NeuroRegulation

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Exploration of Brain Network Measures Across Three Meditation Traditions

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Abstract

Research into the similarities and differences between various forms of meditation practice is still in its early stages. Here, utilizing functional connectivity and graph measures, we present our work examining three meditation traditions: Himalayan Yoga (HT), Isha Shoonya (SNY), and Vipassana (VIP). EEG activity of the meditative block is used to build functional brain connections to exploit the resulting networks between various meditation traditions and a control group. Support vector machine is employed for binary classification, and models are built with features generated via graph theory measures. We obtain maximum accuracy of 84.76% with gamma1, 90% with alpha, and 84.76% with theta in HT, SNY, and VIP, respectively. Our key findings involve (a) higher delta connectivity in Vipassana meditators, (b) synchronization of theta networks in the left hemisphere inspected to be stronger in the anterior frontal area across meditators, (c) greater involvement of gamma2 processing observed among Himalayan and Vipassana meditators, (d) increased left frontal activity contribution for all meditators in theta and gamma bands, and (e) modularity engaged extensively in gamma processing across all meditation traditions. Furthermore, we discuss the implication of this research for neurotechnology products to enable guided meditation among naive practitioners.

Keywords: EEG signals; meditation; functional connectivity; graph measures; support vector machine; machine learning; brainwaves; Himalayan Yoga; Isha Shoonya; Vipassana

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Introduction

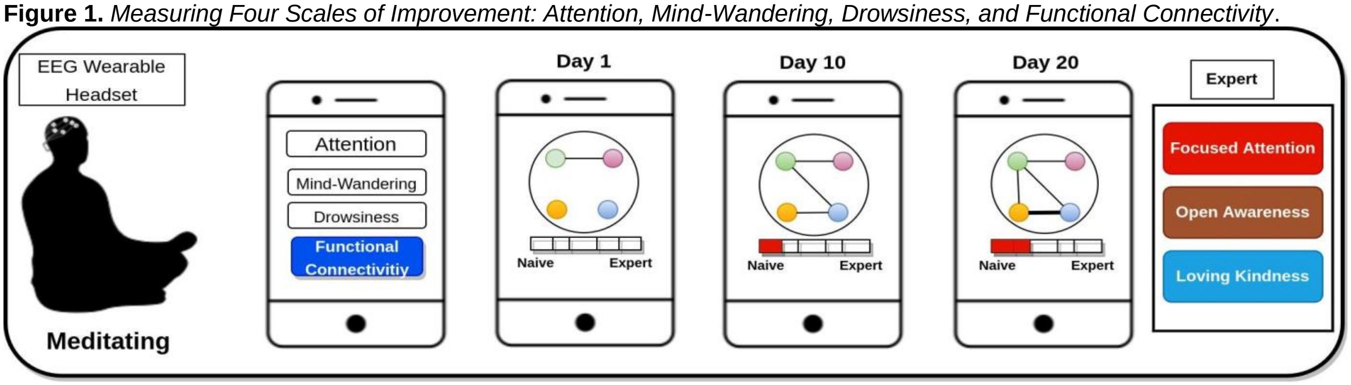
In recent years, neuroscientific research has focused on meditation as a mental practice. This is due to the large-scale benefit it offers, observed in numerous studies, such as improved attentional states, metacognitive awareness, cognitive control, compassion, self-regulation, decreased states of mind wandering, and so on (Brandmeyer & Delorme, 2018). Multiple studies determine how long- and short-term meditation practice (measured in hours of experience) impact the brain (in terms of neural oscillation and executive functioning tasks such as working memory). This approach is designed to integrate mindfulness-based practices like meditation in a clinical context to treat anxiety, depression, chronic pain, and stress (Yordanova et al., 2020). But most of the study misses out on the significance of each meditation type on distinct brain circuitry, frequency bands, and cognitive functions that is unique in itself and cannot be generalized fully to other types of meditation practices. As each meditation type can uniquely influence the person (both psychologically and physiologically) different meditation practices require careful observation and rigorous examination before making a causal interpretation and generalization. With neurotechnological advancements, meditation researchers are using electroencephalogram (EEG), functional magnetic resonance imaging (fMRI), magnetic resonance imaging (MRI), and single-photon emission computerized tomography (SPECT). EEG and fMRI techniques are commonly employed in meditation research. There are many types of meditation traditions practiced worldwide, for example, Himalayan Yoga (HT; focused attention), Vipassana (VIP; open monitoring) and Isha Shoonya (SNY; open awareness meditation), and Loving Kindness meditation.

Spectral analysis used in earlier studies on VIP revealed enhanced gamma activity over the parieto-occipital electrodes (Braboszcz et al., 2017; Cahn et al., 2010; van Lutterveld et al., 2017). Gamma band has been associated with cognitive processes such as attention, working memory, learning, consciousness, microsaccades, and visual imagery (Fries, 2009; Fries et al., 2007), and long-range neural communication (Nikolić et al., 2013). The sample entropy (SE) of VIP meditators was higher in the study by Vivot and colleagues (Vivot et al., 2020), especially in the alpha and low/high gamma bands. The alpha band (7–11 Hz) was identified to have a trait influence as observed in both the conditions of mind wandering and meditation in a recent study by (Braboszcz et al., 2017). According to studies on HT practitioners, their brainwaves are reported to have sensorimotor alpha, frontal-midline theta, and parieto-occipital gamma (Braboszcz et al., 2017; Brandmeyer & Delorme, 2018; Vivot et al., 2020). Working memory has linkages with alpha rhythms which are thought to be prevalent in HT meditation, since it emphasizes the mental repetition of the mantra and the breath (Braboszcz et al., 2017). SNY was linked to gamma frequency in the parieto-occipital, central, and frontal electrodes, according to a study by Braboszcz et al. (2017). Since the explicit focus is on "nothingness," it is unclear what kind of object is sent to the attentional system for SNY practitioners. Since higher gamma power over the frontal and parieto-occipital electrodes is demonstrated as a trait effect, this may indicate that SNY meditation engages attentional processes differently than VIP and HT meditation. According to the research by van Lutterveld et al. (2017), SNY meditators had greater separations in their thought charts observed using Hausdorff distance under the breath awareness condition. In the current study, the brain states connected to three crucial and distinctive types of meditation—HT, VIP, and SNY—are examined. This study's goal is to leverage functional network measurements to examine variations between control subjects and meditators on (a) frequency bands, (b) brain regions, (c) network measures, and (d) commonalities and discrepancies among mediators.

