Meditation and Complexity: A Systematic Review

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Abstract

Recent years have seen growing interest in the use of metrics inspired by complexity science for the study of consciousness. Work in this field shows remarkable results in discerning conscious from unconscious states, and in characterizing states of altered conscious experience following psychedelic intake as involving enhanced complexity. Here we study the relationship between complexity and a different kind of altered state: meditation. We provide a systematic review of the growing literature studying the complexity of neural activity in meditation, disentangling different families of measures, short-term (state) from long-term (trait) effects, and meditation styles. Beyond families of measures used, our review uncovers a convergence toward identifying higher complexity during the meditative state when compared to waking rest or mind-wandering, and decreased baseline complexity as a trait following regular meditation practice. This review contributes to guide current debates and provides a framework for understanding the complexity of neural activity in meditation, while suggesting practical guidelines for future research.

Keywords: Meditation, Consciousness, Complexity, Entropy, Fractal Dimension, Predictive Processing, Neuroimaging, Literature Review

Introduction

Meditation refers to contemplative practices that involve regulating both body and mind through cultivating a state of heightened awareness (Cahn & Polich 2006), and includes a wide variety of techniques and approaches (Goleman, 1988). A large body of ongoing work converges on the positive effects of meditation, including enhanced emotion regulation, wellbeing and stress reduction (Chiesa & Serreti, 2010; Farb et al., 2012, Querstret et al., 2020; Zollars et al., 2019), enhanced attentional skills (Jha et al., 2007, Tang et al., 2022), as well as alterations to the regular sense of self (Dahl et al, 2015; reviewed by Tang et al., 2015) and alleviation of the symptoms of various mental conditions (Zhihong et al., 2018; Parmentier et al., 2019; Haider et al., 2021; Geurts et al., 2021). Given these important implications, uncovering the neural correlates of meditation is a crucial challenge that, if solved, could help us improve our scientific understanding of consciousness, and the implementation of meditation-assisted psychotherapy. While early work focused on uncovering underlying mechanisms of meditation in the frequency domain mostly via electroencephalography (EEG), providing insights into the power or intensity of different frequency bands in brain activity (reviewed by Cahn & Polich, 2006), there have been many efforts in recent years to uncover cortical regions and networks, examining the functional magnetic resonance imaging (fMRI) activity and connectivity patterns between brain elements (e.g., reviewed by Fox et al., 2014, 2016; Fox & Cahn 2018; Young et al, 2018).

In addition to these more traditional approaches, recent years have seen a growing interest in the use of complexity-inspired measures in the study of consciousness, particularly in the characterisation of different altered states of consciousness (ASCs) (partially reviewed in Sarasso et. al, 2021; Lau et. al, 2022). In general, ASCs refer to temporary states in which there is a significant qualitative shift in subjective experience, including changes in perception, thought processes, emotions, and sense of self (Farthing, 1992; Tart, 1990). These ASCs can be induced by various means, including meditation, psychoactive substances, hypnosis, sleep deprivation, sensory deprivation, and other interventions that alter brain function (Tart, 1972; Vaitl et al., 2005). In effect, the field of complexity science (Jensen, 2022) has developed widely applicable theories describing emergent phenomena generated by the interplay of many parts of a system, such as different regions of the human brain (Sporns, 2022), that allow description of the informational richness and self-organization seen in brain activity. As these approaches offer complementary insights into brain functioning, beyond the classical approaches of frequency or network activity and connectivity, they should be combined to gain a more comprehensive understanding of the brain's meditation-induced intricate dynamics.

To date, complexity research of meditation lacks an explicit organizing framework, which should include theory, empirical comparison, and accepted guidelines for conducting research. To fill this gap, here we present a comprehensive review on the existent work relating meditation and complexity, providing an overview of conceptual issues and a review of the existing empirical studies. In the following, we first describe the notion of complexity and entropy of neural activity, and their use in consciousness studies. We then provide an overview on the use of complexity measures in the budding field of psychedelic neuroscience — an ASC relevant as a comparison to the meditative state (Millière et al., 2018; Letheby, 2022). Then, we elaborate on the definition and typology of meditation, and lay out theoretical considerations on complexity and meditation, before presenting a systematic review of the current literature on the subject. We conclude by discussing our main findings and offering suggestions for future research in this growing field.

Consciousness and Complexity

Metrics of Complexity in Neuroscience

Complexity science is a scientific discipline that aims to describe systems in which relatively simple components collectively give rise to emerging system-wide behavior (Mitchel, 2009). As noted by the philosopher Paul Cilliers: “a complex system cannot be reduced to a collection of its basic constituents, not because the system is not constituted by them, but because too much of the relational information gets lost in the process” (Cilliers, 1998, p. 10). The human brain is one of such complex systems, where the intricate interactions between billions of nerve cells give rise to sophisticated processes involving cognition and consciousness (Turkheimer et. al, 2021). In neuroscience, complexity science has provided important conceptual and computational tools to advance our understanding of how the brain works, including brain networks that describe the topology of interactions between brain regions (Sporns, 2011), metastability and dynamical phase transitions that characterize sudden shifts in modes of activity (Kelso, 1995), criticality that distinguishes a balance between rigidity and disorder (Cocchi et. al, 2017; O'Byrne & Jerbi, 2022), and the integration-differentiation coexistence as a key enabler of high brain functions (Tononi et al., 1998).

Measures inspired by principles of complexity science have been found to have the capability for discerning — to some degree — changes in consciousness, presenting an opportunity for empirical convergence beyond classical approaches (Sarasso et al., 2021). Overall, empirical studies show a general trend of increase in the complexity of brain dynamics in relation to an increase in the felt richness of conscious experience — for example, differentiating between sleep stages (Burioka et al., 2005) and indexing depth of anesthesia (Liang et al., 2015; Zhang et al., 2001). Typically, states of lower conscious level, such as anesthesia and non-rapid eye movement (NREM) sleep, score lower on complexity measures than wakefulness (Casali et al., 2013). In turn, states of altered phenomenology of conscious experience, such as the psychedelic state, have been systematically shown to exhibit higher complexity than normal wakefulness (Mediano et al., 2020; Schartner et al., 2017; Timmermann et al., 2019; Varley et al., 2020).

While during the early days of complexity science researchers strived to find a unique and all-encompassing signature of "complexity," there is a growing consensus that there are multiple flavors of complexity (Mitchel, 2009) and that distinguishing and differentiating them is an important contribution of complexity science (Feldman & Crutchfield, 1998). Hence, when talking about complexity it is crucial to specify what type of complexity one is focusing on. Sarasso and colleagues (2021) offer a provisional taxonomy of strategies to approach complexity in neuroscience: topological (spatial), temporal, and a combination of the two. When estimating complexity through the topological strategy, typically topological properties of a network of interdependencies are extracted from time series data, and the complexity of this topology is then captured by measures of network science (i.e. modularity, small-worldness, etc). This strategy can be implemented on networks built from measures such as effective or functional connectivity, and is best applied using measurement techniques with good spatial resolution such as magnetoencephalography (MEG) or functional magnetic resonance imaging (fMRI). In the temporal strategy, complexity is estimated based on the size of the repertoire of patterns generated by the temporal dynamics of neural activity. This strategy can be implemented via measures such as Sample Entropy (SE), Permutation Entropy (PE), Lempel-Ziv complexity (LZc) and Higuchi's Fractal Dimension (HFD), and is best applied using measurement techniques with good temporal resolution such as electroencephalography (EEG) or MEG.

While results obtained from measures utilizing temporal and spatial strategies to estimate complexity may correlate in practical scenarios, they strongly differ conceptually and algorithmically. For the sake of simplicity, the rest of this review will focus only on measures utilizing the strategy of temporal differentiation, motivated by their high empirical accuracy in capturing changes in states of consciousness.

Entropy and Fractal Dimension as Facets of Dynamical Complexity

Even within the topic of temporal complexity, there are many qualitatively different ways in which a system can be said to be complex. Here we draw a distinction between two types of complexity: *entropy* and *fractal dimension*. In essence, entropy[1] quantifies how well one can predict the future state of a system given its past, such that more unpredictable systems are generally seen as more complex. On the other hand, fractal dimension quantifies the degree of self-similarity and scale-invariance of a system, such that a system that exhibits more intricate repeating patterns at larger scales is seen as more complex.

Entropy

Entropy is an important concept in complexity science that stands at the core of thermodynamics and information theory (Thurner et. al, 2017). While entropy was originally introduced to quantify heat transfer, the seminal work of Boltzmann and Gibbs in statistical mechanics established entropy as an informational property — specifically, the degree of uncertainty an observer has about the microscopic realization of a given macroscopic state (Schroeder, 2000). In this context, entropy is sometimes described as quantifying the amount of "order" that the system exhibits, i.e., highly ordered systems tend to have relatively less possible constituting microstates compatible with given macrostates, and therefore less entropy. On a separate line of inquiry, Shannon (1948) found that the same formulation of entropy was capable of characterizing various communication processes, including data transmission and compression. In such scenarios entropy captures the amount of information in a given message, or the informational capabilities of a given communication channel. These seemingly disparate applications of entropy found a unification in the work of E.T. Jaynes (1957), who by adopting a Bayesian perspective proposed that probabilities reflect states of knowledge of observers, and entropy is a natural metric to quantify degrees of uncertainty — which can take place in thermodynamic or communication scenarios.

In the context of neural activity, entropy can be used to measure two important properties: diversity of activity and predictability (Mediano et. al, 2023). On the one hand, entropy is directly related to how diverse the patterns exhibited by the neural system are, as demonstrated by the asymptotic equipartition principle[2]. Crucially, entropy ignores which patterns are exhibited by the system, and just focuses on quantifying how diverse they are.

[1] To be mathematically precise, entropy rate – see Mediano and colleagues (2023).

[2] This theorem shows that the entropy is the number of fair coins that are needed to simulate a variable with an equivalent amount of uncertainty, or, put simply, the number of yes/no questions that are needed in average to reveal the value of the variable in question (Cover & Thomas, 2012).

On the other hand, entropy is also related to how hard it is to predict a system, providing an upper bound to the performance of an optimal predictor (Fano, 1961; Feder & Merhav, 1994). Hence, entropy does not measure the performance of a specific prediction strategy, but captures the intrinsic limitations on prediction given by the statistics of the system. The link between diversity and predictability establishes an important bridge between dynamical systems theory, which focuses on the dynamics of systems, and inferential and learning approaches, both of which have long-standing traditions in neuroscience (Mediano et. al, 2023). An illustration of the differences between time-series exhibiting low and high entropy values can be seen in Fig 1.

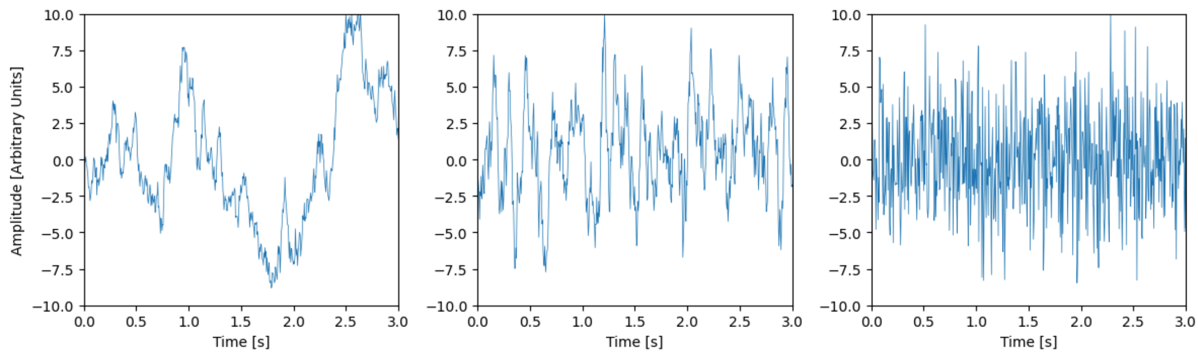

Figure 1. Simulated time-series sampled at 200 Hz with increasing Shannon entropy values. The left graph corresponds to the lowest Shannon entropy.

The entropic brain hypothesis (Carhart-Harris et. al, 2014; 2018), specifically addresses the relationship between entropy and consciousness, suggesting that the rich ASCs, e.g., induced by psychedelic drugs, may depend on a parallel enriching effect on the dynamics of neuronal activity, which is reflected in an increase of the entropy in the corresponding neuroimaging data. Conversely, ASCs involving loss of consciousness, such as anesthesia, would correspond to overly-ordered states where entropy is reduced. Crucially, the entropic brain hypothesis does not propose an identity between consciousness and entropy, but just a correlation, positing entropy as a useful marker of conscious activity. In particular, it is hypothesized (Carhart-Harris et. al, 2014) that the correspondence between entropy and level of consciousness may only hold on the range of normal brain activity, but may break when entropy grows too much — e.g. hot gas is not regarded as having a very rich experience, although it has very high entropy.

