Distilling the neurophenomenological signatures of pure awareness during Transcendental Meditation

Alejandro Chandia-Jorquera[1,8], Sean D. van Mil[2,8], Mar Estarellas[1,3,8], Marina Dauphin[1,4], Claudia Pascovich[1,5], Andres Canales-Johnson[1,6,7,9]

[1]*Department of Psychology, University of Cambridge, CB2 3EB Cambridge, United Kingdom*
[2]*Conscious Brain Lab, Department of Psychology, University of Amsterdam, Nieuwe Achtergracht 129-B, 1018 WT, Amsterdam, The Netherlands*
[3]*Department of Psychiatry, McGill University, Montréal, Quúbec, Canada*
[4]*Mind, Brain and Behavior Research Center, University of Granada, Granada, Spain*
[5]*Laboratory of Sleep Neurobiology, Department of Physiology, Facultad de Medicina, Universidad de la República, Montevideo, Uruguay*
[6]*Neuroscience Center, Helsinki Institute of Life Science, University of Helsinki, P.O. Box 3, Fabianinkatu 33, FI-00014 Helsinki, Finland*
[7]*Neuropsychology and Cognitive Neurosciences Research Center, Faculty of Health Sciences, Universidad Católica del Maule, 3460000 Talca, Chile*
[8]*These authors contributed equally to this work*
[9]*Correspondence to: Andres Canales-Johnson (afc37@cam.ac.uk)*

Abstract

Pure awareness (PA) is described in contemplative traditions as a wakeful state largely devoid of cognitive content, often considered a case of minimal phenomenal experience (MPE). Transcendental Meditation (TM) provides an excellent empirical model for PA because it is standardized, effortless, and reliably induces reports of awareness with minimal content. We combined phenomenological and electrophysiological approaches to study PA in 33 experienced TM practitioners and matched controls (performing mental counting). Using Temporal Experience Tracing, TM practitioners reported greater intensity and variability of PA than controls, regardless of years of meditation practice, consistent with the notion of 'automatic self-transcendence'. Using electroencephalography (EEG) and multivariate classification analyses, our large-scale screening of theoretically motivated EEG markers revealed a double dissociation in neural signatures. When contrasting TM with controls, temporal entropy and aperiodic dynamics were the strongest discriminators, while functional connectivity based on phase coherence contributed the least. In contrast, when TM was compared with its own baseline, low-frequency functional connectivity dominated, while temporal entropy contributed minimally to classification. This dissociation suggests that PA is characterized by enhanced EEG signals' diversity and aperiodic neural dynamics compared to ordinary cognition but stabilized by slow-frequency oscillatory synchronization relative to rest. Finally, TM showed little evidence of carry-over effects from meditation into subsequent rest, in contrast to controls, where counting induced residual changes. Together, these results provide the most systematic electrophysiological characterization of PA to date and establish neurophenomenology as a robust framework for advancing the neuroscience of minimal phenomenal experience.

INTRODUCTION

Pure awareness (PA) refers to a phenomenological experience described in many contemplative traditions (Forman, 1986). It designates a paradigmatic case of minimal phenomenal experience (MPE): an episode of wakeful experiencing stripped of customary structural features of consciousness (Metzinger, 2020). Phenomenologically, PA is marked by the absence of minimal phenomenal selfhood (i.e., no identification with a body or ego), the lack of an explicit temporal register, and the absence of a spatial frame of reference, while retaining a distinctive sense of wakefulness or alert presence (Forman, 1986; Metzinger, 2020; Travis, 2014; Travis and Pearson, 2000; Vieten et al., 2018).

Within the vast repertoire of meditation practices, Transcendental Meditation (TM) offers a tractable empirical model of PA as its procedure is standardized, its induction is effortless and repeatable, and its reported phenomenology closely matches the defining features of minimal phenomenal experience (Travis, 2014; Travis and Pearson, 2000). TM is a mantra-based practice, usually performed seated with eyes closed for 20 minutes twice a day, taught by certified teachers affiliated with the organization established by Maharishi Mahesh Yogi. During practice, TM practitioners begin by repeating a specific, nonsemantic sound (i.e., a 'mantra') that serves as a psychophysiological 'vehicle' for progressive attenuation of discursive mentation. Although the mantra is not actively suppressed, it spontaneously recedes from awareness as attention settles. Practitioners frequently describe a shift from thought-mediated cognition to a state of pure awareness: awake but content-free, lacking an intentional object, devoid of deliberate mental activity, and minimally engaged with sensory input (Travis, 2014; Travis and Pearson, 2000). Crucially, TM is explicitly not framed as focused attention or open monitoring; instead, the mantra is used in a light, non-effortful manner, intended to allow attention to settle, a process described as 'automatic self-transcendence' (Travis et al., 2010). Thus, while the technique is initiated

through the use of a mantra, its aim is the transcendence of the mantra itself, culminating in a putative mode of consciousness in which awareness is present with minimal representational content.

Despite the increasing adoption of neurophenomenological approaches in the neuroscience of consciousness (Chowdhury et al., 2025; Ganesan et al., 2024; Jachs, 2021; Lewis-Healey et al., 2024b; Lutz, 2002; Potash et al., 2025; Timmermann et al., 2023), a comprehensive understanding of how minimal phenomenal experiences, such as PA, relate to neural signatures remains lacking. This may be due to (i) the use of Likert scales to quantify the overall intensity of experiential dimensions, thus ignoring the temporal dynamics of phenomenology, and (ii) the lack of studies performing a large-scale screening of theoretically motivated neural markers that capture the complexity of brain dynamics subserving perception and consciousness (Canales-Johnson et al., 2020a, 2023, 2021a,c; Gelens et al., 2024; Imperatori et al., 2019; Potash et al., 2025; Roberts et al., 2025; Vinck et al., 2023).

Here, we present the current neurophenomenological research as a novel approach to studying PA. To address issue (i), we adopt Temporal Experience Tracing (TET) (Gernert et al., 2024; Jachs, 2021; Jachs et al., 2022; Lewis-Healey et al., 2024a,b; Niedernhuber et al., 2024), a recent methodology that empirically charts the dynamics of subjective experience. In TET, participants retrospectively reconstruct phenomenological time series by sketching, on two-dimensional axes, how the intensity of predefined experiential dimensions fluctuated over time. This produces richer and temporally resolved trajectories that surpass the capabilities of static Likert ratings (Figure 1B). To address issue (ii), we performed a large-scale screening of theoretically motivated EEG neural markers: single-electrode measures of complexity (Lempel-Ziv complexity; LZ), entropy (Permutation entropy; PE), and aperiodic activity (exponent and offset), and functional connectivity measures capturing linear (weighted phase-lag index; WPLI) and nonlinear neural interactions (weighted symbolic mutual information; WSMI) (Figure 2).

We recorded EEG and TET from 33 TM practitioners and their corresponding matched controls (who performed a counting task) to determine phenomenological and neurophysiological differences in PA between TM practitioners and controls. Using multivariate classification analyses, we provide a comprehensive ranking of the most discriminative neural markers separating TM from controls when they experience PA, as well as the most relevant neural markers for distinguishing meditation from baseline periods.

RESULTS

Phenomenology of PA between TM and controls

Both groups first completed a 10-min eyes-closed baseline period (with meditators instructed not to meditate/repeat the mantra), followed by a 30-min task period (TM for meditators; mental self-paced forward counting task by one for controls), after which participants were introduced to and performed the TETs, and finally a second 10-min eyes-closed baseline (again with no meditation for meditators) (Figure 1A).

To capture the temporal dynamics of PA using the TET approach (Figure 1B), we performed a cluster-based permutation test comparing PA intensity between TM and controls (Figure 1C). We found two significant ($p < 0.05$) clusters showing higher PA for meditators than controls (first cluster: 8.32 min to 12.53 min, Cohen's $d = 0.57$; second cluster: 20.00 min to 21.45 min, Cohen's $d = 0.53$). As a complementary analysis, and to compare the maximum PA intensity between groups, we extracted the maximum PA value across the 30-minute TET charts for meditators (TM) and non-meditators (control) and compared the mean between groups. We observed significantly higher PA in TM ($M = 0.697$, $SD = 0.209$) compared with controls ($M = 0.523$, $SD = 0.241$; $t = 3.10$, $p < 0.001$, mean difference = 0.174, 95% *CI* [0.062, 0.286], Cohen's $d = 0.771$; Figure 1D). Lastly, to investigate the temporal variability of the PA experience over the 30-min period (Figure 1A), we calculated the standard deviation (SD) of the PA traces per participant in the TM and control groups. We then, in a separate contrast, statistically compared these SD values between the TM and control groups and found significantly greater temporal variation in TM ($M = 0.154$, $SD = 0.079$) compared with controls ($M = 0.063$, $SD = 0.057$; $t = 5.36$, $p < 0.001$, mean difference = 0.091, 95% *CI* [0.057, 0.126], Cohen's $d = 1.32$; Figure 1C). These results suggest that the intensity and variability of pure awareness dynamics increase during the transcendental meditation period compared to ordinary wakefulness, while performing mental counting. Thus, the results are consistent with the notion that during the meditation period, the phenomenology of TM is characterized by an increase in PA compared to normal wakefulness.

