light colors, respectively. Each session contained 2 blocks; each block type appeared once during both sessions. **(B)** Average number of confidence scores per block, by block type, across all sessions. SAPO and non-SAPO (continuous) blocks have blue and red hues, respectively, while probe and emerge blocks use dark and light colors, respectively. **(C)** Confidence level 4 and 5 scores as a percentage of total high confidence (level 4 or 5) scores, per block type, across all sessions.

Table 1 showcases continuous and high/low depth decoding results across reporting variants and source estimation methods. Emerge trials best predicted continuous depth using generalized eigenvalue source estimation with connectivity (1.15 MAE) and low/high depth using deep learning with variance (0.798 AUC). Probe trials yielded similar results: 1.262 MAE (generalized eigenvalue/connectivity) and 0.807 AUC (deep learning/variance). One-sided t tests rejecting null hypotheses of chance-level performance retained significance ($p < .01$) after Bonferroni correction for 8 comparisons (2 measures $\times$ 2 source localization methods $\times$ 2 experimental conditions).

Combining trials and feature pruning did not improve accuracy. Channel-based models for DMN connectivity or all source channels performed weakly. Pooling trials slightly improved performance but faced computational constraints. Despite the relationship between physical stillness and mental relaxation (118), electromyography + EEG features did not improve results, which were nonsignificant for continuous scale and no enhancement for binary classification (Table S1).

Figure 4 shows receiver operating characteristic curves across sessions for the best-performing model on the low versus high depth prediction using pooled trials. Individual session traces are displayed together with median and interquartile range because the distribution is not normal at most false positive rate levels (per Shapiro-Wilk tests).

Decoding Model Visualizations

Figure 5 visualizes the scalp forward projections (derived from spatial filters W_b) (see the Supplement) of spatial components within each frequency band learned by the best-performing continuous depth prediction model, together with model weights (β_b) for effective connective between these components.

DISCUSSION

This multiday EEG study with expert Vipassana practitioners explored meditation's dynamic phenomenology using self-reported depth during practice. Despite relying on subjective ratings, multivariate machine learning methods accurately decoded depth in unseen participants, suggesting coherent self-rating approaches among participants. Data-driven source components outperformed a priori sources and channel-based measures, achieving 0.81 AUC (chance 0.5) for binary and 1.15 MAE (chance 1.5) for continuous depth decoding. Benchmarking is challenging due to subjective rating variability and the integer scale, which limited intermediate state reporting

