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Mindfulness Training in High-Demand Cohorts Alters Resting-State Electroencephalography: An Exploratory Investigation of Individual Alpha Frequency, Aperiodic 1/*f* Activity, and Microstates

Chloe A. Dziego, Anthony P. Zanesco, Ina Bornkessel-Schlesewsky, Matthias Schlesewsky, Elizabeth A. Stanley, and Amishi P. Jha

ABSTRACT

BACKGROUND: Mindfulness training (MT) programs have demonstrated utility as cognitive training tools, but there is little consensus on the neurophysiological processes that may underlie its benefits. It has been posited that intrinsic brain activity recorded at rest reflects the functional connectivity of large-scale brain networks and may provide insight into neuroplastic changes that support MT. In the current study, we indexed changes in several resting-state electroencephalography (EEG) parameters to investigate the neurophysiological underpinnings of MT.

METHODS: Resting-state EEG data were collected from active-duty U.S. military personnel (N = 80) at 2 testing sessions: before (time [T] 1) and after (T2) engaging in an 8-week MT or active comparison intervention (positivity training). We examined longitudinal and/or groupwise differences in several EEG parameters through parameterization of power spectra (individual alpha frequency and 1/*f* activity) and microstate analysis.

RESULTS: While no significant group × time differences were observed in individual alpha frequency, significant group × time effects were observed in several EEG parameters from T1 to T2. Compared with MT, positivity training was associated with a steepening of the 1/*f* slope and higher 1/*f* intercepts together with decreased duration and increased global field power of microstates.

CONCLUSIONS: Taken together, these results suggest that the effects of interventions may be differentiated in resting-state brain activity in a sample of military personnel. Such findings provide insight into the neural underpinnings of MT-related brain changes, but more research is required to elucidate how these may relate to task-related neural and performance changes with MT and whether results generalize to other mindfulness interventions in alternative cohorts and contexts.

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Previous research has long documented the benefits of mindfulness training (MT) for health and wellbeing (1–3). More recently, MT is being investigated in human performance contexts as mental training to enhance resilience and cognitive functioning. Studies have demonstrated that MT benefits cognitive abilities across a myriad of settings, including performance in traditional laboratory tasks [e.g., (4,5)], dynamic cognitive testing environments (6), and during highly demanding occupational intervals (7–11). While there is significant interest in understanding the neural mechanisms supporting MT's beneficial performance effects, there is a paucity of electroencephalography (EEG) research on this topic. One approach, employed in the current study, is to characterize MT-related changes in spontaneous EEG activity at rest. This activity may putatively reflect structural and functional neuroplastic changes in large-scale neuronal networks (i.e., shifts in local neuronal dynamics or temporal shifts in signal transmission and noise) (12,13). While multiple studies have investigated resting-state brain changes in the context of more general meditation practices or experience [e.g., (14–16)], these studies have not directly considered a human performance perspective in high-demand cohorts. With this in mind, we aimed to investigate more global parameters of the resting-state EEG—such as individual alpha frequency (IAF) (17)—informed by the broader literature proposing a correspondence between these specific EEG features and trait-like individual differences in neurocognitive functioning (18–21).

IAF refers to the peak frequency of alpha power that is notably observed in power spectral density plots (see Figure 1). Individual differences in IAF (approximately between 7 and 13 Hz) have been related to visuoperceptual ability and speed of information processing (22–25), where higher IAF is often

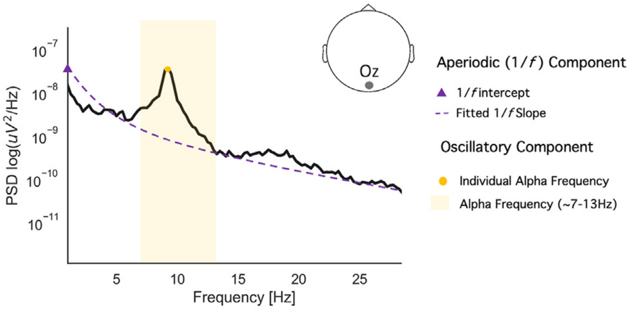

Figure 1. Example schematic of aperiodic (1/*f*) components and individual alpha frequency as observed within the power spectral density (PSD) from Dziego *et al.* (6). The resting-state electroencephalography metrics of interest are indicated in the legend. Here, the y-axis specifies log-transformed power (i.e., strength of neural activity; higher values indicate greater activity), while frequency (Hz, cycles per second) is represented on the x-axis (values farther to the right indicate higher frequency).

related to more favorable performance outcomes. However, lower IAF has also been reported to correspond with greater ability to spatially localize targets (26). Relatedly, studies that have examined long-term meditation practitioners have found that, unlike patterns observed in novices, practitioners' IAF was lower during active breath-focused meditation than at rest (27). Another longitudinal study reported that greater long-term practice experience was associated with lower IAF during mindfulness meditation practice (28). Thus, while individual differences in information processing capacity and previous meditation experience have both been found to be associated with directional changes in IAF, there is heterogeneity in the specific patterns observed across studies.

