



OPEN EEG evidence for reproducible neural states during Buddhist Highest Yoga Tantra meditation

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Meditation offers a naturalistic paradigm for studying introspection, yet the neural dynamics of advanced tantric practices remain largely unexplored. Buddhist Highest Yoga Tantra (BHYT) comprises a sequence of eight dissolution stages culminating in the “clear light” state. We recorded EEG during eyes-closed BHYT meditation performed in monasteries and hermitages (51 sessions from 36 male practitioners; age 31–69 years); analyses compared sessions within this single cohort, and some participants contributed multiple sessions. Using a state-detecting algorithm that combines EEG power spectrum and EEG synchronization features, we segmented each session into discrete EEG-defined states and clustered them. Six reproducible state types emerged, forming three symmetric pairs dominated by delta, alpha/theta, and beta/gamma activity, along with two background-like states. Representing each meditation as a 8-symbolic alphabet sequence enabled quantitative comparison across sessions and practitioners. Although all followed the same canonical BHYT protocol, sequences differed systematically and formed six meditation clusters. Greater expertise was associated with longer and more diverse states within a meditation, with increased presence of oscillatory alpha/theta and beta/gamma states, whereas lower-experience sessions were represented by shorter sequences dominated by background or delta activity. These findings suggest BHYT practice unfolds as structured neural state sequences and provide a quantitative bridge between canonical contemplative descriptions and measurable EEG dynamics.

Introspection — the capacity to examine one’s own thoughts and mental states — remains one of the most elusive domains of neuroscience. Despite growing interest from philosophy, psychology, and clinical science, objective study of introspection is hindered by the lack of standardized experimental paradigms and by pronounced variability between individuals. In parallel, contemplative traditions such as Buddhism have cultivated highly structured methods for systematically exploring inner states, most notably meditation. From a neurophysiological perspective, however, “meditation” represents a broad and heterogeneous category, complicating its use as a model for introspection.

Contemporary frameworks commonly distinguish two broad branches of meditation: focused attention (FA) and open monitoring (OM). Both have been extensively studied with EEG, revealing characteristic oscillatory markers such as enhanced alpha–theta activity and increased stability of neural states. Expertise further modulates these dynamics: experienced practitioners show distinct spectral distributions and greater state stability compared to novices¹. Advanced contemplatives also display changes in autonomic regulation and cross-frequency interactions². At the same time, methodological reviews emphasize that the mapping between EEG features and subjective states remains ambiguous^{3,4}.

The Buddhist tradition itself classifies contemplative practices into two large categories: one-pointed concentration (Sanskrit. *śamatha*) and analytical meditation, or penetrative insight (Sanskrit. *vipāśyanā*), with both elements being present in elaborate protocols of Vajrayana Buddhism, especially Highest Yoga Tantra⁵. Besides that, Buddhist Highest Yoga Tantra (BHYT) relies heavily upon complex visualizations of Buddhist deities and “mandalas” and includes a rigorously codified sequence of eight successive stages culminating in the state of “clear light”. These canonical descriptions offer a uniquely precise framework for investigating the temporal dynamics of introspection. Nevertheless, most prior EEG studies have examined Vajrayana or Taoist

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experts only at the level of average spectral power or connectivity⁶⁻⁸. To date, no study has provided a systematic quantitative validation of the sequential stage structure reported in BHT.

This gap motivated our study. In previous work, we introduced a state-detecting algorithm (SDA) for identifying reproducible functional states in multidimensional EEG data during tantric practice⁹. Building on this foundation, here we analyzed 51 meditation recordings from 36 advanced Tibetan Buddhist monks practicing under naturalistic conditions in monasteries and hermitages. Our aims were threefold: (i) to identify reproducible EEG-defined stage types during tantric meditation, (ii) to determine how these stages are sequentially organized into meditation trajectories, and (iii) to assess how practitioners' expertise shapes the richness and composition of these trajectories. By integrating canonical contemplative frameworks with modern time-series analysis, we sought to establish tantric meditation as a naturalistic yet structured model for the neuroscience of introspection.

Across EEG studies of meditation, state effects are commonly operationalized using spectral features (band-limited power and power ratios) and measures of large-scale coordination between channels or regions³. Coordination is often quantified via correlation, coherence, and phase-based indices (e.g., PLV), with information-theoretic measures (e.g., mutual information) also used in some EEG state analyses^{10–12}. Because sensor-level coupling in scalp EEG is susceptible to field spread and volume conduction, lag-sensitive metrics such as the phase lag index (PLI) are frequently discussed as complementary controls, and connectivity measures are typically interpreted as descriptive rather than uniquely localizing generators¹³.

In our study, we use widely adopted spectral and synchronization descriptors as general-purpose inputs to SDA. We do not claim that these features constitute universal biomarkers of meditation states or that they admit a unique mechanistic interpretation across traditions, recording setups, and analysis pipelines; instead, they serve as pragmatic sensor-level descriptors for tracking reproducible stage dynamics and their sequential organization.

Taken together, we combine a canonically defined, temporally ordered BHYT protocol with data-driven segmentation of multivariate EEG to test whether this stage structure is reflected in reproducible neural dynamics. By extracting recurring stage types and their sequential organization into trajectories, we move beyond trial-averaged summaries and enable principled comparisons across recordings and practitioners, including how expertise relates to the richness and composition of meditation trajectories.

Methods

Dataset

Meditation protocol

Advanced tantric meditation practices of BHYT (including practices of Guhyasamaja, Yamantaka, Chakrasamvara and Vajrayogini performed by the monks within this study) follow a strict protocol. Its essential part is so called “bringing dharmakaya of death into the path” (tib. རེ་ཆོས་པ་ཆོས་སྐུ་འཁོར་ལས་འཁྱུ་རུ། |, ‘chi ba chos sku’i lam ‘khyer), consists of 8 consequent stages of “dissolution of bodily elements and mental states” up to the state of “clear light”.

The duration of each stage is not limited so as the total meditation duration. Some monks include additional meditative techniques to the meditative session such as analytical or focused meditation at the beginning to initialize the process. Some extend the core meditation to perform the tantric practice in its entirety which includes an imaginative process of “self-generation” as a deity as well as passing through the 8 stages of dissolution process in reverse order. This leads to individual variability of time spent in meditation and to an uncertain number of meditative states within a practice. During the experiment there were no external cues or instructions, the ongoing meditation was naturally controlled only by a practitioner.

Participants

The participants of the study were 36 Tibetan Buddhist monks (males) who practiced meditation practices of BHYT on a regular daily basis over years or even decades. The age of the participants ranged from 31 to 69 years, with an average age of 50 (see Supplementary Table 1). Most of them have also spent from several months up to several years in hermit retreats where they dedicated the entire time to practice in seclusion.

EEG data of BHYT meditations were gathered during 5 expeditions over 6 years (2020–2025) in 5 Tibetan Buddhist Monasteries of South India and Nepal (Gyudmed and Gyuto Tantric monasteries, Kopan, Sera Jey and Tashi Lhunpo) and in Himalayas mountain caves during hermit retreats.

For each of 36 practitioners from 1 to 3 meditations were recorded during the expeditions, 51 EEG recordings of meditation in total. In this study we use the following notation to refer to the recordings: Subj##_med#, for example Subj03_med2. The duration of meditation recordings varies from 14 min to 1 h 23 min. All participants reported that the meditation was successful in a post-practice survey.

Detailed information on the participants' age, meditation experience and number of recorded meditations can be found in Supplementary materials (Supplementary Table 1), as well as the date, duration and other details of all 51 meditations (Supplementary Table 2). Autobiographical data were collected for each monk before and after each study.

Supplementary Table 1 also provides information on the individual alpha-peak frequency (IAF) in practitioners, as a descriptive characteristic of the subject's psychophysiological state, cognitive functions, attention processes and fatigue, as well as an indicator of stability and efficiency of brain function¹⁴. IAF was calculated during resting state with closed eyes before and after meditation and averaged over all meditations of the subject. It ranges from 8.35 to 11.3 Hz between subjects, averaging 9.84 Hz.

Participants practice experience

All the participants completed rigorous study programs in respective monasteries having academic degrees of *Geshe*, *Geshe Ngampa* or *Kachen*, but differed in terms of their experience in meditation. This was mainly determined by the objective criteria of undergoing strict retreats where practitioners dedicate 4 sessions a day to ritual and meditation practice in a closed setting of monasteries' retreat centers or meditation huts up in the mountains. Such intensive practice could amount up to 12 h a day and is considered an outstanding achievement in the Tibetan Buddhist community. We also considered the number of hours practitioners dedicate to meditation outside the strict retreats. The information received from monasteries' officials and research coordinators who recommended practitioners for the study was also taken into account. Based on these data practitioners were divided into three groups (Expert, Advanced and Standard).

