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ARTICLE

Electrophysiological correlates of dispositional mindfulness: A quantitative and complexity EEG study

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Abstract

While growing evidence supports that dispositional mindfulness relates to psychological health and cognitive enhancement, to date there have been only a few attempts to characterize its neural underpinnings. In the present study, we aimed at exploring the electrophysiological (EEG) signature of dispositional mindfulness using quantitative and complexity measures of EEG during resting state and while performing a learning task. Hundred twenty participants were assessed with the Five Facet Mindfulness Questionnaire and underwent 5 min eyes-closed resting state and 5 min at task EEG recording. We hypothesized that high mindfulness individuals would show patterns of brain activity related to (a) lower involvement of the default mode network (DMN) at rest (reduced frontal gamma power) and (b) a state of 'task readiness' reflected in a more similar pattern from rest to task (reduced overall q-EEG power at rest but not at task), as compared to their low mindfulness counterparts. Dispositional mindfulness was significantly linked to reduced frontal gamma power at rest and lower overall power during rest but not at task. In addition, we found a trend towards higher entropy during task performance in mindful individuals, which has recently been reported during mindfulness meditation. Altogether, our results add to those from expert meditators to show that high (dispositional) mindfulness seems to have a specific electrophysiological pattern characteristic of less involvement of the DMN and mind-wandering processes.

KEYWORDS
default mode network, dispositional mindfulness, entropy, mind-wandering, quantitative EEG

BACKGROUND

Although there has been an explosion of research on mindfulness over the last years, there is still a long path ahead to fully understand its neurocognitive bases. So far, most efforts have been devoted to unravelling the neuronal changes produced during and after mindfulness meditation, with little research focusing on individual differences in dispositional mindfulness itself. The study of the natural neural imprints of mindfulness as a personality trait might, however, greatly contribute to our understanding of its psychological scope and its changes with later meditation training and expertise.

Mindfulness is a concept derived from the Buddhist tradition that refers to a virtue of consciousness characterized by two attributes: (1) the self-regulation of attention towards the present moment and (2) the adoption of a set of curiosity, openness and acceptance towards the inner and outer experience (Bishop et al., 2004). Dispositional mindfulness refers to the relatively stable tendency to engage in those attributes in everyday life and is traditionally measured with a wide range of questionnaires (i.e., FFMQ, Baer et al., 2006). This tendency has been shown to be naturally present in different degrees in meditation-naïve individuals (i.e., Bilevicius et al., 2018; Lu et al., 2014) and can be trained through the practice of mindfulness meditation (i.e., MBSR, Kabat-Zinn, 2003; MBCT, Teasdale et al., 2000) until it fully manifests (Crescentini & Capurso, 2015; Wheeler et al., 2017). Both dispositional mindfulness and mindfulness meditation have been shown to be related to several benefits in physical (Grossman et al., 2004; Sala et al., 2020) and mental health (i.e., lower anxiety and depression, Brown & Ryan, 2003; Keune et al., 2011), and cognitive performance (Tang et al., 2015; Verhaeghen, 2021). Interestingly, recent cognitive research has shown that, relative to low mindful individuals, those scoring high in dispositional mindfulness tend to be more anchored to the present and perform better when it comes to adapting to contextual changes and recovering after a failure, which has been related to more balanced use of different cognitive control modes (Aguerre et al., 2020). Similarly, mindful individuals show less engagement in mind-wandering (the tendency of the mind to divagate from one thought to another; Mrazek et al., 2012).

While several structural and functional changes have been found in brain regions typically associated with attention control, emotion regulation and self-awareness during mindfulness meditation and in expert meditators at rest (for a review see Tang et al., 2015), little research has focused on the neuropsychological bases of dispositional mindfulness. As part of the few studies focusing on dispositional mindfulness, Lu et al. (2014) found that higher dispositional mindfulness was linked to greater grey matter volume in the right hippocampus/amygdala and bilateral anterior cingulate cortex (ACC), but less grey matter volume in the bilateral posterior cingulate cortex (PCC) and the left orbitofrontal cortex, which have been associated with executive attention, emotion regulation and self-referential processing. In a functional magnetic resonance imaging (fMRI) study at rest, Kong et al. (2016) found that high dispositional mindfulness individuals had enhanced local synchronization of spontaneous brain activity in left orbitofrontal cortex (OFC), left parahippocampal gyrus (PHG) and right insula, which are thought to be implicated in emotion processing, body awareness and self-referential processing. In contrast, they found reduced local synchronization in the right inferior frontal gyrus (IFG), which has largely been related to executive control. Finally, Lim et al. (2018) employed resting-state fMRI to tap into the dynamic functional connectivity associated with high dispositional mindfulness and found enhanced within-network connectivity in the default mode (DMN) and salience networks, and greater anti-correlations between task-positive networks and the DMN, which is thought to reflect task-readiness. Although experiments using MRI are very valuable due to their spatial resolution, this technique is limited when studying complex neural dynamics in the time domain.

In this regard, electroencephalography (EEG), a broadly used technique due to its time resolution, has also been used to investigate the neuronal underpinnings of different personality traits and conditions. Neural oscillations reflect the synchronous firing of large populations of neurons mediated by excitatory/inhibitory interactions. Thus, for example, quantitative-EEG (q-EEG), an index of overall power and/or power of different frequency bands of electrophysiological brain activity, has been used to predict stable individual differences in personality (Jach et al., 2020), addiction (Lee et al., 2014), schizotypy (Fuggetta et al., 2014), attention-deficit hyperactivity disorder (Snyder & Hall, 2006), intelligence (Doppelmayr et al., 2002) and second language learning (Prat et al., 2016). Again, studies using EEG have focused on meditation states and expert meditators (i.e., Hauswald et al., 2015; Hunkin et al., 2021; for reviews see Cahn & Polich, 2006; Lomas et al., 2015), and some have related dispositional mindfulness to EEG patterns associated with better emotion regulation during task performance (Brown et al., 2013; Deng et al., 2021; Teper & Inzlicht, 2014). However, to our knowledge, to date there is no research looking into the electrophysiological correlates of dispositional mindfulness during resting state. A study with meditators compared groups of different levels of expertise (distributed by hours spent in formal meditation) and found that higher expertise was associated with lower gamma activity over the prefrontal areas and overall lower gamma power, which was interpreted as a marker of reduced activity of the DMN, and it has been related to lower mind-wandering (Berkovich-Ohana et al., 2012). In a related study, Berkovich-Ohana et al. (2014) found reduced functional connectivity associated with meditation practice and, specifically, a negative correlation between overall left gamma mean phase coherence and mindfulness (meditation) expertise, which supports the notion that there is a mindfulness-induced reduction in DMN activity that relates to self-reference and mind-wandering.