A second EEG parameter of interest is aperiodic 1/*f* activity (20). This activity manifests as a quasi-straight regression line fitted to power spectral density plots (see Figure 1), wherein lower frequencies indicate higher power and vice versa (29). While many theories exist [e.g., (30–33)], in most of the existing literature, it has been proposed that 1/*f* activity represents global excitation/inhibition balance within the brain (20,34,35), with optimal balance facilitating superior cognitive outcomes (36). A more recent review corroborated and broadened this perspective, outlining that 1/*f* activity is likely shaped by excitation/inhibition together with many additional interacting factors (including synaptic kinetics and aperiodic network dynamics) (37). Several studies that have examined this parameter have reported that steeper slopes are associated with superior information processing, such as faster processing speeds (19), quicker adaptation to novel language input (38), and preserved cognitive functioning in older adults (36,39,40). Steeper 1/*f* slopes have also been reported in individuals with long-term experience with mindfulness and other forms of meditation practice during breath-focused meditation versus rest, a pattern that has not been observed in novices (27). While these results suggest that greater functional capacity may be associated with steeper slopes, a recent report suggests that flatter 1/*f* slopes are related to superior performance in complex testing scenarios (41). Nevertheless, there is a growing consensus that steeper 1/*f* slopes reflect superior information processing capacity, even with the small heterogeneity in the direction of these effects across studies.

Alternative efforts to understand resting-state EEG have explored temporally nuanced phenomena, such as the large-scale neural events known as microstates. Microstates, which were originally described by Lehmann *et al.* (42), refer to distinct topographical patterns in the EEG scalp voltage potentials that vary dynamically over time in spontaneous EEG. These topographical configurations are present for brief periods of time (around 60–120 ms) before rapidly transitioning to an alternate spatial organization. Microstates are highly replicable within and between individuals, and the same topographical configurations have been observed across dozens of studies (43), which supports the notion that microstates reflect the activity of a common electrophysiological brain network architecture in humans. Indeed, 4 to 7 topographical configurations of microstates are reliably identifiable in spontaneous EEG, which are able to explain up to 85% of topographical variance (44). Research has demonstrated that these dynamics may have functional significance for understanding important individual differences, including development, disease progression, and neurocognitive functioning [see review, (45)]. Specific to MT, previous work has demonstrated reductions in amplitude and duration of microstates at rest—and, consequently, increases in the total occurrence rate (46)—following a long-term mindfulness retreat, believed to promote greater dynamic cycling of microstates (and putatively greater information processing capabilities).

In the current project, we aimed to investigate IAF, 1/*f* slopes, and microstates in resting-state EEG data collected from U.S. Army service members undergoing intensive predeployment military training. Data were collected before (time [T] 1) and after (T2) their participation in a 16-hour MT program—known as Mindfulness-based Mind Fitness Training (MMFT)—or a structurally matched positivity training (PT) program. Our investigation was motivated by previous studies that have reported that several EEG parameters are sensitive to individual differences in cognitive functioning and MT. In addition, results from a previous behavioral study conducted with the same individuals who were examined here (8) found significant salutary training-related benefits for attention and working memory task performance among those who received MT versus PT. Given the paucity of previous research related to the functional significance of these EEG parameters, we undertook this novel research project from an exploratory perspective to investigate whether the resting EEG parameters examined here provide insight into neuroplastic changes associated with MT. Consistent with previous literature on the functional links between resting-state EEG and cognitive performance (where higher IAF and steeper 1/*f* slopes were associated with superior information processing capabilities), we hypothesized that higher IAF and steeper 1/*f* slopes would be observed following engagement in the MT program than in the PT program.

METHODS AND MATERIALS

Participants

The current study included 80 healthy active-duty U.S. Army service members assigned—by unit—to 2 intervention groups. One unit, comprising infantry soldiers (n = 40, mean age = 24.68 years, SD = 3.90) engaged in MT, while the second unit, comprising soldiers with military occupational roles in engineering, intelligence, and communications (n = 40, mean age = 24.43 years, SD = 4.45), received the active control intervention (PT). See Jha *et al.* (8) for additional study details and participant demographic characteristics. No participants were excluded based on prior health history or reported any head injuries. All participants provided informed consent, and the study was approved by the relevant university institutional review board. This process was overseen by the Human Research Protections Office of the U.S. Department of Defense. Consistent with the U.S. Department of Defense requirements, participants were not compensated beyond their wages for participation in the study.

Training Programs

MT participants engaged in a 16-hour version of the MMFT program (47–49). The MMFT course is similar in structure to the well-established mindfulness-based stress reduction program by Kabat-Zinn and Hanh (50), but it differs in its approach to MT, the scope of didactic content about stress and resilience, and the inclusion of body-based self-regulation skills training drawn from body-based trauma therapies (51,52). In addition, MMFT mandates less in-class and out-of-class mindfulness practice than mindfulness-based stress reduction. Participants assigned to PT engaged in a 16-hour version of the Positive Emotion Resilience Training (53). This program focused on training skills and concepts from positive psychology (i.e., promoting adaptive emotional responses and increasing positive emotional experiences). Both training programs were delivered by experienced trainers, central to their respective course development, using a parallel program structure across 8 weeks. In addition to in-person didactic content, participants were encouraged to complete 30 minutes of daily practice (whether MT or PT) outside of class time. See Jha *et al.* (8) for a full description of the training programs.

Protocol

Participants' resting EEG data were collected at 2 assessments: prior to (T1) and immediately after (T2) the MT or PT interventions. Interventions took place during a highly demanding predeployment training interval. Resting-state recordings involved 2 intervals, 2 minutes of quiet rest with eyes closed followed by 2 minutes of recording with eyes open. In addition, participants completed a series of computer-based cognitive tasks to assess cognitive functioning at each assessment. Results from these tasks were previously described in Jha *et al.* (8).

Data Analysis

EEG Recording and Preprocessing. EEG data were recorded from 64-active electrodes using the BioSemi Active2 system (BioSemi B.V.) at a sampling rate of 248 Hz. All preprocessing steps were completed in Cartool (54). EEG recordings were average referenced, bandpass filtered offline (1–40 Hz), and screened in 1-second epochs for blink, muscle, or other artifacts and poor signal quality. To aid visual inspection, epochs were flagged if any amplitudes were $>$50 μV. Recordings were included for further analyses only if there was $\geq$60 seconds of clean EEG after removing epochs with poor signal. There were 155 eyes-open and 143 eyes-closed recordings in total across both T1 and T2 that were included for further analyses after screening. Finally, EEG was spatially smoothed for microstate segmentation and fitting to reduce the influence of signal outliers [for a detailed description of the method, see (55)].