Fractal Dimension

Dimensionality refers to the number of independent variables required to describe a system or object. Dimensionality is often associated with the spatial extent of an object, such as the length, area, or volume. However, in complex systems, dimensionality can have a broader interpretation, encompassing not only spatial dimensions but also dimensions in time and in the system’s configuration space. Traditional Euclidean objects have an integer dimension (e.g., the dimension of a line is 1 and the dimension of a surface is 2), yet many natural phenomena do not behave according to these Euclidian idealizations — they tend to possess a property named self-similarity (or self-affinity), exhibiting intricate patterns that repeat at different scales. Classic examples of such phenomena are coastlines, snowflakes, cloud formations, and stock market fluctuations (Husain et al., 2022). This observation has a long history in mathematics, but it was Bennoit Mandlebrot (1967), who formalized this notion introducing the concept of fractal dimension. This formalization allows for non-integer values to describe the dimension of an object. For example, the Koch curve, illustrated in Fig. 2, has a fractal dimension of approximately 1.2619. The fractal dimension goes beyond the traditional notion of integer dimension, capturing the fine details and self-similarity that are present at different levels of scaling by quantifying how a pattern fills space. A pattern that fills space more densely and exhibits more intricate details at smaller scales will have a higher fractal dimension. For dynamical systems, the fractal dimension quantifies how quickly a system fills its space of possible states as it evolves over time.

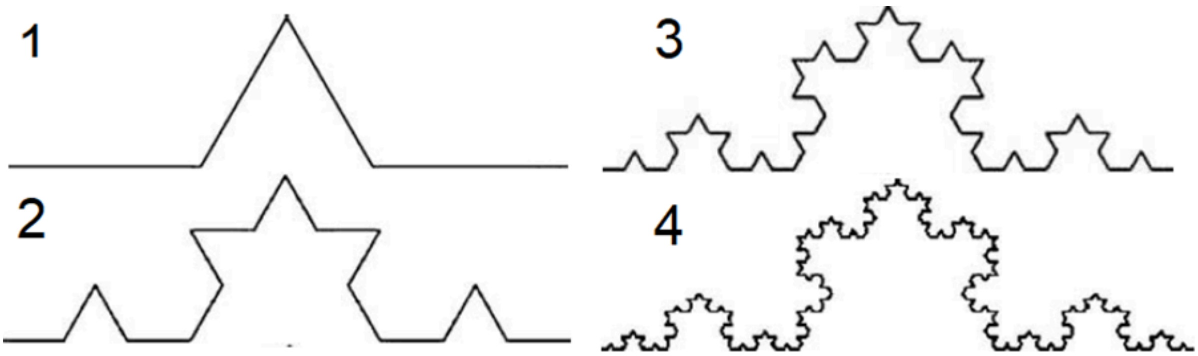

Figure 2. First 4 iterations of the Koch curve, which is created by a repeated application of the following rule: "for each line segment, replace its middle third by two sides of a triangle, each of length 1/3 of the original segment" (Mitchel, 2009 pp. 105-106). The Koch curve has a dimension of approximately 1.2619

The relationship between fractal dimension and complexity stems from the understanding that complex systems often display self-similarity and scale invariance. Fractal dimension then becomes a valuable tool for characterizing complexity because it provides a quantitative measure of the system's structure across different scales. A higher fractal dimension is usually associated with a greater degree of complexity, indicating a more intricate pattern within the system. In the case of neural activity, fractal dimensions offer insight into the complexity and self-organization of the underlying neural dynamics by providing an estimation to the degree of self-similarity of a signal. The fractal dimension of a time series (such as EEG) can be estimated either by reconstructing the multidimensional attractor that represents how neural activity evolves over time in the space of its possible states, or by directly treating the time series as a fractal pattern (Lau et. al, 2021).

Perhaps counterintuitively, measures of fractal dimension are also tightly connected to measures of the "memory" of a process (Mandelbrot, 1985). In time series statistics literature, memory accounts for the amount of information about the past behavior of a system needed to make an optimal prediction regarding the future state of that system. In the complexity literature, a long-memory process is said to have long-range temporal correlations (LRTC).

For this reason, measures of LRTC that were found in the reviewed studies are grouped together with measures of fractal dimension, as they both provide information on the self-similarity of a stochastic process.

Elevated Complexity — the Case of the Psychedelic State

One scenario where studies have found robust increases of complexity associated with changes in conscious experience is the psychedelic state. In effect, multiple studies have shown an increase of the brain entropy of neuroimaging time series (Mediano et al., 2020; Schartner et al., 2017; Timmermann et al., 2019; Varley et al. 2020; for overviews see McCulloch et al., 2022; Girn et. al, 2023), with at least one study also showing an increase in fractal dimension (Varley et al. 2020). One theoretical account of these findings is the "relaxed beliefs under psychedelics" (REBUS) theory (Carhart-Harris & Friston, 2019). Following predicting processing principles (elaborated in the next section), REBUS proposes that the ingestion of a psychedelic substance triggers a "relaxation" of the strength with which high-level priors guide normal processes of hierarchical generative modeling. By reducing the grip of top-down constraints, this yields more complex sensory information to flow up the hierarchy, which would allow for novel experiences that would not be able to arise during normal wakefulness. Correspondingly, the theory posits that the neural dynamics supporting these enriched psychological activity would display higher complexity.

In addition to the empirical findings mentioned above, the REBUS theory has gained further empirical support including studies applying complexity-related measures under the effect of ketamine (Farnes et al., 2020; Li & Mashour, 2019), lysergic acid diethylamide (LSD, Lebedev et al., 2016; Mediano et al., 2020; Ruffini et al., 2023), psilocybin (Schartner et al., 2017; Varley et al., 2020), dimethyltryptamine (DMT, Timmermann et al., 2019, 2023a) and Ayahuasca (Viol et al., 2016). Crucially to the purpose of the present review, the psychedelic state is the only ASC — to date — to consistently exhibit higher complexity than restful wakefulness.

Meditation and its Neurological Basis

In this section we elaborate on the definition of meditation, and describe categorizations of meditation techniques. We then lay out some relevant theoretical perspectives on the neural mechanisms of meditation, drawing mainly upon predictive processing frameworks, and building on that we offer some tentative hypotheses regarding the expected changes in complexity during meditation compared to normal wakefulness.

Meditation — A Gross Typology

Meditation refers to a family of contemplative practices that involve regulating both body and mind through cultivating a state of heightened awareness, which can lead to specific types of ASCs. This is typically accomplished by monitoring mental and/or physical processes, including perception, emotion, and body sensations, by employing a specific attentional set (Cahn and Polich, 2006). Various cultures have developed a range of meditation techniques, resulting in many diverse practices (e.g., Goleman, 1988).

Researchers have attempted to categorize these practices based on their primary aims and techniques, leading to several typologies (such as those proposed by Dahl et al., 2015; Lutz et al., 2008; Travis & Shear, 2010). Despite some variations, it is generally agreed that most practices can be grouped within two broad categories: focused attention (FA) and open monitoring (OM) (Lutz et al., 2008). FA involves maintaining attention on a specific object or sensation, such as the breath, counting, or bodily sensations (examples include one-pointed awareness or visualization meditation), while OM involves cultivating a non-judgmental and non-selective awareness of the present moment (examples include vipassana and mindfulness meditation). Additionally, some practices aim to develop emotional qualities (such as compassion and loving-kindness (LK) towards oneself and others (Lippelt et al., 2014), and some practices aim to transcend the self (ST) and experience a sense of oneness with the universe (e.g., transcendental meditation (Travis & Shear, 2010) and nondual meditation (Dunne, 2011)). This categorization is helpful when attempting to group different traditions for the sake of research, yet clearly over-simplifies the practice of meditation, as many practices involve cultivating skills from different categories, even in one meditation session. Each of these practices results in different subjective ASCs (as recently demonstrated by Woods et al., 2022) and subsequently involves different neural activity patterns (as reported by Amihai et al., 2014; Lehman et al 2001). In this review, we will use the gross categorization of FA, OM, LK and ST practices, albeit its over-simplicity, in order to attempt categorical conclusions.

Predictive Processing Accounts of Meditation and their Implications for Complexity

The use of complexity-related measures in analyzing neural activity allows a link to currently leading predictive processing accounts of brain function. In this section we outline proposed mechanisms of meditation which build upon the predictive processing framework, and offer tentative hypotheses for the directionality of change in complexity in meditation in light of these hypotheses.

Predictive processing (Clark 2013; Hohwy & Seth 2020) is a widely applied theory in neuroscience which assumes that the brain constantly generates and updates an internal model of the environment, which includes the body and the outside world. This generative model has a hierarchical nature, in which higher levels in the hierarchy project predictions of the incoming input to lower levels in the hierarchy, the lowest level being the senses. These predictions are then compared to the actual input and the discrepancy between the two is referred to as the prediction error. Prediction errors travel up the hierarchy, and are given a precision-weighting based on their reliability, which is based on the variance of the signal (Friston, 2010). Importantly, the top-down projection of expected precision is theorized to correspond to the process of attention allocation (Feldman & Friston, 2010). The brain strives to minimize the prediction errors, either by updating the internal model accordingly, or by action that changes the input to fit predictions.

From the lens of the predictive processing framework, meditation may involve the refinement of predictive models by bringing attention to the present moment and attenuating the influence of pre-existing biases and expectations. Through sustained practice, meditators may become more skilled at detecting and disentangling the predictions generated by the brain from the actual sensory inputs. This process may allow for a clearer perception of the present moment and a reduction in cognitive biases and automatic thought patterns (Lutz et al., 2019). Furthermore, as meditation requires maintaining attention to sensory input in the present moment, high precision weighting might be given to bottom-up information. At the same time, the meditative stable posture (as many meditations instruct to inhibit all movements), is suggested to actively inhibit adjustments in bodily posture, thus may inhibit correction of prediction errors via motor action, which otherwise would have allowed for minimization of prediction error without the need to update priors (Pagnoni, 2019). Another predictive processing theoretical account on meditation (Laukkonen & Slagter, 2021) proposes a somewhat similar mechanism to that of the REBUS theory suggested for psychedelics (Carhart-Harris & Friston, 2019), pointing to the possible decreased influence of previously formed generative models on neural processing during meditation. In this proposal, as the depth of meditation increases, conceptual processing in the form of high-level priors gradually falls away, subsequently revealing a state of pure awareness, a process referred to as a “flattening” of the counterfactually and temporally “thick”[3] self-model.

The theoretical frameworks described above do not explicitly generate hypotheses regarding the complexity of neural dynamics during meditation, and could be interpreted in either direction. On the one hand, we may interpret these proposed mechanisms as leading to higher neural complexity during meditation: the practice of meditation may lead to a relaxation of high-level priors and less suppression of prediction error through action, therefore allowing for more information to flow “bottom-up”, resulting in more intricate neural activity. This interpretation is similar to the claims of the REBUS theory for the psychedelic state (Carhart-Harris & Friston, 2019), supported by ample empirical findings in the psychedelic research (e.g. Mediano et al., 2020; Schartner et al., 2017; Timmermann et al., 2019; Varley et al. 2020). On the other hand, the same process of “flattening” the counterfactual depth of the generative self-model, alongside attenuation of sensory information that usually serves as basis for the self-model (as suggested by Limanowski and Friston, 2020) may be interpreted as resulting in a decrease of complexity. This direction may also be supported by findings that

[3] A generative model aimed at predicting the causes of sensory inputs is said to be temporally “thin” and concrete on the lower (sensory) levels of the hierarchy and more abstract and temporally “thick” (making inferences about the past and predictions about the future and generalizing the present moment) in higher levels (Friston, 2008; Corcoran et al.,2020; Laukkonen & Slagter, 2021).

meditation involves “switching off” neural networks supporting the narrative-self, i.e. the default mode network, both as a state (short-term) effect (Brewer et al., 2011; Farb et al., 2007; Garrison et al., 2015) and as a trait (long-term) effect (Berkovich-Ohana et al., 2016; Garrison et al., 2015), or attenuating networks supporting the embodied self (Dor-Ziderman et al., 2013, 2016). In light of these theories and the ambiguous hypotheses regarding changes in complexity in the meditative state offered here, we proceed to review the experimental literature of complexity measures in meditation.