In the present study, we aimed to characterize the electrophysiological brain activity of dispositional mindfulness both at rest and while performing a learning task. To our knowledge, no previous study has addressed this question. Because previous research has shown an association between mindfulness (meditation) experience and frontal gamma power at rest (reduced power in expert meditators thought to be responsible for reduced DMN activity), our main hypothesis was that individuals scoring higher in the continuum of mindfulness trait, even without any meditation practice, would show lower gamma power over frontal areas at rest, relative to lower scoring counterparts. On the other hand, because fMRI studies have revealed that high mindfulness is associated with a more frequent state of 'task-readiness' in addition to decreased mind-wandering during rest (Lim et al., 2018) and that overall q-EEG in healthy adults decreases from rest to task (Stevens et al., 2001), we aimed at exploring whether these patterns differ as a function of dispositional mindfulness. Therefore, we expected participants to exhibit lower overall q-EEG at rest and slighter reductions from rest to task as a function of higher dispositional mindfulness. The latter prediction follows from the assumption that high 'task readiness' is already present at rest in high mindfulness individuals, and, therefore, the reduction in q-EEG associated with task engagement might be slighter than in low mindfulness individuals.

Additionally, we aimed to explore whether mindfulness-related variations in brain activity can be captured by using measures of complexity, such as sample entropy. EEG activity provides fine temporal resolution that makes it especially suitable for investigating complex biological signals arising from brain systems. However, given the non-linear nature of EEG, linear methods (as power analyses of q-EEG) may be limited. Other approaches to interpreting EEG activity have adopted non-linear assumptions from system theories and permit tapping into nonrandom fluctuations over multiple time scales, thus providing more convenient insights about neural connectivity. These methods are increasingly being recognized as a valuable tool for the investigation of typical and pathological states (Costa et al., 2002, 2005; Ouyang et al., 2010) and have been highlighted as promising approaches to the study of differences in brain functioning due to meditation states and expertise (Schoenberg & Vago, 2019). In this respect, several individual differences have been linked to complexity (i.e., age: McIntosh et al., 2008; schizophrenia: Ibáñez-Molina et al., 2018; autism spectrum conditions: Catarino et al., 2011). Interestingly, a recent study found differences in entropy as a function of mindfulness expertise (Vivot et al., 2020). Specifically, Vivot et al. (2020) observed increased entropy in experienced meditators during meditation and during an instructed mind wandering condition as compared to a control group with no meditation experience. Entropy is a physical measure of the amount of disorder in a system, and it describes the irregularity or unpredictability of a signal (Ben-Naim, 2012). High entropy is thought to index the 'richness' of conscious subjective experiences (Carhart-Harris et al., 2014), and it has been related to the difficulty of cognitive tasks (Stam, 2005). Based on these findings, we aimed at testing the possible increase in entropy (SampEn) as a function of dispositional mindfulness both during resting state and during task performance. Evidence for these effects would be indicating richer processing of information in resting and task conditions for mindful individuals, as it occurs in expert meditators. To our knowledge, no study to date has investigated the neural-complexity signatures of dispositional mindfulness.

In sum, as previous research has mainly focused on the neural underpinnings of meditation states and of expert meditators, in the present study we aimed to unravel the electrophysiological correlates of dispositional mindfulness in meditation-naïve participants during resting state and while performing a learning task, which may greatly contribute to our understanding of its psychological scope but also to its changes with later training and expertise. Thus, and based on previous work on expert meditators, we built three hypothesis that may also be operating in dispositional mindfulness. First, we expected that higher levels of dispositional mindfulness would be related to reduced frontal gamma activity during resting state, as a sign of less involvement of the default mode network. Second, we predicted that higher levels of dispositional mindfulness would be linked to lower overall q-EEG at rest, as well as to slighter reductions from rest to task, due to the 'task readiness' of high mindfulness participants. Finally, we predicted increased sample entropy as a function of dispositional mindfulness both during resting state and while performing the task, which would be indicative of more complex information processing in both conditions.

METHOD

Participants

One hundred twenty people (Mage = 23.11, SDage = 4.19, Range = 18–33, 69% female) completed the study in exchange for course credits (0.1credit/40 min) or monetary reward (7€/1 h). This sample took part in a larger individual differences study from which other non-overlapping findings have been already reported (Aguerre et al., 2020, 2021, 2022). To confirm that the sample size of the bigger project was enough to capture the desired effects, we calculated a priori power analysis (G*Power 3.1.9.2; Erdfelder et al., 1996) based on the effect of the linear regression reported by Kong et al. (2016), with an $R^2 = .14$, as we also adopted an regression approach. The analysis revealed that 68 participants were enough to detect a reliable association with 95% power and alpha set at 5%. Participants provided their written informed consent to participate in the study, which was carried out under the Helsinki Declaration guidelines (World Medical Association, 2013) and was approved by the Ethics Committee of the University Affiliation (number 84/CEIH72015). Importantly, participants had no previous experience in mind–body practices.

Materials and procedure

Participants were tested individually in two sessions that lasted 90 and 120 min, respectively. In the first session, they were administered four questionnaires: the Spanish versions of the Five Facets Mindfulness Questionnaire (FFMQ; Cebolla et al., 2012), the Mindful Attention Awareness Scale (MAAS; Soler et al., 2012), the Barratt Impulsiveness Scale (BISS-11; Oquendo et al., 2001) and the Grit Scale (Grit; Duckworth & Quinn, 2009); and four experimental tasks: the Cued Task-Switching Paradigm (CT-S; Chevalier et al., 2015), a Stroop-like Conflict Task (CT; Roelofs et al., 2006), the Operation Span (O-Span; Turner & Engle, 1989) and the AX-CPT (Braver et al., 2009). The second session included MRI and EEG recordings at rest (5 minutes eyes closed) and two experimental tasks: the Stop Signal Task (Stop-It; Verbruggen & Logan, 2008) and an adaptation of the selective retrieval practice procedure (Anderson et al., 1994) that included simultaneous EEG recordings. Completion of questionnaires and tasks was computer-based, individually, in isolated cubicles in the laboratory. The experimenter entered the cubicle to explain each questionnaire and task and was available outside if the participant had any question during completion, which was, otherwise, on their own. Quality control of questionnaires and tasks was applied by controlling the time expended in each of them (as based on the mean time for completion of each duty in the pilot study) and by looking at random response patterns when scoring the questionnaires and tasks. No anomalous responses were identified. As for the mindfulness indexes, we only selected the FFMQ for the present study. This decision was motivated by some concerns expressed about the MAAS that include confounding with perceived inattention due to all items being negatively worded or restricted focus to the attention component of mindfulness (corresponding to the acting with awareness facet of the FFMQ), but not to the open attitude that is also characteristic of the trait (Baer et al., 2006; Sauer et al., 2013; Van Dam et al., 2018). Regarding the EEG indexes, they were obtained from the 5 minutes recording period at rest and from the first 5 minutes recording period during the learning task. It is important to note that participants underwent the resting state condition with closed eyes and the task condition with open eyes. While changes in frequencies are characteristic of the transition from close to open eyes (Barry et al., 2007), previous findings show that this change is minimal when considering the gamma band (Chen et al., 2008). In addition, because all participants went through identical conditions, comparisons between participants differing in mindfulness scores should be more influenced by their differences in mindfulness disposition than by changes occurring during the transition from closed to open eyes recording. The inclusion of resting state with closed eyes followed the resting state condition selected by Berkovich-Ohana et al. (2012).