IAF and 1/*f* Estimation. IAF and 1/*f* parameters were calculated from each participant's preprocessed eyes-open and eyes-closed EEG recordings, consistent with procedures used previously by Dziego *et al.* (41). To calculate IAF, we used the *philistine.mne.savgol_iaf()* function (56) in MNE-Python (57) and extracted center of gravity estimates for further analysis [see (17) for a full discussion of this method]. To estimate 1/*f* intercept and slope values, we used the irregular-resampling autospectral analysis method (58), between 1 and 40 Hz, implemented in the YASA toolbox (59). Metrics were estimated from 9 occipitoparietal electrodes (O1, Oz, O2, PO8, PO4, POz, PO3, PO7, Iz).

Microstate Parameter Estimation: Topographic Segmentation. Resting-state EEG recordings underwent an adapted *k*-means clustering procedure using Cartool (54) to identify topographical microstate configurations. This procedure aims to identify the optimal number of clusters (*k*) of topographical maps that can account for the greatest global explained variance (GEV) in the spatial time series while using the fewest representative configurations. Clustering occurred at 2 stages: clusters were first identified within individual recordings in the first stage, and then results from the first stage underwent a second stage of clustering to identify global configurations that best represent the entire sample. See Zanesco *et al.* (46) for further description of the clustering procedure.

The results of second-level *k*-means clustering revealed that the optimal number of global clusters within our dataset was 5 (explaining 84.72% of the global variance) across the 2187 individual participant-level cluster centroids. Nevertheless, visual inspection of the cluster centroids led us to adopt the 6-cluster solution (GEV = 86.38%) because all 6 maps aligned with configurations that are reliably identified in the literature based on previous meta-analysis and review of microstate configurations [see (43,45)]. These maps were designated as microstates A through F, consistent with standardized labels identified from the meta-analysis and review (43,60). Figure 2 depicts the topographical cluster centroids from the 6-cluster solution derived from 2187 participant-level cluster topographies. Note that all topographies were successfully assigned to a cluster in the second stage (i.e., all spatial correlations $>$ 0.5).

Microstate Parameter Estimation: Topographic Time-Frequency Fitting. Each time series sample of the EEG recordings were categorized according to the 6 microstate configurations identified through clustering; 92.25% (SD = 4.60%) of the EEG recordings were successfully categorized (i.e., all spatial correlations $>$ 0.5). One participant's eyes-open data were excluded from subsequent analyses because $<$75% of their EEG times series was successfully categorized. Of the remaining eligible participants, the 6 microstate configurations explained 59% (SD = 0.05%) of the

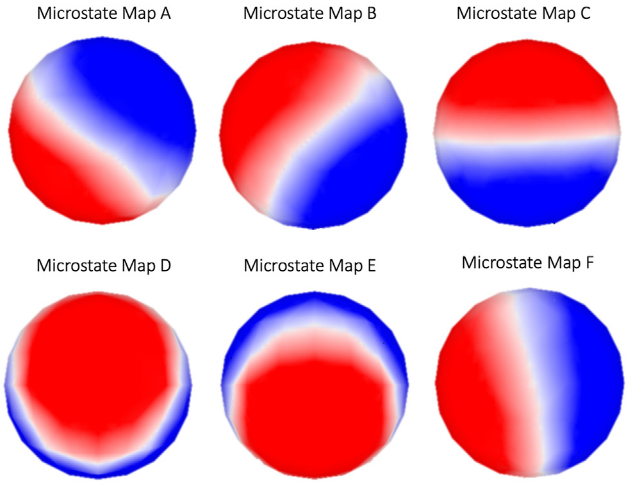

Figure 2. Cluster centroids for topographical configurations of microstates identified within the 6-cluster global solution. Cluster centroids were derived from *k*-means clustering of 4 minutes of resting-state electroencephalography data (2 minutes eyes open, 2 minutes eyes closed). Microstates are labeled A through F. Schematic depicts an isometric view of 3-dimensional maps with nasion at the top of the maps.

topographical variance in resting EEG on average across participants. As expected, likely due to increases in alpha power (61) and decreased noise from external stimulation, microstates explained a significantly greater proportion of topographical variance ($t_{294.98}$ = 10.31, $p < .001$) in the eyes-closed condition (mean = 61.9%, SD = 0.04%) than in the eyes-open condition (mean = 56.7%, SD = 0.04%). We obtained the mean duration, occurrence, GEV, and global field power (GFP) of microstates from the categorized EEG time series.

Statistical Analysis. All statistical analyses were performed with R version 4.3.1 (2023) in R Studio using the following packages: *tidyverse* version 2.0.0 (62), *lme4* version 1.1.34 (63), *car* version 3.1.2 (64), *performance* package version 0.10.4 (65), *ggplot2* version 3.3.0 (66), *ggeffects* version 1.1.3 (67), *ggpubr* version 0.6.0 (68), and *lmerOut* version 0.5.1 (69).

Linear mixed effect models were fit by restricted maximum likelihood and parameter estimates, and p values were calculated using type II Wald χ^2 tests (64). Categorical variables were coded with sum-to-zero contrast coding (where estimates are compared with the grand mean) (70). Directionality of effects at the $p < .05$ level were visualized through nonoverlapping confidence intervals (at 83%). For further discussion of this method, see (71–73).