Complex network theory has recently gained prominence (Li & Yang, 2016). Research has demonstrated that EEG may be utilized to create brain networks that retain several crucial topological characteristics (Sun et al., 2019). The temporal correlation between distant neurophysiological events is often used to describe a functional connection in the brain (Friston, 1994). In recent decades, various neural coupling techniques have been put forth. Coherence (coh), a linear dependency measure between two nodes, has been used to assess functional connectivity (Jalili, 2016). However, coh is affected by volume conduction. Since volume conduction is likely to detect brain activity from the same sources, even if unrelated, it may result in incorrect correlations between nearby electrodes. To lessen the consequences of volume conduction, additional metrics have been incorporated. It has been shown that imaginary coherence (imcoh) can eliminate any instantaneous interactions that are caused by volume conduction (Nolte et al., 2004). The phase lag index (pli), a phase synchronization technique, is insensitive to the volume conduction effect and reveals the genuine coupling strength between pairs of channels by excluding interactions produced by zero phase differences (Stam et al., 2007). In the weighted phase lag index (wpli), a modification of the pli wherein observable phase leads and lags are weighted by the amplitude of the imaginary component of the cross-spectrum (Vinck et al., 2011). Corrected imaginary phase locking value (ciPLV), a metric for assessing synchronization in the presence of volume conduction or source leakage effects, was proposed by Bruña and colleagues (Bruña et al., 2018). We have used all five connectedness metrics because they can distinguish between functional networks that are similar and those that are distinct. Regardless of the coupling method, our main goal is to find the functional networks that discriminate between two groups.

Examining functional connectivity with various graph theoretical measures shows key topological characteristics of brain networks (Rubinov & Sporns, 2010). EEG/MEG, functional MRI, diffusion MRI, and structural MRI are just a few imaging modalities using graph theory analyses of human brain networks (He & Evans, 2010). Modularity, node betweenness, centrality, clustering coefficient, and the occurrence of highly connected hub regions are a few network features that have been addressed often (He & Evans, 2010; Sun et al., 2019; Wang et al., 2010). Additionally, it has been found that these network characteristics change over time under various conditions, such as normal development, aging, and pathological circumstances. Recent work by Hiroyasu and colleagues and a dearth of works on network modeling in meditation have shown how to categorize resting and meditative states using the centrality measure (Hiroyasu & Hiwa, 2017). In earlier research on long-term meditators, trait effects on meditators were examined (Braboszcz et al., 2017). These effects may indicate a change in the functional architecture of the human brain compared to controls. Our research examines the four network features between long-term practitioners of three meditation traditions and the control group. Machine learning classifiers are trained as the most practical method for spotting differences due to their strong pattern learning capabilities. Moreover, there has been a surge in studies using machine learning to categorize meditation states in recent years (Chaudhary et al., 2022; Pandey et al., 2022; Pandey & Miyapuram, 2020; Pandey & Miyapuram, 2021a, 2021c).

Figure 1. *Measuring Four Scales of Improvement: Attention, Mind-Wandering, Drowsiness, and Functional Connectivity*.



Note. A person is wearing an EEG headset while practicing meditation. Four scales of improvement can be examined on the mobile screen, and the last one indicates Functional Connectivity. Recording of Day 1 shows the initial connectivity. With progress in meditation, the application displays the change in connectivity after a few days and even explains the relation with the connectivity of expert meditators. This is an illustration generated by us to display the potential idea for neurotechnology.

Research and Technology Relevance

Cognitive Relevance

Years of neuroscience research have shown several advantages to meditation practice (Brandmeyer et al., 2019). A recent article offered a possible course of action with a unified framework (Dahl et al., 2020). The framework suggests awareness, connection, insight, and purpose as the four fundamental characteristics of well-being. The only way to acquire these qualities that offer direct access to one's well-being is through intentional mental training. A particular dimension denotes a specific method. A practitioner can, for instance, utilize concentrated attention to become aware of mind-wandering occurrences, maintain focus, and use loving kindness to cultivate fruitful relationships with others.

Neurotechnology

Many meditation applications are available to improve awareness and train attention (Migala, 2021). Since no feedback is provided, a novice practitioner feels pushed and gradually reduces their practice to the minimal effort until stopping altogether. Due to the availability of wearable EEG technology, the market has been able to create goods that can assist novice practitioners in learning meditation through real-time feedback and monitoring their progress over time, as demonstrated by the use of Muse and Neuphony meditation products. Here, we suggest a functional connectivity module enabling practitioners to see their incremental development and the changes in connectivity patterns that go along with it.

In Figure 1, three of the four modules can assess attention, daydreaming, and tiredness in real time. When the mind wanders, or a person feels sleepy, practitioners can receive immediate feedback so they can refocus on the meditation object. After some practice, people can evaluate their level of attention, the amount of time their minds wander, and whether they are awake or asleep while meditating. In the final module, users can compare their functional connectivity after a few sessions to that of potential specialists in various types of meditation. With the aid of neurotechnology, cognitive scientists, computer scientists, and signal processing experts can collaborate to identify the brain correlates of various stages of meditation. Therefore, it is conceivable to develop neural markers for various levels of meditation using signal processing and machine learning approaches.

Learning Representation

The most important step in separating the neural signals of experts and beginners so that neurofeedback can be implemented is through feature engineering. Robust feature extraction strategies are presented by deep learning and machine learning to categorize the various stages. Numerous articles from previous years have described the brain correlates of meditation. Pandey and Miyapuram describe a wavelet-based encoding of the oscillatory signature of meditators (Pandey & Miyapuram, 2020). In recent investigations, functional connectivity networks were examined to predict brain activity in meditators (Pandey et al., 2021). Convolutional neural networks are used to create a model that categorizes control and meditators' cognitive states (Pandey & Miyapuram, 2021b). The SHAP (Shapley Additive Explanations) explainable model, which employed three nonlinear dynamics to extract the significance of the scalp area, was used to analyze EEG data collected before and after mindfulness-based stress reduction (MBSR) training to determine the relevance of the data (Pandey & Miyapuram, 2021c). A recent study discusses and further categorizes various mental states associated with meditation using different machine learning approaches (Kora et al., 2021). Cognitive science and machine learning researchers have great potential to identify patterns and leverage them to create systems that can guide novice practitioners.