FFMQ

The FFMQ is a thirty-nine items self-reported questionnaire that measures five facets of mindfulness: observing (i.e., 'I notice the smells and aromas of things'), describing (i.e., 'I'm good at finding words to describe my feelings'), acting with awareness (i.e., 'I am easily distracted'), non-judging of inner experience (i.e., 'I disapprove of myself when I have irrational ideas') and non-reactivity to inner experience (i.e., 'I watch my feelings without getting lost in them'). Items in FFMQ range from 1 (never or very rarely true) to 5 (very often or always true), with higher scores reflecting greater mindfulness. Cronbach's α for the factors of the Spanish translation ranges from 0.80 to 0.91 (Cebolla et al., 2012). In our sample, its range is from 0.68 to 0.90.

Rest

To measure resting-state EEG, participants were instructed to be quietly seated with closed eyes and light off for 5 min.

Selective retrieval task

To measure EEG while performing a task, we selected the first 5 min from the study phase of the selective retrieval task. During this recording period, participants were quiet with open eyes while memorizing a series of category-word pairs that appeared on the screen one at a time, (i.e., MA-Maturity) for an upcoming memory test.

EEG recording and preprocessing

The EEG was recorded from 64 scalp electrodes, mounted on an elastic cap, on an extended 10–20 system. Continuous activity was recorded using NeuroScan SynAmps2 amplifiers (El Paso, TX) and a midline electrode (halfway between Cz and CPz) as reference. Each channel was registered with a sampling rate of 1000 Hz and down-sampled at 500 Hz. Impedances were kept below 10 kΩ. Notch filter was not applied as we would keep analyses from 4 to 40 Hz, and electronic noise in the country is at 50 Hz. Reference was kept to the midline electrode. Before data analyses, a high-pass filter at 1 Hz was applied and the 5 minutes recording was segmented in 2 seconds epochs with 0.5 of overlap. Artefacts were manually removed by carefully inspecting the data using Fieldtrip toolbox73 on Matlab (Oostenveld et al., 2011; Version 7.4.0, MathWorks, Natick, MA, USA). Noisy trials were visually detected and eliminated following a threshold of conservation of 75% of the signal. Bad channels with a high level of artefacts (always below the 10% of the total for each participant) were visually detected and interpolated from the 3 neighbour electrodes by using the fieldtrip function 'ft_prepare_neighbours(cfg, data)' and triangulation method. No more than 3 channels were interpolated for the same subject, from which they were not immediate neighbours. Importantly, the interpolation was needed in one channel of the region of interest only in three participants, what ensures that the data were not biased by interpolation.

Q-EEG analyses

EEG data were analysed using the procedures described in Prat et al. (2016). The mean log power spectrum between 4 and 40 Hz was calculated by first computing each epoch's power spectrum using the fast Fourier transform, log-transforming it, and then averaging the resulting power spectra across all epochs. To reduce spectral leakage, a Hanning window was applied to each epoch before computing the corresponding Fourier transform. The mean log power was then separately calculated across theta (4–7.5 Hz), alpha (8–12.5 Hz), beta (13–29.5 Hz) and low-gamma (30–40 Hz) frequency bands for each channel and in each participant, although analyses will focus in the low-gamma band. Delta (<4 Hz) and high-gamma (> 40 Hz) frequencies were not analysed due to susceptibility to artefacts (Berkovich-Ohana et al., 2012). The low gamma band selected here followed Prat et al. (2016); it was more conservative than the one (24–45 Hz) used by Berkovich-Ohana et al. (2012) in order to more strictly match the conceptualization of low gamma band that is usually considered as starting at 30 Hz (i.e., Buzsaki & Draguhn, 2004) and to differentiate it from high gamma and avoid artefacts (i.e., Colgin, 2015; Dimitriadis et al., 2021). Total q-EEG was calculated as the average of all frequency bands. The frontal region of interest (ROI) was selected following Berkovich-Ohana et al. (2012): AF3, F5, F3, F1, FC3, FC1, AF4, F2, F4, F6, FC2, FC4.

Complexity analyses

The preprocessed EEG series were used as inputs for analyses of the Sample Entropy (SampEn). These measures were estimated using a sliding window procedure with a length of 2-s and 90% of overlap in each time step. The reason for using 2-s windows is that this time period includes the majority of oscillatory activity (from slow to fast rhythmic activity). The overlap criterion was selected to capture all configurations in the structure of the EEG time series (shorter overlaps could have missed patterns between consecutive windows). Estimations were obtained with the median of the resulting complexity series for each participant, electrode and experimental condition.

SampEn is a measure that is sensitive to irregularity patterns in the signal, and it is appropriated for short and noisy time series. The SampleEn algorithm computes the negative of the logarithmic conditional probability that sets of segments of the signal, which are closer than a given tolerance, p, for m contiguous samples, will remain similar at the next time point (length $m+1$). As other measures of entropy, high values of SampEn are associated with random data series (see seminal works of Pincus & Goldberger, 1994; Richman & Moorman, 2000). The free parameters m and p were selected according to the recommendations of the original work of Richman and Moorman (2000) with values of $m = 2$ and $r = 0.10$ times the SD of the EEG series. SampEn has been successfully applied to EEG analysis in multiple areas of research (see for example Chen et al., 2019; Jordan et al., 2008; Yum et al., 2008).