To assess the effects of MT on resting-state EEG measures (IAF, 1/*f* intercept, and 1/*f* slope) and microstate temporal parameters (occurrence, duration, GEV, and GFP), we ran multiple analyses examining effects of time (T1/T2), group (MT or PT), condition (eyes open or eyes closed), and their interactions for each measure of interest. An additional variable (map) was included in analyses to examine whether changes in microstate parameters were exclusive to any topographical configuration (A–F). Random effects at the intercept were included for participants. We also included random slopes by time for participant (see Supplemental Section S1 for all model specifications) when models converged, were not singular, and significantly improved model fit.

RESULTS

Descriptive Statistics

Tables 1 and 2 depict the overall descriptive statistics for oscillatory, aperiodic, and microstate measures of interest. Figure 3 shows a schematic of resting-state EEG metric distributions. Figure 4 summarizes microstate parameters across each of the 6 identified maps. Correlations between all variables of interest are provided in Supplemental Section S2. Correlations between all change (T1–T2) in variables of interest are shown in Supplemental Section S3. Notably, IAF and aperiodic activity were significantly correlated with temporal parameters of microstates.

Modeling Change in Resting-State Neural Metrics

In the following sections, we report all group × time effects observed within our models (relevant to the aims of the article). For brevity, descriptions of other significant effects (and nonsignificant microstate models; occurrence and GEV) are reported in the Supplement (see Supplemental Sections S4–S6).

Aperiodic 1/*f* Activity and IAF. No significant changes were observed across group × time for IAF; however, an effect

Table 1. EEG Resting-State Metrics of Interest (IAF and 1/*f*) Across Eyes-Open and Eyes-Closed Conditions by Group (MT or PT) and Time (1 and 2)

	Time 1			Time 2		
EEG Metrics	Mean (SD)	Range	*n*	Mean (SD)	Range	*n*
Mindfulness Training						
IAF	9.97 (0.51)	8.75 to 11.25	73	9.96 (0.49)	8.75 to 11.25	73
1/*f* slope	−1.34 (0.21)	−1.88 to −0.89	77	−1.32 (0.21)	−1.81 to −0.83	77
1/*f* intercept	−25.03 (0.76)	−27.01 to −23.02	77	−25.10 (0.75)	−27.57 to −23.45	77
Positivity Training						
IAF	9.79 (0.54)	8.5 to 11	72	9.73 (0.59)	8.25 to 11	67
1/*f* slope	−1.34 (0.28)	−1.91 to −0.59	74	−1.4 (0.24)	−1.89 to −0.64	71
1/*f* intercept	−24.93 (0.87)	−26.91 to −22.55	74	−24.76 (0.76)	−26.96 to −22.86	71

EEG, electroencephalography; IAF, individual alpha frequency; MT, mindfulness training; PT, positivity training.

Table 2. Microstate Temporal Parameters of Interest by Time, Group, and Map

	MT						PT					
	Map A	Map B	Map C	Map D	Map E	Map F	Map A	Map B	Map C	Map D	Map E	Map F
Time 1												
Duration, ms	87.9 (8.65)	85.4 (8.13)	108 (15.6)	85.5 (7.84)	83.3 (8.63)	80.9 (9.2)	90.4 (12.4)	88.0 (11.1)	110 (21.2)	86.4 (11.9)	83.6 (10.2)	82.3 (9.79)
Occurrence	1.53 (0.33)	1.45 (0.3)	2.44 (0.34)	1.44 (0.43)	1.25 (0.37)	0.89 (0.29)	1.53 (0.35)	1.48 (0.32)	2.44 (0.36)	1.35 (0.41)	1.21 (0.43)	0.9 (0.25)
GEV	0.09 (0.03)	0.07 (0.02)	0.29 (0.11)	0.06 (0.03)	0.05 (0.04)	0.03 (0.02)	0.1 (0.03)	0.08 (0.03)	0.27 (0.08)	0.06 (0.03)	0.05 (0.03)	0.04 (0.01)
GFP	4.5 (1.36)	4.38 (1.33)	5.1 (1.64)	4.28 (1.29)	4.26 (1.32)	4.16 (1.25)	4.81 (1.58)	4.71 (1.52)	5.3 (1.75)	4.51 (1.49)	4.5 (1.37)	4.47 (1.45)
Time 2												
Duration, ms	89.3 (9.58)	87.8 (7.75)	110 (16.2)	86.7 (9.72)	84.3 (8.69)	83 (8.81)	87.5 (10.9)	87.1 (10.5)	107 (19.7)	84.3 (9.85)	82.4 (11.3)	81.6 (9.2)
Occurrence	1.48 (0.36)	1.46 (0.3)	2.42 (0.37)	1.41 (0.39)	1.13 (0.33)	0.9 (0.28)	1.41 (0.38)	1.62 (0.31)	2.45 (0.34)	1.38 (0.41)	1.28 (0.5)	0.98 (0.27)
GEV	0.09 (0.04)	0.08 (0.03)	0.28 (0.1)	0.06 (0.03)	0.05 (0.02)	0.04 (0.02)	0.09 (0.04)	0.09 (0.03)	0.27 (0.08)	0.06 (0.03)	0.06 (0.04)	0.04 (0.01)
GFP	4.42 (1.51)	4.37 (1.53)	4.97 (1.81)	4.22 (1.47)	4.12 (1.36)	4.10 (1.35)	4.81 (1.52)	4.77 (1.41)	5.34 (1.63)	4.55 (1.37)	4.56 (1.35)	4.47 (1.35)

Values are presented as mean (SD). Occurrence is times per second.