A Systematic Review of Complexity in Meditation

To investigate the current empirical evidence regarding complexity of neural activity in the meditative state (short-term) and trait (long-term) changes in meditators, we conducted a systematic literature review searching the electronic databases PubMed and Google Scholar using the following query: ("meditation" OR "mindfulness") AND ("complexity" OR "entropy" OR "fractal"). Deolindo and colleagues (2020) provided a brief overview on studies of meditation through non-linear measures applied to EEG data, reviewing mixed empirical findings that suggest either an increase or decrease of complexity associated with meditation. Their conclusion was that the considered studies are not directly comparable because of the heterogeneity in designs and measures. Here we substantially broaden the amount of studies reviewed and aspire to provide a comprehensive framework for comparing these studies, that takes into account and explains the methodological differences as best as possible.

We found 20 articles published in peer-reviewed journals, 11 conference proceedings and 1 PhD thesis. Out of these, we include 17 studies in this review, for which we report here only the significant results relevant to our review of complexity in meditation. The inclusion criteria were sufficient sample size (n > 6), report of statistical analyses, description of the directionality of changes, and a relevant contrast (contrasting a similar condition between two groups or contrasting two conditions within one group). We excluded 3 studies due to small sample size (n=3: Davis et al., 2020; n=2: Lin & Li, 2017; n=2: Pradhan & Narayana Dutt, 1995), 4 studies that utilized complexity-related measures in meditation for machine learning classifiers and reported classification accuracy but did not report any descriptive analysis on the directionality of change in complexity (Han et al., 2020; Jachs, 2022; Korde et al., 2018; Pandey et al., 2023), 6 studies which reported results but did not apply basic statistical significance testing (Harne, 2014; Kamthekar & Iyer, 2021; Kaur et al., 2017; Motghare & Thorat, 2018; Lo & Huang, 2007; Pandey & Miyapuram, 2021) and 2 studies contrasting a condition of experienced meditators during meditation vs. resting state of controls, which is an irrelevant contrast for our purposes[4] (Huang & Lo, 2009; Shaw & Routray, 2016).

[4] A contrast which compares both different groups and different conditions does not allow to discern if the measured changes in complexity-related measures arise from the accumulating long-term effect of meditation, which requires a contrast of the same condition between groups, or from the short-term effect of meditation which requires a contrast of different conditions within the same group.

All reviewed studies performed measurement of neural activity via EEG. A summary of the results and design of the reviewed meditation studies can be found in Tables 1-3.

Measures Used in the Reviewed Meditation Studies

Following our identification of two ‘flavors’ of complexity previously described, we divided the measures found in the reviewed studies into these two main families: entropy and fractal dimension measures. A description of each of the reviewed measures can be found in Appendix 1.

The “entropy measures” family includes Shannon entropy, sample entropy (SE), multiscale entropy (MSE), permutation entropy (PE), wavelet entropy (WE) and minimum variance modified fuzzy entropy (MVMFE). These measures all estimate the Shannon entropy of the time series, via different manipulations prior to calculating the entropy. Closely related to the above is Lempel-Ziv complexity (LZc) which counts the number of distinct patterns in a binarized time series, converging to the entropy rate of the process generating the signal.

The “fractal dimension measures” family includes Higuchi’s fractal dimension (HFD) and Sevcik’s fractal dimension (SFD) which directly treat the time series as a fractal pattern, and dimensional complexity (DCx) which estimates the amount of squares/cubes the trajectory of the signal in phase space fills as it evolves. We also include measures of LRTC which came up in our search: Hurst’s exponent (HE) and detrended fluctuation analysis (DFA). Hurst’s exponent quantifies the rate at which autocorrelations between value pairs in the time series decay as the time distance between the pair increases, and DFA computes a scaling exponent which is an estimation of the Hurst exponent by dividing the time-series into segments and calculating the amount of fluctuation in the data as a function of segment size. As mentioned previously, under the assumption of a self-similar time series[5], the Hurst exponent is directly related to the fractal dimension by $FD=2-HE$ for $1<FD<2$ (Mandelbrot, 1985). Specifically in the case of EEG, a signal that contains both fractal and oscillatory aspects, it has been shown that HFD over-estimates the fractal dimension, while DFA under-estimates it (Krakovska & Krakovska, 2021). Therefore it should be kept in mind when reading the review that under the assumption of self-similarity, when a decrease in DFA or HE is demonstrated this actually entails an increase in the fractal dimension, and vice versa.

Review and Analysis of Results

The first observation in our review is that there is substantial discrepancy between the reviewed studies in the designs, analysis methods, measures used, etc. Therefore, a comparison of the results of these studies is not straightforward, and a rigorous mathematical meta-analysis is not possible. Hence, we first split the results into meditation state

[5] It should be noted that for more general stochastic processes this relation is broken, and the Hurst exponent and fractal dimension can be independent of each other (Gneiting & Schlather, 2004).

(short-term) and trait (long-term) studies[6], and then offer an analysis based on study design, categorization of complexity-related measures, meditation experience and style, and preprocessing steps applied in each study. For a detailed description of each study please refer to Tables 1-3.

Studies of the Meditative State (Short-term Effects) - Within Subject Design

First, we review studies contrasting meditation with a control condition, typically eyes-closed rest or mind-wandering, in a within-subjects design. As the variability in baseline neural complexity is large (Mediano et al., 2021), examining changes in complexity-related measures in a within-subject design is preferable. For a summary of results in this category, please refer to Table 1.

Table 1

Table 1. Studies of meditation short term effects in a within-subjects design. Where information for two adjacent cells is the same, cells are merged. Calculated Cohen's d: Where in bold, no effect sizes or standard deviation (SD) of difference were reported, so Cohen’s d was calculated based on groups mean and SD assuming independent samples. Where effect was shown within the same group and condition for different frequency bands/regions, the calculated Cohen’s d is an average of the effect sizes. For Kakumanu and colleagues (2018), effect sizes were reported only through scalp topography graphs, hence a range is written, and the calculated Cohen’s d is a weighted average of the effect sizes seen on the scalp topography.

Six studies demonstrated an increase in measures for the meditative state compared to control conditions. For meditation-naive subjects performing FA meditation, Lu and Rodriguez-Larios (2022) report an increase in LZc, SE and HFD compared to mind-wandering. Four studies demonstrated an increase in measures in experienced meditators for various meditation styles compared to resting state. The first study demonstrated an increase in MVMFE in highly experienced Rajayoga (ST) meditators (Kumar et al., 2021), the second demonstrated an increase in HFD for a ST meditation and an increase in MSE for FA meditation performed by highly experienced meditators (Walter & Hinterberger, 2022), the third demonstrated an increase in PE and HFD for FA, OM and LK meditation conditions for highly experienced meditators, and an increase in HFD and PE for the OM meditation in beginner meditators (Kakumanu et. al, 2018), and the fourth study reported an increase in LZc for both FA and OM meditation performed by highly experienced Theravada meditators (D’Andrea et al., 2024). Additionally, one study demonstrated an increase in HFD in meditation compared to podcast listening for meditation-naive subjects at week 6 of a mindfulness-based stress reduction (MBSR) course, and an increase in HFD in the meditation condition from week 4 to week 6 of the course (Do et. al, 2023). In addition, three studies demonstrated a decrease in the Hurst exponent, as estimated using DFA in

[6] Note that several studies examine both state and trait effects of meditation, and therefore appear in both categories.

meditation compared to resting-state in experienced meditators. The first study reported a decrease in FA meditation for two independent groups (Irmischer et al., 2018), with one of the groups showing an enhanced effect after an additional year of meditation training, the second study reported decreases for different meditation conditions including FA, OM and ST (Walter and Hinterberger, 2022), and the third study reported a decrease for both FA and OM meditation (D'Andrea et al., 2024).

Three studies demonstrated a decrease in different measures for the meditative state compared to control conditions. One study demonstrated a decrease in LZc in highly experienced meditators performing different styles of meditation compared to mind wandering (Young et. al, 2021). Two studies demonstrated a decrease in different measures for the meditative state compared to resting state. The first demonstrated a decrease in DCx in experienced Sahaja Yoga (OM) meditators (Aftanas & Golocheikine, 2002), and the second demonstrated a decrease in WE in novice meditators undergoing an MBSR course (Sik et al., 2017). Additionally, Irmischer et. al. (2018) report an increase in DFA in a FA meditation performed by meditation-naives, compared to resting state.

Two studies reported inconsistent results within a single dataset. The first study demonstrated an increase in SFD and a decrease in PE for an FA meditation and a decrease in PE for an OM meditation performed by experienced meditators (Vyšata et. al, 2014). The second study reported a change in HFD for meditation-naives performing an OM meditation before and after an MBSR course, showing an increase for some EEG channels and a decrease for others, with no significant overall difference (Anasi et al., 2018).

Finally, one study reported a decrease of Shannon entropy in meditation compared to video watching in experienced meditators (Davis et. al, 2023). This may be a poor choice of contrast, as it has been shown that video watching induces a very large increase in LZc compared to resting state (Mediano et. al, 2021). Furthermore, the effect of video-watching substantially diminishes the measurable changes in LZc under LSD ingestion, and also the correlation between LZc and subjective experience ratings (Mediano et al., 2020). Since LSD has been shown in other studies to have a strong and consistent effect on neural complexity, we argue that video-watching probably masks the effects of the subtler meditation. Therefore, this study was omitted from the summarizing Fig. 3.

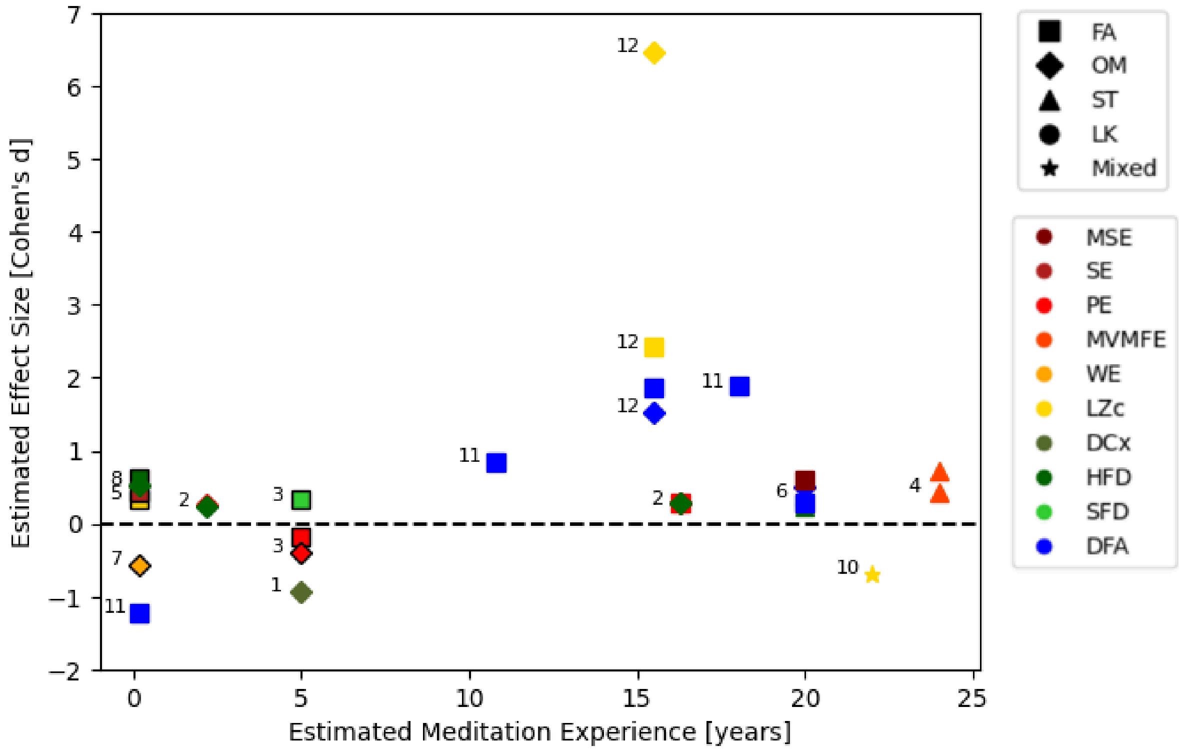

Figure 3. A summary of the within-subject studies comparing meditative state to a control condition of rest or mind-wandering. Each data-point represents a unique combination of group, meditation style and measure, therefore some studies contribute more than one data point. Colors indicate measures, and shapes indicate meditation styles. Data points are annotated with the number of their corresponding study in Table 1. Meditation years are either directly reported or estimated through reported meditation hours (assuming 200 hours per year, where average practice per day was not reported). Cohen's d was calculated with an online tool (based on the book "Practical Meta-Analysis" by Lipsey & Wilson, 2001) from effect sizes (t,F,z or d) where reported, and from means and SD where effect size was not reported. In the latter case, as the SD of the difference is not reported, Cohen's d was calculated assuming independent samples (unpaired t-test) and corresponding data-points are outlined in black. This assumption does not affect the directionality of the results, but typically produces a smaller effect size than when assuming dependent samples. Data-points with no outline indicate an effect size based on dependent samples (paired t-test). It should also be noted that as the Hurst exponent (HE) relates to fractal dimension (FD) through the formula FD=2-HE for 1<FD<2, a decrease in DFA, which estimates the Hurst exponent, will correspond to an increase in fractal dimension. Hence, for the purpose of visualization, we switch the sign of DFA effect sizes. Due to the estimated values, and the different designs of the studies, this figure should be understood as a heuristic schema and not as a rigorous mathematical meta-analysis.