Data Description

Participants and Experimental Design

We used online open-access EEG data (Braboszcz et al., 2017). Data were collected at the Meditation Research Institute in Rishikesh, India, from 32 healthy control individuals and 20 meditators from the VIP school, and 27 meditators from the HT school, and 20 meditators from the SNY school. All meditators were chosen for the study based on their age, gender, and years of meditation practice. Control subjects were also selected for the study based on age, gender, and lack of meditation practice. Researchers wanted to investigate uniform groups of individuals for this study. Therefore, they constructed groups based on age and gender to match the individuals. As a result, there were four groups of 16 subjects in each meditation group: 16 controls (45 ± 10 years, five females), 16 HT meditators (43 ± 12 years, two females), 16 SNY meditators (40 ± 10 years, two females), and 16 VIP meditators (47 ± 15 years, five females). A single set of individuals was a control group for all three meditation traditions.

The experiment was divided into two 20-min sessions, one titled "Meditation" and the other "Instructed Mind Wandering." In the first 10 min of the Meditation block, subjects were instructed to focus on their breathing (breath focus or inhalation and exhalation) to prepare for their meditation practice. This task was used as a primitive practice period in all three meditation traditions to help people relax and deepen the depth of their meditation practice. After 10 min, they were notified to practice their specific meditation for the next 10 min. Both in the first and second half of the Meditation block, control participants were instructed to keep their focus on breath or inhalation and exhalation. In the Instructed Mind Wandering block, for the first 10 min, subjects were instructed to perform mind-wandering tasks, wherein they were asked to recall autobiographical events which were emotionally neutral such as routine childhood life, travels, etc. After the initial 10 min, they were directed to continue their instructed mind-wandering task for the next 10 min to preserve consistency with the Meditation condition. To avoid any order effects, the task sequence was counterbalanced; that is, in each of the meditation groups and control group, eight of the subjects either performed the mind-wandering task first or the meditation task first. In our study, we focused on comparing the second part of the Meditation block between controls (i.e., breath focus) and meditators (i.e., specific HT, VIP, SNY). We used preprocessed open access data, and preprocessing steps are mentioned in this article (Braboszcz et al., 2017). Participants all signed informed consent forms before participating. The Meditation Research Institute Indian ethical committee and University of California San Diego ethical committee approved the project (IRB project # 090731). Interested readers may refer to Braboszcz et al. (2017) for complete details.

Methods

Functional Connectivity

To create the functional connectivity matrix, we employed five coupling methods: coherence (coh), imaginary coherence (imcoh), phase lag index (pli), weighted phase lag index (wpli), and corrected imaginary phase-locking value (ciplv). We started from coh, the earliest measure of functional connectivity, to ciPLV, the latest measure, as every coupling method illustrates some similarities and differentiating synchronization patterns for the same dataset. In this study, we focus on capturing all the crucial connectivity relationships that can provide significant discrimination between control and meditator irrespective of the coupling method. Each brain connectivity preserves some network topology that can be scrutinized and reveal new insights into the meditative state. The subsection on spectral connectivity presents a brief description of five coupling methods (MNE, 2022). All the functional connectivity matrices were calculated every 5 s with a 2.5-s overlapping window for delta (1–4 Hz), theta (4–8 Hz), beta (8–12 Hz), alpha (12–20 Hz), gamma1 (20–60 Hz) and gamma2 (60–100 Hz) frequency bands along with regions described in Figure 2. Primarily four areas are left frontal (LF), right frontal (RF), left parietal (LP), and right parietal (RP). Based on these regions, intra- and interfunctional connectivity are computed. Bands are decided based on the recent article published on the same dataset (Vivot et al., 2020). Regions are determined based on the study discussing different meditation techniques (Yordanova et al., 2020).

Binarization of Brain Networks

The topology of functional networks is often obscured by faulty and weak connections (Sun et al., 2019). Thresholding, which involves removing a portion of the weakest links from the network, is a popular technique for maintaining a sparse network. However, deciding this threshold objectively remains inconclusive. In the recent work of De Vico Fallani and colleagues (De Vico Fallani et al., 2017), they introduce a criterion, the efficiency cost optimization (ECO), to identify the density threshold which filters the connections depending on the network size according to a power law. This method accentuates a network's intrinsic features while maintaining its sparsity. Hence, we used the ECO binarization method to remove the weak links. Obtained networks from coupling methods were binarized and quantitatively analyzed using graph theory measures.

Graph Theory Network Metrics

Several graph measures can characterize brain networks (Rubinov & Sporns, 2010). We computed functional segregation and integration measures of binary brain networks for each subject, including all coupling methods. The capacity for specialized processing to emerge within tightly interconnected clusters of brain regions is referred to as functional segregation. Functional integration in the brain quickly incorporates specialized information from various brain regions. We identified four widely employed network metrics. Functional integration metrics were node betweenness centrality (NB) and edge betweenness centrality (EBC). Functional segregation metrics were clustering coefficient (CC) and modularity (MU). The proportion of all shortest routes in a network that connects a particular vertex is known as NB, whereas the proportion of all shortest routes in the network that involves a particular edge is called EBC. Because the concept of betweenness centrality readily extends to linkages, it could be utilized to detect essential anatomical or functional connections. The CC is the number of triangles surrounding a node and is equal to the number of neighbors who are neighbors of each other. MU is a metric that measures how efficiently a network may be separated into distinct clusters. Mathematical equations and detailed explanations can be accessed in this paper (Rubinov & Sporns, 2010). Network measures were computed in a Matlab environment.