RESULTS

The data from four participants were removed from the analyses due to either problem during the EEG recording (two participants) and for missing scores in the FFMQ (two participants). The descriptive statistics for the remaining participants (116) are available in Supplementary Material.

Correlations matrix

We firstly ran Pearson correlation analyses to identify relationships between isolated neural indexes and mindfulness as measured with FFMQ (see Table 1). Two correlations emerged that were in line with our hypotheses. On the one hand, there was a negative association between FFMQ and frontal gamma at rest. On the other hand, there also was a negative association between FFMQ and global q-EEG at rest (but not at task, such as we predicted). As for entropy, it correlated with FFMQ, but only at task. Finally, power EEG indexes correlated with one another (frontal gamma and global q-EEG at rest and at task), but not with the entropy indexes, which also failed to show associations between them.

Power model

To identify the best predictor of dispositional mindfulness (as measured with FFMQ), we performed a stepwise multivariate regression model with the scores in FFMQ as the dependent variable. Importantly, we firstly included age, gender and education variables in the model to control for them. Then, frontal gamma at rest and q-EEG at rest were introduced as the independent variables since they were the only factors that reliably correlated with FFMQ scores.[1] A statistically significant model emerged that only included the global q-EEG index at rest as a predictor accounting for 5% of variance (see Table 2 and Figures 1 and 2). Partial correlation analyses did not reveal associations between FFMQ and age, gender or education.

Complexity model

As for entropy, we performed a simple regression analysis over mindfulness (FFMQ) scores because it was only entropy at task that exhibited a statistically significant correlation with FFMQ scores. After controlling for age, gender and education, the model did not reach the threshold for statistical significance, although it approached it (see Table 3).

TABLE 1 Pearson's correlations of the main EEG indexes at rest and at task and the mindfulness (FFMQ) score.

	FFMQ	F-gamma at rest	Q-EEG at rest	Q-EEG at task	Entropy at rest
F-Gamma at Rest	−.18*				
Q-EEG at Rest	−.21*	.64**			
Q-EEG at task	−.15	.49**	.77**		
Entropy at Rest	−.15	.03	.12	.03	
Entropy at Task	.18†	−.04	−.15	−.11	−.00

Note: Asterisks represent statistically significant correlations after controlling for multiple comparisons with the Benjamini-Hochberg method with false discovery rate at .15 (Benjamini & Hochberg, 1995).

*$p < .05$; **$p < .001$; †$p = .05$.

[1]We also tested the regression model by considering q-EEG at task as an independent variable. Not surprisingly, this factor was not included in the final model.

TABLE 2 Stepwise regression analysis of frontal gamma at rest and overall q-EEG during rest over the FFMQ scores.

	R^2	ΔF	*B*	*SE*	*ß*	*p*	2.5% CI	97.5% CI
Model	.05	6.13				.01		
Q-EEG at rest			−13.75	5.55	−.23	.014	−24.76	−2.74
				Partial correlations				
Excluded variables				**Partial Corr.**		*p*	**Collinearity**	
F-Gamma at rest				−.05		.57	0.57	
Age				−.01		.91	0.97	
Gender				.03		.75	1	
Education				−.04		.67	0.95	

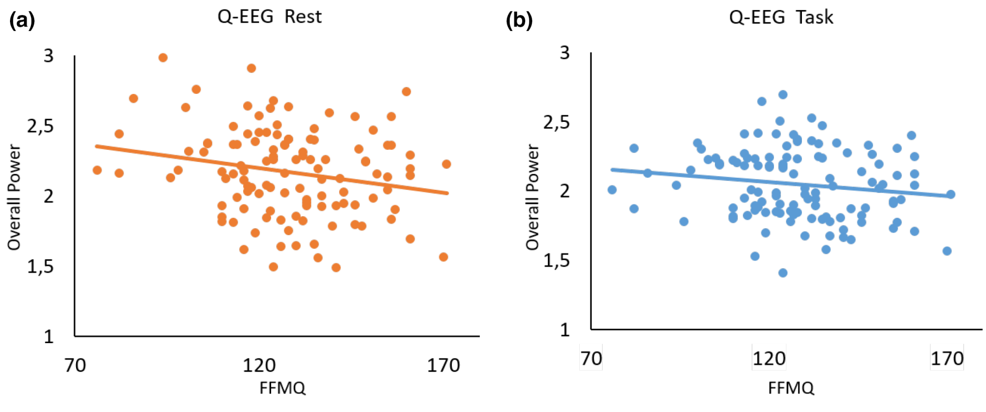

FIGURE 1 Scatterplot representation of the overall power q-EEG as a function of FFMQ at rest (a) and at task (b).

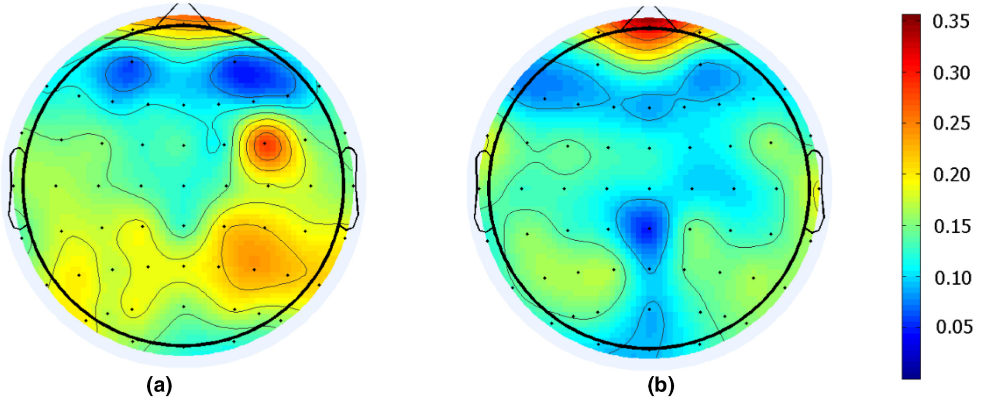

FIGURE 2 Representation of the change from rest to task (subtraction of the overall power at task to overall power at rest) in low mindfulness (FFMQ) individuals (a) and in high mindfulness (FFMQ) individuals (b). Groups (38 participants each) were created from the tertile scores of the whole sample.

DISCUSSION

To our knowledge, the present study is the first attempt to investigate the electrophysiological underpinning of dispositional mindfulness at rest and in the transition from rest to task. We expected dispositional mindfulness to be associated with different patterns of brain activity at resting state so that the higher the scores in the trait the lower the involvement of the default mode network (DMN). In addition, we

TABLE 3 Regression analysis of entropy at task over the FFMQ scores.