The *Expert group* included monks who either already underwent one or several long-term meditation retreats (one year, 3 years or longer) or were in retreat at the time of the study. Such monks typically practiced BHYT 6–10 h a day in retreat or 3–5 h a day outside retreat.

The *Advanced group* included monks without long-term retreat experience; most of them underwent short retreats lasting from several weeks to several months (usually 1–3 months), however were reported as advanced practitioners by monasteries' officials and research coordinators, with several of them serving in capacity of tantric teachers in respective monasteries. Such monks typically practiced BHYT 2–3 h a day outside retreat.

The *Standard group* included monks with either limited or no retreat experience and practiced BHYT 1–3 h a day with some describing their practice as “irregular” or “not serious”.

Supplementary Table 1 provides detailed information about the individual meditation experience for each practitioner.

Ethical statement

The studies involving humans were approved by Sera Jey Science Center, Karnataka State, India. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

EEG recording and preprocessing

In order to provide environmental validity, the study took place in Tibetan monasteries, in temple premises, retreat huts or quiet rooms appropriate for the meditation practices.

The EEG signals were recorded with the NVX-52 acquisition system (Medical Computer Systems Ltd., Moscow, Russia) at 500 Hz sampling rate, with analog band-pass filtering between 0.1 and 200 Hz. A digital 50 Hz notch filter was applied to remove artifacts caused by power line noise. 40 EEG channels positioned according to the 10–05 system were used with Cz as a reference electrode. The 5 expeditions involved 3 different channel sets, which can be found in Supplementary materials (Supplementary Fig. 1).

The following processing of raw EEG data was performed with MNE-python¹⁵. The EEG signals were re-referenced to average reference. A 0.9–40 Hz bandpass filter was applied to remove low-frequency artifacts (breath, electro-dermal activity) and high-frequency muscle activity¹⁶. Independent component analysis was performed, and ICA components corresponding to artifacts such as eye movements, muscle activities, heart rate, rheogram etc. were excluded if present. For the further analysis the EEG data were split into 1 s epochs. Figure 1A shows the preprocessing steps.

Since most clustering techniques are sensitive to outliers, we included an additional step of cleaning the data from artifacts – epochs, which had the average PSD value exceeding 3 standard deviations in one of the 5 frequency bands, were rejected from the analysis (EEG features are described in the Sect. 2.2). Thus, about 5% of all epochs were removed from each EEG recording.

EEG features

Bands for averaging features

Frequency features were computed for each channel within 1 s epoch (ear electrodes A1 and A2 were excluded from the analysis). Then data were averaged in frequency domain within five conventional bands: delta (0.9–4 Hz), theta (4–8 Hz), alpha (8–14 Hz), beta (14–25 Hz) and gamma (25–40 Hz), as in^{8,17}.

Since electrode schemes differed between EEG recordings (see the Sect. 2.3.1) to unify features we grouped EEG channels (34 or 38 channels depending on scheme type) into 11 spatial ROIs (regions of interest) based on raw signal correlation: prefrontal, left frontal, midline frontal, right frontal, left central, midline central, right central, left temporal, right temporal, parietal, occipital, and the resulting frequency features were obtained by channel-averaging within each ROI. Reduction schemes into spatial ROIs for all three channel sets used in the study, are described in detail in Supplementary materials (Supplementary Fig. 1).

EEG input to SDA

The calculation of EEG features used in the article is based on the methods implemented in the MNE-python library¹⁵. EEG power spectral densities were calculated using the adaptive Multitaper method¹⁸, 55 PSD features in total (5 frequency bands $\times$ 11 brain regions).

We also calculated 16 power ratios in 11 brain regions, 176 PSD ratio features in total: theta/delta, alpha/delta, alpha/theta, alpha/(delta+theta), beta/delta, beta/theta, beta/alpha, beta/(delta+theta), beta/(theta+alpha), gamma/delta, gamma/theta, gamma/alpha, gamma/beta, gamma/(delta+theta), gamma/(theta+alpha) and gamma/(alpha+beta).

Obtained PSDs and PSD ratios were log-scaled to approximate the normal distribution.

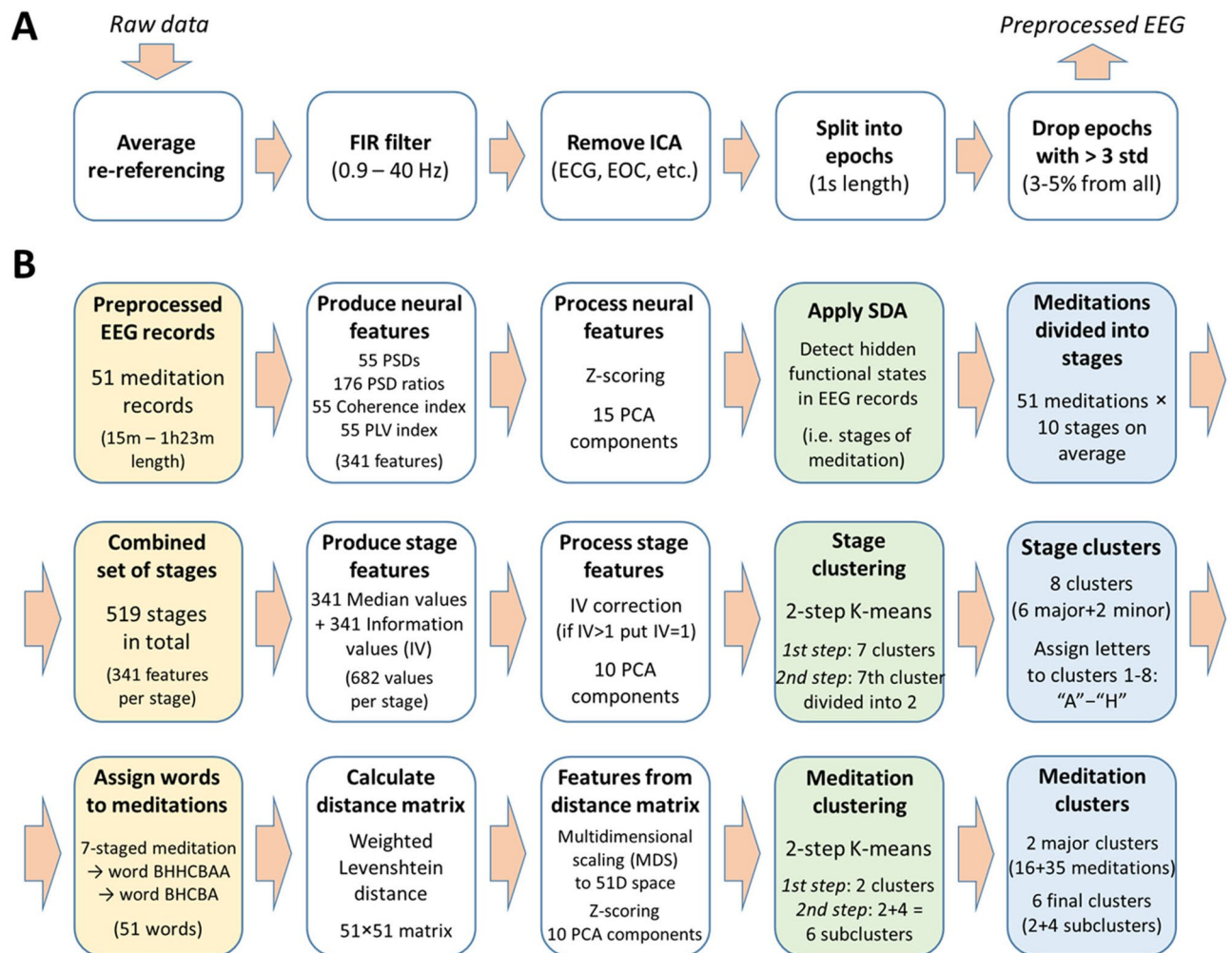


Fig. 1. Data processing. (A) Steps of preprocessing collected EEG data. (B) Feature processing scheme. The 1st row illustrates SDA pipeline⁹, the 2nd row — stage clustering pipeline, and the 3rd row — meditation clustering pipeline. Yellow color of pipeline blocks denotes input data, green color — core algorithms of pipelines, blue color — output data, and white blocks contain feature processing steps.

For each EEG recording EEG features also include coherence indices and phase-locking value (PLV) indices as a measure of intrasubject power and phase synchronization, calculated for each channel as the number of channels synchronized with the current one with coherence (PLV value respectively) greater than or equal 0.7. Refer to Supplementary materials for the exact formulas and details of coherence and PLV calculation^{19,20}. Coherence and PLV indices were computed for 5 frequency bands and averaged within 11 brain regions, resulting in 55 coherence index and 55 PLV index features (5 bands × 11 regions).