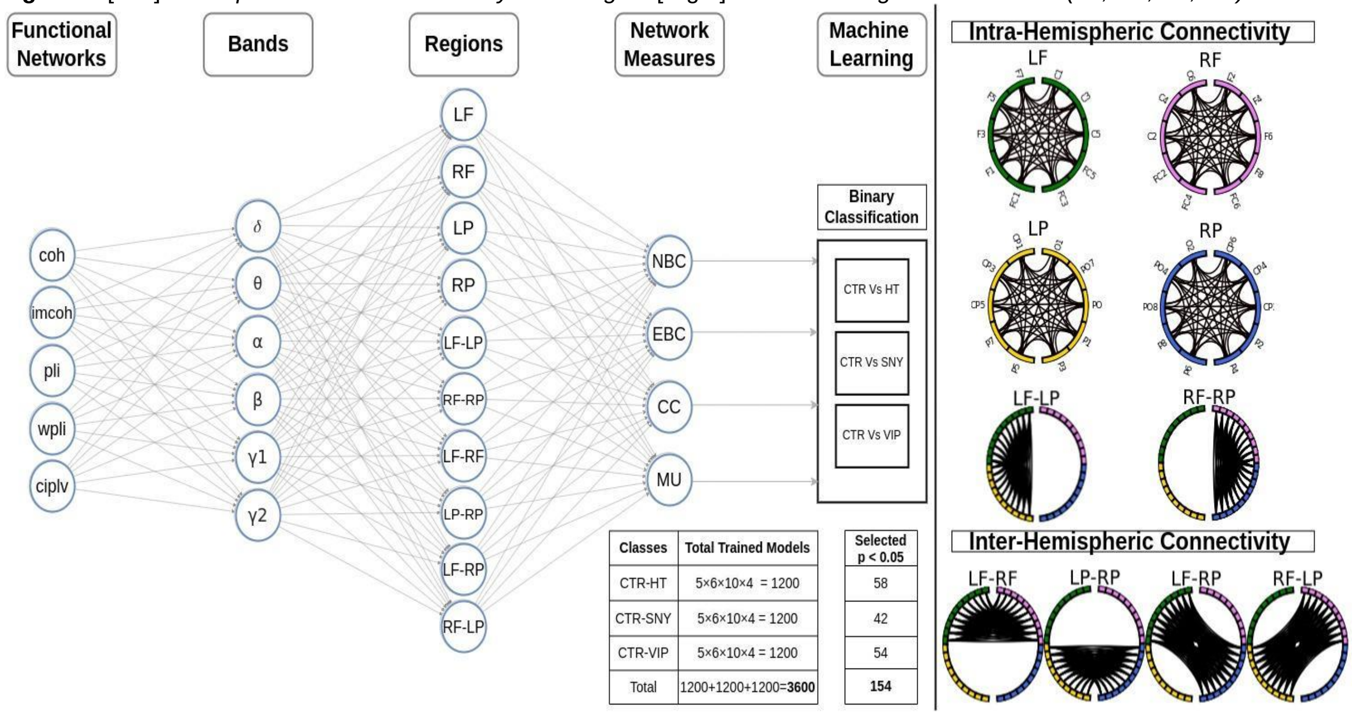
Machine Learning

Features generated from different network measures were used for classification. This study trained binary classifiers between the control and meditator groups. Support vector machine was selected for this research due to its well-established theory and more eloquent quality of easy interpretability. We trained models by tuning hyperparameters, and validation was performed using the 10-fold stratified technique. The classifier's performance was evaluated using accuracy, precision, recall, and F1 score. In line with this, we further assessed the statistical significance of the classifier using the permutation test with 10,000 rounds. Several articles have used this test (Ojala & Garriga, 2009) and discussed the effectiveness of the results via permutation tests. There were 1,200 models trained for each group encompassing connectivity methods, frequency bands, brain regions, and network measures. A total of 3,600 models were developed, of which only 154 models were selected based on the significance of $p < .05$, and division is provided in Figure 2. Since there was no class imbalance present in our data, we found accuracy and the *p*-value were sufficient for the presentation. Models were developed using scikit-learn python (Pedregosa et al., 2011). The outcome of classifiers between the control and meditators resulted from differences in network features and furthermore explained the differences in connectivity and synchronization patterns.

Results

The results presented in our study were based on 154 significant models ($p < .05$), selected using permutation tests as illustrated in Figure 2. Each model exhibited a unique combination of coupling methods, bands, regions, and network metrics. These values emphasized the discrimination between control and meditation traditions. We

Figure 2. [Left] *The Pipeline Illustrates Primarily Five Stages.* [Right] *Four Main Regions Are Shown (LF, RF, LP, RP).*



Note 1 [Left]. The coupling method is selected, followed by the frequency band and region for constructing the brain network from EEG recordings. The topology of the connectivity graph is explored using graph theory network metrics. Binary classifiers are built based on the property of a graph. Permutation tests are performed to obtain the significant models ($p < .05$) for analysis.

Note 2 [Right]. A combination of 10 electrodes forms each region. All four intrahemispheric regions are further used to form two more intrahemispheric regions (LP-LF and RP-RF) and four interhemispheric regions (LF-RF, LP-RP, LF-RP, RF-LP), overall making a total of 10 regions.

focused our study on bands, regions, and network metrics. Hence, these 154 unique combinations were segregated and discussed.