	R^2	ΔF	*B*	*SE*	*ß*	*p*	2.5% CI	97.5% CI
Model	.03	3.74				.056		
Entropy at Task			72.45	37.46	.18	.056	−1.79	146.69

	Partial Correlations		
Excluded variables	**Partial Corr.**	***p***	**Collinearity**
Age	.02	.84	1
Gender	−.00	.96	0.99
Education	.02	.84	1

hypothesized that the resting state configuration of those individuals scoring high in mindfulness would be more similar to its brain configuration at task, which would reflect task readiness, in comparison to their low mindfulness counterparts. Finally, we explored whether dispositional mindfulness relates to changes in complexity of brain activity.

In line with our hypothesis, results showed that higher scores in dispositional mindfulness are associated with less frontal gamma power at rest. However, a multivariate regression analyses revealed that it was the global q-EEG index that better explained the differences in dispositional mindfulness. Global q-EEG had not been considered in previous studies but it could be providing us with additional information about the neural signature of mindfulness (dispositional in the case of the present study). Given our main finding regarding this EEG index, future studies on (trained and dispositional) mindfulness should pay attention to it.

A general reduction in power from rest to task has been observed in healthy individuals indicating a reorganization of the resources to respond to the task requirements (Stevens et al., 2001). We hypothesized that because dispositional mindfulness would entail a state of 'task readiness' even during rest, reorganization to adjust to the task requirements (reduction in power from rest to task) might be less evident for individuals with higher mindfulness scores. The results of the regression analyses support this idea. Thus, mindfulness scores were significantly predicted by reduced power at rest, but there was no association between mindfulness and power during task engagement. While we cannot attribute this lower power at rest uniquely to a reduced DMN activity, our results provide evidence that high mindfulness individuals exhibit less overall brain oscillations/activity, which could be interpreted as 'a quieter mind' at rest.

The finding regarding frontal gamma is in line with those observed in expert meditators (Berkovich-Ohana et al., 2012), whereby lower frontal gamma has been interpreted as reflecting less involvement of the DMN. Specifically, gamma power increases have been linked to activity in the prefrontal hub of the DMN (Chen et al., 2008; Mantini et al., 2007), which is closely related to self-referential processing (Northoff et al., 2006). These results might be indicating that high mindfulness, independent of whether it results from a dispositional trait or training, can be characterized by brain activity at rest that is thought to reflect lower mind-wandering and self-referential processing.

Even though suggestive, the present findings should be held with caution. The effect sizes are relatively small, and it is, to our knowledge, the very first time that the electrophysiological substrates of dispositional mindfulness are reported. Nevertheless, previous research using MRI has found a theoretically similar link between resting-state activity and dispositional mindfulness (Kong et al., 2016 in regional homogeneity in resting-state fMRI; Lim et al., 2018 in dynamic functional connectivity in resting-state fMRI; and Lu et al., 2014 in grey matter) that supports the idea of lower involvement of mind-wandering processes and self-referential processing in high mindfulness individuals. Further, studies examining the expert meditators' brain at rest have found the same pattern of reduced DMN activity (for a review, see Tang et al., 2015). While it has been previously argued that dispositional mindfulness may be a different construct than mindfulness that results from training (Grossman, 2008), growing evidence indicates that both are characterized by reduced DMN activity. However, it remains unknown if this pattern is different at earlier stages of meditation training.

While power-based analyses provided valuable information regarding the neural underpinnings of dispositional mindfulness, we also wanted to explore the relationship between mindfulness and non-linear measures of brain complexity as they have been highlighted as a method to be incorporated in the study of brain changes related to mindfulness (Schoenberg & Vago, 2019). In the present study, mindfulness was only marginally related to higher entropy at task. The amount of entropy of the individual brain activity is thought to index the 'richness' of conscious subjective experience (Carhart-Harris et al., 2014), which may be representing processing of contextual information during task performance as a more 'on task' behaviour. Some have argued that the increment in entropy found in several cognitive tasks reflects increments in information processing as a function of the complexity of the task (Lamberts, 2000; Müller et al., 2003; Stam, 2005). This result aligns with those from the study of Vivot et al. (2020), which found increased entropy of brain oscillatory activity in expert meditators during meditation and in an instructed mind wandering condition. Although it is important to keep in mind that we found an association that only approached statistical significance, its convergence with Vivot et al.'s (2020) results is suggestive of the need of further investigation. Altogether, these findings might be indicating differential information processing in mindful participants with an allocation of attention more anchored to the present.

In sum, our results add to those from expert meditators to show that high (dispositional) mindfulness seems to be linked to lower overall power during resting state, maybe due to less involvement in mind-wandering processes. In addition, increased entropy seems also to characterize mindful individuals suggesting differences, relative to less mindful individuals, in task engagement. Because the present results are the very first in bringing attention to the electrophysiological signature of dispositional mindfulness during resting state, further studies are needed to better characterize dispositional mindfulness in terms of brain activity. In these future directions, it would be of interest to add objective measures of mindfulness as the breath counting task (Lim et al., 2018), as well as testing these effects in different stages and techniques of mindfulness meditation to see whether dispositional and practised mindfulness differ. Delimitating the neural correlates of dispositional mindfulness will be critical to understanding the disposition, but also to identify potential indexes of improvement in mindfulness-based therapies.

AUTHOR CONTRIBUTIONS

Nuria V. Aguerre: Conceptualization, data curation, formal analysis, funding acquisition, writing – original draft. **Carlos J. Gómez-Ariza:** Conceptualization; funding acquisition; supervision; writing – review and editing. **Antonio J. Ibáñez-Molina:** Formal analysis; methodology. **M. Teresa Bajo:** Conceptualization; funding acquisition; project administration; resources; writing – review and editing.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

The datasets generated during and/or analysed during the current study is available at https://osf.io/tr5e6/?view_only=bdf4bc23bcc54eb893cdcf631901a4d4.

ETHICAL APPROVAL

The study was approved and carried out following the recommendations of the Research Ethics Committee of the University of Granada in accordance with the Declaration of Helsinki (World Medical Association 2013).

INFORMED CONSENT

Informed consent was obtained from all individual participants included in the study.