GEV, global explained variance; GFP, global field power; MT, mindfulness training; PT, positivity training.

of group (χ^2_1 = 4.47, $p < .05$) indicated that IAF was overall higher for those in MT. For the 1/*f* slope, models demonstrated a significant interaction of group × time (χ^2_1 = 4.27, $p < .05$), where the slope steepened across time for those in the PT group but was stable for the MT group. For the 1/*f* intercept, models demonstrated a significant group × time interaction (χ^2_1 = 5.61, $p < .05$), where the intercept decreased across time for the MT group, while the intercept increased for the PT group. See Figure 5 for plots of modeled effects. All model estimates are depicted in Supplemental Section S1.

Microstate Parameters. The model predicting microstate duration revealed a significant interaction of group × time (χ^2_1 = 8.25, $p < .01$) wherein overall map duration increased across time for MT but decreased for PT. See Figure 6 for modeled effects. The GFP model also demonstrated significant interactions of group × time × condition (χ^2_1 = 4.92, $p < .05$) wherein GFP (i.e., the overall amplitude of the signal, reflecting the coordination/strength of microstates) (74) was stable across time and groups for the eyes-closed condition. For the eyes-open condition, GFP decreased across time for MT and increased for PT (see Figure 6).

DISCUSSION

In the current study, we assessed resting-state neurophysiology (IAF, 1/*f* parameters, and microstates) across an 8-week, 16-hour MT program, MMFT, compared with a time-matched PT program (8). EEG data were analyzed before (T1) and after (T2) interventions, during which military personnel were instructed to quietly rest for 4 minutes (2 minutes eyes closed, 2 minutes eyes open). Prior examination of cognitive task performance in the same participants (8) found that performance degraded over time (during the high-demand predeployment interval), but declines were mitigated in those who received MT compared with those who received PT. The current study allowed us to explore neurocognitive adaptations in large-scale brain networks as service members experienced high-demand contexts and how MT/PT interventions alter

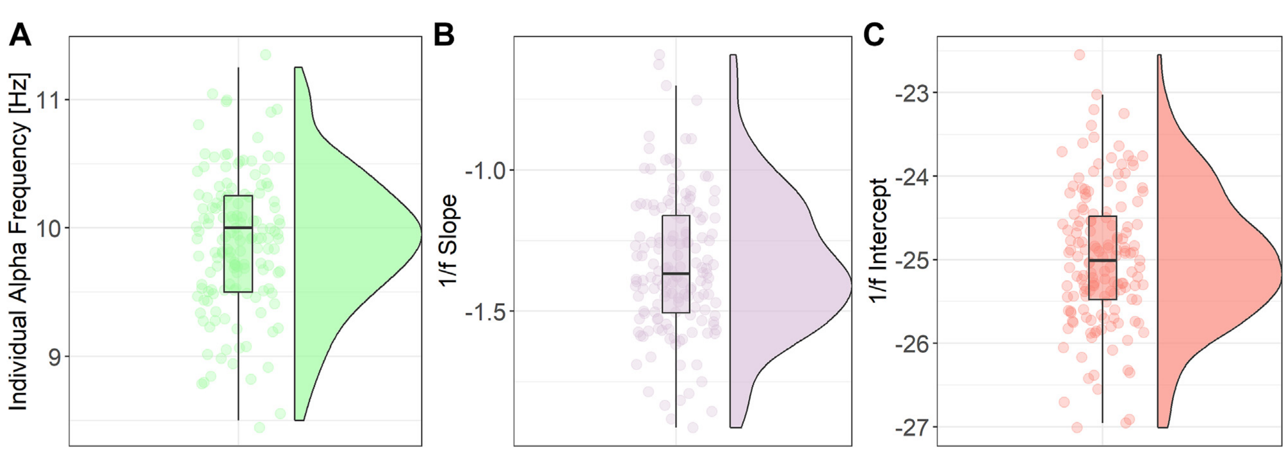

Figure 3. Summary of distributions of **(A)** individual alpha frequency, **(B)** 1/*f* slope, and **(C)** the 1/*f* intercept estimated from 4 minutes of resting-state electroencephalography data (eyes open and eyes closed). Data points represent individual participant estimates from both time 1 and time 2 across both mindfulness training and positivity training groups. Thick horizontal lines represent mean values, while lower and upper hinges correspond to the first and third quartiles, respectively.