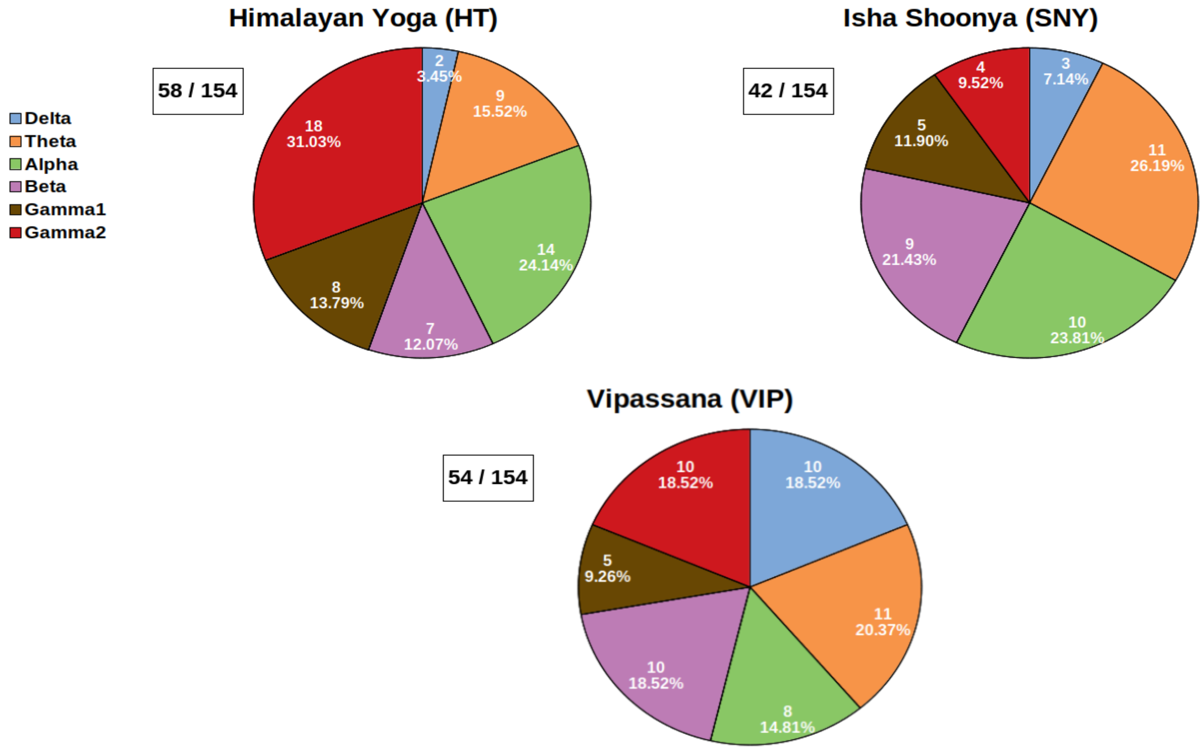
Role of Frequency Bands

For each meditation tradition, we have shown the spread of 154 significant values across all frequency bands in Figure 3. Each meditation type has some consistency and some degree of variability in the role played by a particular frequency band. Broadly, theta frequency band was found to be uniform across all meditators. For both HT and VIP meditators, gamma2 was more dominant. VIP meditators were found to have a greater amount of slow frequency delta waves than other meditators. For the CTR-HT group, all the accuracy was above 70% for most of the frequency bands except in the gamma1 band, whose accuracy was found to be around 85% ($p < .01$), as shown in Table 1. All bands appear to function well in distinguishing HT from control, but gamma1 played a more prominent role than the others. For the CTR-SNY group, most of the frequency bands, accuracy prediction was within 70% to discriminate controls from SNY meditators. The accuracy of alpha-band prediction, on the other hand, was found to be 90% ($p < .01$), with substantially higher efficiency. For the CTR-VIP group, accuracy predictions were within the range of 70–80%, except for the theta band, which had an accuracy of 85% ($p < .01$).

Participation of Regions

As shown in Figure 4, the synchronization of delta networks was significant for a few clusters in a variable fashion among all three meditation traditions (HT, SNY, VIP). For VIP, synchronization was found intrahemispheric in the LF, RF, and LP regions and interhemispheric between LF-RF, LF-RP, and LP-RP regions. During the synchronization of theta networks, among all the meditation traditions (HT, VIP, SNY), a stronger anterior-posterior connectivity in the left hemisphere (LF-LP), and anterior frontal connectivity (left to the right hemisphere; i.e., LF-RF regions were found to be

Figure 3. *A Significant Interaction of Bands With Meditation Traditions and Controls*.



Note. The significant counts ($p < .05$) were obtained by performing permutation tests. It represents how 154 significant models were distributed across each of the frequency bands, observed among meditators while they performed distinct meditation types (HT, VIP, SNY).

Table 1
Representation of Accuracy to Correctly Distinguish Controls With Distinct Meditative States in Frequency Bands.

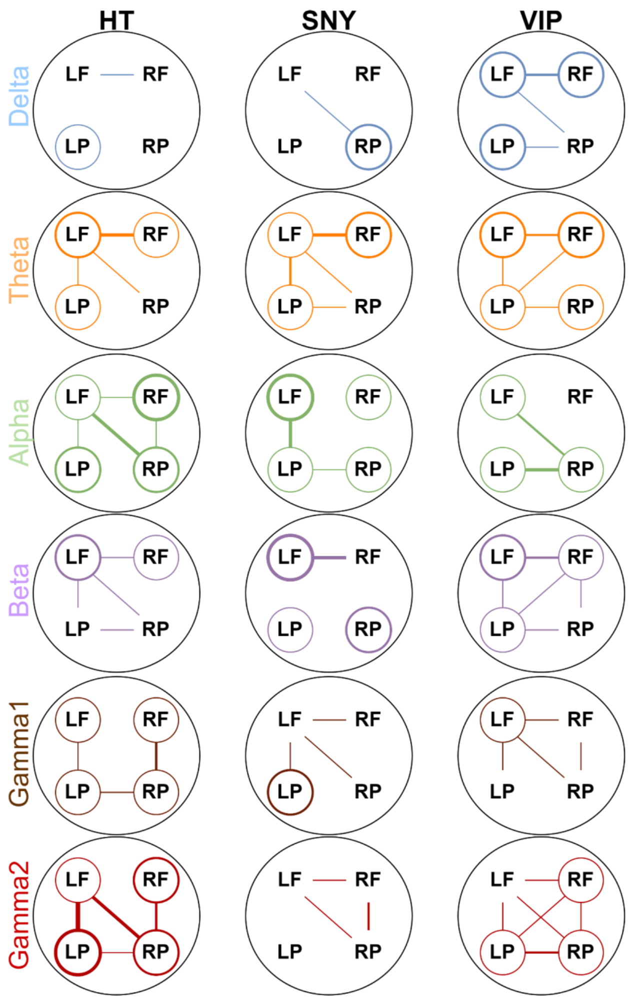
	CTR-HT		CTR-SNY		CTR-VIP	
Band	Accuracy (%)	*p*-value	Accuracy (%)	*p*-value	Accuracy (%)	*p*-value
delta	71.90	0.02	71.90	0.02	78.57	0.001
theta	78.57	0.003	75.71	0.01	**84.76**	**0.0004**
alpha	81.42	0.002	**0.90**	**0.0001**	79.04	0.001
beta	74.28	0.01	78.57	0.001	80.95	0.002
gamma1	**84.76**	**0.00009**	71.90	0.02	76.19	0.007
gamma2	80.95	0.001	75.71	0.008	80.95	0.003

All the *p*-values shown in the table are $p < .05$. Blue highlighted values suggest maximum accuracy in a particular column.

consistent). RF-LP regions were observed to have interhemispheric connections only in the VIP meditators. In the HT and SNY meditation, LF-RP interhemispheric connections were observed. During the synchronization of alpha networks, interhemispheric connections between LF-LP were common among HT and SNY meditators. A stronger connectivity in the LF-RP region among the HT and VIP meditators was observed. Moderate connections in the SNY and VIP groups were present in the LP-RP region. Overall, across all the meditators, synchronization in LF, LP, and RP clusters was indicative of its consistency.

