Microstate temporal dynamics predict valence but not arousal in tactile stimulation

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***Abstract*—Electroencephalographic (EEG) microstates reflect transient large-scale brain network dynamics, yet it remains unclear whether they encode global brain states or spatially specific sensory processing, and how they relate to subjective experience. In this study, we examined microstate dynamics during spatially distinct vibrotactile stimulation. Linear mixed model analysis was used on the microstate parameters (coverage, mean duration, occurrence rate) to assess effects of condition and stimulation location. In a complementary analysis, behavioural measures (Valence, Arousal) were modelled as dependent variables to test whether microstate dynamics predict subjective experience. Stimulation location significantly modulated microstate coverage and occurrence rate, whereas condition showed no effect, indicating spatially specific rather than global modulation. Mean duration remained unchanged across conditions. Notably, microstate dynamics predicted Valence, but not Arousal. These findings suggest that microstates reflect spatially specific neural processing and encode subjective affective experience, linking large-scale brain dynamics to perception.**

Keywords—Valence, Arousal, EEG, microstates)

I. INTRODUCTION

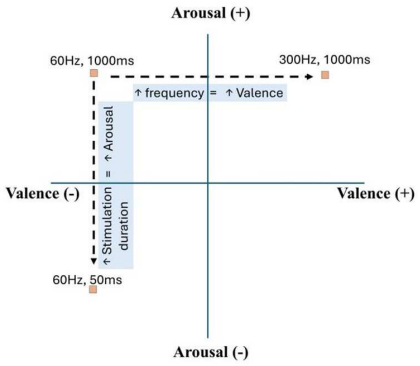
Understanding how the brain dynamically organizes activity across large-scale networks is a central challenge in systems neuroscience. Rather than operating as a static system, the brain continuously transitions between transient, quasi-stable states that reflect coordinated activity across distributed regions. One prominent framework for capturing these dynamics is that of EEG microstates, which describe brief periods (~60–120 ms) of stable scalp topographies thought to represent the momentary activation of large-scale functional networks. Since their introduction by Lehmann et al. [1], [2], microstates have been proposed as the "atoms of thought," providing a temporally precise window into the building blocks of cognition.

A growing body of work has demonstrated that microstate properties—such as coverage, duration, and occurrence rate—are systematically modulated by cognitive demands, perceptual processing, and clinical conditions [3], [4]. These parameters are thought to capture distinct aspects of brain dynamics: duration reflects the temporal stability of network states, whereas coverage and occurrence index their relative dominance and switching behaviour. Converging evidence from simultaneous EEG–fMRI studies further suggests that canonical microstates correspond to activity in large-scale networks such as the default mode, salience, and attentional systems [5], [6]. Despite these advances, a key question remains unresolved: to what extent do microstate dynamics reflect global brain states versus spatially specific, stimulus-driven processing?

In the context of somatosensory stimulation, this question is particularly relevant. Sensory inputs are known to engage spatially localized cortical representations, especially within primary somatosensory cortex [7]–[10]. However, microstates are often interpreted as global network phenomena, raising the possibility that they may either (i) reflect generalized brain responses to stimulation or (ii) encode fine-grained spatial differences in sensory processing. Disentangling these possibilities is critical for understanding the functional specificity of microstate dynamics.

A second, related challenge concerns the relationship between microstates and subjective experience. While prior studies have linked microstate dynamics to broad cognitive and affective processes [11], [12], it remains unclear whether these dynamics merely track external stimulus properties or whether they directly relate to internal perceptual and affective states, such as Valence (degree of pleasantness) and Arousal (degree of emotional activation) [13], [14]. Addressing this requires moving beyond conventional stimulus-driven analyses toward frameworks that explicitly test whether brain dynamics can predict behavioural reports.

The present study addresses these gaps by investigating microstate dynamics in response to spatially distinct somatosensory stimulation, while simultaneously examining



(b)

Fig. 1 representation of stimulus-driven modulation in the valence–arousal space. The horizontal axis denotes valence (negative to positive), and the vertical axis represents arousal (negative to positive). Increasing stimulation frequency (from 60 Hz to 300 Hz at 1000 ms duration) shifts responses toward higher valence and arousal, while reducing stimulation duration (e.g., 60 Hz, 50 ms) is associated with lower arousal and more negative valence. The dashed arrows illustrate the directional influence of frequency and duration on perceived affective states.