After having established self-reported PA differences between TM and controls, our objective was to test the second core idea of TM proponents regarding PA, that is, rapid, effort-independent access to PA, conceptualized as 'automatic self-transcendence' (Travis, 2001), is *independent* of years of meditation practice. This notion implies that both short- and long-term practitioners can, in principle, experience the same level of pure awareness in a single sitting. To empirically test this idea, we correlated the PA values obtained from TM practitioners with their years of practice, and expected no association between them. Consistent with the prediction of the TM framework, we found no significant association between years of meditation practice and PA [PA intensity (maximum): Pearson's r = -0.13; p = 0.445; PA variability (SD): Pearson's r = -0.10; p = 0.550)].

Extracting theoretically motivated EEG neural measures

To better characterize the neural dynamics during periods where PA was reported, we computed and performed multivariate classification analyses on theoretically motivated EEG neural measures (Figure 2). At the level of single-electrode dynamics, we computed (i) the aperiodic (1/f) exponent, (ii) Lempel–Ziv complexity (LZ), and (iii) permutation entropy (PE), providing insights into local EEG neural dynamics (see Methods).

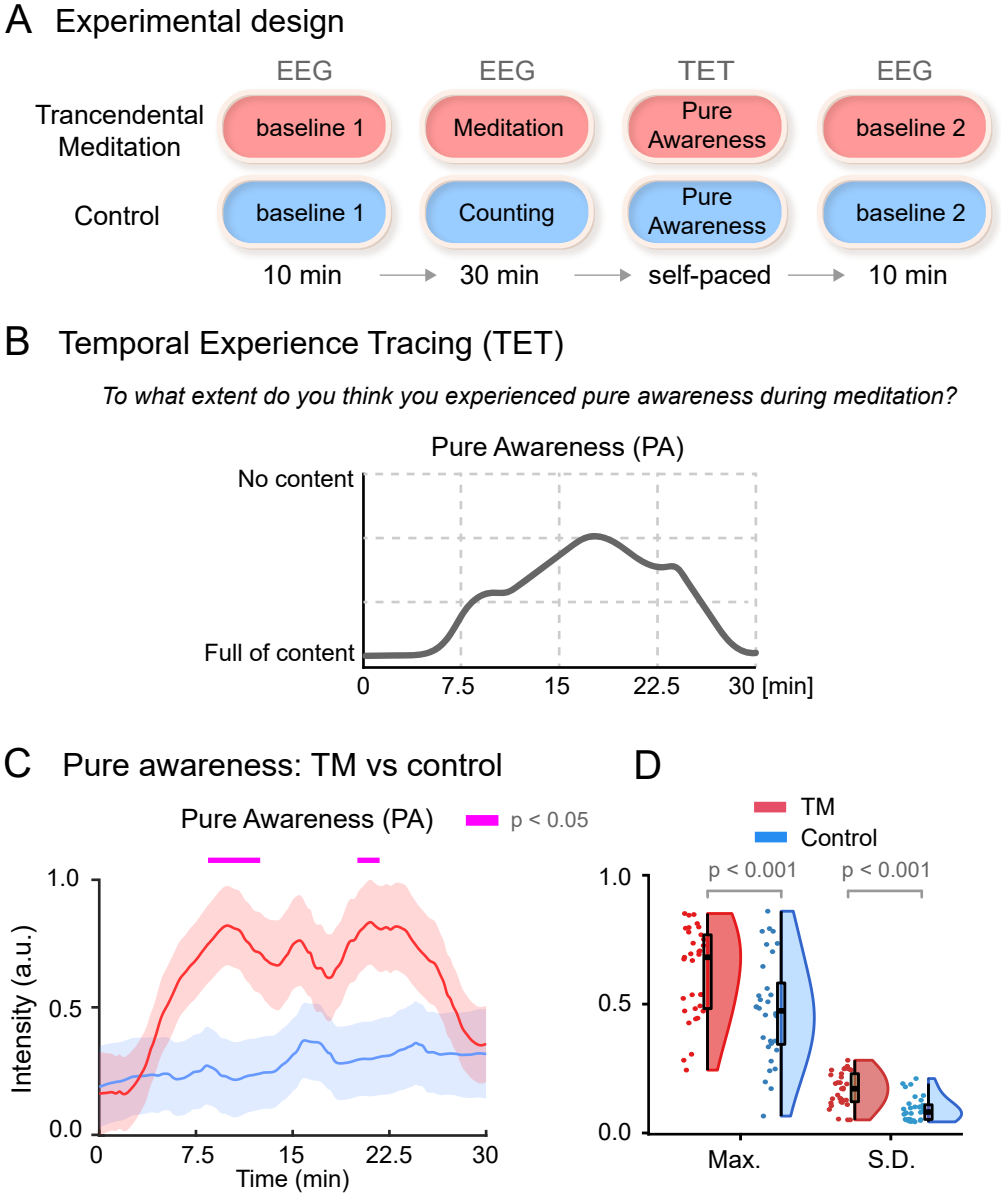

Figure 1: Experimental design, temporal experience tracing, and pure awareness differences. **(A)** High-density EEG from TM and control participants was recorded during a baseline condition (B1) for 10 minutes, eyes closed, without any specific instructions. Then, they practiced TM for 30 minutes (M), after being instructed to start repeating their mantra. After meditation, they were immediately instructed to report their experience of pure awareness (PA) using the TETs. Finally, a last baseline condition (B2) was recorded for another 10 mins without any specific instructions except for keeping their eyes closed. **(B)** Pure awareness report using TET. Schematic trace representation of single-participant reporting PA during the 30-min meditation session (see Methods). **(C)** Group-level differences in PA between TM and controls. The average TET values across TM (in red) and control (in blue) participants. A cluster-based permutation test over time reveals significant temporal clusters with higher PA in TM compared to controls (see Results and Methods sections). Shaded bars indicate standard error of the mean (S.E.M.). **(D)** Maximum PA intensity and SD across time (see Results and Methods sections) were compared between the TM and control groups. Box plots display the sample median alongside the interquartile range. Individual dots represent individual PA values per subject (TM in red, controls in blue).

In brief, (i) the parameterization of power spectra into aperiodic components isolates a broadband background whose exponent (slope) and offset (intercept) vary with age, arousal, and task demands. Modeling studies have linked the exponent to shifts in cortical excitation–inhibition balance, thereby enhancing the interpretability of spectral power beyond spectral narrowbands (Donoghue et al., 2020b) (Figure 2B); (ii) LZ applied to EEG signals estimates the rate at which novel information patterns appear in a signal and is related to algorithmic complexity, making it sensitive to the richness of neural activity in conscious states and perceptual tasks (Canales-Johnson et al., 2023, 2020b; Schartner et al., 2015, 2017; Sitt et al., 2014) (Figure 2C); and (iii) PE quantifies the temporal ordering of amplitude patterns and is grounded in dynamical systems theory (Bandt and Pompe, 2002), tracking neural signal unpredictability while maintaining robustness to noise (Frohlich et al., 2022; King et al., 2013; Sitt et al., 2014) (Figure 2D).