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REFERENCES

Aguerre, N. V., Bajo, M. T., & Gómez-Ariza, C. J. (2020). Dual mechanisms of cognitive control in mindful individuals. *Psychological Research*, *85*, 1909–1921. https://doi.org/10.1007/s00426-020-01377-2

Aguerre, N. V., Gómez-Ariza, C. J., & Bajo, M. T. (2022). The relative role of executive control and personality traits in grit. *PLoS One*, *17*(6), e0269448. https://doi.org/10.1371/journal.pone.0269448

Aguerre, N. V., Gómez-Ariza, C. J., Ibáñez-Molina, A. J., & Bajo, M. T. (2021). Electrophysiological Prints of Grit. *Frontiers in Psychology*, *12*, 730172. https://doi.org/10.3389/fpsyg.2021.730172

Anderson, M. C., Bjork, R. A., & Bjork, E. L. (1994). Remembering can cause forgetting: Retrieval dynamics in long-term memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *20*(5), 1063–1087. https://doi.org/10.1037/0278-7393.20.5.1063

Baer, R. A., Smith, G. T., Hopkins, J., Krietemeyer, J., & Toney, L. (2006). Using self-report assessment methods to explore facets of mindfulness. *Assessment*, *13*(1), 27–45. https://doi.org/10.1177/1073191105283504

Barry, R. J., Clarke, A. R., Johnstone, S. J., Magee, C. A., & Rushby, J. A. (2007). EEG differences between eyes-closed and eyes-open resting conditions. *Clinical Neurophysiology*, *118*(12), 2765–2773. https://doi.org/10.1016/j.clinph.2007.07.028

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society, Series B*, *57*, 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Berkovich-Ohana, A., Glicksohn, J., & Goldstein, A. (2012). Mindfulness-induced changes in gamma band activity - implications for the default mode network, self-reference and attention. *Clinical Neurophysiology*, *123*(4), 700–710. https://doi.org/10.1016/j.clinph.2011.07.048

Berkovich-Ohana, A., Glicksohn, J., & Goldstein, A. (2014). Studying the default mode and its mindfulness-induced changes using EEG functional connectivity. *Social Cognitive and Affective Neuroscience*, *9*(10), 1616–1624. https://doi.org/10.1093/scan/nst153

Bilevicius, E., Smith, S. D., & Kornelsen, J. (2018). Resting-state network functional connectivity patterns associated with the mindful attention awareness scale. *Brain Connectivity*, *8*(1), 40–48. https://doi.org/10.1089/brain.2017.0520

Bishop, S. R., Lau, M., Shapiro, S., Carlson, L., Anderson, N. D., Carmody, J., Segal, Z. V., Abbey, S., Speca, M., Velting, D., & Devins, G. (2004). Mindfulness: A proposed operational definition. *Clinical Psychology: Science and Practice*, *11*, 230–241 10.1093/clipsy/bph077

Braver, T. S., Paxton, J. L., Locke, H. S., & Barch, D. M. (2009). Flexible neural mechanisms of cognitive control within human prefrontal cortex. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(18), 7351–7356. https://doi.org/10.1073/pnas.0808187106

Brown, K. W., Goodman, R. J., & Inzlicht, M. (2013). Dispositional mindfulness and the attenuation of neural responses to emotional stimuli. *Social Cognitive and Affective Neuroscience*, *8*(1), 93–99. https://doi.org/10.1093/scan/nss004

Brown, K. W., & Ryan, R. M. (2003). The benefits of being present: Mindfulness and its role in psychological well-being. *Journal of Personality and Social Psychology*, *84*(4), 822–848. https://doi.org/10.1037/0022-3514.84.4.822

Buzsaki, G., & Draguhn, A. (2004). Neuronal oscillations in cortical networks. *Science*, *304*(5679), 1926–1929. https://doi.org/10.1126/science.1099745

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

Catarino, A., Churches, O., Baron-Cohen, S., Andrade, A., & Ring, H. (2011). Atypical EEG complexity in autism spectrum conditions: A multiscale entropy analysis. *Clinical Neurophysiology*, *122*(12), 2375–2383. https://doi.org/10.1016/j.clinph.2011.05.004

Cebolla, A., García-Palacios, A., Soler, J., Guillen, V., Baños, R., & Botella, C. (2012). Psychometric properties of the Spanish validation of the five facets of mindfulness questionnaire (FFMQ). *The European Journal of Psychiatry*, *26*(2), 118–126. https://doi.org/10.4321/S0213-61632012000200005

Chen, A. C. N., Feng, W., Zhao, H., Yin, Y., & Wang, P. (2008). EEG default mode network in the human brain: Spectral regional field powers. *NeuroImage*, *41*(2), 561–574. https://doi.org/10.1016/j.neuroimage.2007.12.064

Chen, H., Chen, W., Song, Y., Sun, L., & Li, X. (2019). EEG characteristics of children with attention-deficit/hyperactivity disorder. *Neuroscience*, *406*, 444–456. https://doi.org/10.1016/j.neuroscience.2019.03.048

Chevalier, N., Martis, S. B., Curran, T., & Munakata, Y. (2015). Metacognitive processes in executive control development: The case of reactive and proactive control. *Journal of Cognitive Neuroscience*, *27*(6), 1125–1136. https://doi.org/10.1162/jocn

Colgin, L. L. (2015). Do slow and fast gamma rhythms correspond to distinct functional states in the hippocampal network? *Brain Research*, *1621*, 309–315.

Costa, M., Goldberger, A. L., & Peng, C. K. (2002). Multiscale entropy analysis of complex physiologic time series. *Physical Review Letters*, *89*(6), 6–9. https://doi.org/10.1103/PhysRevLett.89.068102

Costa, M., Goldberger, A. L., & Peng, C. K. (2005). Multiscale entropy analysis of biological signals. *Physical Review E - Statistical, Nonlinear, and Soft Matter Physics*, *71*(2), 1–18. https://doi.org/10.1103/PhysRevE.71.021906

Crescentini, C., & Capurso, V. (2015). Mindfulness meditation and explicit and implicit indicators of personality and self-concept changes. *Frontiers in Psychology*, *6*(JAN), 1–6. https://doi.org/10.3389/fpsyg.2015.00044

Deng, X., Yang, M., & An, S. (2021). Differences in frontal EEG asymmetry during emotion regulation between high and low mindfulness adolescents. *Biological Psychology*, *158*, 107990. https://doi.org/10.1016/j.biopsycho.2020.107990

Dimitriadis, S. I., Perry, G., Foley, S. F., Tansey, K. E., Jones, D. K., Holmans, P., … Linden, D. E. (2021). Genetic risk for schizophrenia is associated with altered visually-induced gamma band activity: Evidence from a population sample stratified polygenic risk. *Translational Psychiatry*, *11*(1), 1–8.