Thus, the SDA input data includes 55 PSD features, 176 PSD ratios, 55 coherence indices and 55 PLV indices, 341 neural features in total. In order to reduce the dimension of feature space the features for SDA input were preprocessed, namely, the principal component analysis was applied to the 341 z-scored neural features as described in⁹. As a result, each 1 s epoch was represented by a point in the space of 15 principal components for further use in the SDA.

The first row of Fig. 1B illustrates the steps of neural feature processing and their use in SDA segmentation.

Information value approach

Calculating IV

Information value (IV) is a numerical value that quantifies the predictive power or influence of an independent continuous or categorical variable on the value of a specified binary variable, i.e., measures the importance of a feature. It provides one of the most effective tools to select important features in a binary classification problem^{21,22}.

The problem of finding characteristic features for each cluster in a clustered data (e.g., neural correlates in given functional states of EEG data) is similar to a classification problem with binary indicator variables for each cluster, so it can be solved using the Information value approach.

For each particular class of an independent variable x and dependent binary variable y , we can calculate Information value as following:

$$IV = \sum_{Bins} (\%Events - \%NonEvents) * \ln \left(\frac{\%Events}{\%NonEvents} \right),$$

where $\%Events$ is the ratio of the number of events in the certain class of variable x to the number of events in total, and $\%NonEvents$ is similarly the proportion of non-events.

For categorical variables each value forms a class, and continuous variables are divided into classes by percentile-based binning. In general, 10 bins with deciles of variable x are taken.

Interpreting IV

The rule of thumb for using Information value to understand the predictive ability of neural features for a given functional cluster of EEG recording (i.e. target binary variable) is as follows:

- IV is less than 0.2, then the feature has no influence on target variable;
- IV varies from 0.2 to 0.4, then the feature has weak predictive power;
- IV from 0.4 to 0.6 — the feature has medium predictive power;
- IV from 0.6 to 1 — predictive power of the feature is strong;
- IV > 1, very strong predictive power of the feature.

More details about the Information value approach in application to EEG data and examples of calculating and interpreting IV can be found in our previous paper⁹.

State-detecting algorithm

SDA (State-Detecting Algorithm) is a novel approach designed to detect time-continuous states in multidimensional time-series data. SDA operates on unlabelled data and detects optimal change-points between intrinsic functional states in time-series data, maximizing clustering quality metrics in a given feature space. SDA is a two-step iterative segmentation method based on Ward hierarchical clustering with time-connectivity constraint. It is described in detail and validated in⁹.

The input for SDA is a set of features, calculated for each point of time-series data (1 s epoch of EEG data in our case). The result of SDA is a segmentation of time-series, i.e. epoch indices which are the best boundaries between different functional states in a given feature space. We applied SDA to our EEG dataset (see Sect. 2.1 and 2.2) and obtained functional states, i.e. time-continuous segments of EEG recording with different neural behavior, which could be relevant to stages of meditation.

Hereafter we refer to the stages of meditation as functional brain states that differ in the neural aspect, that is, EEG segments with relatively stable neural features behavior within the segment and maximally different from adjacent segments in behavior of neural features.

Clustering techniques

Clustering method

In this study we use the K-means method for clustering functional states detected by SDA into several types, as well as for further clustering of whole meditations, since this method is the most suitable for our task of clustering relatively small dataset represented in high-dimensional vector space into convex groups of elements with similar feature behavior, i.e. small Euclidean distance between feature vectors²³.

The clustering method was implemented using function `kMeans` of `scikit-learn` module in Python with parameters `init='k-means++'`, `n_init=1000` to provide the best output of 1000 consecutive runs with different centroid seeds.

To choose an optimal number of clusters for K-means clustering we used silhouette coefficient method. Silhouette coefficient is an intrinsic clustering quality measure, evaluating how similar objects are to their own cluster (cohesion) compared to other clusters (separation) on average and varies from -1 for incorrect clustering to 1 for highly dense clustering. For details see SDA paper⁹.

Silhouette scores, calculated for pairs of clusters, can be considered as a kind of cluster distances, and unlike centroid distances, they take into account not only the mutual arrangement of clusters, but also their structure, in particular cohesion and separation.

Stage clustering

Construct stage features. First we used SDA to produce the optimal division into functional states, maximizing intrinsic clustering quality metrics in neural feature space, for each of 51 meditation recordings (see Sect. 2.4). The process of SDA segmentation resulted in 10 functional states on average per meditation and 519 states in total, treated as meditation stages with specific neural feature behavior (SDA results for all EEG recordings can be found in Supplementary Table 2).

In order to explore similarities between obtained functional states (i.e. stages of meditation) in terms of neural correlates, for each stage we calculated a feature vector accumulating the main descriptors of this stage. Stage feature vector consists of 341 median stage values of z-scored initial neural features used as the input for SDA and of 341 normalized information values of the features, which are numeric indicators of feature importance for a given stage, 682 values in total (see Sect. 2.2.2 and Sect. 2.3 for the details).

For each neural feature information value (IV) is calculated for a binary classification task in which epochs of a given stage are treated as events and other EEG record epochs as non-events and thus IV indicates predictive power of the feature for a given meditation stage (the details of IV calculation can be found in the Sect. 2.3.1).

The vector of information values of all neural features makes up a unique portrait of a meditation stage and characterizes the stage specifics well in terms of neural feature behavior. The vector of neural feature median values captures the subtleties of feature behavior worse, but informationally complements the IV vector, since the median value of a z-scored feature with a high enough IV can be either above or below zero.

The calculated information values are normalized as follows. If the received information value is greater than 1, it is considered equal to 1 to avoid outlier effects and to provide equal influence of features with very strong and extremely strong predictive power on further clustering process (see the Sect. 2.3.2).

Clustering process. PCA decomposition was performed in the obtained stage feature space in order to extract key information from stage feature vectors and to get rid of feature correlations for further stage clustering. Then a dataset of 519 stages was clustered by K-means method in 10-dimension PCA component space (explaining 67% of variance), as described in the Sect. 2.5.1. The optimal number of clusters was chosen based on the value of silhouette score and amounted to 7 clusters with silhouette coefficient 0.24, consisting of 30, 34, 36, 46, 50, 73 and 250 stages respectively for clusters 1–7 and representing groups of stages with similar neural feature behavior, i.e. stage types.

The largest 7th cluster turned out to be a high-density cluster with near-zero values of stage features, which means general average behavior of neural features with low information values (that is, the lack of important neural features). We performed one more iteration of K-means clustering for the 7th stage cluster in order to capture minor feature differences in it and use subclusters in further meditation clustering to achieve greater sensitivity of the weighted Levenshtein distance (see Sect. 2.5.3.2). The best division was into 2 subclusters (0.15 silhouette score).

As a result of 2-step clustering process we got the optimal division of stages into 8 stable clusters of sizes 30, 34, 36, 46, 50, 73, 92 and 158 stages respectively: 6 major clusters retrieved as a result of 1st clustering iteration and 2 minor ones, which are subclusters of the initial 7th cluster. We assigned a letter symbol to each stage cluster as follows: letters “A”, “B”, “C”, “D”, “E”, “F” to major clusters 1–6 (we call them major letters) and letters “G” and “H” to minor clusters 7–8 respectively (minor letters).

The described steps of stage feature processing for K-means stage clustering are shown in the second row of Fig. 1B.

Statistical analysis of stage clusters. Statistical significance was estimated for all 341 obtained neural features, averaged within 11 topographic brain regions (PSDs, PSD ratios, coherence indices, and PLV indices), complete list of analyzed EEG features is provided in the Sect. 2.2. A dataset for statistical significance assessment was formed from merged z-scored neural features of all 51 meditation records, calculated within 1 s epochs as described in the Sect. 2.2. Feature statistical differences were examined between each pair of obtained stage clusters A–H, indicating types of meditation stages, and for each stage cluster in comparison with the median value of the feature.

Since the calculated neural features are non-normally distributed (even most of the PSD features with logarithmic scaling did not pass the Shapiro–Wilk normality test) we used the non-parametric Mann–Whitney U-test to analyze pairs of stage clusters and one-sample Wilcoxon signed-rank test to compare stage clusters with the feature general median value. The obtained p-values were then corrected for multiple comparisons using the Bonferroni correction procedure as the strictest correction technique²⁴. The Bonferroni correction was applied once for all pairwise comparisons as well as for comparisons with general average.