At the level of global EEG neural dynamics, functional con-

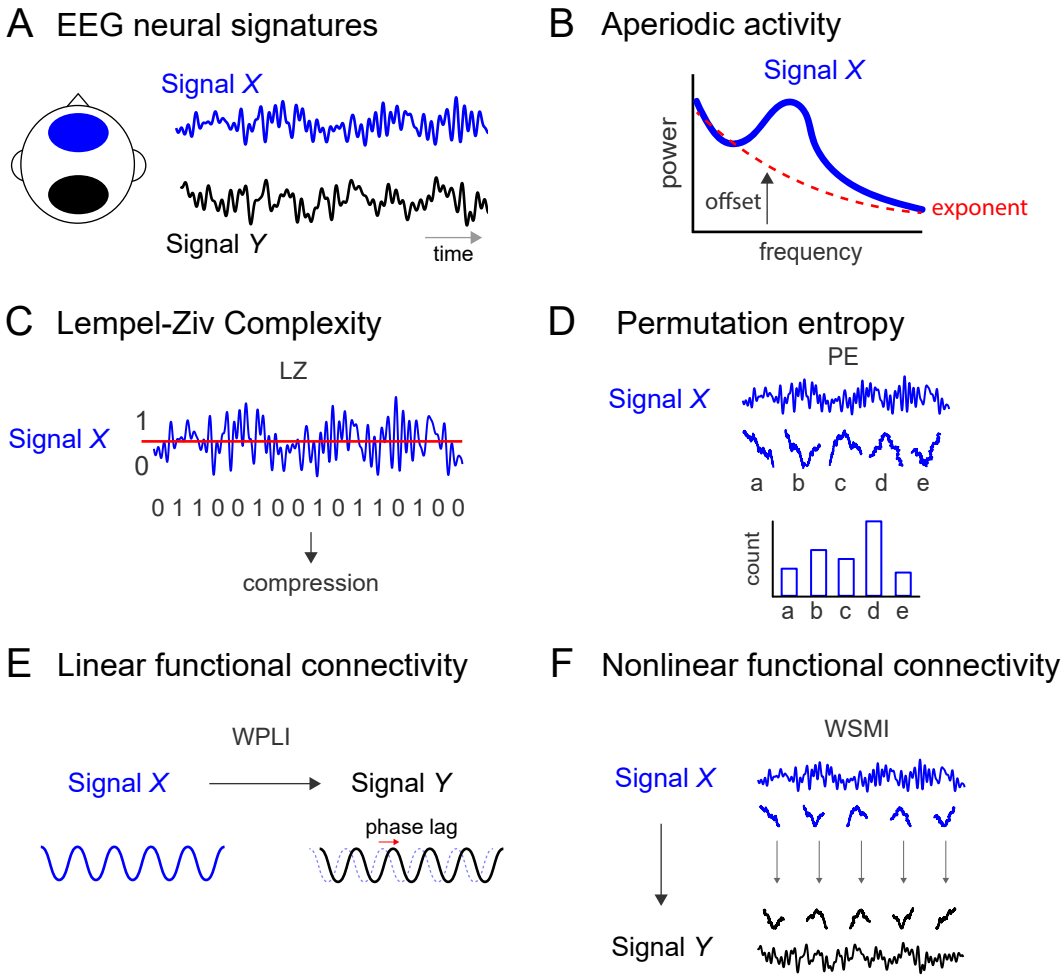

Figure 2: Theoretically motivated EEG neural measures. **(A)** Extracting neural features from EEG signals. In this diagram, neural signals are depicted for signal X (in blue) and signal Y (in black) corresponding to two arbitrary electrodes of interest. **(B)** Aperiodic activity. **(C)** Lempel-Ziv complexity. **(D)** Permutation entropy. **(E)** Linear transformations between two correlated signals at the same frequency. The transformed signal (signal Y) is the result of a phase-lagged version of the original signal (signal X) at the same frequency (e.g., a 10 Hz signal X can result in a phase-shifted signal Y at the same 10 Hz). The WPLI metric (weighted phase lagged index) captures this type of linear functional connectivity. **(F)** Nonlinear transformations cause systematic relationships across different frequencies between signal X and Y, potentially in the absence of linear transformations. Thus, non-linear connectivity measures quantify arbitrary mappings between temporal patterns in one signal (signal X) and another signal (signal Y). This type of nonlinear mapping is captured by the WSMI measure (weighted symbolic mutual information).

nectivity measures can be categorized into those that predominantly capture (i) linear and (ii) nonlinear functional connectivity (Imperatori et al., 2019; Vinck et al., 2025, 2023). (i) WPLI emphasizes consistent non-zero-lag phase relationships, thereby reducing sensitivity to volume conduction and noise relative to traditional coherence, which makes it a principled marker of large-scale phase coherence in EEG (Vinck et al., 2011, 2023) (Figure 2E). In contrast, (ii) WSMI estimates shared information between symbolized EEG signals, capturing distributed, nonlinear dependencies that index global information sharing in alertness and meditation states (Canales-Johnson et al., 2021c; Imperatori et al., 2019; King et al., 2013; Potash et al., 2025; Sitt et al., 2014) (Figure 2F). Therefore, using linear and nonlinear functional connectivity measures together offers a complementary assessment of global dynamics: WPLI for rhythmic coupling and WSMI for arrhythmic, nonlinear information exchange across EEG electrodes.

Neural dynamics of PA distinguishing meditation from control

To determine whether these theoretically motivated neural signatures contain relevant information for distinguishing meditation from counting between the TM and control groups, we performed a multivariate Random Forest (RF) classification. The RF classifier trained on meditation and counting EEG trials achieved an overall precision of 65%, corresponding to a balanced accuracy of 65% (Figure 3A). Meditators were correctly identified in 67% of cases, while controls were correctly classified in 62% of cases. Misclassifications were distributed so that 33% of the meditators were labeled as controls and 38% of the controls were labeled as meditators.

These results indicate that, when comparing meditation with counting, the selected EEG neural markers contained sufficient information to distinguish practitioners from controls with robust reliability, with meditators showing higher classification consistency compared with controls. These findings suggest