We can see that meditation experience is an important factor when interpreting results of our reviewed studies. When meditation experience exceeds 5 years, almost all studies show an increase, while for less experienced meditators results vary. On the other hand, meditation style is not very informative when attempting to discern factors of variation in the direction of change. ST meditation consistently produces an increase in the measures, LK which was investigated in only one study shows an increase, yet OM and FA meditation show both.

The family of entropy measures (yellow-red colors) show an increase in the majority of studies, with an average effect size of d=0.717. When accounting for meditation experience 5 years or less these measures produce an average effect size of d=-0.001 and above 5 years an average effect size of d=1.201. Fractal dimension measures (green colors) show an increase in the majority of studies, with an average effect size of d=0.173, with d=0.142 for inexperienced meditators (5 years or less) and d=0.25 for experienced meditators (more than 5 years). DFA shows decrease in the majority of studies (corresponding to an increase in fractal dimension), with an average effect size of d=-0.755, while the average effect size is d=-1.037 for experienced meditators and an increase (corresponding to a decrease in fractal dimension) for meditation-naives (shown in one study) with effect size of d=1.22. It should be noted that this averaging of effect sizes takes one data point for each measure and group, averaging across meditation styles to create each data point. In principle, there are several ways to create the data points for averaging and we chose the aforementioned scheme to account for different measures, therefore this analysis should be read as a general way of showing numerical trends and not as a rigorous mathematical meta-analysis.

We furthermore attempted to analyze the discrepancies in results based on different data acquisition procedures and preprocessing pipelines applied in the studies. In principle, factors such as sampling frequency, number of EEG sensors, frequency filters, cleaning of the EEG signal, data points per epoch for measure calculation and other preprocessing such as a detrend of the data and Hilbert transformation of the signal prior to measure calculation can have a substantial impact on measure outcome (Durschmid et. al, 2020; Lau et. al, 2022). When analyzing the results in light of these factors, we could perform only a limited analysis due to the fact that not all studies fully reported their pre-processing pipelines. In the analysis done, we didn't find any specific trend regarding the effect of different preprocessing pipelines on measure outcomes.

Studies of Meditation State (Short-term Effects) - Between Subjects Design

Next, we review between-subject designs. Here the small number of studies do not allow for a thorough analysis of the inconsistencies in results (as done in the previous section) as well as impede reaching a conclusion. For a summary of results in this category please refer to Table 2.

Table 2

Table 2. Studies of meditation state (short-term) effects in a between-subjects design. The "Number" column continues and corresponds to the count from Table 1. Where information for two adjacent cells is the same, cells are merged.

We found two studies demonstrating an increase in measures when comparing a meditation condition of experienced meditators with novices (i.e., inexperienced controls). Martínez Vivot and colleagues (2020) demonstrated higher SE in meditation of Himalayan Yoga (FA) and Vipassana meditators (OM) compared to an FA meditation performed by controls. The second study utilized the same dataset for the Himalayan Yoga and control groups, confirmed the result of higher SE in the meditators than in controls, and also reported lower HE for the same comparison, as well as higher SE and lower HE for an additional Hare Krishna mantra (ST) group, compared to controls FA (Singh et al., 2023).

On the other hand, Kakumanu and colleagues (2018) demonstrated that for all meditation conditions (OM, FA, LK), overall HFD and PE values were lower for seniors and teachers when compared to beginner meditators.

Finally, Irmischer and colleagues (2018) also contrasted the difference between meditation and rest, between the meditator and control groups. They demonstrate that for meditators there is a stronger decrease in DFA during FA meditation than for the controls doing the same meditation.

Studies of Meditation Trait (Long-term Effects)

Studies in which analysis were carried out during resting state or cognitive tasks, comparing experienced meditators to novice meditators or comparing the same participants before and after a meditation intervention, are regarded as trait studies. Albeit the small amount of studies, the results here seem less ambiguous, showing a decrease in trait entropy and fractal dimension measures, as a function of meditation proficiency. For a summary of results in this category please refer to Table 3.

Table 3

Table 3. Studies of meditation trait (long-term) effects. The "Number" column continues and corresponds to the count from Tables 1,2. Where information for two adjacent cells is the same, cells are merged.

Kakumanu and colleagues (2018) compared resting-state between experienced meditators (seniors and teachers) and beginner meditators, and reported that HFD and PE values were considerably lower for the experienced group. Tibdewal and colleagues (2022) compared resting-state of meditation-naives before and after a one-month meditation intervention, and reported a post-intervention increase in SE for the delta and beta bands and a decrease for the theta and alpha bands. Irmischer and colleagues (2018) examined resting state of experienced meditators before and after a one year FA meditation intervention. They demonstrated a post-intervention increase in resting-state DFA. Finally, Gupta and colleagues (2021) compared a cognitive task performed by meditation-naives before and after a two-month FA meditation intervention, and reported a post-intervention decrease in HFD .

Discussion

In this paper we provided an organizing framework for the study of complexity of neural activity in meditation, and reviewed the empirical work that has accumulated in this field. As studies varied in their design, applied measures, and preprocessing pipeline, ambiguous findings were reported. In order to organize the results, we divided our review by differentiating between state from trait effects, different families of complexity-related measures, meditation styles and experience, and also pre-processing steps. Our findings show that the most meaningful differentiation was meditation state-vs-trait, and meditation experience, as discussed below. Analyzing other factors of variation such as meditation style, or pre-processing factors (including number of EEG sensors, frequency filter values, signal cleaning and time window for calculation) did not yield meaningful results.

Our analyses support a trend towards higher complexity in the meditative state compared to resting-state wakefulness and mind-wandering, with a majority of the meditation-state studies reviewed pointing to this direction. This increase is more prominent in studies examining experienced (>5 years) meditators, and more consistent for the fractal dimension measures than for entropy measures.
Our analyses also showed that during meditation proficient meditators, compared to novices, tend to have higher neural complexity — albeit one study (Kakumanu et. al, 2018) showing opposite results. In contrast, studies of trait (long-term) effect consistently show a reduction in baseline complexity as a function of meditation proficiency, when comparing individuals before and after meditation training in a within-subject design, and when comparing between individuals with low and high meditation proficiency.
This finding of elevated complexity during the meditative state and decreased complexity as a trait in experienced meditators has also received direct empirical support in a recent fMRI study pre-print (Atasoy et. al, 2023).

Overall, the results of our review suggest that meditation practice may operate in a way that increases complexity of neural activity during the practice, and decreases baseline complexity as a function of meditation proficiency. In the following, we first discuss these tentative findings in light of predictive processing theories of meditation and in relation to the psychedelic state, and finally offer guidelines for future research in the field.

Results in Light of Predictive Processing Accounts of Meditation

The trend towards increased neural complexity in the meditative state (compared to mind-wandering and rest) can be interpreted, under predictive processing principles, as suggesting that meditation increases bottom-up information flow. This interpretation stands in stark contrast with the idea that a “switching off” of neural networks during meditation could be thought of as leading to lower complexity in the neural dynamics. That said, one possible way to integrate the idea of a “switching off” of neural networks with the observed trend of higher complexity could be to argue that the prediction-based control of high-level networks (such as the DMN, which is known to decrease in activity during meditation (Brewer et al., 2011; Farb et al., 2007; Garrison et al., 2015)) may regularly suppress information conveyed by lower-level systems (e.g. systems conveying sensory information), but this suppression may be weakened during meditative states.

The result of our analysis is also consistent with claims that, in meditation, prediction errors travel farther up the predictive processing hierarchy thanks to a combination of (i) a relaxation of high-level priors, and (ii) the refraining from physical action or mental gestures that would otherwise minimize prediction errors (Lutz et. al, 2019). Under the assumption that information about the world is conveyed in the form of prediction errors, it can be argued that more information is processed in the brain during meditation — and indeed, this has been phenomenologically demonstrated by Petitmenging and colleagues (2018). Moreover, the process of relaxation of high-level priors and a refraining from action to minimize prediction error can be seen as somewhat orthogonal to the basic tendency to minimize prediction errors. This may allow for a temporary state in which the brain is forced to account for information that is usually repressed. Interestingly, this interpretation directly relates to some of the traditional definitions of the purposes of meditation (Harvey, 2015), as in Buddhism, meditation is used for "a direct experiential realization of the nature of reality" (Dreyfus & Thompson, 2007), which might correspond to the relaxation of priors. In a similar vein, equanimity, defined as an even-mindedness toward all experiences regardless of their origin or affective valence (Desbordes et al., 2015), may correspond to the process (and long-term realization) in which prediction errors are less automatically suppressed.

Comparison to the Psychedelic State

Our analysis suggests that the meditative state, similar to psychedelic ingestion, is characterized by higher complexity compared to normal wakefulness. In the entropic brain hypotheses, Carhart-Harris and colleagues (2014) suggest that in normal waking consciousness, the brain is operating in a subcritical regime, and that states of primary consciousness (such as early psychosis, sensory deprivation, dreaming, psychedelics, and infant consciousness) may push neural dynamics closer to the point of criticality. Following this line of reasoning, it could be argued that meditative states also involve states of primary consciousness, following the idea that the meditative state corresponds to a "begginer" state of mind in which previously formed biases (i.e., predictions of previously formed generative models) are attenuated, allowing for a more present-focused state (Austin, 1999; Suzuki & Dixon, 1982).

While sometimes ignored, the entropic brain hypothesis also makes a prediction that an increase in entropy surpassing the critical point may lead to a loss of consciousness. However, to the best of our knowledge no ASCs have been yet observed reflecting this change of trend. The results of this review allow us to propose a candidate ASC for the category of loss of consciousness due to an increase in entropy possibly, which build on the fact that meditation is a gradual process that involves a continuous practice, and that finding that the meditative state tends to entail increased entropy of the corresponding neural activity. The ASC we propose is the state of Nirodha-Samapatti, which is a pinnacle of meditation practice and is phenomenologically characterized by an increasing sense of meditative depth, followed by a transient cessation in conscious experience (Sharp 2011; Berkovich-Ohana 2015; Laukkonen et. al, 2023). The study of this ASC, and the process leading to it, in the context of complexity of neural activity, is a promising avenue for future work, which may propose a first example of passing beyond the hypothesized critical point proposed by the entropic brain hypotheses.

Another interesting phenomena arising from our analysis is the reduction of baseline complexity as a function of meditation experience. It has been suggested (Carhart-Harris & Nutt, 2017; Carhart-Harris & Friston, 2019) that transient increase in entropy induced by psychedelics allows for the neural system to explore new regimes of information processing, which could in principle allow the brain to find new and more efficient functional pathways that may persist after the experience (Hipólito et al., 2022). We see the results of increased complexity during the meditative state, and decreased baseline complexity as a function of meditation experience as a support to this notion, with numerous potential mental-health implications.

Limitations and Guidance for Future Studies in the Field

Firstly, although in our analysis we didn't find any specific trend in results as a factor of different preprocessing pipelines, complexity-related measures are in principle sensitive to preprocessing steps, and especially to the time-window used for calculation, the signal to noise ratio (Lau et. al, 2022), and the values of frequency filters (Durschmid et. al, 2020). Therefore we call for more open data practices, which will allow a re-examination of reported results under different pipelines. In the case that sharing data is not possible, we encourage researchers to fully report the study design, especially the meditation instructions or phenomenology if it exists, and the employed data preprocessing pipelines. While some studies did report these in detail, this practice is still not widely adopted, and the lack of it adds unnecessary difficulties when attempting to reach overarching conclusions.