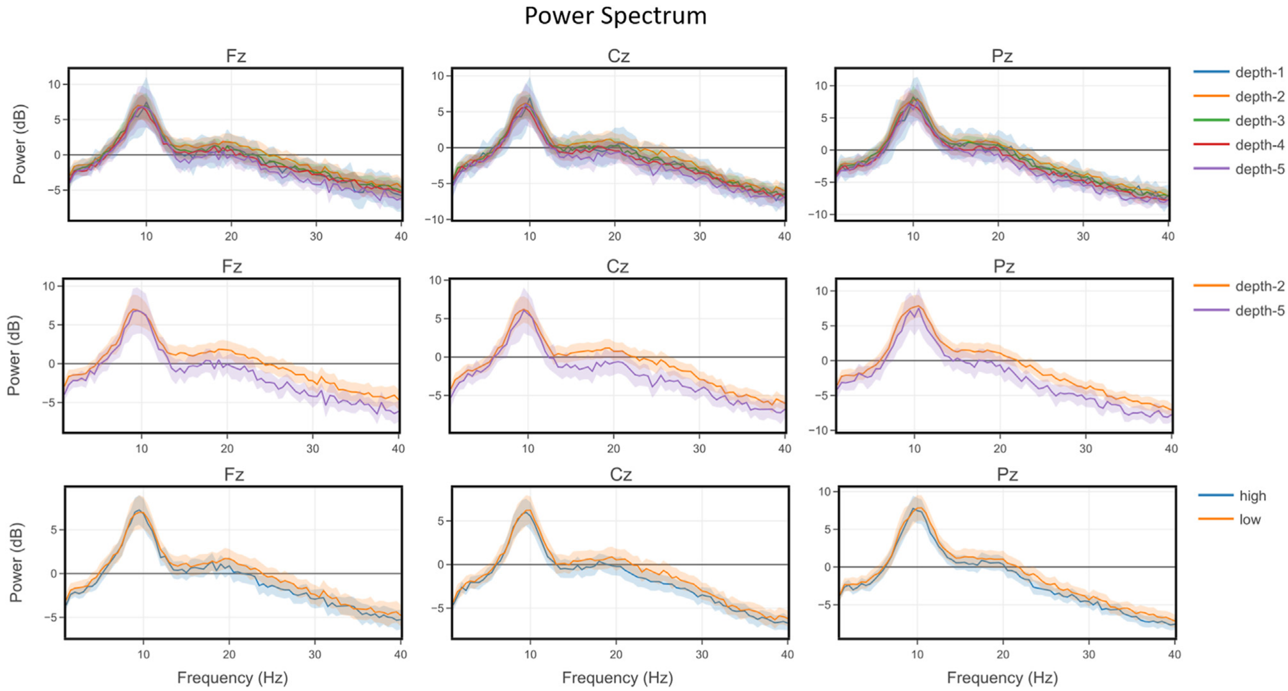

Figure 3. Mean spectral power across participants by depth for midline channels Fz, Cz, and Pz. Shaded regions around lines represent 95% CIs. Top shows all depths overlaid, middle shows only depth level 2 (orange) vs. depth level 5 (purple), and bottom shows high (4,5; blue) vs. low (1,2; orange) depths. Power bands were defined as delta (1–4 Hz), theta (4–7 Hz), alpha (7–12 Hz), beta (12–32 Hz), and gamma (32–40 Hz).

(e.g., 3.5). Nevertheless, performance paralleled left/right motor imagery decoding (119). Spontaneous emergence outperformed probed-based reporting, offering ecological validity, less obtrusiveness, more trials, better continuous depth prediction, and stronger correlations with postexperimental outcomes.

While the aim of this study was to assess the feasibility of decoding meditative depth without delving into underlying mechanisms, model weights indicate the predictive power of constituent neural features. Components positively correlated with deeper meditation states implicate frontal midline, parietal, and occipital brain regions. Conversely, the components most anticorrelated with deeper meditation states implicate possible eye- and neck muscle–related activity, among potential brain sources that include frontal, frontopolar, and inferior occipital sources. In the theta band, we noted prominent model weights near the frontal midline (Figure 5; component C), a region that has been implicated in higher-order cognitive functions, downregulation of the DMN, and focused-attention meditation (75), as well as its connectivity with right posterior parietal (component B) and frontopolar (component D) regions. In the alpha band, we noted prominent model weight distributed over bilateral occipital regions (component B) as well as posterior parietal regions (component C), which corroborates research that has shown that trait-level mindfulness mediates parietal activity during meditation (120) and is consistent with findings of occipitoparietal alpha power modulation in Vipassana meditators (52). We also noted modest model weight distributed over dorsolateral frontal and frontopolar regions (components D and E), which may corroborate the alpha modulation that has been seen in advanced practitioners during rest and meditation (52,56,121). In the gamma band, modest model weights were associated with a dipolar central midline source (component A) and over a posterior parietal region (component B), which appears consistent with a posterior cingulate source—a region known to be implicated in meditation practice (60). The overall distribution of weight over occipitoparietal and midline parietal regions is consistent with findings of increased gamma activity in these regions in Vipassana meditators (52), which is also associated with heightened sensory awareness in Vipassana practitioners (122). Katyal and Goldin (123) found results similar to our alpha and theta (but not gamma) findings, with a univariate encoding model (compared with our multivariate decoding model) based on postblock self-reported meditation depth.