Information value analysis of stage clusters. As in the analysis of statistical significance, a dataset for IV analysis (see Sect. 2.3) was combined of 341 z-scored neural features, described in the Sect. 2.2, calculated within 1 s epochs for each staged EEG record and concatenated. The target variables for calculating IV in each cluster of stages were constructed as binary cluster indicators (epochs of stages in the cluster were marked as events, and other epochs of the dataset were marked as non-events). Since obtained stage clusters differ from each other substantially and have a large number of statistically significant features, we thresholded neural features with medium and strong predictive power ($IV \geq 0.4$) during the IV analysis.

Meditation clustering

Assign words to meditations. After clustering stages into groups, denoted as latin letters we can reduce staged SDA annotation of each EEG recording of meditation to letter sequence, i.e. to word-like structure, for example “BHHCBAA”. In this word each letter corresponds to the stage cluster to which a specific SDA-stage belongs to.

If adjacent stages in an EEG record are assigned the same letter (belong to the same stage cluster), they are treated as one stage as far as they have similar type of neural feature behavior. Thus, consecutive identical letters in meditation codewords are replaced by one occurrence of this letter, for example the word “BHHCBAA” is converted to the word “BHCBA”. Since there is no time limitation on length of stages in Highest Yoga Tantra meditation protocol, this step is used to unify SDA results for different EEG recordings. Merging adjacent stages belonging to the same cluster provides a less sensitive but more universal approach to stage classification.

As a result, 51 ‘word’-representation of 51 EEG meditation recordings were obtained.

Levenshtein distance. We use weighted Levenshtein distance to measure similarity between the whole meditations encoded by words²⁵.

Levenshtein distance, also known as *edit distance*, is a string metric for measuring the difference between two letter sequences. Levenshtein distance between two words is the minimum number of single-character edits (insertions, deletions or substitutions) required to change one word into the other. In case of weighted Levenshtein distance individual weights or costs are assigned to insertions, deletions and substitutions of different letters, and the resulting distance is the lowest total cost required to convert one word to another.

We assign the cost of substitution one letter by another equal to centroid distance between corresponding stage clusters, which results in lower distance between more similar types of stages. The cost of insertion or deletion of a letter is calculated as average centroid distance from the corresponding stage cluster to all other clusters, so that the highest cost of insertion or deletion corresponds to the letter assigned to the most distant stage cluster.

Clustering process. The weighted Levenshtein pairwise distance matrix was calculated for all 51 words assigned to meditation EEG recordings. Then 51 data points represented by Levenshtein distance matrix were embedded into 51-dimensional Euclidean space using multidimensional scaling method (implemented using the function *manifold.MDS* of scikit-learn module in Python). Next PCA decomposition was applied to the obtained 51-length meditation features in order to reduce the dimension of the space and get rid of feature correlations. Then K-means clustering was applied to the first 10 principal components, explaining 86% of the variance (see Sect. 2.5.1).

The first iteration of K-means clustering resulted in a split into two well separated clusters of sizes 16 and 35 respectively with silhouette score of 0.27, named major clusters. In order to explore the inner structure of both the major clusters we performed a 2nd iteration of K-means clustering process to each major cluster. Major cluster 1 was divided into 2 stable subclusters of sizes 5 and 11 respectively with silhouette score of 0.17. Major cluster 2 was divided into 4 subclusters of sizes 6, 7, 9 and 13 respectively with silhouette score of 0.16. Combining the results, we got 6 well-defined meditation clusters with specific letter patterns, that is, specific patterns of neural activity during meditation.

The described steps of meditation clustering process can be found in the third row of Fig. 1B.

Results

Stage clustering results

Stage clusters structure

In this study, we focused on the task of analyzing, comparing, and interpreting meditation recordings of different practitioners in terms of neural correlates and identifying similar meditation stages, i.e. functional states of the brain during meditation. The pipeline we developed for this purpose is shown in Fig. 1B.

As described in the Sect. 2.5.2, a two-step K-means clustering process was implemented to a combined set of 519 meditation stages obtained by applying SDA to 51 EEG recordings, which resulted in 8 optimal stage clusters: 6 major clusters with assigned letters A–F and 2 minor ones (letters G–H). Each letter corresponds to a certain type of meditation stages with specific neural feature behavior which may occur in meditation EEG recordings (not necessarily in all of them) one or more times.

Points A and B of Fig. 2 describe mutual arrangement of stage clusters or “letters” in 2D and 3D projections of PCA feature space. From Fig. 2A we can see that pairs of stage clusters A and B, C and E, D and F are diametrically opposed in 2D space of the first two principal components and clusters G and H are worse separated and located in the center in the vicinity of zero. And Fig. 2B shows that minor clusters G and H are distant from major clusters along the z-axis (the 3rd principal component).

Figure 2C illustrates pairwise silhouette scores of stage clusters. They are consistent with the relative location of stage clusters illustrated in Fig. 2 and average 0.4, indicating high quality of clustering and reliable separation (see the Sect. 2.5.1).

Characteristic features

Each of major stage clusters (A–F) has a distinctive neural feature behavior in a certain frequency band which is opposite in pairs and consistent with the diametric arrangement of the clusters (Fig. 2A).

Figure 2D illustrates the behavior of PSD features in stage clusters. Clusters A and B have pronounced opposite behavior of PSD features in the delta band (high values in cluster A and low values in cluster B), clusters C and E are characterized by opposite behavior of power features in alpha band and less pronounced in theta band (the lowest PSD values in C and the highest in E cluster), and for clusters D and F a pronounced opposite behavior of PSD features in gamma and, to a lesser extent, in beta band is specific (the lowest values in D versus the highest ones in F cluster), on the background of general average behavior of neural features in other frequency bands.

Minor stage clusters G and H have a common average behavior of all the neural features (near-zero for z-scored features). We can consider their elements as a kind of background stages in meditations. The median values of neural features in clusters G and H differ slightly but statistically significantly for almost all the features (see Figs. 3 and 4B).

Topographic maps of PSD features represented in Fig. 3 also illustrate the described dynamics of neural features mirrored in letter pairs of major stage clusters, as well as power cortex localization in stage clusters A–H. For additional details on spatial patterns of neural features refer to Supplementary data.

Complementary differences were confirmed by PSD ratios and synchrony indicators (coherence and PLV indices). They are consistent with PSD behavior and described in detail in Supplementary materials (Supplementary Sect. 2 and Supplementary Figs. 2–5).

Figure 3.

Statistical significance

The methodology of statistical analysis of stage clusters is described in detail in Sect. 2.5.2.3. Figure 4B illustrates statistical differences ($p < 0.01$) for each pair of stage clusters A–H. According to Fig. 4B the proportion of statistically significant features between any pair of stage clusters post-practice survey varies from 81 to 95%, averaging 90%. Such a predominance of significant features confirms a high quality of obtained stage clustering in terms of differences in the behavior of neural features.