TABLE I
STIMULUS SETTINGS USED IN TO EXPERIMENT

Stimulus	Frequency (Hz)	Duration (ms)
Stim 1	300	1000
Stim 2	60	1000
Stim 3	60	50

their relationship to subjective experience. Specifically, we adopt a two-part analytical approach. First, we assess how experimental factors viz. stimulus and stimulation location modulate microstate parameters. Second, we reverse the modelilng framework and treat behavioural variables (Valence and Arousal) as dependent measures, enabling us to evaluate whether microstate dynamics themselves explain variance in subjective experience. The stimuli were chosen from prior studies [15], [16] who have shown that systematic variation of vibrotactile stimulation frequency and duration can engage the participants to induce systematic behavioural variations of Valence and Arousal ratings (see Fig. 1).

We hypothesized that if microstates primarily reflect global brain states, their dynamics would be modulated by condition irrespective of stimulation location. Conversely, if they encode spatially specific processing, modulation should be driven by location-dependent effects. Furthermore, if microstates are functionally relevant for perception, their temporal properties should predict subjective experience, particularly along the Valence dimension.

By integrating experimental manipulation with bidirectional brain–behaviour modelling, this study aims to provide a more comprehensive account of microstate function, linking spatial specificity, temporal dynamics, and subjective experience within a unified framework.

II. Methods

A. Experimental paradigm

Data was collected from 19 right-handed. Ethical approvals were obtained from the institute's ethical committee.

Stimuli were employed across six locations: the index finger, arm, back, stomach, leg and toe. Three stimulation types were delivered across these locations, henceforth referred to as Stim 1, 2 and 3 were deployed across these locations (see Table I). Each condition consisted of 200 trials, organized into two blocks of 100 trials each (see Fig. 2) for the schematic diagram of the paradigm. After each block, Valence and Arousal scales were displayed in the screen and ratings were verbally obtained from the participants.

B. Data pre-processing

A 128-channel EEG system was used. EEG recordings were processed in Python using the MNE-Python framework. Individual electrode coordinates obtained from 3D scans [17] were used to define the montage. Signals were band-pass filtered from 1 to 310 Hz with a second-order Butterworth filter, and 50 Hz line noise (including harmonics) was attenuated using a notch filter. Channels and data segments with excessive noise were identified and excluded through inspection of both the raw signals and their power spectral density.

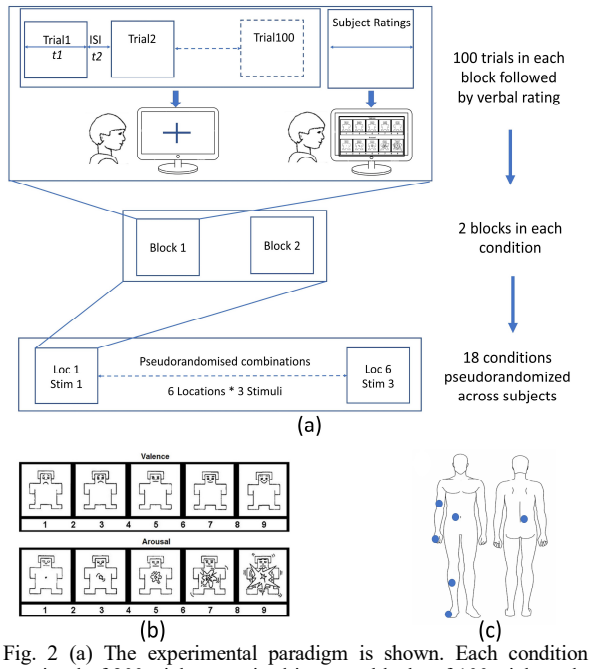


Fig. 2 (a) The experimental paradigm is shown. Each condition consisted of 200 trials, organized into two blocks of 100 trials each. (b) After each block, Valence and Arousal scales were displayed in the screen and ratings were verbally obtained from the participants (c) the locations of stimulation are shown.