Vipassana meditation is foundational to mindfulness-based stress reduction and cognitive therapy (35). The current work provides a more nuanced and pragmatic understanding of Vipassana's neural correlates, demonstrating predictive power in decoding gradations of depth within this practice. This advancement paves the way for developing tools (e.g., multivariate neurofeedback) that could significantly facilitate interventions. Focusing on intrameditative phenomenology, neurofeedback optimization using depth gradations offers a more fine-tuned approach, reducing misinterpretations of other states as meditative and providing more precise guidance for practitioners.

Table 1. Performance of Different Source Estimation Techniques Combined With Different Measures for Both Depth Scales

Source Estimation Method	Measure	Continuous Depth, MAE	Low/High Depth, AUC
Emergence Reporting			
Channel-Based—Subset	Variance	1.453 ± 0.363	0.629 ± 0.109
	Connectivity	1.478 ± 0.346	0.606 ± 0.115
Channel-Based—All	Variance	1.379 ± 0.344	0.667 ± 0.125
sLORETA	Variance	1.276 ± 0.288	0.683 ± 0.154
	Connectivity	1.372 ± 0.279	0.671 ± 0.141
Generalized Eigenvalue	Variance	1.303 ± 0.324	0.722 ± 0.147
	Connectivity	1.150 ± 0.263	0.770 ± 0.118
Deep Learning	Variance	1.265 ± 0.253	0.798 ± 0.108
	Connectivity	1.254 ± 0.239	0.765 ± 0.122
EEGNet	N/A	1.325 ± 0.264	0.766 ± 0.145
Probe Reporting			
Channel-Based—Subset	Variance	1.501 ± 0.372	0.634 ± 0.159
	Connectivity	1.522 ± 0.359	0.610 ± 0.135
Channel-Based—All	Variance	1.391 ± 0.302	0.724 ± 0.101
sLORETA	Variance	1.397 ± 0.350	0.714 ± 0.180
	Connectivity	1.457 ± 0.330	0.684 ± 0.150
Generalized Eigenvalue	Variance	1.426 ± 0.516	0.722 ± 0.150
	Connectivity	1.262 ± 0.300	0.754 ± 0.110
Deep Learning	Variance	1.289 ± 0.292	0.807 ± 0.117
	Connectivity	1.335 ± 0.313	0.798 ± 0.128
EEGNet	N/A	1.329 ± 0.385	0.756 ± 0.157
Emergence and Probe (Pooled) Reporting			
Channel-Based—Subset	Variance	1.450 ± 0.370	0.636 ± 0.157
Channel-Based—All	Variance	N/A	0.731 ± 0.115
Generalized Eigenvalue	Variance	1.309 ± 0.281	0.748 ± 0.149
	Connectivity	1.196 ± 0.269	0.807 ± 0.105
Deep Learning	Variance	1.239 ± 0.273	0.806 ± 0.117
	Connectivity	N/A	0.798 ± 0.128
EEGNet	N/A	1.237 ± 0.296	0.791 ± 0.142

Based on ratings reported upon emergence, probe, or emergence and probe (pooled). Chance levels are 1.51 (MAE) and 0.5 (AUC). Channel-based (subset) models used F3, F4, Fz, P3, P4, and Pz (126) for default mode network connectivity (channel count matching the number of regions and spatial components in other models). For MAE, lower is better, and for AUC, higher is better.

AUC, area under the curve; MAE, mean absolute error; N/A, not applicable; sLORETA, standardized low resolution brain electromagnetic tomography.

Limitations

Potential cross-session variability (e.g., cap placement) and our focus on ecological validity enhanced machine learning robustness but complicated mass-univariate analysis and interpretability beyond classification outcomes. This approach, while consistent with our primary goal of demonstrating successful meditation depth decoding, limited our ability to disentangle specific contributions of anāpānasati versus body scan techniques and their neural underpinnings.