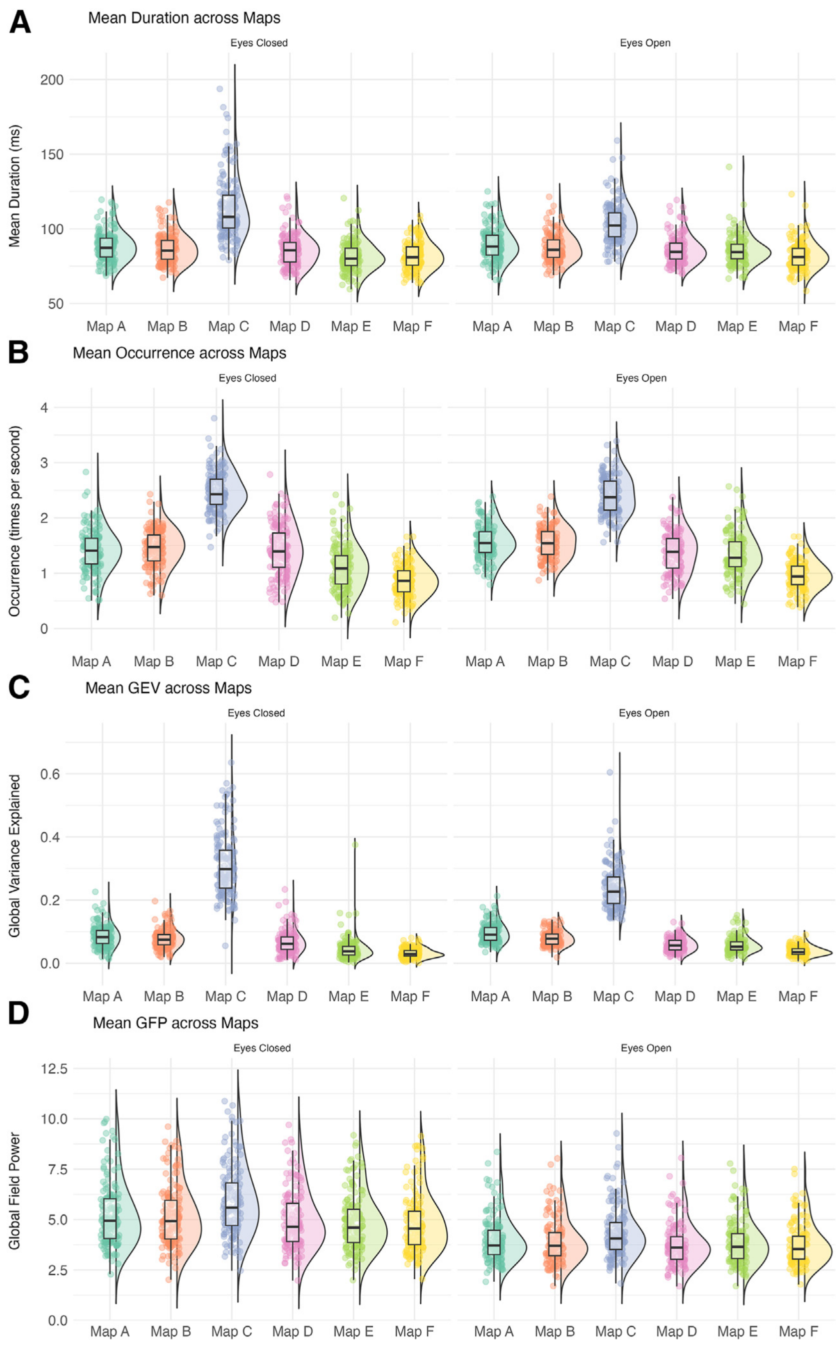

Figure 4. Summary of **(A)** mean duration (ms), **(B)** occurrence (times per second), **(C)** global explained variance (GEV), and **(D)** global field power (GFP) across each microstate map (A–F, depicted on the x-axis). Note the increased occurrence and duration of map C. Plots include all data from positivity training (PT) and mindfulness training (MT) groups across time.

resting EEG parameters that have previously been found to be sensitive to individual differences in information processing capacity (19–21).

IAF and Aperiodic 1/*f* Activity

In contrast to our hypothesis, we did not observe significant differences in IAF across time in either the MT or the PT group. While previous studies suggest a correspondence between individual differences in cognitive functioning and IAF (where often, higher is better) (19,21,41), other studies that have aimed to examine IAF in relation to cognitive training interventions (MT or other) have had mixed results. For example, Saggar *et al.* (28) demonstrated that IAF decreased across a 3-month residential mindfulness meditation retreat, whereas Dziego *et al.* (6) did not observe any changes in IAF after 1 week of audio-delivered MT despite observing enhancements in performance. These findings suggest that a shorter form of MT may not be robust enough to induce neuroplastic change in

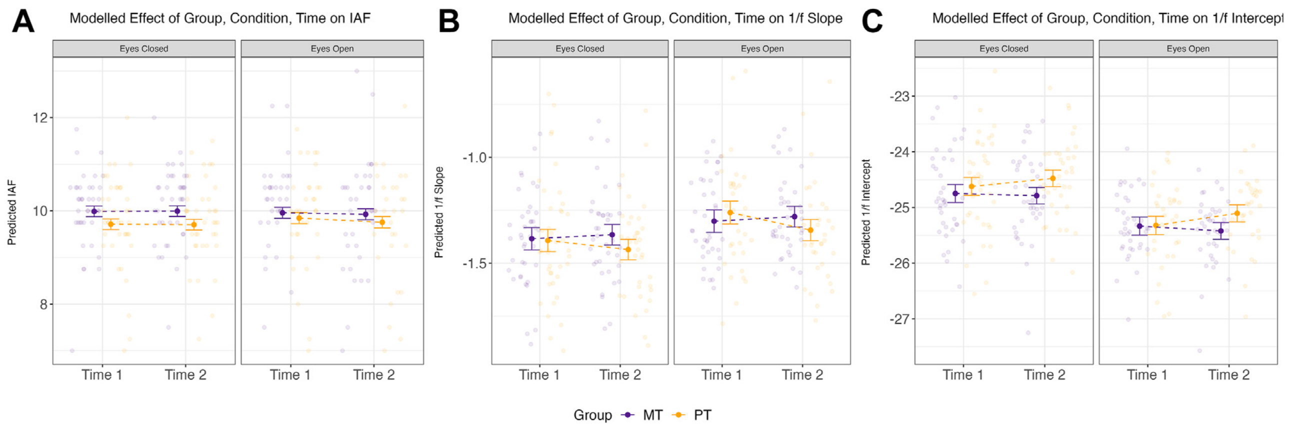

Figure 5. Modeled parameters of linear mixed models depicting change from time 1 to time 2 for individual alpha frequency (IAF) **(A)**, aperiodic 1/*f* slope **(B)**, and aperiodic 1/*f* intercept **(C)**. Predicted values are depicted on the y-axis, while time is depicted on the x-axis. Group assignment is indicated by color (purple denotes the mindfulness training [MT] group, and yellow denotes the positivity training [PT] group). Error bars represent confidence intervals at the 83% level, and plots are facetted by condition (eyes open or eyes closed). Individual data points represent raw participant data.