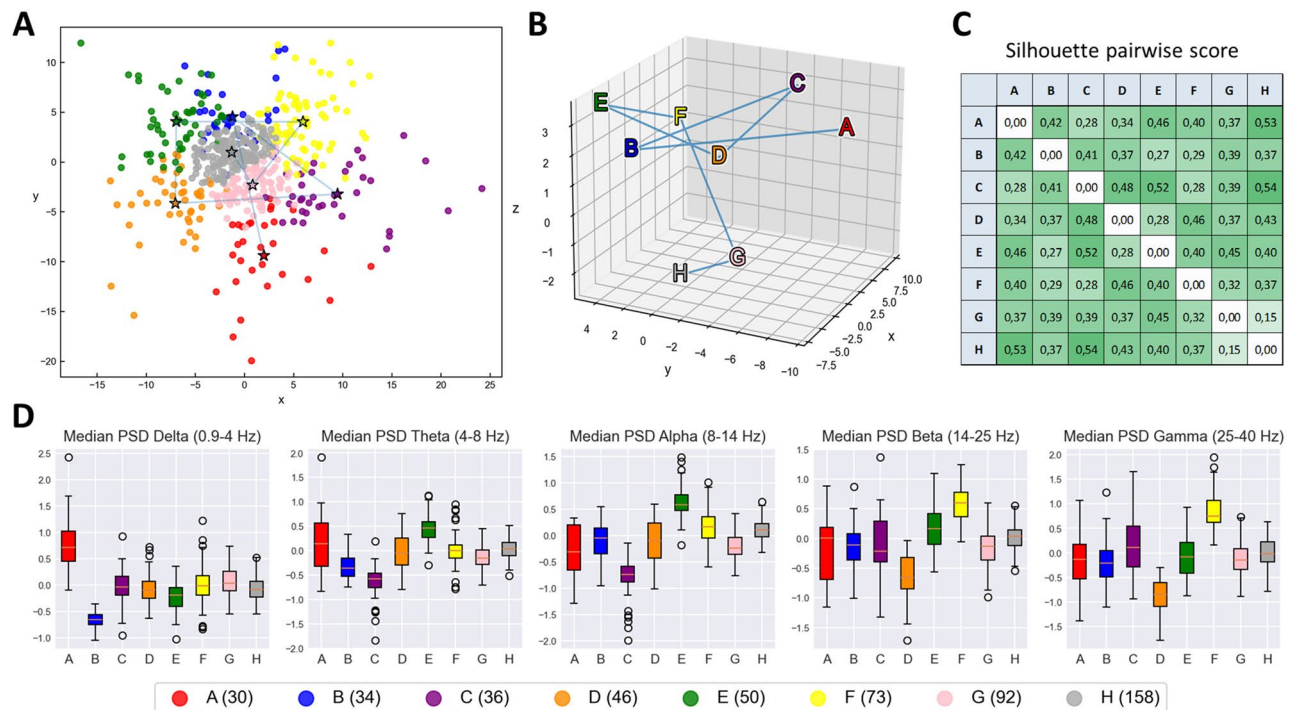


Fig. 2. Stage clusters. (A) 2D projection of stage clusters onto the 1st (x axis) and 2nd (y axis) principal components in PCA feature space. Asterisks denote centroids of stage clusters and are connected with blue lines in alphabetical order of cluster letters. (B) 3D projection of stage cluster centroids onto the 1st (x axis), 2nd (y axis) and 3rd (z axis) principal components in PCA feature space. Cluster centroids are denoted with letters assigned to stage clusters and are connected with blue lines alphabetically. (C) Pairwise silhouette scores. For each pair of stage clusters at the intersection of the corresponding row and column, their silhouette coefficient is indicated. (D) Box-plots of z-scored stage PSD median values in 5 frequency bands (columns), averaged over 11 brain regions. Horizontal axis denotes letters assigned to stage clusters. The box extends from the 1st quartile to the 3rd quartile of the data, with a line at the median. The whiskers extend from the box to the farthest data point lying within 1.5*IQR from the box. Flier points are those past the end of the whiskers. The label bar in the bottom of the Figure denotes colors and letters assigned to stage clusters with cluster size in parentheses for all the points (A)–(C).

Similar results are observed for feature significance in stage clusters versus overall average value. Figure 3 illustrates that PSD features significantly differ from general median ($p < 0.01$) almost for all electrodes (denoted with yellow markers) in all clusters. Detailed information on feature significance in stage clusters versus feature median value is provided in Supplementary Table 3.

IV of features in stage clusters

In order to identify characteristic features for each cluster we explored their information values as one of the most effective methods to measure feature predictive power in a binary classification task and therefore to detect descriptive features of clusters (see Sect. 2.3 and Sect. 2.5.2.4 for details).

Figure 4A represents the detailed IV analysis results for stage clusters A–H. The proportion of features with $IV \geq 0.4$ (features with medium and strong predictive power) in major stage clusters A–F varies from 21 to 31% from the total number of 341 EEG features. In contrast, in minor stage clusters G and H the proportion of important features ($IV \geq 0.4$) is zero, and the maximum information value is 0.19, which means the absence of features even with weak predictive power (see Sect. 2.3.2). This fact confirms the conclusion in Sect. 3.1.2 about common average behavior of neural features in clusters G and H.

Figure 4A also provides detailed information on the proportion of important features (with $IV \geq 0.4$) in different feature groups for stage clusters (5 frequency band groups, 11 spatial ROI groups and 4 type-specific groups of EEG features). In frequency band groups of Fig. 4A we can observe a similar pattern of neural feature behavior mirrored in pairs of major clusters, described in Sect. 2.3.2 (see Figs. 2D and 3). Within spatial ROIs stage clusters A and B have the highest proportion of important features in central cortex regions, clusters C and E — in parietal and occipital regions, and clusters D and F — in frontal cortex regions. And for clusters A, C and E more important are synchronization features (coherence and PLV indices), while for clusters B, D and F more important are power features (PSD and PSD ratios). Detailed analysis of characteristic neural features in stage clusters based on Fig. 4A can be found in Sect. 3 of Supplementary materials.

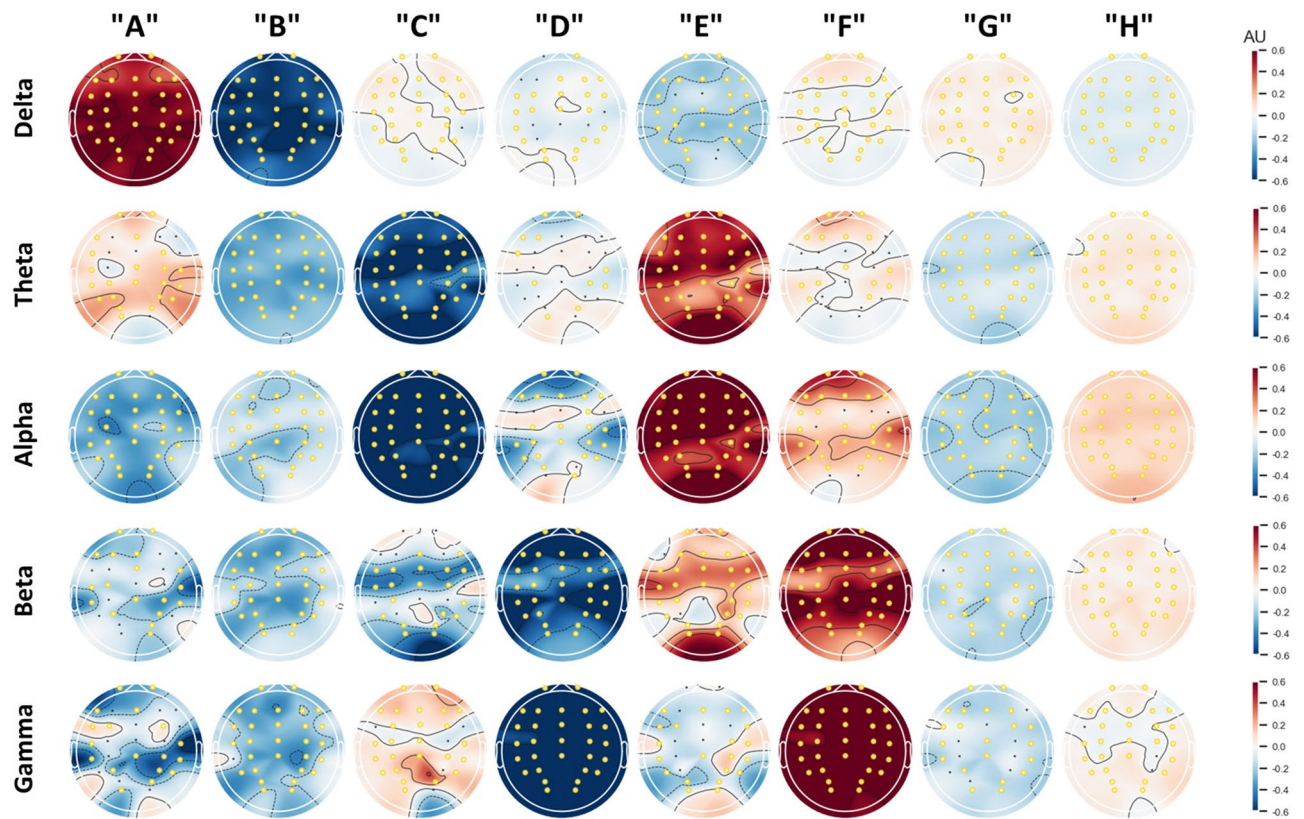


Fig. 3. Topographic maps of PSD features in stage clusters. PSDs are computed within the obtained stage clusters A–H (columns) and five frequency bands (rows). Yellow markers denote a significant ($p < 0.01$) difference with median PSD value of the total dataset according to the one-sample Wilcoxon signed-rank test, followed by Bonferroni correction.

Meditation clustering results

Meditation clusters structure

After we have identified specific types of meditation stages in terms of neural feature behavior (stage clusters A–H), we converted meditation records to words in the obtained “alphabet” and calculated edit distance between words using weighted Levenshtein method in order to find similarities in stage structure of meditations. Based on Levenshtein distance we clustered all the meditations into groups with similar properties.

As a result of the two-step clustering process, 2 major clusters were obtained, divided into 2 and 4 subclusters respectively, with a total of 6 stable meditation clusters (see Sect. 2.5.3 for details). Levenshtein distance weights are provided in Fig. 4C: replacing costs are centroid distances, and costs of insertion or deletion of a letter are represented in row Avg of Fig. 4C.

Figure 5 illustrates the mutual arrangement of 2 major clusters (5 A) and 6 final meditation clusters (5 C and 5D). Figure 5B provides cluster distances in terms of pairwise silhouette score calculated based on the Levenshtein distance matrix, averaging 0.25, which ensures fairly high clustering quality.