Variability in trial numbers due to natural emergence responses, uneven depth/confidence distribution, and participants' use of personal 1 to 5 depth scales complicated analysis and statistical weighting. Emergence conditions yielded more trials than probe conditions, which limited direct comparisons but is consistent with our focus on ecological decoding. Determining representative meditation windows was challenging due to subjective ratings and unclear subject strategies. The inherent variability in short (5-second) EEG segments, which we call single trials here, challenged generalization. While longer decoding windows may reduce this variability, they would compromise the model's responsiveness to rapid depth changes, thus representing a tradeoff between accuracy and temporal resolution.

Occipital and temporal gamma-band EEG activity is difficult to distinguish from neck muscle activation. Despite state-of-the-art artifact removal (116), some model output may also be explained by nonbrain activity. However, EEG + electromyography analyses reduced classification accuracy and showed that nonbrain sources were not strong predictors of meditative depth. While our methods may be sensitive to subtle nonbrain physiological signals, the cross-participant depth decoding performance suggests an ensemble of neural features that are both generalizable and useful.

Future Work

Future work will develop a real-time variant of this post hoc approach. The zero-training nature of our model allows immediate application to new participants without additional data

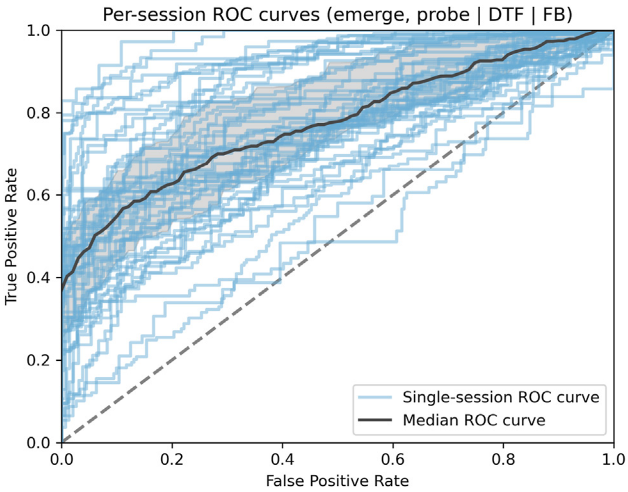

Figure 4. Receiver operating characteristic (ROC) curves for the best-performing model on low- vs. high-depth prediction. ROC curves per session for the best-performing model, which used generalized eigenvalue-based source estimation in conjunction with the directed transfer function (DTF) connectivity measure. Individual light blue traces represent area under the curves for each session, with high meditation depth as the positive class. The black trace indicates the median ROC curve across sessions, while the shaded region spans the 25th to 75th percentiles. The dashed diagonal line represents chance performance. Because the distribution of traces across sessions is not well described by a normal distribution at most false positive rate levels (according to the Shapiro-Wilk tests), all individual per-session traces are shown together with their median and interquartile range. FB, frequency band.