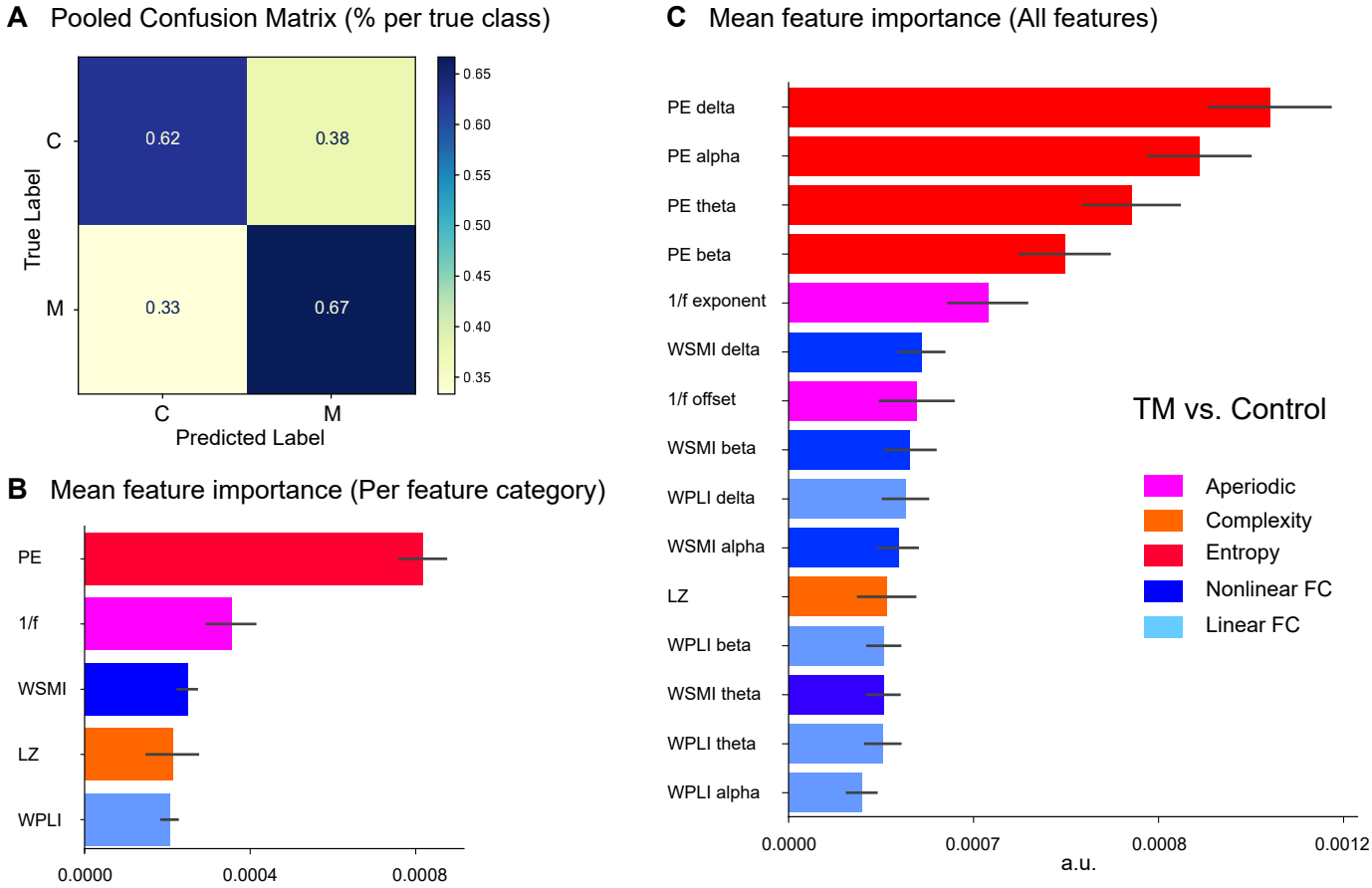

Figure 3: Multivariate Random Forest (RF) classification contrasting meditation (TM) and counting (control). **(A)** Pooled confusion matrix showing classification performance across 100 outer cross-validation repetitions (i.e., percent of true class samples correctly/incorrectly labeled). **(B)** Mean feature importance aggregated by feature category, averaged across repetitions. Single-electrode features: Permutation entropy (PE; in red), Aperiodic activity (1/f; in pink), Lempel-Ziv complexity (LZ; in orange). Functional connectivity features (between-electrodes): Nonlinear functional connectivity computed with weighted symbolic mutual information (WSMI; blue), and Linear functional connectivity computed with weighted phase-lag index (WPLI; light blue). **(C)** Mean feature importance (in arbitrary units; a.u.) at the level of individual features, color-coded by feature category (Entropy: PE in delta, theta, alpha and beta bands; Aperiodic activity: exponent and offset; Complexity: LZ, Linear functional connectivity: WPLI in delta, theta, alpha and beta bands; and Nonlinear Functional Connectivity: WSMI in delta, theta, alpha and beta bands). Error bars denote the standard error of the mean (S.E.M.) across repetitions. Together, the results highlight the predominance of temporal entropy measures (i.e., PE) in driving group separability, followed by aperiodic parameters and, to a lesser extent, functional connectivity and complexity features.

that the meditation condition, in which meditators exhibited a higher phenomenology of PA compared to the control group, is associated with a more distinctive neural signature.

Feature of PA distinguishing meditation from control

To identify the contribution of each neural marker in separating meditation from counting (control) in more detail, we ranked the neural markers by their classification relevance. Inspection of feature importance indicated that PE contributed most strongly to group classification, with the highest mean values observed in the delta, theta, and alpha frequency bands. These were followed by PE beta, which also showed above-average importance. The exponent and offset of the aperiodic spectral activity provided intermediate contributions, while the nonlinear functional connectivity measure WSMI and the linear functional connectivity measure WPLI across the delta, theta, alpha, and beta bands, as well as LZ complexity, displayed relatively lower importance. Overall, the temporal entropy features accounted for the majority of discriminative power, with spectral slope and nonlinear functional connectivity measures providing more modest contributions.

PE neural markers consistently outperformed all other categories, highlighting the information diversity of temporal signals on multiple scales as the most reliable discriminator of group membership in this task context. This finding is consistent with previous evidence that meditation practice is associated with increased entropy and dynamical richness of neural activity, reflecting a broadened repertoire of brain microstates (Vivot et al., 2020). The secondary contribution of the spectral slope parameters (exponent and offset) suggests that alterations in the aperiodic 1/f background also carry meaningful information to distinguish meditation from counting. This result is consistent with reports linking contemplative states with shifts in the cortical excitation-inhibition balance (Colombo et al., 2019; Rodriguez-Larios et al., 2021). Taken together, these findings suggest that the most robust neural signatures of meditation dur-

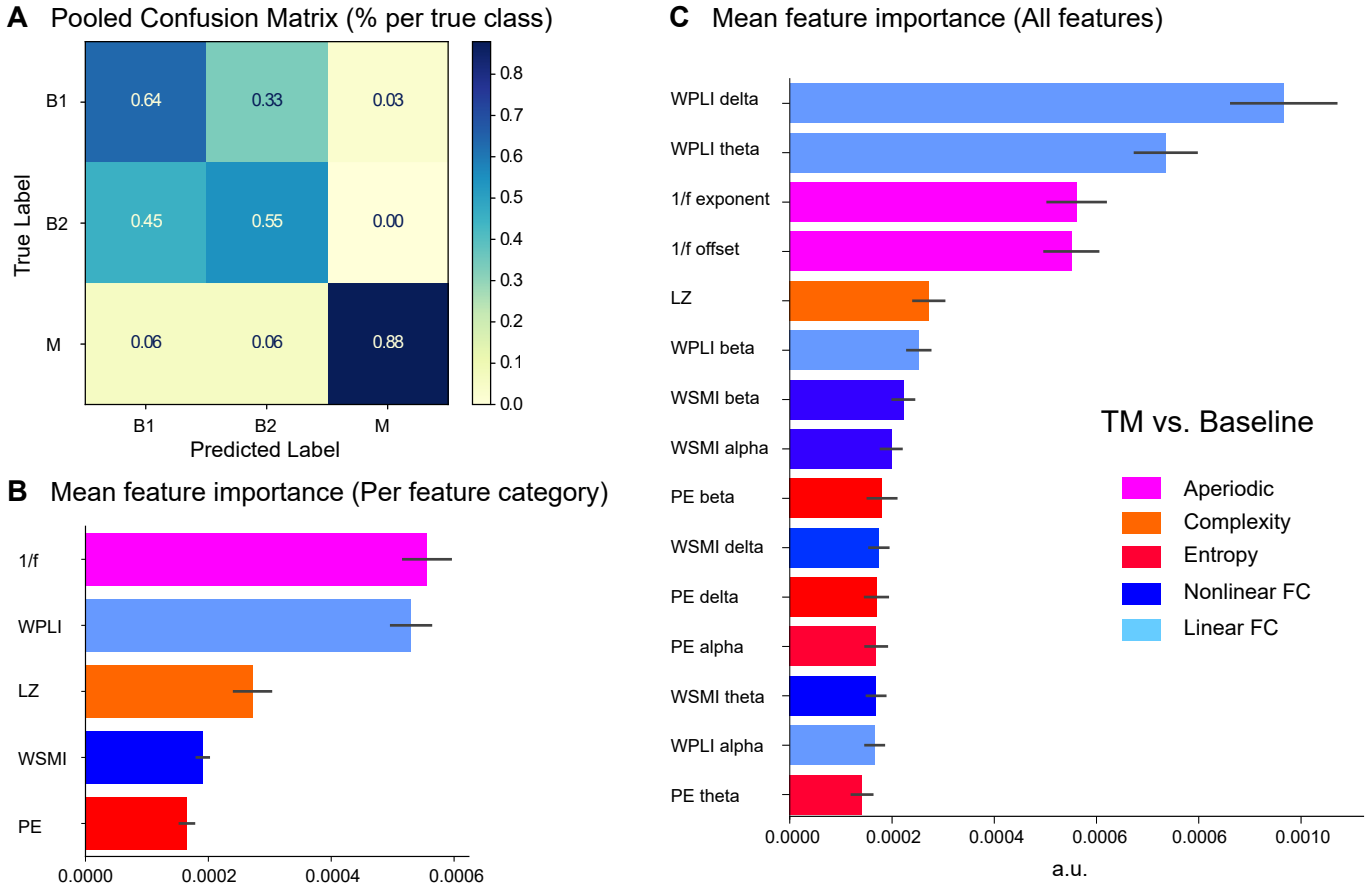

Figure 4: Multivariate Random Forest (RF) contrasting meditation (TM) from baselines (B1 and B2). **(A)** Pooled confusion matrix showing classification performance across 100 outer cross-validation repetitions (i.e., percent of true class samples correctly/incorrectly labeled). **(B)** Mean feature importance aggregated by feature category, averaged across repetitions. Single-electrode features: Permutation entropy (PE; in red), Aperiodic activity (1/f; in pink), Lempel-Ziv complexity (LZ; in orange). Functional connectivity features (between-electrodes): Nonlinear functional connectivity computed with weighted symbolic mutual information (WSMI; blue), and Linear functional connectivity computed with weighted phase-lag index (WPLI; light blue). **(C)** Mean feature importance (in arbitrary units; a.u.) at the level of individual features, color-coded by feature category (Entropy: PE in delta, theta, alpha and beta bands; Aperiodic activity: exponent and offset; Complexity: LZ, Linear functional connectivity: WPLI in delta, theta, alpha and beta bands; and Nonlinear Functional Connectivity: WSMI in delta, theta, alpha and beta bands). Error bars denote the standard error of the mean (S.E.M.) across repetitions. Together, the results highlight the predominance of linear functional connectivity (i.e., WPLI) and aperiodic parameters, as well as complexity features, nonlinear functional connectivity, and entropy, to a lesser extent.

ing the active engagement (meditation versus counting) are expressed in the temporal structure of the EEG dynamics.