Second, as previously elaborated, the notion of complexity is (to date) more a set of overarching principles rather than a single well-specified measurable property. Consequently, we encourage researchers to take caution when interpreting results of complexity-related measures, bearing in mind that each measure may only be able to capture aspects of a specific facet of a complex system. In light of these issues, we encourage researchers to apply a predefined set of measures when attempting to estimate complexity, as well as analyze the dependencies and correlations that may exist between these measures, as discussed in Walter & Hinterberger (2022). In particular, the following is a set of measures that we deem as useful: MSE, LZc, and HFD, as each of these measures theoretically captures a complementary aspect of complexity. Additionally, it is worth keeping in mind that changes observed in complexity-related measures can, in many cases, be accounted for by traditional spectral measures (Mediano et al, 2023). This issue can be addressed by computing both spectral and complexity-related measures and contrasting the variance explained by each of these, or by applying estimators that inherently disentangle spectral power from complexity effects, such as the one presented by Mediano and colleagues (2023).

Finally, analyzing the results according to our categorization of meditation styles failed to account for differences in results. This finding may have at least two interpretations: either complexity-related measures are able to characterize meditation beyond the differences in meditation techniques, or this categorization is gross and does not truly reflect the actual experience of meditators (especially for novices). Confirming or rejecting the first interpretation is an interesting avenue for future experimental work that may directly compare different meditation styles. The second interpretation points toward the deeper challenge of bridging first-person experience (and reports of the experience) and third-person measurements. This challenge has been discussed thoroughly in the literature, and a research program that we regard as particularly promising is neurophenomenology (Varela, 1996).

Thus, considering the important variance introduced by the wide range of meditation techniques, and given that our analysis shows that a categorization of meditation styles fails to account for discrepancies between studies, we recommend neurophenomenology as a framework to aid bridging the gap between subjective and objective data. Phenomenological studies can be developed through many methods. For example, deep phenomenology allows us to go beyond classical categorizations of meditation and address the specific experience of participants (e.g. Nave et al., 2021). Also, the use of neurophenomenology in the study of ASCs has been strongly advocated by Timmerman and colleagues (2023b), and a practical guide for some strategies of application was offered by Berkovich-Ohana and colleagues (2020). Some examples of such methods include micro-phenomenology (Petitmengin, 2006), temporal experience tracking (Jachs, 2021), descriptive experience sampling (Hurlburt & Akhter, 2006) and even repeatedly introducing a simple question during measurement of neural activity (Lu & Rodriguez-Larios, 2022). Considering the range of choices, choosing a neuro-phenomenological method for investigation should take into account the following aspects: depth of reports, practical implications, relevance to the time-course of the experience and the risk of biased information.

We hope that this review will inform the growing field of applying complexity-related measures to the study of meditation and its underlying neural activity, and will serve as an organizing back-bone for future studies, as well as inspire the use of open data and neurophenomenology, to enable reaching wider conclusions.

Bibliography

Aftanas, L. I., & Golocheikine, S. A. (2002). Non-linear dynamic complexity of the human EEG during meditation. *Neuroscience Letters*, *330*(2), 143–146. https://doi.org/10.1016/S0304-3940(02)00745-0

Amihai, I., & Kozhevnikov, M. (2014). Arousal vs. Relaxation: A Comparison of the Neurophysiological and Cognitive Correlates of Vajrayana and Theravada Meditative Practices. *PLOS ONE*, *9*(7), e102990. https://doi.org/10.1371/journal.pone.0102990

Anasi, C., Zarka, D., Álvarez, R., Cevallos, C., Cheron, G., & Vásquez, F. (2018). Individual analysis of EEG brain dynamics produced by mindfulness-based stress reduction training program. *2018 IEEE Third Ecuador Technical Chapters Meeting (ETCM)*, 1–6. https://doi.org/10.1109/ETCM.2018.8580346

Atasoy, S., Escrichs, A., Stark, E., Terry, K. G. M., Camara, E., Sanjuan, A., Chandaria, S., Deco, G., & Kringelbach, M. L. (2023). *The meditative brain: State and trait changes in harmonic complexity for long-term mindfulness meditators* (p. 2023.11.16.567347). bioRxiv. https://doi.org/10.1101/2023.11.16.567347

Bandt, C., & Pompe, B. (2002). Permutation Entropy: A Natural Complexity Measure for Time Series. *Physical Review Letters*, *88*(17), 174102. https://doi.org/10.1103/PhysRevLett.88.174102

Berkovich-Ohana, A. (2015). A case study of a meditation-induced altered state: Increased overall gamma synchronization. *Phenomenology and the Cognitive Sciences*, 1–16. https://doi.org/10.1007/s11097-015-9435

Berkovich-Ohana, A., Dor-Ziderman, Y., Trautwein, F.-M., Schweitzer, Y., Nave, O., Fulder, S., & Ataria, Y. (2020). The Hitchhiker's Guide to Neurophenomenology – The Case of Studying Self Boundaries With Meditators. *Frontiers in Psychology*, *11*, 1680. https://doi.org/10.3389/fpsyg.2020.01680

Berkovich-Ohana, A., Harel, M., Hahamy, A., Arieli, A., & Malach, R. (2016). Data for default network reduced functional connectivity in meditators, negatively correlated with meditation expertise. *Data in Brief*, *8*, 910–914. https://doi.org/10.1016/j.dib.2016.07.015

Brewer, J. A., Worhunsky, P. D., Gray, J. R., Tang, Y.-Y., Weber, J., & Kober, H. (2011). Meditation experience is associated with differences in default mode network activity and connectivity. *Proceedings of the National Academy of Sciences*, *108*(50), 20254–20259. https://doi.org/10.1073/pnas.1112029108

Burioka, N., Miyata, M., Cornélissen, G., Halberg, F., Takeshima, T., Kaplan, D. T., Suyama, H., Endo, M., Maegaki, Y., Nomura, T., Tomita, Y., Nakashima, K., & Shimizu, E. (2005). Approximate Entropy in the Electroencephalogram During Wake and Sleep. *Clinical EEG* *and Neuroscience : Official Journal of the EEG and Clinical Neuroscience Society (ENCS)*, *36*(1), 21–24.

Cahn, B. R., & Polich, J. (2006). Meditation states and traits: EEG, ERP, and neuroimaging studies. *Psychological Bulletin*, *132*(2), 180–211. https://doi.org/10.1037/0033-2909.132.2.180

Carhart-Harris, R. L. (2018). The entropic brain—Revisited. *Neuropharmacology*, *142*, 167–178. https://doi.org/10.1016/j.neuropharm.2018.03.010

Carhart-Harris, R. L., & Friston, K. J. (2019). REBUS and the Anarchic Brain: Toward a Unified Model of the Brain Action of Psychedelics. *Pharmacological Reviews*, *71*(3), 316–344. https://doi.org/10.1124/pr.118.017160

Carhart-Harris, R. L., & Nutt, D. J. (2017). Serotonin and brain function: A tale of two receptors. *Journal of Psychopharmacology (Oxford, England)*, *31*(9), 1091–1120. https://doi.org/10.1177/0269881117725915

Carhart-Harris, R., Leech, R., Hellyer, P., Shanahan, M., Feilding, A., Tagliazucchi, E., Chialvo, D., & Nutt, D. (2014). The entropic brain: A theory of conscious states informed by neuroimaging research with psychedelic drugs. *Frontiers in Human Neuroscience*, *8*, 20. https://doi.org/10.3389/fnhum.2014.00020

Casali, A. G., Gosseries, O., Rosanova, M., Boly, M., Sarasso, S., Casali, K. R., Casarotto, S., Bruno, M.-A., Laureys, S., Tononi, G., & Massimini, M. (2013). A theoretically based index of consciousness independent of sensory processing and behavior. *Science Translational Medicine*, *5*(198), 198ra105. https://doi.org/10.1126/scitranslmed.3006294

Chiesa, A., & Serretti, A. (2010). A systematic review of neurobiological and clinical features of mindfulness meditations. *Psychological Medicine*, *40*(8), 1239–1252. https://doi.org/10.1017/S0033291709991747

Cilliers, P. (1998). *Complexity and Postmodernism: Understanding Complex Systems*. New York: Routledge.

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, *36*(03), 181–204. https://doi.org/10.1017/S0140525X12000477

Cocchi, L., Gollo, L. L., Zalesky, A., & Breakspear, M. (2017). Criticality in the brain: A synthesis of neurobiology, models and cognition. *Progress in Neurobiology*, *158*, 132–152. https://doi.org/10.1016/j.pneurobio.2017.07.002

Corcoran, A. W., Pezzulo, G., & Hohwy, J. (2020). From allostatic agents to counterfactual cognisers: Active inference, biological regulation, and the origins of cognition. *Biology & Philosophy*, *35*(3), 32. https://doi.org/10.1007/s10539-020-09746-2

Costa, M., Goldberger, A. L., & Peng, C.-K. (2002). Multiscale Entropy Analysis of Complex Physiologic Time Series. *Physical Review Letters*, *89*(6), 068102. https://doi.org/10.1103/PhysRevLett.89.068102

Cover, T. M., & Thomas, J. A. (2012). *Elements of Information Theory*. John Wiley & Sons.

Dahl, C. J., Lutz, A., & Davidson, R. J. (2015). Reconstructing and deconstructing the self: Cognitive mechanisms in meditation practice. *Trends in Cognitive Sciences*, *19*(9), 515–523. https://doi.org/10.1016/j.tics.2015.07.001

D'Andrea, A., Croce, P., O'Byrne, J., Jerbi, K., Pascarella, A., Raffone, A., Pizzella, V., & Marzetti, L. (2024). Mindfulness meditation styles differently modulate source-level MEG microstate dynamics and complexity. *Frontiers in Neuroscience*, *18*. https://www.frontiersin.org/articles/10.3389/fnins.2024.1295615

Davis, J. J. J., Kozma, R., & Schübeler, F. (2023). Analysis of Meditation vs. Sensory Engaged Brain States Using Shannon Entropy and Pearson's First Skewness Coefficient Extracted from EEG Data. *Sensors*, *23*(3), Article 3. https://doi.org/10.3390/s23031293

Davis, J. J. J., Schübeler, F., Ji, S., & Kozma, R. (2020). *Discrimination Between Brain Cognitive States Using Shannon Entropy and Skewness Information Measure*. 4026–4031. https://doi.org/10.1109/SMC42975.2020.9283315

Deolindo, C. S., Ribeiro, M. W., Aratanha, M. A., Afonso, R. F., Irrmischer, M., & Kozasa, E. H. (2020). A Critical Analysis on Characterizing the Meditation Experience Through the Electroencephalogram. *Frontiers in Systems Neuroscience*, *14*, 53. https://doi.org/10.3389/fnsys.2020.00053

Desbordes, G., Gard, T., Hoge, E. A., Hölzel, B. K., Kerr, C., Lazar, S. W., Olendzki, A., & Vago, D. R. (2015). Moving beyond Mindfulness: Defining Equanimity as an Outcome Measure in Meditation and Contemplative Research. *Mindfulness*, *6*(2), 356–372. https://doi.org/10.1007/s12671-013-0269-8

Do, H., Hoang, H., Nguyen, N., An, A., Chau, H., Khuu, Q., Tran, L., Le, T., Le, A., Nguyen, K., Vo, T., & Ha, H. (2023). Intermediate effects of mindfulness practice on the brain activity of college students: An EEG study. *IBRO Neuroscience Reports*, *14*, 308–319. https://doi.org/10.1016/j.ibneur.2023.03.003

Dor-Ziderman, Y., Ataria, Y., Fulder, S., Goldstein, A., & Berkovich-Ohana, A. (2016). Self-specific processing in the meditating brain: A MEG neurophenomenology study. *Neuroscience of Consciousness*, *2016*(1), niw019. https://doi.org/10.1093/nc/niw019

Dor-Ziderman, Y., Berkovich-Ohana, A., Glicksohn, J., & Goldstein, A. (2013). Mindfulness-induced selflessness: A MEG neurophenomenological study. *Frontiers in Human Neuroscience*, *7*. https://www.frontiersin.org/articles/10.3389/fnhum.2013.00582

Dreyfus, G., & Thompson, E. (2007). Asian perspectives: Indian theories of mind. In *The Cambridge handbook of consciousness* (pp. 89–114). Cambridge University Press. https://doi.org/10.1017/CBO9780511816789.006

Dunne, J. (2011). Toward an understanding of non-dual mindfulness. *Contemporary Buddhism*, *12*(1), 71--88.

Dürschmid, S., Reichert, C., Walter, N., Hinrichs, H., Heinze, H.-J., Ohl, F. W., Tononi, G., & Deliano, M. (2020). Self-regulated critical brain dynamics originate from high frequency-band activity in the MEG. *PLOS ONE*, *15*(6), e0233589. https://doi.org/10.1371/journal.pone.0233589

Farb, N. A. S., Anderson, A. K., & Segal, Z. V. (2012). The Mindful Brain and Emotion Regulation in Mood Disorders. *Canadian Journal of Psychiatry. Revue Canadienne De Psychiatrie*, *57*(2), 70–77.