Meditation clusters properties

Figure 6A describes the quantitative characteristics of meditation clusters: average meditation length, experience of meditators and average parameters of words, i.e. average word length, number of major and minor letters, proportion of major letters, number of unique major letters, number of particular letters. And Fig. 6B contains similar information on participants' experience.

According to Fig. 6A meditation cluster 1 contains the longest words with the highest average number and proportion of major letters, as well as the highest variety of major letters A–E, that is, it consists of meditations with the most intense neural feature dynamics in all frequency bands.

Meditation cluster 2 also contains long words with a high average number and proportion of major letters. But unlike cluster 1, cluster 2 has pronounced neural feature dynamics only in alpha and beta bands, reflected in the highest average number of letters C and E and a relatively low content of other major letters.

Together meditation clusters 1 and 2 compose major cluster 1 of meditations with the most pronounced neural feature behavior. Meditation clusters 3–6 compose major cluster 2 with less intense neural feature dynamics and also have their own inner differences.

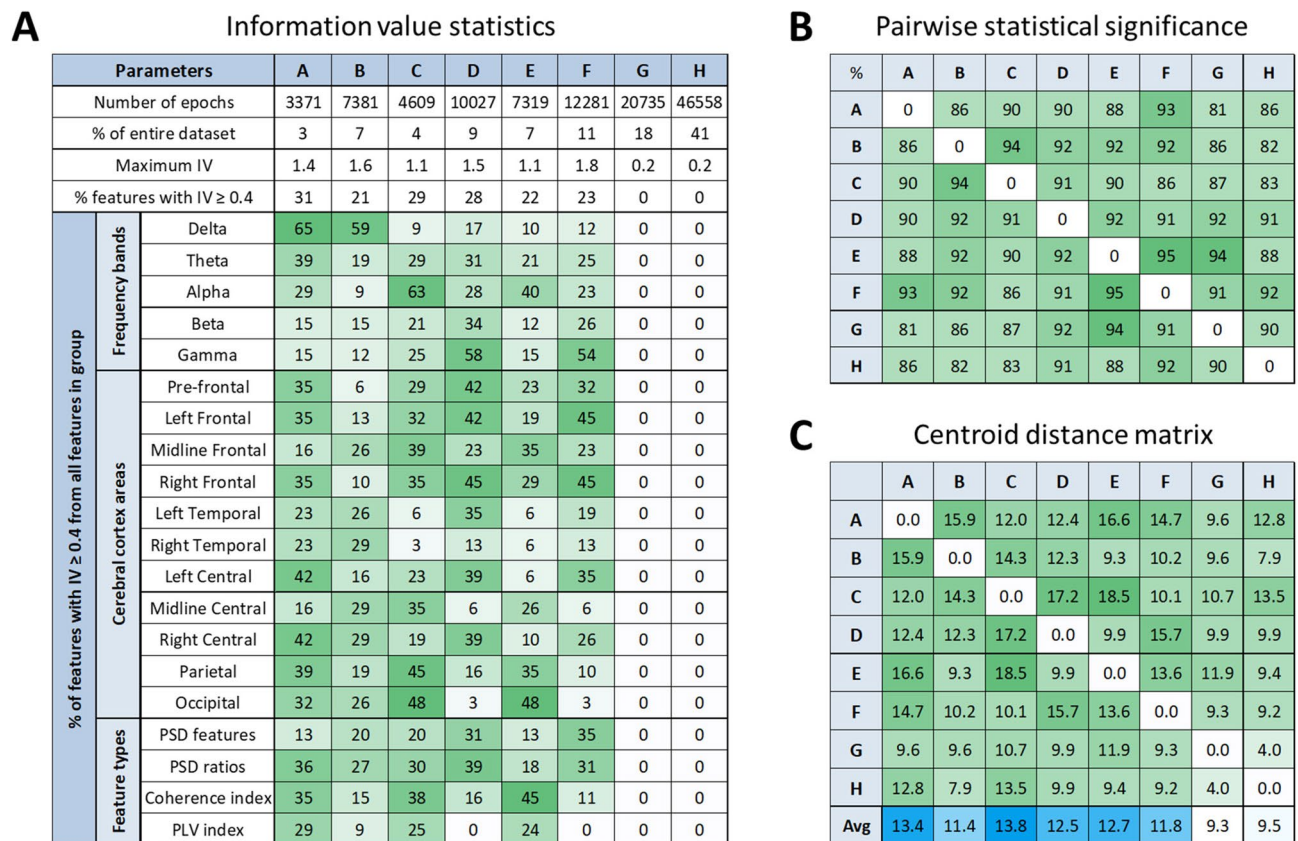


Fig. 4. Stage clusters analysis results. (A) Information value analysis in stage clusters. Columns corresponding to stage cluster letters A–H contain cluster size info, maximum cluster IV score and the percentage of features with cluster IV ≥ 0.4 from all features in a group indicated in the corresponding row. (B) Stage cluster pairwise statistical significance. For each pair of letters at the intersection of the corresponding row and column, the percentage of significantly different features in the corresponding stage clusters is indicated according to the Mann–Whitney U-test with Bonferroni correction ($p < 0.01$). (C) Stage cluster pairwise centroid distances. For each pair of letters at the intersection of the corresponding row and column, Euclidean distance between centroids of corresponding stage clusters is indicated. The last row with the name Avg contains average centroid distance from the stage cluster marked with a letter in the corresponding column to the remaining stage clusters.

Words in cluster 3 are also relatively long, but in contrast with clusters 1 and 2 they consist mainly of alternating minor letters G and H. Cluster 3 has the highest average number of minor letters and the lowest proportion of major letters, as well as the lowest diversity of major letters.

Meditation clusters 4 and 5 have medium quantitative word parameters and similar content of major letters with the prevalence of letters D and F (gamma and beta fluctuations), but generally the opposite order of major letters in a word, which is reflected in upward power trend in gamma and beta bands for cluster 4 and, on the contrary, in a downward gamma and beta trend for cluster 5.

Meditation cluster 6 has the lowest average word length and number of major letters, as well as the poorest letter content of words reflecting the least pronounced dynamics of neural features during meditation.

Detailed description of neural feature behavior in meditation clusters based on Fig. 6A can be found in Sect. 4 of Supplementary materials.

Meditators' experience impact

An important reference parameter is the monk's individual experience in meditation practice (refer to Sect. 2.1.3 for details). Meditations of highly experienced practitioners of combined expert and advanced categories turned out to be concentrated in meditation clusters 1, 2 and 5 (100%, 82% and 89% respectively), as shown in Fig. 6A. And meditations of expert-level practitioners only (the most experienced monks) make up 80%, 45% and 56% of clusters 1, 2 and 5 respectively and are almost missing from the rest of the clusters. This fact indicates that letter patterns of meditation clusters 1 and 2 (which compose major cluster 1) along with cluster 5 are reasonably specific for highly experienced practitioners.

According to permutation T-test major clusters 1 and 2 differ significantly with a p-value < 0.01 in number of expert-level meditations, combined expert and advanced-level meditations, word length, number and