Neural dynamics distinguishing meditation from baselines

Having established the more relevant neural signatures that distinguish meditation from counting within the TM group, we investigated whether these neural markers also distinguished meditation from non-meditation periods. To this end, we performed a second RF classification analysis comparing meditation with the baseline periods in the TM group (Figure 4A). The RF classifier achieved a robust separation between meditation and baselines, but struggled to distinguish between baseline 1 (B1) and baseline 2 (B2) (Figure 4A). Meditation epochs were correctly identified with 88% sensitivity, with only 12% misclassified as baseline. By contrast, the classification of baselines was more ambiguous. B1 trials were split between correct classification (64%) and misclassification as B2 (33%), while B2 was correctly classified in 55% of cases but mislabeled as B1 in 45%.

Feature relevance distinguishing meditation from baselines

To quantify the contribution of each neural marker to classification performance between TM and baselines, we ranked the neural features by their relative importance (Figure 4B). Examination of these ranks indicated that linear functional connectivity in the low-frequency ranges, i.e., WPLI in the delta and theta bands, accounted for the most significant amount of discriminative power (Figure 4C). The neural markers of aperiodic activity (exponent and offset) followed with intermediate importance, with LZ complexity contributing at a comparable but slightly lower level. By contrast, the nonlinear connectivity measures WSMI and PE exhibited comparatively modest contributions. In sum, linear functional connectivity in the lower frequency bands dominated the classification analysis, aperiodic spectral parameters provided secondary relevance, and sig-

nal entropy and complexity measures added only limited incremental information. Taken together, the strong sensitivity in detecting meditation trials indicates that the meditation period engages a distinctive neural pattern that reliably diverges from both baselines. By contrast, the difficulty in separating B1 from B2 suggests the EEG of meditators at rest is highly comparable before and after meditation. These results suggest a negligible carry-over effect after TM, highlighting the specificity and transcience of PA.

Neural dynamics distinguishing control from baselines

After identifying the more relevant neural markers for distinguishing meditation from rest in the TM group, we evaluated how well these features separated counting from the two resting baselines in the control group (Figure 5A). The RF classifier achieved a clear separation across conditions (Figure 5A). Counting epochs were correctly classified in 84% of cases, with only limited spillover into baseline labels (12% in B1; 3% in B2). Similarly, baselines were also well classified: B1 was correctly classified in 84%) of trials (16% mislabeled B2), and B2 was correctly classified in 81% of trials (19% mislabeled as B1). Notably, no baseline segments were confused with counting.

Feature relevance distinguishing controls from baselines

Similarly to the previous sections, we ranked features by classification relevance to quantify their relative contributions (Figure 5B,C). The aperiodic spectral exponent emerged as the strongest contributor, followed by linear functional connectivity in the lowest frequency band (WPLI delta), the aperiodic offset, and WPLI theta. PE in the delta and theta ranges, as well as remaining connectivity features, provided comparatively lower contributions. Taken together, these findings demonstrate that the counting task elicits a robust EEG signature distinct from rest, primarily characterized by broadband spectral parameters and low-frequency linear functional connectivity. Crucially, the ability to differentiate between B1 and B2 indicates detectable carryover effects from task engagement to subsequent rest, suggesting that resting activity is not merely a return to baseline levels before task engagement in the control (counting) group.

DISCUSSION

This study utilized a large and rigorously controlled sample, comprising 33 experienced TM practitioners with carefully age- and sex-matched controls. To our knowledge, this is the most extensive and systematically controlled neurophenomenological study of PA to date, allowing us to distinguish neural signatures of PA from potential demographic confounds. Methodologically, we advanced the field by employing Temporal Experience Tracing (TET) to study PA. We demonstrated that TM practitioners reliably report greater intensity and variability of PA, independent of years of practice, supporting the principle of automatic self-transcendence. Our large-scale neural screening and multivariate classification analyses revealed a conceptual double dissociation: relative to ordinary cognition in controls, PA is best characterized by increased entropy and scale-free neural dynamics, whereas relative to the meditators' own baseline, PA is marked instead by enhanced low-frequency functional connectivity. In other words, PA appears as a state that is both broader and more variable than ordinary cognition, yet also more stabilized and coherent than resting baselines. Importantly, TM showed no carry-over effects, unlike controls whose task induced residual changes, highlighting the specificity and transience of PA.

Towards a neurophenomenology of minimal phenomenal experiences

Our findings can be situated within the broader theoretical discourse on minimal phenomenal experience (MPE) as articulated by Metzinger (2020). According to this framework, MPEs represent consciousness stripped of its ordinary structural scaffolds (i.e., selfhood, temporality, spatiality) while retaining tonic alertness. PA, as reported by practitioners of TM, closely exemplifies this condition: an episode of wakefulness largely devoid of representational content, intentionally cultivated through an effortless, standardized practice.

The neurophenomenological signatures of PA uncovered in this study were characterized by increased temporal entropy and aperiodic dynamics relative to ordinary cognition, as well as stable slow-frequency phase coherence relative to rest, mapping well onto the hypothesized architecture of MPE. Modulations in the temporal entropy of the EEG signals suggest an expanded, content-reduced repertoire of neural microstates, consistent with a form of alert presence that lacks specific intentional objects. At the same time, changes in low-frequency phase coherence provide a potential substrate for maintaining a wakeful but content-reduced mode of awareness. Notably, the absence of carry-over effects in TM highlights the transience and state-specificity of PA, distinguishing it from potential trait-like effects such as drowsiness or boredom that counting during 30 minutes might have elicited in the controls.

Furthermore, our findings align with an expanding literature demonstrating that jointly acquiring phenomenological reports and neural recordings enhances the characterization of the neural dynamics underlying complex conscious states (Ganesan et al., 2024; Lewis-Healey et al., 2024b; Lutz, 2002; Olivares et al., 2015; Potash et al., 2025; Timmermann et al., 2023; Varela, 1996). While conventional Likert scales are valuable for coarsely characterizing subjective experience (Lanfranco et al., 2021), they are inherently static, temporally sparse, prone to ceiling or floor effects, as well as recall compression, limitations that can obscure the fine-grained structure of experience. In contrast, the TET approach used here yielded subject-specific, high-resolution trajectories that captured temporal fluctuations within each subject during the experience of pure awareness.

It is worth noticing that while TET provided fine-grained phenomenological trajectories, it necessarily relied on retrospective reporting. In the case of TM, this was a methodological requirement: introducing the dimensions of the TET beforehand would have imposed a cognitive or metacognitive load, directly undermining the effortless quality essential for TM and