Intrahemispheric connectivity in the RF and LF were more robust in the HT and SNY meditators, respectively. Higher intra- and interhemispheric connections were present in the HT meditators compared to the other two groups. During the synchronization of beta networks, a stronger LF

Figure 4. *Diagrammatic Representation of Statistically Significant Differences (p < .05), Based on the Allocation of 154 Values on Frequency Bands and Regions Across Three Meditation Traditions.*



Note. Circles indicate within-cluster (LF, LP, RF, RP) significance; lines designate intraconnectivity (LF-LP, RF-RP) and interconnectivity relationship (LF-RF, LP-RP, LF-RP, RF-LP). Stronger links are shown by denser circles and lines, based on the number of values obtained after the permutation test. Different colors represent frequency bands.

connectivity is observed for all meditators. Interhemispheric connectivity is observed in the LF-RF region and is seen across all meditators. A greater interhemispheric connection can be viewed in the HT and VIP meditators such as LF-LP, LP-RP, etc. During the synchronization of gamma1 networks, both intra- and interhemispheric connections were seen across meditators. Intrahemispheric LF-LP connectivity was common for all meditators. LP region had stronger connections among SNY meditators. Higher intra- and interhemispheric connections were found among HT meditators. RF-RP synchronization was found among VIP and HT meditators, whereas LP-RP connectivity was only observed in HT meditators. Interhemispheric connections in the LF-RF and LF-RP regions were consistent only in the SNY and VIP meditators. During the synchronization of gamma2 networks, consistent and higher intra- and interhemispheric connections are observed in HYT and VIP meditators (i.e., stronger connectivity in the LF-LP, LF-RP, LP-RP, RF-RP regions). Connectivity in the SNY meditators is not so dense both in the intra- and interhemispheric regions.

In Table 2, across all meditation traditions, the accuracy of most brain regions with frequency bands is greater than 70%. Across all intrahemispheric regions, the LF region was revealed to have the highest accuracy, especially for the HT (in gamma1) and VIP (in theta) meditation groups. For HT and SNY meditators, the alpha band was shown to play a role in the RF region, with an accuracy of 81% and 75%, respectively. In the RF-RP region, the SNY meditator's maximum accuracy was obtained in the LP region in the alpha band. In the LF-LP region, gamma2 was expressed in both HT and VIP meditator groups. Gamma2 bands can be seen for the mediators, notably for the HT and SNY groups. The beta band was observed only in RF and RF-RP regions for VIP and in the LF region for SNY meditators, but not for HT meditators. Broadly, most brain regions were found to have an accuracy within 70–80%, distinguishing frequency bands across all the meditation traditions, as shown in Table 3. In the anterior LF-RF region, a beta band is present across HT and SNY meditators, with 70% and 79%, respectively. In LP-RP region, maximum accuracy of 78% is obtained for HT group in gamma1 band and 90% in SNY group in alpha band. Maximum accuracy is obtained in the RF-LP regions for VIP meditators in the theta band, but RF-LP regions for HT and SNY meditators did not have significant accuracy.

Significance of Network Metrics

We observed the maximum number of allocations in modularity followed by NB as shown in Figure 5. EBC showed the maximum involvement between interconnectivity of the left and right frontal areas (LF-RF). The CC primarily engaged in the left and right frontal regions. In Figure 6 (regions), the interconnectivity of the left frontal and left parietal of SNY and VIP were observed in MU, NB, and EBC. In contrast, HT was engaged in MU and. NB was attributed across all regions in VIP, whereas MU was

Table 2

Maximum Classification Accuracy of Intrahemispheric Brain Regions Along With Frequency Bands.

Region	CTR-HT Accuracy (%)	CTR-HT Band	CTR-HT *p*-value	CTR-SNY Accuracy (%)	CTR-SNY Band	CTR-SNY *p*-value	CTR-VIP Accuracy (%)	CTR-VIP Band	CTR-VIP *p*-value
LF	**84.76**	**gamma1**	**0.0009**	75.71	beta	0.005	**84.76**	**theta**	**0.0004**
RF	81.42	alpha	0.002	75.23	alpha	0.009	80.95	beta	0.002
LP	80.95	gamma2	0.001	**78.57**	**alpha**	**0.005**	78.57	delta	0.001
RP	70.47	gamma1	0.02	71.90	delta	0.02	69.04	gamma2	0.04
LF-LP	77.61	gamma2	0.005	75.71	theta	0.01	80.95	gamma2	0.003
RF-RP	76.19	gamma2	0.004	74.76	gamma2	0.02	78.57	beta	0.003

Blue highlighted accuracy values suggest maximum accuracy in a particular column. All the *p*-values shown in the table are $p < .05$.

Table 3

Maximum Accuracy Obtained to Distinguish Specific Meditation Traditions Based on Interhemispheric Regions and Frequency Bands.

Region	CTR-HT Accuracy (%)	CTR-HT Band	CTR-HT *p*-value	CTR-SNY Accuracy (%)	CTR-SNY Band	CTR-SNY *p*-value	CTR-VIP Accuracy (%)	CTR-VIP Band	CTR-VIP *p*-value
LF-RF	70.47	beta	0.02	78.57	beta	0.001	76.19	gamma1	0.007
LP-RP	**78.09**	**gamma1**	**0.007**	**90.46**	**alpha**	**0.0001**	78.09	beta	0.007
LF-RP	77.61	alpha	0.005	72.38	gamma2	0.01	78.09	delta	0.003
RF-LP		-			-		**79.04**	**theta**	**0.003**

Blue highlighted accuracy values suggest maximum accuracy in a particular column. All the *p*-values shown in the table are $p < 0.05$.

involved in HT and SNY. VIP showed a greater number of connections in interconnectivity between left and right parietal, including EBC and NB. The right frontal of SNY was less involved than other groups, and network properties were captured with modularity and CC. Only VIP exhibited interconnectivity of the right frontal and left parietal with MU and NB. In Figure 6 (bands), VIP involved all network metrics in the delta and gamma2, whereas theta, alpha, and gamma2 in HT and SNY were involved in alpha and beta. NB and EBC were contributed across all bands in VIP, whereas MU in SNY. The similarity between all meditators was observed in frequency bands: (a) theta band engaged in left and right frontal interconnectivity via EBC, (b) more cross-connections involved in gamma processing using MU, and (c) beta waves in left frontal and interconnection with right frontal reflected connections with NB and EBC.