Independent component analysis (ICA) was then applied for artifact correction, with EOG and ECG recordings guiding the identification of physiological artifacts. Components reflecting stimulation-related electrical noise were detected via their spectral profiles and removed. The data were subsequently reconstructed and screened again to ensure the removal of any residual artifacts, resulting in the final cleaned dataset. This data was then epoched based on the trigger channels, and the corresponding evoked objects were obtained.

C. Microstates extraction

Grand-average evoked responses from all subjects and conditions were used to derive representative scalp topographies for microstate analysis. For each evoked dataset, the global field power (GFP) was computed as the standard deviation across channels at each time point. Local maxima of the GFP time series were identified using a minimum peak distance constraint to ensure temporal independence of maps.

Topographic maps corresponding to these GFP peaks were extracted and concatenated across all datasets to form a single pool of maps for clustering. This approach ensures that only time points with high signal-to-noise ratio contribute to microstate identification. The resulting dataset consisted of channel-wise topographies (channels × maps), along with their corresponding GFP values, which were retained as weights for subsequent analysis.

D. Microstates clustering and selection

Microstate topographies were identified using a modified k-means clustering algorithm as implemented in *pycrostates*. Clustering was performed across a range of cluster numbers (k = 2–9), with multiple initializations (n = 200) to ensure stability of the solution.

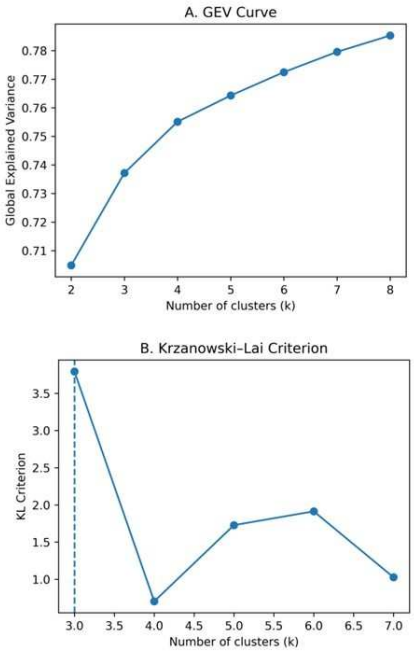


Fig. 3 (a) Global explained variance (GEV) as a function of the number of clusters (k = 2–8). The GEV increases monotonically, with a pronounced rise between k = 2 and k = 4, followed by a gradual plateau, indicating diminishing returns in explained variance for higher k values. (b) Krzanowski–Lai (KL) criterion across cluster solutions. A clear peak is observed at k = 3 (dashed line), suggesting the most parsimonious clustering solution. Beyond this point, KL values decrease and do not exhibit comparable peaks.
Together, these results indicate that while k = 3–4 captures the primary structure of the data, higher values (e.g., k = 5) provide additional but diminishing improvements, supporting the selection of k = 5 as a balance between parsimony and descriptive richness.

To determine the optimal number of microstates, two complementary criteria were employed (see Fig. 3):

- Global Explained Variance (GEV): For each k, the GEV was computed by correlating each map with its best-matching cluster centroid, weighted by GFP. The optimal solution was identified based on the elbow point of the GEV curve.
- Krzanowski–Lai (KL) Criterion: A dispersion-based metric was computed across cluster solutions, and the KL criterion was used to identify the point of maximum curvature in model fit improvement.

Based on these criteria, the number of microstates was selected (k = 5), and a final clustering was performed to obtain the global microstate maps (see Fig. 4).

E. *Backfitting microstates to individual data*

The derived global microstate maps were backfitted to individual subject data using epoched data. Microstate segmentation was performed using a temporal smoothing procedure (factor = 10, half-window size = 30 samples) to reduce spurious rapid transitions. Each time point was assigned to the microstate with the highest spatial correlation.