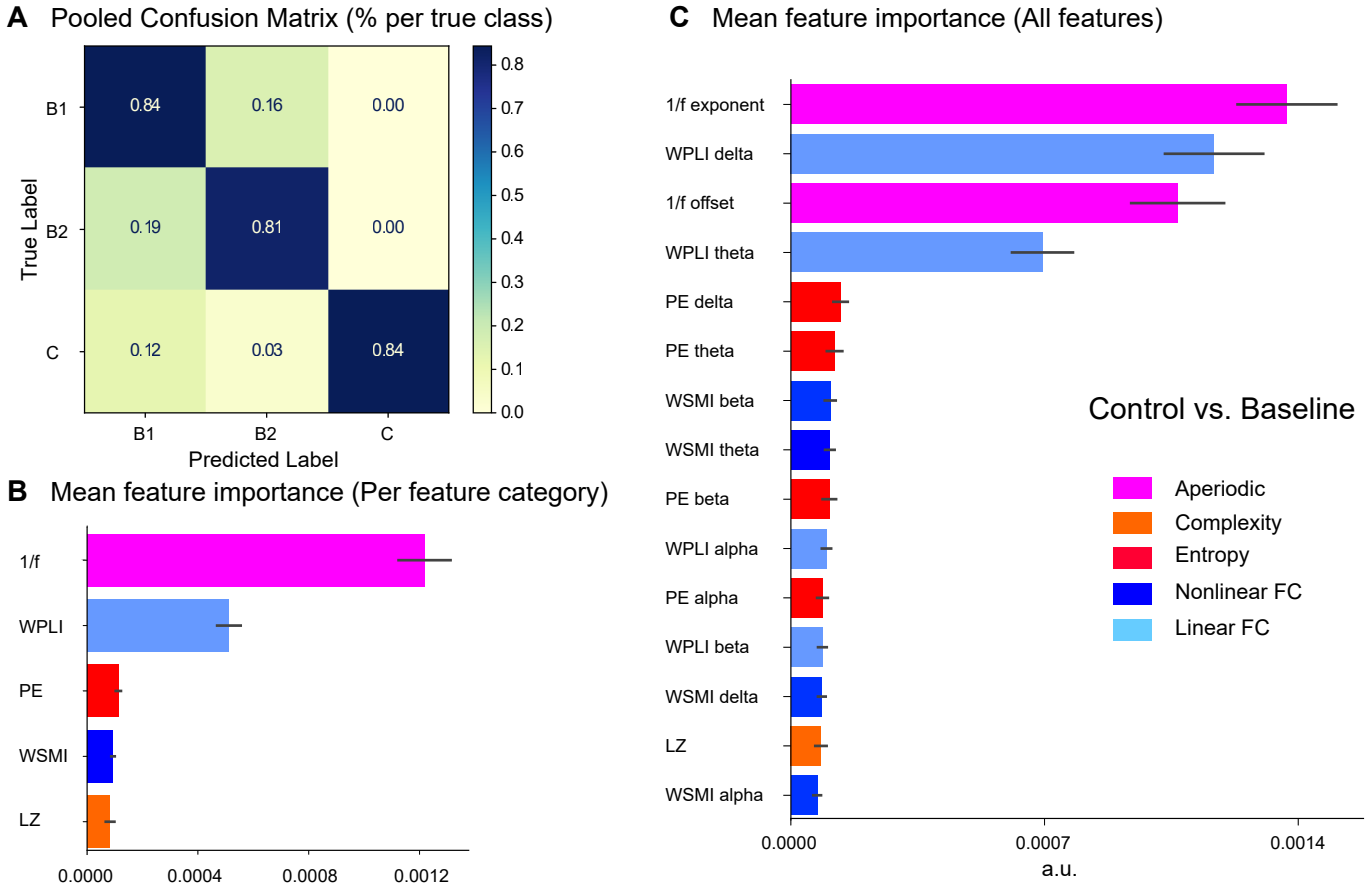

Figure 5: Multivariate Random Forest (RF) contrasting control (counting) from baselines (B1 and B2). **(A)** Pooled confusion matrix showing classification performance across 100 outer cross-validation repetitions (i.e., percent of true class samples correctly/incorrectly labeled). **(B)** Mean feature importance aggregated by feature category, averaged across repetitions. Single-electrode features: Permutation entropy (PE; in red), Aperiodic activity (1/f; in pink), Lempel-Ziv complexity (LZ; in orange). Functional connectivity features (between-electrodes): Nonlinear functional connectivity computed with weighted symbolic mutual information (WSMI; blue), and Linear functional connectivity computed with weighted phase-lag index (WPLI; light blue). **(C)** Mean feature importance (in arbitrary units; a.u.) at the level of individual features, color-coded by feature category (Entropy: PE in delta, theta, alpha and beta bands; Aperiodic activity: exponent and offset; Complexity: LZ, Linear functional connectivity: WPLI in delta, theta, alpha and beta bands; and Nonlinear Functional Connectivity: WSMI in delta, theta, alpha and beta bands). Error bars denote the standard error of the mean (S.E.M.) across repetitions. Together, the results highlight the predominance of linear functional connectivity (i.e., WPLI) followed by aperiodic parameters and, to a lesser extent, nonlinear functional connectivity and entropy/complexity features.

generating pure awareness. Finally, it must be considered that control participants, unlike TM practitioners, may lack familiarity with the experiential profile of pure awareness, which could potentially introduce demand-characteristic effects in their reports.

Accordingly, future work on the neurophenomenology of minimal phenomenal experiences should prioritize comprehensive, time-resolved phenomenological methods, such as TET, to leverage neural classifiers more effectively and to recover the richness and temporal organization of subjective experience that static scales systematically miss. Looking forward, future studies could broaden the scope of TET by incorporating additional phenomenological dimensions of PA, such as degrees of bodily awareness, affective tone, or selfhood, thereby enriching the neurophenomenological profile of this state. Moreover, comparing TM with other contemplative traditions that explicitly report PA, such as Dzogchen or Mahamudra practices, would enable testing the generalizability of our findings across cultural contexts.

Functional connectivity results and previous TM literature

Our results revealed that nonlinear functional connectivity (WSMI) provided greater discriminative power than linear phase coherence measure (WPLI) when separating TM from controls. This suggests that PA engages complex, arrhythmic information sharing across brain regions, rather than a predominance of stable oscillatory coupling. Such nonlinear dynamics capture non-proportional dependencies between signals that go beyond simple phase-locking, aligning with prior evidence that nonlinear information exchange is crucial for differentiating conscious states and contents (Canales-Johnson et al., 2020b; Imperatori et al., 2019; King et al., 2013; Potash et al., 2025; Sitt et al., 2014; Vinck et al., 2023). Interestingly, this stands in contrast to earlier studies reporting increased alpha coherence as a hallmark of TM (Travis, 2001; Travis et al., 2010).

Our multivariate screening instead places alpha phase coherence among the least informative features. One likely reason is methodological: traditional coherence is highly sensitive to volume conduction, whereas WPLI explicitly controls for spurious zero-lag correlations (Vinck et al., 2011). A second issue arises with the interpretation of alpha coherence as a signature of inter-areal communication or integration, as recent evidence has shown that coherence is a consequence rather than the cause of inter-areal communication (Schneider et al., 2021; Vinck et al., 2025, 2023). However, phase coherence does becomes more relevant when distinguishing TM from baseline, where low-frequency WPLI supports state stabilization, although primarily in the delta and theta bands. Together, these observations suggest that nonlinear functional connectivity may capture the transient aspects of PA relative to ordinary cognition. In contrast, linear connectivity reflects the stability of PA relative to its resting state.

This reinterpretation offers a significant conceptual advancement for the neuroscience of TM. Previous studies have reported increased alpha coherence as a defining neural signature of TM, linking it to heightened integration and restful alertness. Our results build on this foundation but reframe it within a modern information-theoretic perspective. By contrasting linear and nonlinear functional connectivity measures, we demonstrate that the neural signatures of pure awareness are not limited to oscillatory phase-locking in a single frequency band, but encompass a broader shift toward nonlinear connectivity measures and single-electrode entropy measures. In this view, alpha coherence may capture a surface-level manifestation of PA, while the underlying mechanism involves deeper, more complex forms of information sharing that extend beyond rhythmic synchronization. This synthesis reconciles the classical TM literature with contemporary approaches, positioning information-theoretic measures as a more principled and sensitive index of the state of pure awareness.

Conclusion

Overall, this study provides the most comprehensive neurophenomenological characterization to date of PA, a paradigmatic case of minimal phenomenal experience induced through TM. By combining a large, rigorously matched sample with temporally resolved phenomenological reports and a systematic screening of theoretically motivated neural markers, we were able to distill the distinctive neural architecture of PA. Finally, it significantly expands the neurophysiological characterization of TM, which can inform future studies on well-being and the clinical population.

METHODS

Participants

Meditators and controls were male and female, aged between 18 and 50 years. Participants with no chronic mental health, sleep-related, or neurological medical problems were included in the study. In the Transcendental Meditation (TM) group (N = 33; 21 male; M = 40.3 years old, SD = 6.2), we selected participants with a minimum of 4 years of regular meditation practice (twice a day, 20 minutes per session; M = 12.9 years of practice; SD = 7.7). The Control group (C) included participants who had not practiced TM before (N = 33; 21 male; M = 38,9 years old; SD = 7.5). To control for potential age and sex-related differences between groups, we individually matched controls to meditators by sex and age (±3 years). Meditators were recruited by the David Lynch Foundation UK (DLF UK) in collaboration with the Maharishi Foundation from all over the United Kingdom. Healthy controls were recruited through the University of Cambridge online recruitment system. All participants signed an informed consent, and the Cambridge Psychology Research Ethics Committee approved the experimental protocol.