Doppelmayr, M., Klimesch, W., Stadler, W., Pöllhuber, D., & Heine, C. (2002). EEG alpha power and intelligence. *Intelligence*, *30*(3), 289–302. https://doi.org/10.1016/s0160-2896(01)00101-5

Duckworth, A. L., & Quinn, P. D. (2009). Development and validation of the short grit scale (grit-S). *Journal of Personality Assessment*, *91*(2), 166–174. https://doi.org/10.1080/00223890802634290

Erdfelder, E., Faul, F., & Buchner, A. (1996). GPOWER: A general power analysis program. *Behavior Research Methods, Instruments, & Computers*, *28*(1), 1–11. https://doi.org/10.3758/BF03203630

Fuggetta, G., Bennett, M. A., Duke, P. A., & Young, A. M. J. (2014). Quantitative electroencephalography as a biomarker for proneness toward developing psychosis. *Schizophrenia Research*, *153*(1–3), 68–77. https://doi.org/10.1016/j.schres.2014.01.021

Grossman, P. (2008). Invited commentary. *Physical Therapy*, *88*(4), 460–461. https://doi.org/10.2522/ptj.20070251.ic

Grossman, P., Niemann, L., Schmidt, S., & Walach, H. (2004). Mindfulness-based stress reduction and health benefits: A meta-analysis. *Journal of Psychosomatic Research*, *57*(1), 35–43. https://doi.org/10.1016/S0022-3999(03)00573-7

Hauswald, A., Übelacker, T., Leske, S., & Weisz, N. (2015). What it means to be Zen: Marked modulations of local and interareal synchronization during open monitoring meditation. *NeuroImage*, *108*, 265–273. https://doi.org/10.1016/j.neuroimage.2014.12.065

Hunkin, H., King, D. L., & Zajac, I. T. (2021). Evaluating the feasibility of a consumer-grade wearable EEG headband to aid assessment of state and trait mindfulness. *Journal of Clinical Psychology*, *77*(11), 2559–2575. https://doi.org/10.1002/jclp.23189

Ibáñez-Molina, A. J., Lozano, V., Soriano, M. F., Aznarte, J. I., Gómez-Ariza, C. J., & Bajo, M. T. (2018). EEG multiscale complexity in schizophrenia during picture naming. *Frontiers in Physiology*, *9*, 1–12. https://doi.org/10.3389/fphys.2018.01213

Jach, H. K., Feuerriegel, D., & Smillie, L. D. (2020). Decoding personality trait measures from resting EEG: An exploratory report. *Cortex*, *130*, 158–171. https://doi.org/10.1016/j.cortex.2020.05.013

Jordan, D., Stockmanns, G., Kochs, E. F., Pilge, S., & Schneider, G. (2008). Electroencephalographic order pattern analysis for the separation of consciousness and unconsciousness. *Anesthesiology*, *109*(6), 1014–1022. https://doi.org/10.1097/aln.0b013e31818d6c55

Kabat-Zinn, J. (2003). Mindfulness-based stress reduction (MBSR). *Constructivism in the Human Sciences*, *8*(2), 73. https://doi.org/10.1016/j.jaci.2012.05.050

Keune, P. M., Bostanov, V., Hautzinger, M., & Kotchoubey, B. (2011). Mindfulness-based cognitive therapy (MBCT), cognitive style, and the temporal dynamics of frontal EEG alpha asymmetry in recurrently depressed patients. *Biological Psychology*, *88*(2–3), 243–252. https://doi.org/10.1016/j.biopsycho.2011.08.008

Kong, F., Wang, X., Song, Y., & Liu, J. (2016). Brain regions involved in dispositional mindfulness during resting state and their relation with well-being. *Social Neuroscience*, *11*(4), 331–343. https://doi.org/10.1080/17470919.2015.1092469

Lamberts, K. (2000). Information-accumulation theory of speeded categorization. *Psychological Review*, *107*(2), 227–260. https://doi.org/10.1037/0033-295X.107.2.227

Lee, J., Hwang, J. Y., Park, S. M., Jung, H. Y., Choi, S. W., Kim, D. J., Lee, J. Y., & Choi, J. S. (2014). Differential resting-state EEG patterns associated with comorbid depression in internet addiction. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *50*, 21–26. https://doi.org/10.1016/j.pnpbp.2013.11.016

Lim, J., Teng, J., Patanaik, A., Tandi, J., & Massar, S. A. A. (2018). Dynamic functional connectivity markers of objective trait mindfulness. *NeuroImage*, *176*(March), 193–202. https://doi.org/10.1016/j.neuroimage.2018.04.056

Lomas, T., Ivtzan, I., & Fu, C. H. Y. (2015). A systematic review of the neurophysiology of mindfulness on EEG oscillations. *Neuroscience and Biobehavioral Reviews*, *57*, 401–410. https://doi.org/10.1016/j.neubiorev.2015.09.018

Lu, H., Song, Y., Xu, M., Wang, X., Li, X., & Liu, J. (2014). The brain structure correlates of individual differences in trait mindfulness: A voxel-based morphometry study. *Neuroscience*, *272*, 21–28. https://doi.org/10.1016/j.neuroscience.2014.04.051

Mantini, D., Perrucci, M. G., Del Gratta, C., Romani, G. L., & Corbetta, M. (2007). Electrophysiological signatures of resting state networks in the human brain. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(32), 13170–13175. https://doi.org/10.1073/pnas.0700668104

McIntosh, A. R., Kovacevic, N., & Itier, R. J. (2008). Increased brain signal variability accompanies lower behavioral variability in development. *PLoS Computational Biology*, *4*(7), e1000106. https://doi.org/10.1371/journal.pcbi.1000106

Mrazek, M. D., Smallwood, J., & Schooler, J. W. (2012). Mindfulness and mind-wandering: Finding convergence through opposing constructs. *Emotion*, *12*(3), 442–448. https://doi.org/10.1037/a0026678

Müller, V., Lutzenberger, W., Preißl, H., Pulvermüller, F., & Birbaumer, N. (2003). Complexity of visual stimuli and non-linear EEG dynamics in humans. *Cognitive Brain Research*, *16*(1), 104–110. https://doi.org/10.1016/S0926-6410(02)00225-2

Northoff, G., Heinzel, A., de Greck, M., Bermpohl, F., Dobrowolny, H., & Panksepp, J. (2006). Self-referential processing in our brain-a meta-analysis of imaging studies on the self. *NeuroImage*, *31*(1), 440–457. https://doi.org/10.1016/j.neuroimage.2005.12.002

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J. M. (2011). FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational Intelligence and Neuroscience*, *2011*, 1–9. https://doi.org/10.1155/2011/156869

Oquendo, M. A., Baca-García, E., Graver, R., Morales, M., Montalvan, V., & Mann, J. (2001). Spanish adaptation of the Barratt impulsiveness scale (BIS-11). *European Journal of Psychiatry*, *15*(3), 147–155.