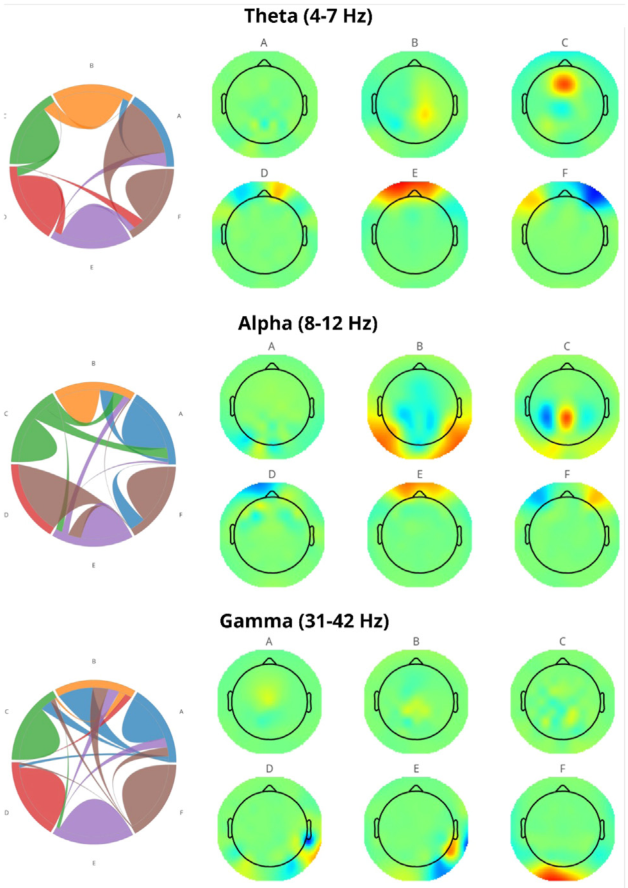

Figure 5. Connectivity weights and scalp projections for best-performing continuous depth model. Left panel: Connectivity weights between 6 spatial components (A–F) estimated using the generalized eigenvalue technique across theta, alpha, and gamma frequency bands. These weights are calibrated to the 0 to 5 depth scale using the frequency band specific patterns of covariance method. The conical representations indicate outflow from source to target regions, with the base diameter of each cone indicating the absolute model weight for outflow from the source region to the target region. Autoconnectivity is represented by a self-directed cone from a region to itself. These visualizations illustrate the directional information flow and neural dynamics most predictive of continuous meditation depth. Right panel: Topographical maps showing scalp forward projections of learned electroencephalography sources corresponding to the connectivity nodes, obtained using the frequency band specific patterns of covariance method. These projections are derived from the spatial filters W_b (see the Supplement) using either the method of Haufe *et al.* (125) or, for generalized eigenvalue solutions, the transpose of eigenvector matrices Φ. The top row of the topographical maps are the components most positively correlated with meditation depth, while the bottom row are the components most negatively correlated with meditation depth. These visualizations provide insight into the spatial distribution of the electroencephalography sources most relevant to predicting meditation depth on a continuous scale.

collection, thereby offering practical relevance despite potentially lower performance than individually adapted approaches. This study, which enabled continuous real-time meditation depth measurement and a normalized distance from ideal states, lays the groundwork for developing multivariate neurofeedback protocols. These protocols could leverage expert-initialized weights and use multitask learning (124) for personalization over time.

Future studies could compare this personalized, multivariate approach with traditional univariate neurofeedback, assessing impacts on meditative depth and well-being. Additional avenues include analyzing SAPO tone responses from the current dataset as a function of depth, disentangling shared and distinct neural features of probe versus emerge responses, examining differences in decoding accuracy as a function of Meditation Depth Index–stratified subgroups, and investigating the specific contributions of attention orientation to meditative depth and its neural correlates (e.g., dedicated blocks for anāpānasati and body scan techniques).

Conclusions

This study successfully decoded self-reported meditative depth from EEG in unseen participants and achieved high accuracy rates, particularly in binary classification of high versus low states (0.81 AUC). Source localization methods, which capture complex neural dynamics through learned latent brain sources, outperformed traditional approaches, reflecting the nuanced phenomenology of discrete meditative states. Our novel spontaneous emergence method proved to be ecologically valid, yielding more reports that scaled better with established outcome measures than overtly probed reporting. These findings demonstrate the potential to detect nuanced intrastate phenomenological differences that could be leveraged by advanced neurofeedback techniques to facilitate meditative practices.

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Data will be made publicly available (under the Creative Commons Attribution 4.0 International License for data) and shared with the ENIGMA meditation working group upon completion of peer review.

NR was responsible for study conceptualization and procurement of funding. NR, TB, CK, SM, and TM were responsible for study design. NR, NS, and SM were responsible for study implementation and data collection. CK, GH, SM, and NR were responsible for data analysis. NR, NS, TB, CK, GH, SM, and TM were responsible for manuscript writing and editing (all drafts). All authors approved the final version for submission.

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