Temporal experience tracing (TET)

TET has previously been used to study the phenomenological dynamics of different meditation styles (Jachs et al., 2022; Lewis-Healey et al., 2024b), the temporal dynamics of stress in autism (Gernert et al., 2024), chronic pain (Niedernhuber et al., 2024), and the neural and experience dynamics of medium- and high-dose DMT (Lewis-Healey et al., 2024a). With the TET methodology, the dimensions of subjective experience most relevant to the study phenomenon are identified. These dimensions are subcomponents of the contents of consciousness relating to the affective, attentional, or motivational aspects of experience. After completing a session on the particular phenomenon under study, participants complete a retrospective trace of the intensity of each specific dimension. Below is the definition of pure awareness, which the participants were asked to trace as depicted in Figure 1B:

Pure awareness – To what extent do you think that you experience pure awareness during meditation/counting?

- Higher level of pure awareness = an experience free from content defining everyday working experiences (e.g., internal thoughts, perception of the external world), absence of time, space, and body sensation.

- Lower level of pure awareness = normal waking consciousness with a variety of internal and external content.

Experimental design and procedure

Transcendental Meditation. In the meditation session, participants began with a baseline condition of 10 minutes (baseline 1), during which they were instructed to keep their eyes closed without reciting the mantra. The participants were then instructed to start mentally repeating the mantra with their eyes closed and perform 30 minutes of TM (meditation condition). After meditation (or counting), the participants were introduced to the process of completing the TET reports, accompanied by an explanation of the phenomenological dimension of pure awareness (PA). After completion of the TETs, the participants performed a second baseline condition of 10 minutes (baseline 2), in which they were again instructed to keep their eyes closed without repeating the mantra (Figure 1A). The experimenter indicated the beginning and end of each condition.

Non-meditative control task. A control task was developed to involve participants in cognitive processes different from meditation but with similar automaticity and decreased cognitive control as during mantra repetition performed by the TM group. The control task was a counting task, in which participants were instructed to count in increments of 1 with their eyes closed, in a self-paced manner, and to restart the count at any time if they lost track. The participants completed the control task after 30 minutes (Figure 1A). Counting was preceded and followed by a baseline condition of 10 minutes (B1 and B2, respectively) in which participants had no instruction except to keep their eyes closed and stay awake (Figure 1A). The experimenter indicated the beginning and end of each condition.

TET data preprocessing

TET data were converted to vectors using a semi-automatic custom MATLAB script, as employed in previous studies (Gernert et al., 2024; Jachs et al., 2022; Lewis-Healey et al., 2024a,b; Niedernhuber et al., 2024). The script converted the image coordinates of the TET data to graph coordinates, based on the orientation of the x-axis and y-axis. The phenomenological dimension of PA was manually checked to ensure the vectors were similar to the TET traces themselves. After conversion, the phenomenological dimension was concatenated in a column-wise fashion, creating a 1xN TET matrix for each condition per participant, where N is the corresponding number of data points generated for that session.

TET data analysis

Next, we performed two analyses on the generated PA time series to (i) compare the maximum PA value across groups, and (ii) compare the temporal variability of PA within participants.

Maximum PA value. For each participant, we identified the global maximum of their PA time course. To obtain a robust estimate of this peak, we extracted a fixed-length window corresponding to 1 minute in time (15,000 samples) centered on the maximum. The mean PA value within this peak-centered window was then computed, yielding a peak-window average PA score per participant. Group differences were statistically assessed using Welch's independent-samples *t*-test, chosen because it provides reliable inference under unequal group sizes and does not assume equal population variances.

Within time course variability. To quantify temporal variability in PA, we computed the standard deviation of the PA time series across all time points for each participant, yielding a single variability index per participant. Group comparisons of these variability indices were again carried out using Welch's *t*-test for the same reasons outlined above.

For the group comparison of PA values, we employed a non-parametric framework to address the multiple-comparisons problem, with temporal clustering implemented in FieldTrip (Maris et al., 2007). The process requires the calculation of t values at each temporal point followed by clustering of adjacent t values, which was repeated 1000 times, with recombination and randomized resampling before each repetition. This Monte Carlo method generated a non-parametric estimate of the p-value representing the statistical significance of the originally identified cluster. The cluster-level t value was calculated as the sum of the individual t values at the points within the cluster. Cluster threshold: 0.05

EEG data preprocessing

EEG signals were recorded using a 128-channel HydroCel Geodesic Sensor Net (GSN 128 1.0) and a GES400 Electrical Geodesics amplifier, sampled at 250 Hz with NetStation software (EGI, USA). During recording and analysis, the average across electrodes was used as the reference electrode. Two bipolar derivations were designed to monitor vertical and horizontal ocular movements. Eye movement contamination (blinks were rare as eyes were closed, vertical and horizontal saccades or slow movements were also infrequent), and muscle artifacts (i.e., cardiac and neck movements) were removed from the data before further processing using an independent component analysis (ICA) (Delorme and Makeig, 2004). All conditions yielded at least 96% of artifact-free trials. Trials that contained voltage fluctuations exceeding ±200 μV and transients exceeding ±100 μV were excluded. No low-pass or high-pass filtering was performed during the pre-processing stage. The EEGLAB Matlab toolbox was used for data pre-processing and pruning (Delorme and Makeig, 2004).

Single-electrode EEG neural measures

Aperiodic exponent and offset. We quantified the aperiodic component of the EEG power spectrum—often termed '1/f' or 'scale-free' activity by parameterizing the spectrum into a broadband (aperiodic) background and narrowband (periodic) oscillatory peaks (Donoghue et al., 2020b). Following established approaches (i.e., FOOOF), the aperiodic background was modeled in log–log space as a linear function of frequency, optionally with a knee. At the same time, oscillatory peaks were fit as Gaussians and removed before estimating broadband parameters. Two parameters summarize the aperiodic background: (i) the exponent (slope), which captures how power decays with frequency (steeper, more negative slopes indicate relatively greater low-frequency power), and (ii) the offset (intercept), which reflects the overall broadband power level (a vertical shift of the spectrum) independent of narrowband oscillations. These parameters were extracted from artifact-cleaned spectra over predefined frequency ranges, excluding line-noise bands, and used as features in subsequent analyses. Previous work has shown that separating aperiodic from periodic activity improves the interpretability of spectral measures and mitigates band-ratio confounds. The exponent has been linked to age- and state-related changes, and in modeling work, to shifts in the synaptic excitation-inhibition balance, while the offset indexes broadband power differences between conditions or individuals (Ameen et al., 2024a,b; Donoghue et al., 2020a,b; Voytek et al., 2015).

Lempel-Ziv complexity (LZ). LZ complexity (Lempel and Ziv, 1976; Ziv and Lempel, 1978) is a robust measure that has been used extensively in the cognitive neuroscience of consciousness (Atad et al., 2025; Casali et al., 2013; Lewis-Healey

et al., 2024b; Pascovich et al., 2022; Schartner et al., 2015, 2017). In brief, the electrophysiological signal is first binarized by a median split, where samples above the median are coded as 1 and those below as 0 (Figure 2C). A sequential parsing algorithm then traverses the binary string to detect previously unseen substrings, thereby assembling a 'dictionary' of patterns. The number of unique entries serves as the raw complexity estimate, which we normalize by dividing by the complexity obtained from a randomly shuffled version of the same data. We computed LZ separately for each channel in the broadband signal (0.5-40 Hz), and the resulting values were passed to the classification analyses (see below).

Permutation entropy (PE). PE (Bandt and Pompe, 2002) is a robust method for comparing electrophysiological signals between states of consciousness (Frohlich et al., 2022; King et al., 2013; Sitt et al., 2014) and distinguishing between different types of behavior (e.g., periodic, chaotic, or random). One key feature of the method is its robustness to low signal-to-noise ratios compared to other similar methods (Bandt and Pompe, 2002). The basic principle of this method is to transform the time signal into a sequence of symbols before estimating entropy (Figure 2D). The transformation is made by considering consecutive sub-vectors of the signal of size n. These sub-vectors can be made of either consecutive elements or of elements separated by τ samples (where τ is an integer). The τ parameter thus defines a broad frequency-specific window of sensitivity for this measure. Since using τ values larger than 1 induces aliasing effects, the signal was low-pass filtered before PE calculation to maintain the frequency-band specificity of each measure (Sitt et al., 2014). Each sub-vector of length n is associated with a unique symbol, based solely on the ordering of its n signal amplitudes. Given the parameter n, there are n! possible vectors, corresponding to distinct categories of signal variations. After the symbolic transform, the probability of each symbol is estimated, and PE is computed by applying Shannon's classical formula to the probability distribution of the symbols. In our case, we computed PE for every electrode and in every trial, using parameters n = 3 and τ = [64 ms (~1-3 Hz), 32 ms (~4-7 Hz), 16 ms (~8-14 Hz), and 8 ms (~15-29 Hz)], corresponding to PE delta, PE theta, PE alpha, and PE beta, respectively. The resulting values were passed to the classification analyses (see below).