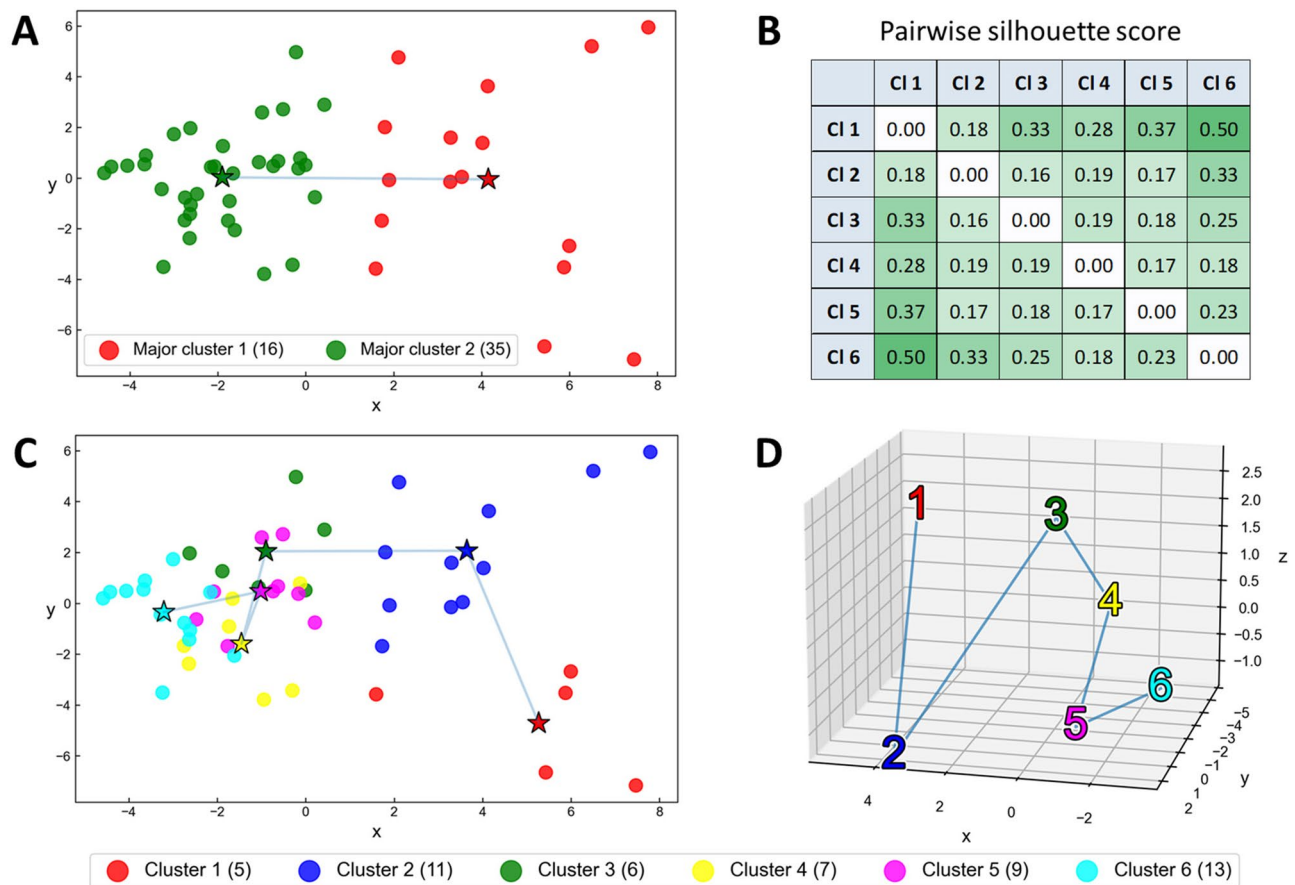


Fig. 5. Meditation clusters. (A) 2D projection of major meditation clusters onto the 1st (x axis) and 2nd (y axis) principal components in PCA feature space. Asterisks denote centroids of major clusters and are connected with blue lines in ascending order of cluster indices. The label bar contains colors of major clusters and number of their elements in parentheses. (B) Pairwise silhouette scores. For each pair of meditation clusters at the intersection of the corresponding row and column, their silhouette coefficient is indicated. (C) 2D projection of meditation clusters onto the 1st (x axis) and 2nd (y axis) principal components in PCA feature space. Asterisk denotes cluster centroids. (D) 3D projection of meditation cluster centroids onto the 1st (x axis), 2nd (y axis) and 3rd (z axis) principal components in PCA feature space. Cluster centroids are denoted with numbers assigned to meditation clusters and are connected with blue lines in ascending order. The label bar in the bottom of the Figure contains cluster colors and cluster size in parentheses for points (C) and (D).

percentage of major letters, number of unique major letters, and number of letters C and E, corresponding to alpha and theta fluctuations (Fig. 6A).

Figure 6B illustrates the impact of practitioners' experience on meditation structure. For highly experienced monks, according to permutation T-test, longer words and greater number and variety of major letters are statistically significant, which means more brain functional states and more intense and variative neural feature dynamics during meditation. Among all major letters the most significant (with p-value < 0.01) for experienced monks are greater number of letters C and E, corresponding to alpha and theta power and coherence oscillations. Also significant are fewer letters B (delta power drops), more letters D (gamma and beta power drops and desynchronization) and F (gamma and beta splashes).

Supplementary Table 4 contains the detailed information on meditation clusters: meditation IDs and time duration, their corresponding words underlying the clustering process, meditators' age and experience.

Discussion

The aim of this study was to test whether the canonical staged structure of advanced meditations of BHYT, namely "bringing dharmakaya of death into the path", can be quantitatively validated with EEG recordings from advanced Tibetan monks-practitioners.

According to Buddhist tradition, the practice unfolds through eight successive phases culminating in the state of "clear light." We hypothesized that distinct stages of this process would correspond to reproducible EEG patterns. Moreover, we anticipated that the level of expertise of the monks might modulate the EEG dynamics across meditation stages, thereby revealing the physiological correlates of meditative proficiency.

A

Meditation clusters parameters

Cluster parameter		Major cluster 1		Major cluster 2			Maj_cl1 vs Maj_cl2		
		Clust 1	Clust 2	Clust 3	Clust 4	Clust 5		Clust 6	
Size (N meditations)		5	11	6	7	9	13		
Meditation length, sec		2104	2349	2129	2217	2345	2040		
Practitioners' age		53	52	49	46	53	48		
% expert		80%	45%	0%	0%	56%	8%	**	
% advanced+expert		100%	82%	50%	43%	89%	15%	**	
Word length		12.4	9.9	8.5	7.4	7.3	5.2	**	
N major letters		9.4	6.1	2.3	4.1	3.6	2.3	**	
N minor letters		3.0	3.8	6.2	3.3	3.8	2.8		
% major letters		76%	62%	26%	56%	48%	46%	**	
N unique major letters		4.6	3.3	1.5	2.9	2.8	2.2	**	
N unique minor letters		1.8	1.7	2.0	1.9	1.9	1.6		
Number of letters	Major letters	A	0.8	0.6	0.5	0.6	0.2	0.4	
		B	0.4	0.1	1.3	0.4	0.1	0.7	
		C	1.4	1.8	0.0	0.0	0.4	0.2	**
		D	1.8	0.3	0.2	1.0	1.1	0.4	
		E	2.0	2.5	0.2	0.3	0.3	0.1	**
		F	3.0	0.8	0.2	1.9	1.3	0.5	
	Minor letters	G	1.4	1.8	2.8	1.1	1.3	1.2	
		H	1.6	2.0	3.3	2.1	2.4	1.6	

B

Experience level parameters

Parameter		Experience level			Expert vs others	Standard vs others	
		Standard	Advanced	Expert			
Size (N meditations)		21	15	15			
Meditation length, sec		2109	2253	2279			
Practitioners' age		46	50	56	**	**	
Word length		6.6	8.6	9.3	**	**	
N major letters		3.0	4.4	6.0	**	**	
N minor letters		3.6	4.2	3.3			
% major letters		45%	51%	62%	*	*	
N unique major letters		2.3	2.9	3.4	**	**	
N unique minor letters		1.8	1.8	1.8			
Number of letters	Major letters	A	0.4	0.6	0.5		
		B	0.7	0.5	0.1	*	
		C	0.3	0.6	1.2	**	*
		D	0.5	0.6	1.1	*	
		E	0.4	0.8	1.6	**	**
		F	0.7	1.3	1.5		*
	Minor letters	G	1.5	1.7	1.5		
		H	2.0	2.5	1.8		

Fig. 6. Meditation clusters and experience impact analysis. Statistical significance was measured using the permutation T-test (one asterisk in a cell denotes p -value < 0.05 , two asterisks denote p -value < 0.01). (A) Detailed statistics on meditation clusters. Columns Clust 1–Clust 6 correspond to meditation clusters and contain information about cluster size (number of meditations), average meditation length (number of 1 s epochs in preprocessed EEG data), percentage of meditations by highly experienced practitioners, and parameters of words assigned to meditations, averaged across a cluster: word length, number of major and minor letters in a word, percentage of major letters in a word, number of unique occurrence of major and minor letters in a word, and number of certain letters A–H in a word. Column “Maj_cl1 vs. Maj_cl2” indicates statistical significance of parameters in rows in Major cluster 1 vs. Major cluster 2. (B) Detailed statistics on the experience level of practitioners. Columns Standard, Advanced and Expert correspond to the experience level of meditators and contain meditation parameters averaged by group, the same as in table A. Column “Expert vs. others” indicates statistical significance in Expert group vs combined Advanced and Standard groups, column “Standard vs. others” — in combined Advanced and Expert groups vs Standard group.

Analysis of 51 EEG recordings from 36 monks (some monks had repeated recordings), represented by a set of 341 neural features, consistently revealed stages characterized by distinct EEG patterns after SDA application⁹.

The number of stages per recording averages 10 and may not exactly correspond to the canonical eight-stage protocol of BHYT meditation due to possible presence of preceding or conclusive meditative techniques accompanying the main meditation.