IAF. Likewise, Grandy *et al.* (75) observed that measures of IAF were longitudinally stable across 100 hours of more traditional cognitive training. Notably, we observed overall group differences in IAF. One noteworthy difference that could have contributed to this effect is that the MT and PT groups comprise different military occupational specialities [see (8) for discussion]. Presumably, differences in military occupational specialities may reflect distinct aptitudes that may be captured by fundamental differences in cognitive functioning across a variety of domains.

Unexpectedly, we observed that the 1/*f* slope decreased (steepened) across time for those who engaged in PT but was unchanged for those who engaged in MT. While several previous studies have demonstrated that steeper 1/*f* slopes were associated with heightened performance outcomes [e.g., (19,20)], more recent work has demonstrated in contrast that flatter slopes may be associated with more optimal performance in some contexts (41). Flatter 1/*f* slopes were proposed to correspond with greater complexity within biological systems (41,76,77), which may reflect more informationally rich neural processing. On the other hand, steeper slopes may reflect faster information processing, which may not always be advantageous in complex situations or activities (41).

Our findings are also consistent with average spectral changes observed in experienced and novice meditators external to meditation engagement (78,79), whereby increases in higher frequency and decreases in lower frequency ranges can be seen across the EEG frequency spectrum. In the current study, for the 1/*f* intercept, we observed a decrease across time for those in the MT group but an increase across time for those in the PT group. While mechanistic interpretations of the 1/*f* intercept are more elusive, recent reports claim correlations with overall neural population spiking in the brain (80,81). These so-called frequency band variations could alternatively be explained through an exponent shift (20) in 1/*f* activity, suggesting that aperiodic change might have driven previously reported oscillatory power findings. However, understanding the relationships between oscillatory and aperiodic changes in response to meditation interventions will require more research that considers these components in tandem [c.f., (82)].

Microstates

The temporal dynamics of microstates were also found to be of longer duration at T2 in MT training participants than in PT participants. Moreover, the overall amplitude of microstates at T2 was reduced in the MT group, compared with the PT group, during the eyes-open condition. These changes occurred irrespective of a particular topographical configuration (i.e., map). While the functional significance of changes in overall microstate duration is still unknown, longitudinal reductions in duration were previously observed in a study of 3 months of residential mindfulness meditation practice (46). Here, it was speculated that decreases in duration, together with increases in the overall occurrence rate of microstates, reflected more lability and flexibility in dynamic switching between large-scale brain networks. The different pattern of findings observed in the current study may arise from the previous experience and context of the participants, as well as the intensity and duration of the interventions. While the current experiment included military personnel who were novices assessed across a high-demand interval, Zanesco *et al.* (46) studied experienced mindfulness meditators during an intensive (6–10 hours daily practice) residential retreat intervention.

While changes in microstate duration contrasted with previous research, reductions in the overall strength of microstates [i.e., reduced GFP (74)] in the MT group were consistent with patterns observed in the earlier study by Zanesco *et al.* (46). Importantly, changes in aperiodic 1/*f* components paralleled patterns of change in microstates in both MT and PT groups (see Supplemental Section S3), providing additional insight into our mechanistic understanding of microstates and their spectral correlates in aperiodic activity. Reductions in 1/*f* intercepts paralleled reductions in GFP, while steeper 1/*f* slopes were related to decreases in overall microstate duration. It has been suggested that microstates display