Ouyang, G., Dang, C., Richards, D. A., & Li, X. (2010). Ordinal pattern based similarity analysis for EEG recordings. *Clinical Neurophysiology*, *121*(5), 694–703. https://doi.org/10.1016/j.clinph.2009.12.030

Pincus, S. M., & Goldberger, A. L. (1994). Physiological time-series analysis: What does regularity quantify? *American Journal of Physiology - Heart and Circulatory Physiology*, *266*(4), 35–34. https://doi.org/10.1152/ajpheart.1994.266.4.h1643

Prat, C. S., Yamasaki, B. L., Kluender, R. A., & Stocco, A. (2016). Resting-state qEEG predicts rate of second language learning in adults. *Brain and Language*, *157–158*, 44–50. https://doi.org/10.1016/j.bandl.2016.04.007

Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate entropy and sample entropy maturity in premature infants physiological time-series analysis using approximate entropy and sample entropy. *Americal Journal of Physiology Heart and Circulatory Physiology*, *278*, H2039–H2049.

Roelofs, A., Van Turennout, M., & Coles, M. G. H. (2006). Anterior cingulate cortex activity can be independent of response conflict in Stroop-like tasks. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(37), 13884–13889. https://doi.org/10.1073/pnas.0606265103

Sala, M., Rochefort, C., Lui, P. P., & Baldwin, A. S. (2020). Trait mindfulness and health behaviours: A meta-analysis. *Health Psychology Review*, *14*(3), 345–393. https://doi.org/10.1080/17437199.2019.1650290

Sauer, S., Walach, H., Schmidt, S., Hinterberger, T., Lynch, S., Büssing, A., & Kohls, N. (2013). Assessment of mindfulness: Review on state of the art. *Mindfulness*, *4*(1), 3–17. https://doi.org/10.1007/s12671-012-0122-5

Schoenberg, P. L., & Vago, D. R. (2019). Mapping meditative states and stages with electrophysiology: Concepts, classifications, and methods. *Current Opinion in Psychology*, *28*, 211–217. https://doi.org/10.1016/j.copsyc.2019.01.007

Snyder, S. M., & Hall, J. R. (2006). A meta-analysis of quantitative EEG power associated with attention-deficit hyperactivity disorder. *Journal of Clinical Neurophysiology*, *23*(5), 441–456. https://doi.org/10.1097/01.wnp.0000221363.12503.78

Soler, J., Tejedor, R., Feliu-Soler, A., Pascual, J. C., Cebolla, A., & Soriano, J. (2012). Propiedades psicométricas de la versión española de la escala Mindful Attention Awareness Scale (MAAS). *Actas Españolas de Psiquiatría*, *40*(Barcelona 08025), 18–25.

Stam, C. J. (2005). Nonlinear dynamical analysis of EEG and MEG: Review of an emerging field. *Clinical Neurophysiology*, *116*(10), 2266–2301. https://doi.org/10.1016/j.clinph.2005.06.011

Stevens, A., Kircher, T., Nickola, M., Bartels, M., Rosellen, N., & Wormstall, H. (2001). Dynamic regulation of EEG power and coherence is lost early and globally in probable DAT. *European Archives of Psychiatry and Clinical Neuroscience*, *251*(5), 199–204. https://doi.org/10.1007/s004060170027

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

Teasdale, J. D., Segal, Z. V., Williams, J. M. G., Ridgewaya, V. A., Soulsby, J. M., & Lau, M. A. (2000). Prevention of relapse/recurrence in major depression by mindfulness-based cognitive therapy. *Journal of Consulting and Clinical Psychology*, *68*(4), 615–623. https://doi.org/10.1037/0022-006X.68.4.615

Teper, R., & Inzlicht, M. (2014). Mindful acceptance dampens neuroaffective reactions to external and rewarding performance feedback. *Emotion*, *14*(1), 105–114. https://doi.org/10.1037/a0034296

Turner, M. L., & Engle, R. W. (1989). Is working memory capacity task dependent? *Journal of Memory and Language*, *28*(2), 127–154. https://doi.org/10.1016/0749-596X(89)90040-5

Van Dam, N. T., van Vugt, M. K., Vago, D. R., Schmalzl, L., Saron, C. D., Olendzki, A., Meissner, T., Lazar, S. W., Kerr, C. E., Gorchov, J., Fox, K. C. R., Field, B. A., Britton, W. B., Brefczynski-Lewis, J. A., & Meyer, D. E. (2018). Mind the hype: A critical evaluation and prescriptive agenda for research on mindfulness and meditation. *Perspectives on Psychological Science*, *13*(1), 36–61. https://doi.org/10.1177/1745691617709589

Verbruggen, F., & Logan, G. D. (2008). Response inhibition in the stop-signal paradigm. *Trends in Cognitive Sciences*, *12*(11), 418–424. https://doi.org/10.1016/j.tics.2008.07.005

Verhaeghen, P. (2021). Mindfulness as attention training: Meta-analyses on the links between attention performance and mindfulness interventions, long-term meditation practice, and trait mindfulness. *Mindfulness*, 12(3), 564–581. https://doi.org/10.1007/s12671-020-01532-1

Vivot, R. M., 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

Wheeler, M. S., Arnkoff, D. B., & Glass, C. R. (2017). The neuroscience of mindfulness: How mindfulness alters the brain and facilitates emotion regulation. *Mindfulness*, *8*(6), 1471–1487. https://doi.org/10.1007/s12671-017-0742-x

World Medical Association. (2013). World medical association declaration of Helsinki: Ethical principles for medical research involving human subjects. *JAMA*, *310*, 2191–2194. https://doi.org/10.1001/jama.2013.281053

Yum, M. K., Jung, K. Y., Kang, H. C., Kim, H. D., Shon, Y. M., Kang, J. K., Lee, I. K., Park, K. J., & Kwon, O. Y. (2008). Effect of a ketogenic diet on EEG: Analysis of sample entropy. *Seizure*, *17*(6), 561–566. https://doi.org/10.1016/j.seizure.2008.02.007

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