Discussion

Our findings show that (a) VIP practitioners have higher delta connectivity; (b) theta network synchronization in the left hemisphere is observed to be greater and more constant across meditators in the LF-LP region and in the anterior frontal area; (c) high levels of gamma2 processing in HT and VIP practitioners favorably correlated with the number of hours spent meditating in these two meditation traditions; (d) the left frontal activity contributes to theta and gamma bands for all meditators; (e) in contrast to EBC and CC, MU and NB are heavily weighted in graph measurements; and (f) MU is engaged extensively in gamma processing across all meditation traditions. Furthermore, left-right intra-inter hemisphere networks are engaged in varied ways, with each meditation state having unique synchronization patterns.

We observed that gamma2 was more noticeable in both HT and VIP meditators. This might result from

Figure 5. *This Image Illustrates an Overall Distribution of Network Metrics Across Regions and Bands, Including All Traditions*.

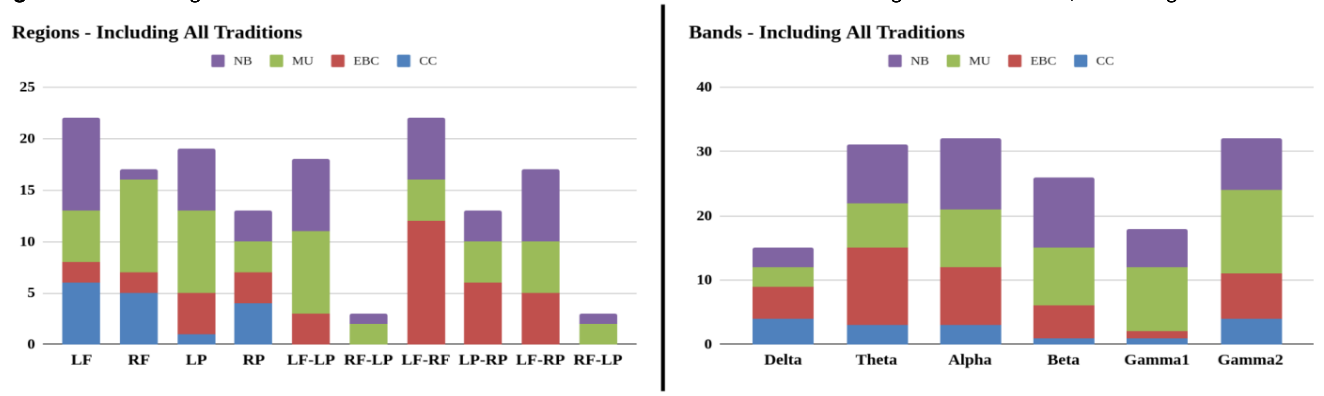
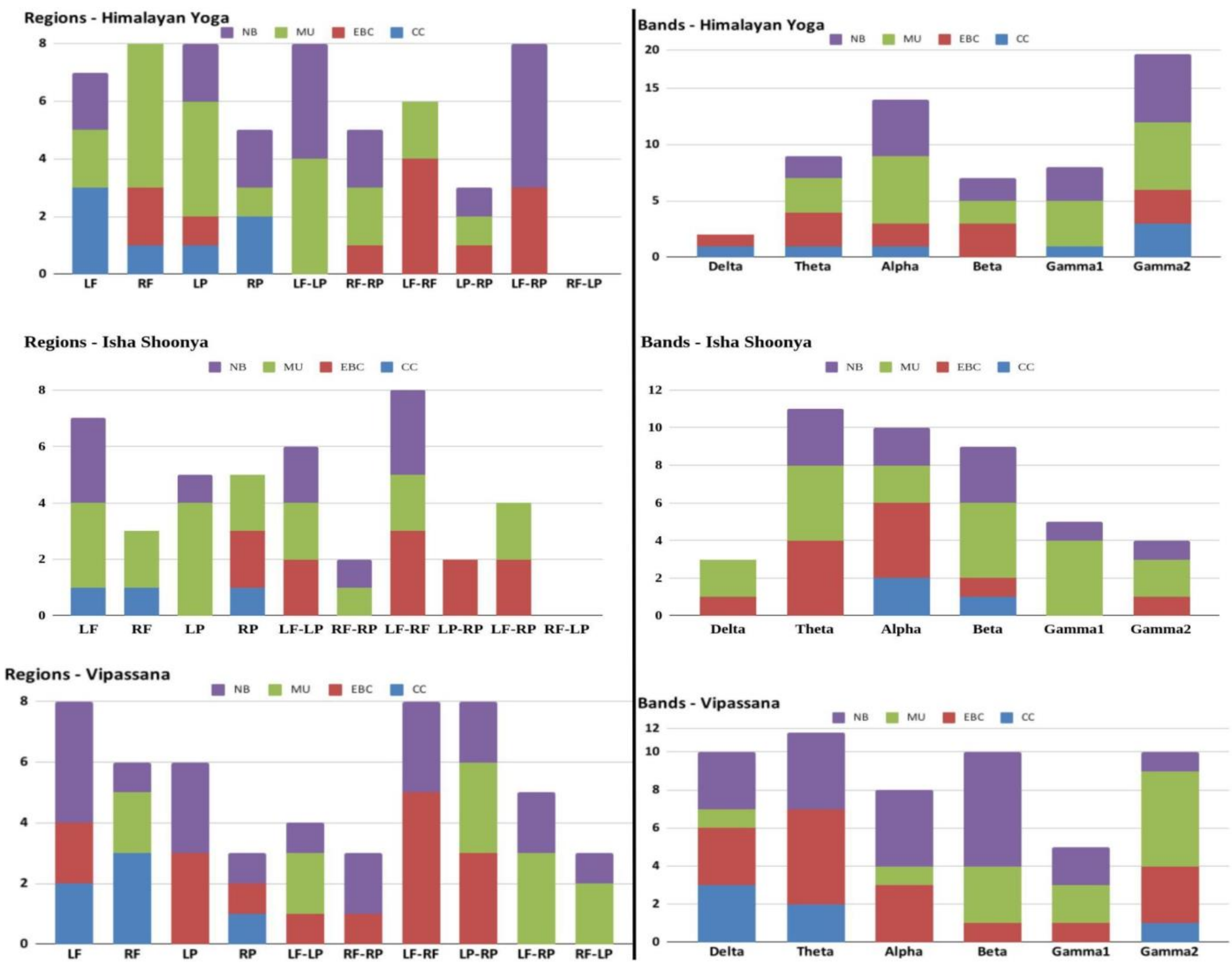


Figure 6. *Detailed Representation of Network Metrics Concerning Regions and Bands Across Meditator Traditions.*



more hours of meditation practice (Braboszcz et al., 2017), which can be presented as a trait effect exhibiting gamma2. Previous studies had observed high-frequency gamma band activity during meditation when participants had an increased hour of meditation experience (Ferrarelli et al., 2013; Hauswald et al., 2015).