Farb, N. A. S., Segal, Z. V., Mayberg, H., Bean, J., McKeon, D., Fatima, Z., & Anderson, A. K. (2007). Attending to the present: Mindfulness meditation reveals distinct neural modes of self-reference. *Social Cognitive and Affective Neuroscience*, *2*(4), 313–322. https://doi.org/10.1093/scan/nsm030

Farnes, N., Juel, B. E., Nilsen, A. S., Romundstad, L. G., & Storm, J. F. (2020). Increased signal diversity/complexity of spontaneous EEG, but not evoked EEG responses, in ketamine-induced psychedelic state in humans. *PloS One*, *15*(11), e0242056. https://doi.org/10.1371/journal.pone.0242056

Farthing, G. W. (1992). *The Psychology of Consciousness*. Prentice-Hall.

Feder, M., & Merhav, N. (1994). Relations between entropy and error probability. *IEEE Transactions on Information Theory*, *40*(1), 259–266. https://doi.org/10.1109/18.272494

Feldman, D. P., & Crutchfield, J. P. (1998). Measures of statistical complexity: Why? *Physics Letters A*, *238*(4), 244–252. https://doi.org/10.1016/S0375-9601(97)00855-4

Feldman, H., & Friston, K. (2010). Attention, Uncertainty, and Free-Energy. *Frontiers in Human Neuroscience*, *4*. https://www.frontiersin.org/articles/10.3389/fnhum.2010.00215

Fox, K. C. R., & Cahn, B. R. (2018). Meditation and the brain in health and disease. In Farias, Brazier, & Lalljee (Eds.), *The Oxford Handbook of Meditation*. Oxford University Press.

Fox, K. C. R., Dixon, M. L., Nijeboer, S., Girn, M., Floman, J. L., Lifshitz, M., Ellamil, M., Sedlmeier, P., & Christoff, K. (2016). Functional neuroanatomy of meditation: A review and meta-analysis of 78 functional neuroimaging investigations. *Neuroscience & Biobehavioral Reviews*, *65*, 208–228. https://doi.org/10.1016/j.neubiorev.2016.03.021

Friston, K. (2008). Hierarchical Models in the Brain. *PLOS Computational Biology*, *4*(11), e1000211. https://doi.org/10.1371/journal.pcbi.1000211

Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, *11*(2), 127–138.

Garrison, K. A., Zeffiro, T. A., Scheinost, D., Constable, R. T., & Brewer, J. A. (2015). Meditation leads to reduced default mode network activity beyond an active task. *Cognitive, Affective & Behavioral Neuroscience*, *15*(3), 712–720. https://doi.org/10.3758/s13415-015-0358-3

Geurts, D. E. M., Schellekens, M. P. J., Janssen, L., & Speckens, A. E. M. (2021). Mechanisms of Change in Mindfulness-Based Cognitive Therapy in Adults With ADHD. *Journal of Attention Disorders*, *25*(9), 1331–1342. https://doi.org/10.1177/1087054719896865

Girn, M., Rosas, F. E., Daws, R. E., Gallen, C. L., Gazzaley, A., & Carhart-Harris, R. L. (2023). A complex systems perspective on psychedelic brain action. *Trends in Cognitive Sciences*, *27*(5), 433–445. https://doi.org/10.1016/j.tics.2023.01.003

Gneiting, T., & Schlather, M. (2004). Stochastic models which separate fractal dimension and Hurst effect. *SIAM Review*, *46*(2), 269–282. https://doi.org/10.1137/S0036144501394387

Goleman, D. (1988). *The meditative mind–the varieties of meditative experience*. GP Putnam & Sons.

Gupta, S. S., Manthalkar, R. R., & Gajre, S. S. (2021). Mindfulness intervention for improving cognitive abilities using EEG signal. *Biomedical Signal Processing and Control*, *70*, 103072. https://doi.org/10.1016/j.bspc.2021.103072

Haider, T., Dai, C.-L., & Sharma, M. (2021). Efficacy of Meditation-Based Interventions on Post-Traumatic Stress Disorder (PTSD) Among Veterans: A Narrative Review. *Advances in Mind-Body Medicine*, *35*(1), 16–24.

Han, Y., Huang, W., Huang, H., Xiao, J., & Li, Y. (2020). Assessing Meditation State Using EEG-based Permutation Entropy Features. *2020 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, 663–666. https://doi.org/10.1109/AIM43001.2020.9158980

Harne, B. P. (2014). Higuchi Fractal Dimension Analysis of EEG Signal Before and After OM Chanting to Observe Overall Effect on Brain. *International Journal of Electrical and Computer Engineering (IJECE)*, *4*(4), Article 4.

Harvey, P. (2015). Mindfulness in Theravāda Samatha and Vipassanā Meditations, and in Secular Mindfulness. In E. Shonin, W. Van Gordon, & N. N. Singh (Eds.), *Buddhist*

Foundations of Mindfulness (pp. 115–137). Springer International Publishing. https://doi.org/10.1007/978-3-319-18591-0_7

Higuchi, T. (1988). Approach to an irregular time series on the basis of the fractal theory. *Physica D: Nonlinear Phenomena*, *31*(2), 277–283. https://doi.org/10.1016/0167-2789(88)90081-4

Hipólito, I., Mago, J., Rosas, F., & Carhart-Harris, R. (2022). *Pattern Breaking: A Complex Systems Approach to Psychedelic Medicine*. PsyArXiv. https://doi.org/10.31234/osf.io/ydu3h

Hohwy, J., & Seth, A. (2020). Predictive processing as a systematic basis for identifying the neural correlates of consciousness. *Philosophy and the Mind Sciences*, *1*. https://doi.org/10.33735/phimisci.2020.II.64

Huang, H.-Y., & Lo, P.-C. (2009). EEG dynamics of experienced Zen meditation practitioners probed by complexity index and spectral measure. *Journal of Medical Engineering & Technology*, *33*(4), 314–321. https://doi.org/10.1080/03091900802602677

Hurlburt, R. T., & Akhter, S. A. (2006). The Descriptive Experience Sampling method. *Phenomenology and the Cognitive Sciences*, *5*(3–4), 271–301. https://doi.org/10.1007/s11097-006-9024-0

Hurst, H. E. (1951). Long-Term Storage Capacity of Reservoirs. *Transactions of the American Society of Civil Engineers*, *116*(1), 770–799. https://doi.org/10.1061/TACEAT.0006518

Husain, A., Nanda, M. N., Chowdary, M. S., & Sajid, M. (2022). Fractals: An Eclectic Survey, Part-I. *Fractal and Fractional*, *6*(2), Article 2. https://doi.org/10.3390/fractalfract6020089

Irrmischer, M., Houtman, S. J., Mansvelder, H. D., Tremmel, M., Ott, U., & Linkenkaer‐Hansen, K. (2018). Controlling the Temporal Structure of Brain Oscillations by Focused Attention Meditation. *Human Brain Mapping*, *39*(4), 1825–1838. https://doi.org/10.1002/hbm.23971

Jachs, B. (2022). *The Neurophenomenology of Meditative States: Introducing Temporal Experience Tracing to Capture Subjective Experience States and their Neural Correlates*. https://www.repository.cam.ac.uk/handle/1810/332709

Jaynes, E. T. (1957). Information Theory and Statistical Mechanics. *Physical Review*, *106*(4), 620–630. https://doi.org/10.1103/PhysRev.106.620

Jensen, H. J. (2022, November 17). *Complexity Science: The Study of Emergence*. Higher Education from Cambridge University Press; Cambridge University Press. https://doi.org/10.1017/9781108873710

Jha, A. P., Krompinger, J., & Baime, M. J. (2007). Mindfulness training modifies subsystems of attention. *Cognitive, Affective, & Behavioral Neuroscience*, *7*(2), 109–119. https://doi.org/10.3758/CABN.7.2.109

Kakumanu, R. J., Nair, A., Venugopal, R., Sasidharan, A., Ghosh, P., John, J., Mehrotra, S., Panth, R., & Kutty, B. (2018). Dissociating meditation proficiency and experience dependent EEG changes during traditional Vipassana meditation practice. *Biological Psychology*. https://doi.org/10.1016/j.biopsycho.2018.03.004

Kamthekar, S., & Iyer, B. (2021). Tratak Meditation As a CAM for Stress Management: An EEG Based Analysis. *2021 International Conference on Intelligent Technologies (CONIT)*, 1–6. https://doi.org/10.1109/CONIT51480.2021.9498288

Kaur, K., Singh, K., & Uppal, R. S. (2017). ANALYZING THE EFFECTS OF MEDITATION ON ELECTROENCEPHALOGRAPH SIGNALS. *International Journal of Advanced Research in Computer Science*, *8*(7), Article 7. https://doi.org/10.26483/ijarcs.v8i7.4584

Kelso, J. A. S. (1995). *Dynamic Patterns: The Self-Organization of Brain and Behavior*. Bradford Books.

Korde, K. S., Paikrao, P. L., & Jadhav, N. S. (2018). Analysis of EEG Signals and Biomedical Changes Due to Meditation on Brain by Using ICA for Feature Extraction. *2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS)*, 1479–1484. https://doi.org/10.1109/ICCONS.2018.8663129

Krakovská, H., & Krakovská, A. (2021). Problems of Estimating Fractal Dimension by Higuchi and DFA Methods for Signals That Are a Combination of Fractal and Oscillations. *2021 13th International Conference on Measurement*, 84–87. https://doi.org/10.23919/Measurement52780.2021.9446804

Kumar, G. P., Sharma, K., Ramakrishnan, A. G., & Adarsh, A. (2021). Increased Entropy of Gamma Oscillations in the Frontal Region during Meditation. *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. https://www.academia.edu/74987146/Increased_Entropy_of_Gamma_Oscillations_in_the_Frontal_Region_during_Meditation

Lau, Z. J., Pham, T., Chen, S. H. A., & Makowski, D. (2022). Brain entropy, fractal dimensions and predictability: A review of complexity measures for EEG in healthy and neuropsychiatric populations. *European Journal of Neuroscience*, *56*(7), 5047–5069. https://doi.org/10.1111/ejn.15800

Laukkonen, R. E., & Slagter, H. A. (2021). From many to (n)one: Meditation and the plasticity of the predictive mind. *Neuroscience & Biobehavioral Reviews*, *128*, 199–217. https://doi.org/10.1016/j.neubiorev.2021.06.021

Laukkonen, R., Sacchet, M., Barendregt, H. (Hendrik), Devaney, K., Chowdhury, A., & Slagter, H. (2023). *Cessations of consciousness in meditation: Advancing a scientific understanding of nirodha samāpatti*. https://doi.org/10.1016/bs.pbr.2022.12.007

Lebedev, A. V., Kaelen, M., Lövdén, M., Nilsson, J., Feilding, A., Nutt, D. J., & Carhart-Harris, R. L. (2016). LSD-induced entropic brain activity predicts subsequent personality change. *Human Brain Mapping*, *37*(9), 3203–3213. https://doi.org/10.1002/hbm.23234

Lehmann, D., Faber, P. L., Achermann, P., Jeanmonod, D., Gianotti, L. R., & Pizzagalli, D. (2001). Brain sources of EEG gamma frequency during volitionally meditation-induced, altered states of consciousness, and experience of the self. *Psychiatry Research*, *108*(2), 111–121. https://doi.org/10.1016/s0925-4927(01)00116-0

Lempel, A., & Ziv, J. (1976). On the Complexity of Finite Sequences. *IEEE Transactions on Information Theory*, *22*(1), 75–81. https://doi.org/10.1109/TIT.1976.1055501

Letheby, C. (2022). Psychedelics and Meditation: A Neurophilosophical Perspective—PhilPapers. In R. Repetti (Ed.), *The Routledge Handbook of the Philosophy of Meditation*. Routledge. https://philpapers.org/rec/LETPAM

Li, D., & Mashour, G. A. (2019). Cortical dynamics during psychedelic and anesthetized states induced by ketamine. *NeuroImage*, *196*, 32–40. https://doi.org/10.1016/j.neuroimage.2019.03.076

Liang, Z., Wang, Y., Sun, X., Li, D., Voss, L. J., Sleigh, J. W., Hagihira, S., & Li, X. (2015). EEG entropy measures in anesthesia. *Frontiers in Computational Neuroscience*, *9*, 16. https://doi.org/10.3389/fncom.2015.00016

Limanowski, J., & Friston, K. (2020). Attenuating oneself. *Philosophy and the Mind Sciences*, *1*(I), 6–6. https://doi.org/10.33735/phimisci.2020.I.35

Lin, H., & Li, Y. (2017). Using EEG Data Analytics to Measure Meditation. In V. G. Duffy (Ed.), *Digital Human Modeling. Applications in Health, Safety, Ergonomics, and Risk Management: Health and Safety* (pp. 270–280). Springer International Publishing. https://doi.org/10.1007/978-3-319-58466-9_25

Lippelt, D. P., Hommel, B., & Colzato, L. S. (2014). Focused attention, open monitoring and loving kindness meditation: Effects on attention, conflict monitoring, and creativity–A review. *Frontiers in Psychology*, *5*. https://doi.org/10.3389/fpsyg.2014.01083

Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis* (pp. ix, 247). Sage Publications, Inc.