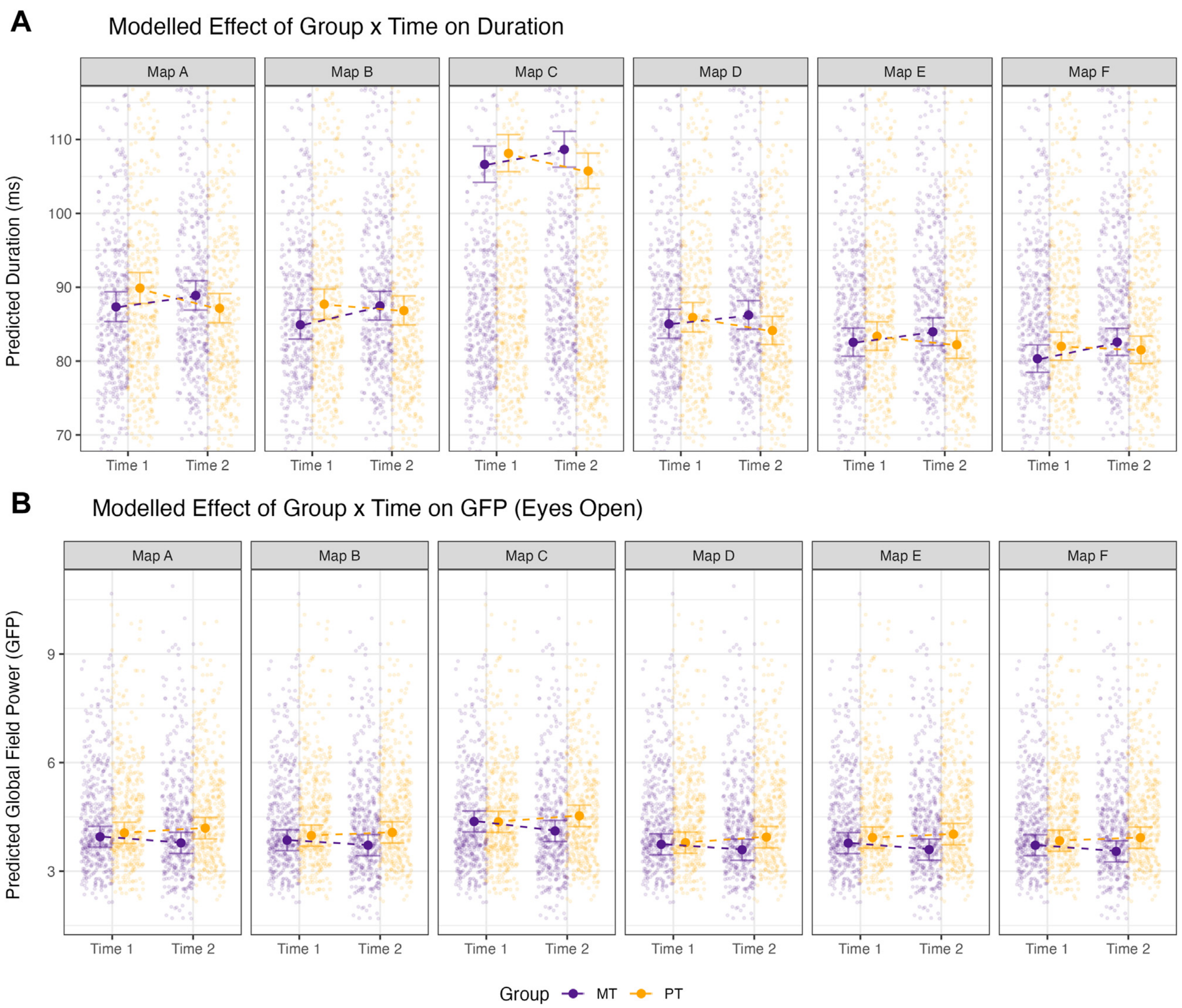

Figure 6. Schematic of the modeled effects of group × time on duration **(A)** and global field power (GFP) **(B)** of microstate maps. The y-axis represents the model's predicted outcome value, while the x-axis depicts time. Model estimates for the mindfulness training (MT) group are shown in purple, while estimates for the positivity training (PT) group are shown in yellow. Plots are facetted by map and error bars represent confidence intervals at the 83% level.

long-range dynamics in their fluctuations (83) that may be related to aperiodic 1/*f* activity identified through other EEG analytic methods. Likewise with 1/*f* activity, microstate parameters have also been tentatively associated with excitation/inhibition balance (84), thus supporting this theoretical link. Future studies should continue to examine associations between microstate dynamics and other measures of periodic and aperiodic neural activity to mutually inform our understanding of the neurocognitive significance of these indices.

We also note some critical replications of previous findings about the characteristics of resting EEG microstates. Here, map C consistently dominated the resting EEG, with the highest frequency of occurrence, longest duration, and largest portion of variance explained. These findings are consistent with theories that microstate C is associated with key hubs of the default mode network that predominate during resting-state conditions, while maps A, B, and E may reflect neural activity that underlies more externally oriented perceptual and attentional processes (45).

Limitations and Future Directions

We note that the recruitment strategies and group assignment that were used in this research might have introduced unavoidable, preexisting differences between groups prior to implementation of the interventions [see Jha *et al.* (8)]. Furthermore, it is unclear whether similar patterns of neurophysiological change would be elicited as a result of MT and PT outside of highly demanding intervals. Across some of our resting-state EEG parameters, we observed larger changes in the PT than the MT group, consistent with performance findings (8), which suggest that MT training could be associated with more preventive effects. In particular, we could conjecture that participants were affected by chronic sleep deprivation, and consequent physiological declines were mitigated by engagement in MT. Consistently, there is recent evidence to suggest that arousal and sleep may influence resting-state EEG [i.e., 1/*f* slope is known to predict sleep stages and sleepiness (85–87), while subjective sleepiness is correlated with microstates A and D (88)]. Alternatively, 1/*f* activity has been utilized as a marker of muscle activity (89) and could be differentiating groups based on general levels of relaxation. Finally, the functional significance of aperiodic activity and microstate dynamics is still largely unknown. It is unclear precisely how this intrinsic activity assessed in the resting-state context may reflect the functioning and connectivity of large-scale neuronal circuits or underlie individuals' neurocognitive ability. Critically, the results reported above were not corrected for multiple comparisons (for adjusted *p* values, see Supplemental Section S7). Following correction, only the group × time interaction effect on microstate duration remained significant. Nevertheless, beyond our study's exploratory analyses of neurophysiological changes with MT, our findings provide an important initial contribution toward understanding associations between IAF, aperiodic activity, and microstates (see Supplemental Section S2) and how different analytic approaches for quantifying features of spontaneous EEG activity reveal related properties of brain function.

Conclusions

In the current exploratory study, we aimed to describe neurophysiological change associated with MT in military service members in a high-demand setting. As predicted, our resting-state EEG metrics of interest were sensitive to the effects of our interventions. Unexpectedly, we found that at T2, the PT group exhibited steeper 1/*f* slopes and higher intercept values than the MT group, as well as decreased duration and increased amplitude of all microstates. Further exploration of these neurophysiological adaptations in alternative contexts and cohorts is needed to better elucidate the complex interrelationships between MT, neuroplastic change, and cognitive functioning.

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ARTICLE INFORMATION

From the Cognitive Neuroscience Laboratory, Australian Research Centre for Interactive and Virtual Environments, University of South Australia, Adelaide, South Australia, Australia (CAD, IB-S, MS); Department of Psychology, University of Miami, Coral Gables, Florida (APZ, APJ); and Edmund A. Walsh School of Foreign Service, Georgetown University, Washington, DC (EAS).

Address correspondence to Chloe A. Dziego, B.Psych (Hons), at Chloe.Dziego@mymail.unisa.edu.au.

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