Theta band activity was observed in the current study across all meditation practices. This can be linked with the cultivation of long-term meditation practice exhibiting theta activity over the frontal cortex, which is associated with sustained and internally directed attention states (Brandmeyer & Delorme, 2018). Theta activity is related to executive functioning tasks such as working memory and others that require cognitive control (Cavanagh & Frank, 2014; Cavanagh & Shackman, 2015). Theta rhythm was observed among all meditation traditions with stronger left anterior-posterior (LF-LP) and anterior frontal connectivity (LF-RF). Theta band's importance in meditation has been mostly related to top-down control mechanisms, such as heightened conflict monitoring and neural communication over long and broad networks related to cognitive processing (Cavanagh & Frank, 2014). In work by (Manna et al., 2010; Marzetti et al., 2014; Yordanova et al., 2020), similar observations of theta coupling across the left hemisphere anterior posterior (LF-LP areas) have been reported throughout three meditation traditions (focused attention, open monitoring, and loving kindness). The engagement of leftward asymmetry (Cahn & Polich, 2009), anterior frontal (Banquet, 1973), and frontal midline (Brandmeyer & Delorme, 2018) in the theta band has been observed consistently among meditators.

VIP practitioners were shown to have an increase in delta power. Past findings were found to support our results (Cahn et al., 2010; Cahn & Polich, 2009) and found that decreased frontal delta power in long-term VIP practitioners, while increased frontal delta in long-term meditators has been reported in zen (Faber et al., 2008) and qi-gong (Tei et al., 2009). VIP meditators may reflect a functional inhibition of brain appraisal systems in keeping detached from analysis, judgment, and expectation. For VIP meditators, delta power synchronizes intra- (LF, RF, LP) and interhemispheric (LF-RF, LF-RP, LP-RP). Prior research on meditation has shown that this increased frontal delta activity manifests as a baseline relative suppression of cognitive attention and a more vital detachment from current daily experiences (Faber et al., 2008; Tei et al., 2009).

The LF, LP, and RP clusters for alpha synchronization were seen among all meditation techniques. The LF, LP, and RP clusters of alpha synchronization were observed for all meditation practices. Alpha power is essential for processing and integrating somatosensory information, working memory, and cognitive entrainment during meditation (Brandmeyer & Delorme, 2018). According to studies, different meditation types may affect alpha power changes (Amihai & Kozhevnikov, 2015). This can be inferred to some extent from our study's observations of regional variability (inter- and intrahemisphere) due to different meditation practices, such as the increased power of alpha LF-LP frequently observed among HT and SNY meditators but not VIP practitioners.

The study by Yordanova et al. (2020) specifically for open monitoring meditation found left frontal coupling in beta bands, documented for all meditation traditions. We identified that lateralized increase in intra- and interhemispheric beta synchronization distinguished particular stages of meditation with shared involvement in the related clusters. The most frequently associated tasks with beta oscillations are endogenous, top-down regulated processing, and conscious processing, which promotes long-range re-entrant connections between cortical areas and greater communication through coherence. Lateralized beta connection may represent the amount of selected information (little vs. large) or the type of attentional process of selection (narrow/focused vs. wide/monitoring; Yordanova et al., 2020).

During the gamma1 synchronization, LF-LP connectivity was common for all meditation types. While LP-RP connectivity was only noticed in HT meditators, VIP and HT meditators displayed RF-RP synchronization. This is due to the function of gamma in the overall attentive state, working memory activation, information integration, and neuronal transmission underlying conscious awareness (Braboszcz et al., 2017; Cahn et al., 2013; Vivot et al., 2020). Neural coupling of gamma 2 frequency is primarily seen with higher inter- and intrahemispheric interaction between brain regions in HT and VIP meditators. It indicates the trait effect with increased hours of meditation practice, leading to neuroplastic change with the increase in neural connections.

Our research showed that modularity makes a considerable contribution. Modules are crucial for breaking more extensive networks into basic "building blocks," like internally highly connected clusters with weaker linkages. In neurobiology, modular divisions are significant because they distinguish brain parts with similar functions (Sporns, 2022). There appears to be ample room for future research to comprehend the underlying phenomena of modularity between two groups (meditators vs. controls).

Our results have been presented using a data-driven methodology, making them more interpretable and subject to further investigation for graph measures. However, this work offers a viable concept for consumer wearable headsets that can show how functional connectivity evolves as meditation practice progresses. The naive practitioner can comprehend the relationship between their functional connectivity patterns with different types of experienced meditators.

Conclusion

In this study, we compared three meditation traditions to a control group to find differences in frequency bands, regions, and network topological organization. Five coupling methods—including coh, imcoh, pli, wpli, and ciplv—were used to construct functional brain networks from the earliest to the most recent. Four separate graph theory network metrics (NBC, EBC, CC, MU), including functional segregation and integration, were used to examine six frequency bands, six intrahemispheric, and four interhemispheric connections. The 3600 models were reduced to 154 for examination using permutation tests, which provided diverse insights into the meditator groups. Left hemisphere theta synchronization (LF-LP) and anterior frontal (LF-RF) areas were visible for all meditation practitioners. Here, the presence of the gamma2 band (strong connections between the intra-interhemispheres) is consistently observed across HT and VIP meditators, indicating a characteristic influence (due to the increased hours of meditation practice). The research done in earlier literature on a comparable dataset supports this. Additional data showed the importance of various frequency bands and brain regions in differentiating between different styles of meditation, such as elevated delta power in VIP and improved left parietal (LP) connectivity in SNY practitioners. These neural connections among meditators are still in the early stages of research as to how and why they develop. Using brain connectivity and graph measurements, this study generally sheds light on the interaction effect of neural oscillations with intra- and interhemispheric brain areas during a particular meditative state, both globally and specifically. Future research can focus on the biomarkers found in graph measures for the various meditation traditions.

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Author Disclosure

The author declares no conflicts of interest.

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