Lo, P., & Huang, H. (2007). Investigation of meditation scenario by quantifying the complexity index of EEG. *Journal of the Chinese Institute of Engineers*, *30*(3), 389–400. https://doi.org/10.1080/02533839.2007.9671267

Lu, Y., & Rodriguez-Larios, J. (2022). Nonlinear EEG signatures of mind wandering during breath focus meditation. *Current Research in Neurobiology*, *3*, 100056. https://doi.org/10.1016/j.crneur.2022.100056

Lutz, A., Mattout, J., & Pagnoni, G. (2019). The epistemic and pragmatic value of non-action: A predictive coding perspective on meditation. *Current Opinion in Psychology*. https://doi.org/10.1016/j.copsyc.2018.12.019

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

Mandelbrot, B. (1967). How Long Is the Coast of Britain? Statistical Self-Similarity and Fractional Dimension. *Science*, *156*(3775), 636–638. https://doi.org/10.1126/science.156.3775.636

Mandelbrot, B. B. (1985). Self-Affine Fractals and Fractal Dimension. *Physica Scripta*, *32*(4), 257. https://doi.org/10.1088/0031-8949/32/4/001

Martínez Vivot, R., Pallavicini, C., Zamberlan, F., Vigo, D., & Tagliazucchi, E. (2020). Meditation Increases the Entropy of Brain Oscillatory Activity. *Neuroscience*, *431*, 40–51. https://doi.org/10.1016/j.neuroscience.2020.01.033

McCulloch, D. E.-W., Knudsen, G. M., Barrett, F. S., Doss, M. K., Carhart-Harris, R. L., Rosas, F. E., Deco, G., Kringelbach, M. L., Preller, K. H., Ramaekers, J. G., Mason, N. L., Müller, F., & Fisher, P. M. (2022). Psychedelic resting-state neuroimaging: A review and perspective on balancing replication and novel analyses. *Neuroscience & Biobehavioral Reviews*, *138*, 104689. https://doi.org/10.1016/j.neubiorev.2022.104689

Mediano, P. A. M., Ikkala, A., Kievit, R. A., Jagannathan, S. R., Varley, T. F., Stamatakis, E. A., Bekinschtein, T. A., & Bor, D. (2021). *Fluctuations in Neural Complexity During Wakefulness Relate To Conscious Level and Cognition* (p. 2021.09.23.461002). bioRxiv. https://doi.org/10.1101/2021.09.23.461002

Mediano, P. A. M., Rosas, F. E., Luppi, A. I., Noreika, V., Seth, A. K., Carhart-Harris, R. L., Barnett, L., & Bor, D. (2023). *Spectrally and temporally resolved estimation of neural signal diversity* (p. 2023.03.30.534922). bioRxiv. https://doi.org/10.1101/2023.03.30.534922

Mediano, P., Rosas, F., Timmermann, C., Roseman, L., Nutt, D., Feilding, A., Kaelen, M., Kringelbach, M., Barrett, A., Seth, A., Muthukumaraswamy, S., Bor, D., & Carhart-Harris, R. (2020). *Effects of external stimulation on psychedelic state neurodynamics*. https://doi.org/10.1101/2020.11.01.356071

Millière, R., Carhart-Harris, R. L., Roseman, L., Trautwein, F.-M., & Berkovich-Ohana, A. (2018). Psychedelics, Meditation, and Self-Consciousness. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.01475

Nave, O., Trautwein, F.-M., Ataria, Y., Dor-Ziderman, Y., Schweitzer, Y., Fulder, S., & Berkovich-Ohana, A. (2021). Self-Boundary Dissolution in Meditation: A Phenomenological Investigation. *Brain Sciences*, *11*(6), Article 6. https://doi.org/10.3390/brainsci11060819

O'Byrne, J., & Jerbi, K. (2022). How critical is brain criticality? *Trends in Neurosciences*, *45*(11), 820–837. https://doi.org/10.1016/j.tins.2022.08.007

Pagnoni, G. (2019). The contemplative exercise through the lenses of predictive processing: A promising approach. *Progress in Brain Research*, *244*, 299–322. https://doi.org/10.1016/bs.pbr.2018.10.022

Pandey, P., & Miyapuram, K. P. (2021). Nonlinear EEG analysis of mindfulness training using interpretable machine learning. *2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 3051–3057. https://doi.org/10.1109/BIBM52615.2021.9669457

Pandey, P., Rodriguez-Larios, J., Miyapuram, K. P., & Lomas, D. (2023). Detecting moments of distraction during meditation practice based on changes in the EEG signal. *2023 IEEE Applied Sensing Conference (APSCON)*, 1–3. https://doi.org/10.1109/APSCON56343.2023.10101045

Parmentier, F. B. R., García-Toro, M., García-Campayo, J., Yañez, A. M., Andrés, P., & Gili, M. (2019). Mindfulness and Symptoms of Depression and Anxiety in the General Population: The Mediating Roles of Worry, Rumination, Reappraisal and Suppression. *Frontiers in Psychology*, *10*. https://www.frontiersin.org/articles/10.3389/fpsyg.2019.00506

Peng, C. K., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1995). Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. *Chaos (Woodbury, N.Y.)*, *5*(1), 82–87. https://doi.org/10.1063/1.166141

Petitmengin, C. (2006). Describing one's subjective experience in the second person: An interview method for the science of consciousness. *Phenomenology and the Cognitive Sciences*, *5*(3), 229–269.

Petitmengin, C., van Beek, M., Bitbol, M., Nissou, J.-M., & Roepstorff, A. (2018). Studying the experience of meditation through micro-phenomenology. *Current Opinion in Psychology*. https://doi.org/10.1016/j.copsyc.2018.10.009

Pradhan, N., & Narayana Dutt, D. (1995). An analysis of dimensional complexity of brain electrical activity during meditation. *Proceedings of the First Regional Conference, IEEE Engineering in Medicine and Biology Society and 14th Conference of the Biomedical Engineering Society of India. An International Meet*, 1/92-1/93. https://doi.org/10.1109/RCEMBS.1995.511692

Pritchard, W. S., & Duke, D. W. (1995). Measuring “chaos” in the brain: A tutorial review of EEG dimension estimation. *Brain and Cognition*, *27*(3), 353–397. https://doi.org/10.1006/brcg.1995.1027

Querstret, D., Morison, L., Dickinson, S., Cropley, M., & John, M. (2020). Mindfulness-based stress reduction and mindfulness-based cognitive therapy for psychological health and well-being in nonclinical samples: A systematic review and meta-analysis. *International Journal of Stress Management*, *27*, 394–411. https://doi.org/10.1037/str0000165

Raghu, S., Sriraam, N., Kumar, G. P., & Hegde, A. S. (2018). A Novel Approach for Real-Time Recognition of Epileptic Seizures Using Minimum Variance Modified Fuzzy Entropy. *IEEE Transactions on Biomedical Engineering*, *65*(11), 2612–2621. https://doi.org/10.1109/TBME.2018.2810942

Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *American Journal of Physiology-Heart and Circulatory Physiology*, *278*(6), H2039–H2049. https://doi.org/10.1152/ajpheart.2000.278.6.H2039

Ruffini, G., Damiani, G., Lozano-Soldevilla, D., Deco, N., Rosas, F. E., Kiani, N. A., Ponce-Alvarez, A., Kringelbach, M. L., Carhart-Harris, R., & Deco, G. (2023). LSD-induced increase of Ising temperature and algorithmic complexity of brain dynamics. *PLOS Computational Biology*, *19*(2), e1010811. https://doi.org/10.1371/journal.pcbi.1010811

Sarasso, S., Casali, A. G., Casarotto, S., Rosanova, M., Sinigaglia, C., & Massimini, M. (2021). Consciousness and complexity: A consilience of evidence. *Neuroscience of Consciousness*, niab023. https://doi.org/10.1093/nc/niab023

Schartner, M. M., Carhart-Harris, R. L., Barrett, A. B., Seth, A. K., & Muthukumaraswamy, S. D. (2017). Increased spontaneous MEG signal diversity for psychoactive doses of ketamine, LSD and psilocybin. *Scientific Reports*, *7*, 46421. https://doi.org/10.1038/srep46421

Schroeder, V. D. (2000). *An introduction to thermal physics*. London.

Seth, A. K., Barrett, A. B., & Barnett, L. (2015). Granger Causality Analysis in Neuroscience and Neuroimaging. *Journal of Neuroscience*, *35*(8), 3293–3297. https://doi.org/10.1523/JNEUROSCI.4399-14.2015

Sevcik, C. (2006). On fractal dimension of waveforms. *Chaos, Solitons & Fractals*, *28*(2), 579–580. https://doi.org/10.1016/j.chaos.2005.07.003

Shannon, C. E. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal*, *27*(3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Sharp, P. (2011). *Buddhist Enlightenment and the Destruction of Attractor Networks: A Neuroscientific Speculation on the Buddhist Path from Everyday Consciousness to Buddha-Awakening*. https://philarchive.org/rec/SHABEA

Shaw, L., & Routray, A. (2016). Statistical features extraction for multivariate pattern analysis in meditation EEG using PCA. *2016 IEEE EMBS International Student Conference (ISC)*, 1–4. https://doi.org/10.1109/EMBSISC.2016.7508624

Sik, H. H., Gao, J., Fan, J., Wu, B. W. Y., Leung, H. K., & Hung, Y. S. (2017). Using Wavelet Entropy to Demonstrate how Mindfulness Practice Increases Coordination between Irregular Cerebral and Cardiac Activities. *Journal of Visualized Experiments: JoVE*, *123*, 55455. https://doi.org/10.3791/55455

Singh, S., Gupta, V., Reddy, T. K., Behera, L., & Samanta, S. (2023). Meditative State Classification Using Neuronal Multi-IMF Band Power and Complexity Features. *2023 National Conference on Communications (NCC)*, 1–6. https://doi.org/10.1109/NCC56989.2023.10067947

Sporns, O. (2011). *Networks of the brain* (pp. xi, 412). MIT Press.

Sporns, O. (2022). The complex brain: Connectivity, dynamics, information. *Trends in Cognitive Sciences*, *26*(12), 1066–1067. https://doi.org/10.1016/j.tics.2022.08.002

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

Tang, Y.-Y., Tang, R., Posner, M. I., & Gross, J. J. (2022). Effortless training of attention and self-control: Mechanisms and applications. *Trends in Cognitive Sciences*, *26*(7), 567–577. https://doi.org/10.1016/j.tics.2022.04.006

Tart, C. T. (1972). *Altered states of consciousness.* Doubleday.

Tart, C. T. (1990). *Altered States of Consciousness*. (Third Edition).