A central question concerned whether the observed EEG patterns across segments represented stochastic fluctuations or instead reflected consistent, meditation-related staged processes. Cluster analysis of the 341-dimensional feature space demonstrated that the segment patterns formed well-delineated groups, yielding eight clusters (A–H) (Figs. 2A and B and 4C).

Six clusters (A–F) exhibited robustly differentiated neurophysiological signatures (spectral features, spectral connectivity), accounting for nearly half of the detected stages (260 of 541 stages), while clusters G and H, though statistically distinct, displayed less specific and more amorphous patterns, with minimal deviations in spectral features (Figs. 2A and C and 4B).

These results indicate that repeatable and stereotyped EEG signatures (obtained clusters) underpin the staged dynamics experienced by the monks during meditation which can be tracked on boxplots with PSD values for obtained clusters on Figs. 2C and 3.

To assess the contribution of specific EEG features to the clusterization of segments we estimated the information value (IV) of each variable.

For minor clusters G and H, the IV of most features hovered at the statistical threshold and remained below the criterion of $IV < 0.4$. By contrast, up to 65% of features contributed substantially ($IV > 0.4$) to the classification of major clusters A–F (Fig. 4).

A–F segments correspond to stage clusters, relatively distant from the dataset center (see Fig. 2A), and are characterized by intense neural feature dynamics. This finding suggests that a broad set of cortical structures and functional domains is engaged across the successive stages of tantric meditation, whereas segments G and

H likely represent low-energy states (close to the dataset center) with minimal reconfiguration of neural activity, corresponding to baseline activity. Thus, major letters are of more interest for meditation analysis than minor ones.

Importantly, the major clusters were not isolated but organized in symmetrical pairs with opposing spectral profiles (A–B in the delta range, C–E in the alpha/theta range, and D–F in the beta/gamma range), see Figs. 2 and 3. Such paired organization highlights that the staged structure of BHYT is underpinned by a dynamic interplay across multiple frequency bands and cortical regions, providing a neurophysiological framework for understanding the oscillatory mechanisms of meditative states.

To further characterize the sequential organization of meditation, each EEG recording was encoded as a symbolic sequence, with each segment labeled according to its cluster assignment (A–H).

Despite following the same canonical protocol, individual monks exhibited divergent organizations of stage sequences. However, comparison of these symbolic sequences using Levenshtein distance revealed systematic regularities.

Cluster analysis identified two major groups that could be further subdivided into six compact clusters of meditation sequences (Fig. 5). Notably, repeated sessions from the same monk consistently mapped to the same cluster, indicating intra-subject stability. This finding underscores the intra-subject stability of the approach (see Supplementary Table 4).

Expertise emerged as a critical factor shaping meditation dynamics. Analysis of group composition revealed a marked asymmetry: the majority of experienced practitioners (experts alone, or experts and advanced combined) clustered within major group 1 (comprising two of the six meditation clusters) whereas the remaining groups contained statistically fewer advanced practitioners (Fig. 6A).

Statistical comparisons confirmed a strong association between expertise and the symbolic structure of meditation sequences (Fig. 6B).

Meditations by advanced and expert monks were characterized by longer symbolic words enriched with a higher proportion and diversity of major letters (A–F), reflecting a richer repertoire of neural states and more intense oscillatory dynamics, particularly in the alpha and theta bands. In contrast, less experienced monks tended to produce shorter sequences dominated by minor letters (G–H) or delta-related patterns, indicative of less complex neural trajectories. These results suggest that proficiency in meditations of BHYT is expressed not only in spectral features but also in the structural richness and variability of sequential state organization.

Importantly, these effects were independent of overall meditation duration, which did not differ significantly between meditation clusters or expertise levels (Fig. 6, Supplementary Table 4).

Together, these results provide the first quantitative evidence that meditations of BHYT unfold as a structured sequence of reproducible EEG states. Variability across practitioners reflects not randomness, but systematic differences linked to meditative expertise.

Our findings extend earlier reports of expertise-related differences in oscillatory patterns and stability of meditative states^{1,2} by demonstrating that expertise also shapes the compositional structure of meditation stages. They also align with evidence from Taoist practitioners showing divergent physiological strategies even among experts⁸, highlighting that multiple neurophysiological routes can underlie advanced meditation (compare clusters 1 and 2 vs. cluster 5).

Building on this background, our study provides the first quantitative evidence that meditations of BHYT can be systematically described as a sequence of reproducible functional EEG states, organized in opposing oscillatory pairs and significantly modulated by practitioners' expertise. These findings suggest that variability of meditative trajectories—previously considered a challenge for interpretation—can in fact be objectively captured through symbolic sequence analysis of EEG-defined states. In this framework, expertise systematically shapes not only oscillatory features but also the compositional structure of meditation.

This offers a novel framework for the neuroscience of introspection: meditations of BHYT emerges as a naturalistic yet structured model that bridges canonical contemplative descriptions with measurable neurophysiological dynamics, with implications extending from basic neuroscience to clinical interventions aimed at enhancing self-regulation and resilience through structured training of introspective states.

Future work will extend this approach by conducting detailed case-study analyses of representative meditations within each cluster, with particular attention to cluster 5, which includes both advanced and expert practitioners but displays less pronounced dynamics compared to clusters 1 and 2 of major group 1. In addition, we plan to incorporate new datasets with explicit phenomenological annotations currently being collected in Tibetan monasteries, which will allow for more precise alignment of EEG-defined states with practitioners' subjective reports.

Despite the strengths of ecological validity and the inclusion of a unique sample of highly trained meditators of BHYT, several limitations should be acknowledged.

First, the identification of meditation stages relied exclusively on data-driven segmentation of EEG signals, without concurrent annotation during the recordings. Although descriptive reports were collected before and after each session, these narratives did not provide time-resolved correspondence with EEG segments. In addition, our data-driven approach can be sensitive to background physiological dynamics present in long-lasting EEG recordings, caused by cognitive fatigue or attentional dynamics^{26,27}. Consequently, the alignment between canonical stages and EEG-derived clusters remains indirect; future work should incorporate in-situ phenomenological markers to strengthen this link.

Second, although recordings were performed under naturalistic conditions, technical variability existed across expeditions, including the use of different electrode montages. Harmonized setups in upcoming expeditions will help reduce this source of variability.

Third, the sample size (36 monks, 51 sessions), while remarkable for this rare population, is still modest for complex clustering analyses. Larger datasets would improve statistical robustness and generalizability.

Fourth, EEG provides limited spatial resolution and does not capture subcortical contributions that may be critical for introspective states. Multimodal approaches such as EEG–fNIRS or fMRI studies could address this limitation.

Finally, the unsupervised clustering approach, although validated, may be sensitive to feature selection and hyperparameters.

Overall, future studies combining multimodal neuroimaging, standardized protocols, and phenomenological data will be essential for refining the link between canonical contemplative stages and their neurophysiological correlates.

Conclusions

This study demonstrates that meditations of BHYT can be systematically described as a sequence of reproducible EEG-defined states. These states, often organized in symmetrical pairs with opposing oscillatory profiles, reflect a dynamic balance of cortical activity across meditation.

By representing stage clusters as symbolic sequences and applying edit-distance analysis, we identified distinct meditation trajectories that were highly stable within individuals but varied systematically between practitioners.

Crucially, expertise shaped the structural composition of these trajectories: highly experienced monks produced longer, more diverse sequences enriched with major stage types and marked by pronounced alpha, theta, and gamma dynamics, whereas less experienced practitioners (among experienced meditators recorded in an ecologically valid environment) showed shorter sequences dominated by minor or delta-related states.

These findings indicate that variability of meditation is not random but structured and experience-dependent. More broadly, our approach highlights meditations of BHYT as a naturalistic model for the neuroscience of introspection, bridging traditional contemplative frameworks with measurable neural dynamics and informing applied research on self-regulation and resilience.

Data availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation upon reasonable request.

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Author contributions

EM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing — original draft. AR: Conceptualization, Investigation, Methodology, Project administration, Supervision, Validation, Visualization, Writing — original draft, Writing — review & editing. VC: Conceptualization, Formal analysis idea, Investigation, Project administration, Supervision, Validation, Methodology, Writing — review & editing. YZ: Data curation, Methodology, Field study management, Resources, Writing — review & editing. AK: Conceptualization, Data curation, Funding acquisition, Project administration, Resources, Supervision, Validation, Writing — original draft, review & editing. NN: Field study management. LS: Field study management.

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Declarations

Competing interests

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethics statement

The studies involving humans were approved by Sera Jey Science Center, Karnataka State, India. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Informed consent

was written in English. As some of the participants were not proficient in English, the text of the informed consent, the purpose of the study, and its procedure were translated and explained to them in their native Tibetan language with the assistance of professional Tibetan translators.

Additional information

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1038/s41598-026-45893-4>.

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