Between-electrode EEG measures: functional connectivity

Weighted phase lag index (WPLI). The WPLI (Figure 2D), a widely used measure of phase coherence in EEG data (Canales-Johnson et al., 2021b,c; Imperatori et al., 2019; Olivares et al., 2025; Potash et al., 2025; Vinck et al., 2011), measures the extent to which phase angle differences between two time series $x(t)$ and $y(t)$ are distributed towards positive or negative parts of the imaginary axis in the complex plane (similar to the PLI). The underlying idea is that volume-conducted activity accounts for the highest proportion of detected 0° or 180° phase differences between signals. Therefore, only phase angle distributions that predominantly fall on the positive or negative side are considered to obtain a conservative estimate for real, non-volume-conducted activity. The PLI is the absolute value of the sum of the signs of the imaginary part of the complex cross-spectral density Sxy of two real-valued signals $x(t)$ and $y(t)$ at a time point or trial t. While PLI is already insensitive to zero-lag interactions, the weighted Phase-Lag Index (Vinck et al., 2011) further addresses potential confounds caused by volume conduction, by scaling contributions of angle differences according to their distance from the real axis, as almost 'almost-zero-lag' interactions are considered as noise affecting real zero-lag interactions:

$$\mathrm{WPLI} = \frac{\left|\sum_{t=1}^{n} \left|\mathrm{Im}(S_{xy,t})\right| \, \mathrm{sgn}(\mathrm{Im}(S_{xy,t}))\right|}{\sum_{t=1}^{n} \left|\mathrm{Im}(S_{xy,t})\right|}$$

The WPLI is based only on the imaginary component of the cross-spectrum, and thus implies robustness to noise compared to coherence, as uncorrelated noise sources cause an increase in signal power. WPLI was computed using the Fieldtrip toolbox (multi-taper method, fast Fourier transform, single Hanning taper, 0.5 Hz frequency resolution). For each frequency range (i.e., 1-3 Hz, 4-7 Hz, 8-14 Hz, 15-29 Hz; corresponding to WPLI delta, WPLI theta, WPLI alpha, and WPLI beta, respectively) and epoch. The resulting values per pair of electrodes were passed to the classification analyses.

Weighted symbolic mutual information (WSMI). We quantified the information sharing between electrodes by calculating the weighted symbolic mutual information (WSMI). This index estimates the extent to which two EEG signals exhibit non-random joint fluctuations (Figure 2F). WSMI has been proposed as a measure of neural information sharing in the cognitive neuroscience of consciousness literature (Canales-Johnson et al., 2021c; Imperatori et al., 2019; King et al., 2013; Olivares et al., 2025; Potash et al., 2025; Sitt et al., 2014) and has three main advantages. First, it is a rapid and robust estimate of the signals' entropy (i.e., the statistical uncertainty in signal patterns), as it reduces the signal's length (i.e., its dimensionality) by looking for qualitative or 'symbolic' patterns of increase or decrease in the signal. Second, it efficiently detects highly nonlinear coupling between signals (i.e., non-proportional relationships between signals), as it has been shown with simulated data (Imperatori et al., 2019) and experimental EEG, electrocorticography (ECoG), and local field potentials (LFP) data (Canales-Johnson et al., 2020a,b; Imperatori et al., 2019; King et al., 2013; Olivares et al., 2025; Potash et al., 2025; Sitt et al., 2014). Third, it rejects spurious correlations between signals that share a common source, thus prioritizing non-trivial pairs of symbols.

We calculated WSMI between each pair of electrodes, for each trial, after transforming the EEG signal into a sequence of discrete symbols defined by ordering of k time samples with a temporal separation between each pair (or τ). The symbolic transformation is determined by a fixed symbol size (κ = 3, i.e., 3 samples represent a symbol) and the variable τ between samples (temporal distance between samples), thus determining the frequency range in which WSMI is estimated (King et al., 2013). The frequency specificity f of WSMI is related to k and τ as follows:

$$f = fs/(\tau * \kappa)$$

With a fs = 250 Hz, as per the above formula, and a k size of 3, τ = 64 ms is sensitivity to frequencies ~1-3 Hz, τ = 32 ms (~4-7 Hz), τ = 16 ms (~8-14 Hz), and τ = 8 ms (~15-29 Hz), corresponding to WSMI delta, WSMI theta, WSMI alpha, and WSMI beta, respectively. The weights were added to discard the conjunction of identical and opposite-sign symbols, which indicate spurious correlations due to volume conduction. The WSMI (in bits) can be calculated as:

$$\mathrm{WSMI}(\hat{X}, \hat{Y}) = \frac{1}{log(k!)} \sum_{\hat{x} \epsilon \hat{X}} \sum_{\hat{y} \epsilon \hat{Y}} w(\hat{x}, \hat{y}) p(\hat{x}, \hat{y}) log \frac{p(\hat{x}, \hat{y})}{p(\hat{x}) p(\hat{y})}$$

Where x and y are all symbols present in signals X and Y respectively, $w(x, y)$ is the weight matrix, and $p(x, y)$ is the joint probability of co-occurrence of symbol x in signal X and symbol y in signal Y. Finally, $p(x)$ and $p(y)$ are the probabilities of those symbols in each signal, and $K!$ is the number of symbols used to normalize the mutual information (MI) by the signal's maximal entropy. The resulting values for each pair of electrodes were then passed to the classification analyses.

Implementation and evaluation of classifiers for neural markers

Model and Training. A multivariate Random Forest (RF) classifier was implemented within a scikit-learn pipeline consisting of feature standardization followed by classification. The feature set included spectral (aperiodic exponent and offset), functional connectivity (WPLI and WSMI), entropy (PE) and complexity (LZ) measures. The model's hyperparameters (number of trees, maximum depth, split criterion, feature subsampling strategy, minimum samples per leaf, and bootstrap setting) were optimized using an exhaustive grid search. To prevent information leakage, subject's identity was used as the grouping variable in all cross-validation. Model training and evaluation followed a nested cross-validation scheme: the outer loop employed five-fold group cross-validation to estimate generalization, while the inner loop performed five-fold cross-validation on the training split to select hyperparameters. To reduce variance from any single partitioning, the outer loop was repeated 100 times with permuted fold assignments, and the best estimator from each repetition was retrained on the training fold and evaluated on the corresponding held-out test fold.

Performance metrics. For each repetition, we calculated the overall accuracy, balanced accuracy (to account for class imbalance), and class-specific precision, recall, and F1-scores. Precision was defined as the proportion of true positives among predicted positives, recall as the proportion of true positives among actual positives, and F1 as the harmonic mean of precision and recall. Confusion matrices were constructed to visualize misclassifications patterns. Model performance was summarized across repetitions by reporting median values and variability estimates.

Feature importance. To identify the neural markers contributing most to classification, RF feature importance values were extracted from the best estimator of each repetition. Importance values were analyzed both at the single-feature level and after grouping features by family (i.e., aperiodic, linear functional connectivity, nonlinear functional connectivity, entropy, and complexity) and frequency band. Grouped importance were averaged across repetitions to provide a stable estimate of feature relevance.

Contrasts. Across all analyses, the same RF pipeline was applied; what differed was the subset of participants and conditions used to construct the feature matrix and labels. Three contrasts were defined. First, to test for state-expressed trait differences, we compared meditation epochs in TM practitioners with those in controls (Contrast 1: Meditation vs. Counting [TM vs. Controls]). Second, to isolate state effects within experienced practitioners, we compared meditation and baseline epochs from the same TM participants (Contrast 2: Meditation vs. Baselines within TM). Finally, to establish a benchmark in individuals without training, we compared counting and baseline epochs in the control group (Contrast 3: Counting vs. Baselines within Controls).

Software and analyses

Statistical and signal processing analyses were performed using MATLAB (2023a), Python, and JASP statistical software (open source).

Data Availability

The data and software code supporting this study's findings are available from the corresponding author upon reasonable request, in accordance with the Department of Psychology, University of Cambridge's data sharing policies.

Authorship contribution

Conceptualization and methodology: A.C-J. Investigation and data collection: A.Ch-J., S.V.M., C.P., and A.C-J. Data analysis: M.E., M.D., S.V.M, A.Ch-J., and A.C-J. Visualization: M.E., M.D., S.V.M., and A.C-J. Writing and editing: A.Ch-J, S.V.M, M.E., M.D., C.P., and A.C-J. Supervision: A.C-J. Funding acquisition: A.C-J..

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