Thurner, S., Corominas-Murtra, B., & Hanel, R. (2017). Three faces of entropy for complex systems: Information, thermodynamics, and the maximum entropy principle. *Physical Review E*, *96*(3), 032124. https://doi.org/10.1103/PhysRevE.96.032124

Tibdewal, M. N., Nagbhide, D. N., Mahadevappa, M., Ray, A., Dhoke, A., & Malokar, M. (2022). Multi-feature extraction, analysis, and classification for control and meditators' electroencephalogram. *Signal, Image and Video Processing*, *16*(8), 2259–2267. https://doi.org/10.1007/s11760-022-02191-6

Timmermann, C., Bauer, P. R., Gosseries, O., Vanhaudenhuyse, A., Vollenweider, F., Laureys, S., Singer, T., Antonova, E., & Lutz, A. (2023). A neurophenomenological approach to non-ordinary states of consciousness: Hypnosis, meditation, and psychedelics. *Trends in Cognitive Sciences*, *27*(2), 139–159. https://doi.org/10.1016/j.tics.2022.11.006

Timmermann, C., Roseman, L., Haridas, S., Rosas, F. E., Luan, L., Kettner, H., Martell, J., Erritzoe, D., Tagliazucchi, E., Pallavicini, C., Girn, M., Alamia, A., Leech, R., Nutt, D. J., & Carhart-Harris, R. L. (2023). Human brain effects of DMT assessed via EEG-fMRI. *Proceedings of the National Academy of Sciences of the United States of America*, *120*(13), e2218949120. https://doi.org/10.1073/pnas.2218949120

Timmermann, C., Roseman, L., Schartner, M., Milliere, R., Williams, L. T. J., Erritzoe, D., Muthukumaraswamy, S., Ashton, M., Bendrioua, A., Kaur, O., Turton, S., Nour, M. M., Day, C. M., Leech, R., Nutt, D. J., & Carhart-Harris, R. L. (2019). Neural correlates of the DMT experience assessed with multivariate EEG. *Scientific Reports*, *9*(1), 1–13. https://doi.org/10.1038/s41598-019-51974-4

Tononi, G., Edelman, G. M., & Sporns, O. (1998). Complexity and coherency: Integrating information in the brain. *Trends in Cognitive Sciences*, *2*(12), 474–484. https://doi.org/10.1016/s1364-6613(98)01259-5

Travis, F., & Shear, J. (2010). Focused attention, open monitoring and automatic self-transcending: Categories to organize meditations from Vedic, Buddhist and Chinese traditions. *Consciousness and Cognition*, *19*, 1110–1118. https://doi.org/10.1016/j.concog.2010.01.007

Turkheimer, F. E., Rosas, F. E., Dipasquale, O., Martins, D., Fagerholm, E. D., Expert, P., Vasa, F., Lord, L.-D., & Leech, R. (2021). A complex systems perspective on neuroimaging studies of behavior and its disorders. *399*. https://doi.org/10.1177/1073858421994784

Vaitl, D., Birbaumer, N., Gruzelier, J., Jamieson, G. A., Kotchoubey, B., Kübler, A., Lehmann, D., Miltner, W. H. R., Ott, U., & Pütz, P. (2005). Psychobiology of altered states of consciousness. *Psychological Bulletin*, *131*(1), 98–127.

Varela, F. J. (1996). Neurophenomenology: A Methodological Remedy for the Hard Problem. In J. Shear (Ed.), *Explaining Consciousness: The Hard Problem* (1995th-7 by the Journal of Consciousness Studies ed., p. 337).

Varley, T. F., Carhart-Harris, R., Roseman, L., Menon, D. K., & Stamatakis, E. A. (2020). Serotonergic psychedelics LSD & psilocybin increase the fractal dimension of cortical brain activity in spatial and temporal domains. *NeuroImage*, *220*, 117049. https://doi.org/10.1016/j.neuroimage.2020.117049

Viol, A., Palhano-Fontes, F., Onias, H., de Araujo, D., & Viswanathan, G. (2016). Shannon entropy of brain functional complex networks under the influence of the psychedelic Ayahuasca. *Scientific Reports*, *7*. https://doi.org/10.1038/s41598-017-06854-0

Vyšata, O., Schätz, M., Kopal, J., Burian, J., Procházka, A., Kuchyňka, J., Hort, J., & Valis, M. (2014). Non-Linear EEG measures in meditation. *Journal of Biomedical Science and Engineering*, *7*, 731–738. https://doi.org/10.4236/jbise.2014.79072

Walter, N., & Hinterberger, T. (2022). Determining states of consciousness in the electroencephalogram based on spectral, complexity, and criticality features. *Neuroscience of Consciousness*, *2022*(1), niac008. https://doi.org/10.1093/nc/niac008

Woods, T. J., Windt, J. M., & Carter, O. (2022). The path to contentless experience in meditation: An evidence synthesis based on expert texts. *Phenomenology and the Cognitive Sciences*. https://doi.org/10.1007/s11097-022-09812-y

Young, J. H., Arterberry, M. E., & Martin, J. P. (2021). Contrasting Electroencephalography-Derived Entropy and Neural Oscillations With Highly Skilled Meditators. *Frontiers in Human Neuroscience*, *15*, 162. https://doi.org/10.3389/fnhum.2021.628417

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

Zhang, X. S., Roy, R. J., & Jensen, E. W. (2001). EEG complexity as a measure of depth of anesthesia for patients. *IEEE Transactions on Bio-Medical Engineering*, *48*(12), 1424–1433. https://doi.org/10.1109/10.966601

Zheng-you, H., Xiaoqing, C., & Guoming, L. (2006). Wavelet Entropy Measure Definition and Its Application for Transmission Line Fault Detection and Identification; (Part I: Definition and Methodology). *2006 International Conference on Power System Technology*, 1–6. https://doi.org/10.1109/ICPST.2006.321939

Zhihong, R. E. N., Yawen, Z., & Guangrong, J. (2018). Effectiveness of mindfulness meditation in intervention for anxiety: A meta-analysis. *Acta Psychologica Sinica*, *50*(3), 283. https://doi.org/10.3724/SP.J.1041.2018.00283

Zollars, I., Poirier, T. I., & Pailden, J. (2019). Effects of mindfulness meditation on mindfulness, mental well-being, and perceived stress. *Currents in Pharmacy Teaching & Learning*, *11*(10), 1022–1028. https://doi.org/10.1016/j.cptl.2019.06.005

Appendix - Measures Used in the Reviewed Studies

To facilitate an easier reading of the review, here we provide a brief description of the complexity measures considered in the studies reviewed. For a complete description of each measure, please refer to the relevant article in which the measure was formulated, or to the relevant study in the review utilizing the measure.

Entropy and Related Measures

Shannon Entropy (Shannon, 1948), is a measure of the uncertainty associated with a random variable. It quantifies the average amount of information that is gained when an observed measures the variable in question, or equivalently, the information needed to describe or predict it. Shannon Entropy is calculated by taking the average value of the logarithm of the probability of each possible event.

Permutation Entropy (PE, Bandt & Pompe, 2002) is a measure that quantifies the diversity of patterns of a time series by analyzing the distribution of ordinal sequences, which are determined by the relative orderings of data points within a sliding window. PE then calculates the Shannon Entropy of the ordinal pattern distribution, providing a measure of the complexity or unpredictability of patterns observed on the time series.

Sample Entropy (SE, Richman & Moorman, 2000) is a measure similar to PE, also used to quantify the diversity of patterns in time series. It calculates the probability of finding repeating patterns of a certain length within the data by comparing the similarity of overlapping subsequences. The Shannon Entropy is then calculated based on these probabilities to determine the SE value.

Multiscale Entropy (MSE, Costa et al., 2002) is an extension of SE, which calculates SE at different multiple levels of down-sampling or smoothing of the time series, choosing different values for a scaling factor. MSE thus provides a scale-dependent assessment of irregularity, allowing the identification of complex dynamics at different temporal resolutions.

Wavelet Entropy (WE, Zheng-you et al., 2006) is a measure that combines the concepts of wavelet analysis, using wavelet decomposition to capture both frequency and temporal information of the data and calculating the Shannon entropy of the resulting wavelet coefficients. Wavelet Entropy can reveal the complexity of different frequency components and their interactions within the time series.

Minimum Variance Modified Fuzzy Entropy (MVMFzEn, Raghu et al, 2018) combines fuzzy sets and Shannon entropy to capture both fuzziness and irregularity in the data. Fuzziness represents uncertainty or vagueness, indicating the lack of clear boundaries when assigning membership to categories or sets. It is calculated by assessing the ambiguity or overlap between different membership values. Irregularity refers to randomness or the absence of a predictable pattern. MVMFzEn incorporates a modification to enhance robustness by reducing sensitivity to outliers and noise.

Lempel-Ziv Complexity (LZc, Lempel & Ziv, 1976) measures the complexity or compressibility of a binary string by identifying repeated patterns. It quantifies the number of distinct patterns found in the data. For estimating the complexity of a non-binary time series, such as EEG neural activity, a threshold is defined for binarization, usually chosen as the mean of the detrended time series. Under the condition of stationarity of the data, the LZc can be used as an effective estimator of the entropy rate of the time series (Mediano et. al, 2023).

Fractal Dimension and Related Measures

Higuchi's Fractal Dimension (HFD, Higuchi,1988) is a method used to estimate the fractal dimension of a time series. This approach analyzes the scaling behavior of the curve through a process of dividing the time series into shorter segments and measuring the average length of the curve in each segment. The fractal dimension is then obtained by fitting a linear regression to the relationship between segment length and the corresponding average curve length.

Sevcik's Algorithm (Sevcik, 2006) is another method for estimating the fractal dimension of a time series. Sevcik's Algorithm calculates the autocorrelation function of the time series and then uses a specialized algorithm to estimate the fractal dimension based on the decay rate of the autocorrelation.

Dimensional Complexity (DCx, Pritchard & Duke, 1995) is a measure used to assess the complexity of a dynamical system, capturing the richness and diversity of its dynamics by evaluating the system's behavior in its phase space. This is done by laying a grid over a phase space reconstructed from the time-series and estimating the amount of squares/cubes the trajectory of the signal in this space fills as it evolves through time.

Hurst Exponent (Hurst, 1951) is a measure of long range temporal correlation (LRTC) of a time series. It describes the rate at which autocorrelations between value pairs in the time series decay as the time distance between the pair increases. The interpretation of the Hurst exponent in the context of complexity is not straightforward, as a value of $H=0.5$ indicates no temporal correlations while values of $0<H<0.5$ indicate the presence of anti-correlations, stronger when closer to 0 and values of $0.5<H<1$ indicate the presence of correlations which are stronger when closer to 1. For monofractals, the Hurst exponent (H) directly relates to the fractal dimension (D) following the formula $D=2-H$. Correspondingly, a smaller value of H entails a larger fractal dimension and vice versa.

Detrended Fluctuation Analysis (DFA, Peng et. al, 1995) is a method for estimating the Hurst exponent of a time-series. DFA involves dividing the time series into smaller segments, removing the local trends within each segment, and then calculating the fluctuation of the detrended data as a function of segment size. By examining the relationship between the fluctuation and the segment size, DFA computes a scaling exponent, which is an estimation of the Hurst exponent.

Appendix Bibliography

Bandt, C., & Pompe, B. (2002). Permutation Entropy: A Natural Complexity Measure for Time Series. *Physical Review Letters*, *88*(17), 174102. https://doi.org/10.1103/PhysRevLett.88.174102

Costa, M., Goldberger, A. L., & Peng, C.-K. (2002). Multiscale Entropy Analysis of Complex Physiologic Time Series. *Physical Review Letters*, *89*(6), 068102. https://doi.org/10.1103/PhysRevLett.89.068102

Higuchi, T. (1988). Approach to an irregular time series on the basis of the fractal theory. *Physica D: Nonlinear Phenomena*, *31*(2), 277–283. https://doi.org/10.1016/0167-2789(88)90081-4

Hurst, H. E. (1951). Long-Term Storage Capacity of Reservoirs. *Transactions of the American Society of Civil Engineers*, *116*(1), 770–799. https://doi.org/10.1061/TACEAT.0006518

Lempel, A., & Ziv, J. (1976). On the Complexity of Finite Sequences. *IEEE Transactions on Information Theory*, *22*(1), 75–81. https://doi.org/10.1109/TIT.1976.1055501

Peng, C. K., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1995). Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series. *Chaos (Woodbury, N.Y.)*, *5*(1), 82–87. https://doi.org/10.1063/1.166141

Pritchard, W. S., & Duke, D. W. (1995). Measuring "chaos" in the brain: A tutorial review of EEG dimension estimation. *Brain and Cognition*, *27*(3), 353–397. https://doi.org/10.1006/brcg.1995.1027

Raghu, S., Sriraam, N., Kumar, G. P., & Hegde, A. S. (2018). A Novel Approach for Real-Time Recognition of Epileptic Seizures Using Minimum Variance Modified Fuzzy Entropy. *IEEE Transactions on Biomedical Engineering*, *65*(11), 2612–2621. https://doi.org/10.1109/TBME.2018.2810942

Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *American Journal of Physiology-Heart and Circulatory Physiology*, *278*(6), H2039–H2049. https://doi.org/10.1152/ajpheart.2000.278.6.H2039

Sevcik, C. (2006). On fractal dimension of waveforms. *Chaos, Solitons & Fractals*, *28*(2), 579–580. https://doi.org/10.1016/j.chaos.2005.07.003

Shannon, C. E. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal*, *27*(3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Zheng-you, H., Xiaoqing, C., & Guoming, L. (2006). Wavelet Entropy Measure Definition and Its Application for Transmission Line Fault Detection and Identification; (Part I: Definition and Methodology). *2006 International Conference on Power System Technology*, 1–6. https://doi.org/10.1109/ICPST.2006.321939