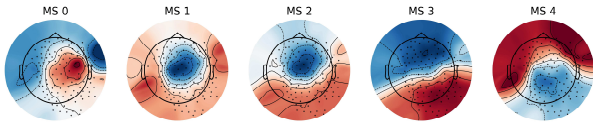


Fig. 4 Representative scalp topographies of the five identified microstates (MS0–MS4). Each map depicts the spatial distribution of normalized EEG potentials across the scalp, with red and blue regions indicating opposite polarities of electrical activity. Black dots represent electrode locations.

F. *Temporal metrices*

For each condition, the following standard microstate metrics were computed (see Fig. 5 for details):

- Coverage: Fraction of the recording time spent in a given microstate.
- Mean Duration: Average length (in milliseconds) of uninterrupted segments of a microstate.
- Occurrence Rate: Frequency at which a microstate appears per second.

Microstate segments were defined based on contiguous label sequences, and durations were computed using the sampling frequency of the recordings.

G. *Transition Probability Analysis*

State transition dynamics were quantified by constructing transition matrices for each subject. The number of transitions between all pairs of microstates was computed and normalized row-wise to obtain transition probabilities. Both individual-level and group-level transition matrices were derived, enabling comparison across experimental conditions.

H. *Statistical Aggregation and Visualization*

Linear mixed-effects models [18], [19] were fitted to account for both fixed effects of experimental variables and random inter-subject variability. Subject was included as a random intercept in all models.
To assess the effect of experimental conditions on microstate parameters, a hierarchical modelling approach was adopted. Separate models were constructed with increasing complexity, beginning with a null model and sequentially adding condition and stimulation location as fixed effects. Model comparisons were performed using likelihood ratio

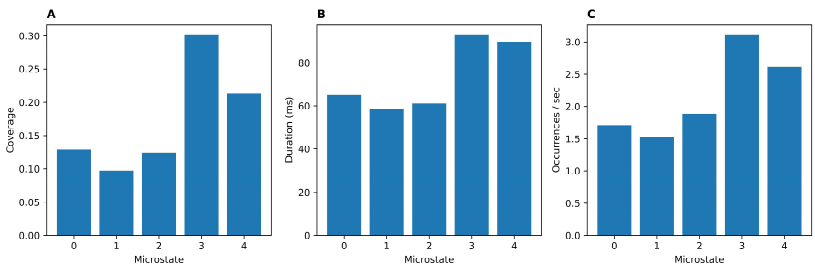


Fig. 5 Microstate temporal parameters: (a) coverage, (a) mean duration, and (c) occurrence rate for MS0–MS4. MS3 shows the highest coverage and occurrence, while duration remains relatively consistent across states.

TABLE II
EFFECT OF EXPERIMENTAL CONDITIONS ON MICROSTATE PARAMETERS

Parameter	Effect Added	χ^2 (df)	p-value
State	Condition	0.00 (5)	1.000
	Location	0.00 (2)	1.000
Coverage	Condition	0.62 (5)	0.987
	Location	6.06 (2)	0.048*
Mean Duration (s)	Condition	0.80 (5)	0.977
	Location	2.00 (2)	0.368
Occurrence (/s)	Condition	2.25 (5)	0.813
	Location	8.16 (2)	0.017*

tests, and improvements in model fit were evaluated using changes in log-likelihood and information criteria.

To examine the relationship between microstate dynamics and subjective experience, a complementary set of models was implemented in which behavioural variables (Valence and Arousal) were treated as dependent measures. In these models, microstate parameters (state, coverage, mean duration, and occurrence rate) were included as predictors. This reversed modelling framework allowed us to test whether temporal properties of microstates explain variance in subjective reports, beyond stimulus-driven effects.

For all analyses, statistical significance was assessed using likelihood ratio tests, with a threshold of $p < 0.05$.

III. RESULTS

A. Optimal number of microstates

The GEV curve showed a monotonic increase with the number of clusters (k = 2–8), with a marked improvement from k = 2 to k = 4 followed by a clear plateau, indicating diminishing returns in explained variance beyond this range (Fig. A). In contrast, the Krzanowski–Lai (KL) criterion exhibited a pronounced peak at k = 3 (Fig. B), suggesting this as the most parsimonious solution.

Taken together, these results indicate that the largest gain in explanatory power occurs within k ≈ 3–4, with only marginal improvements thereafter. Despite the KL criterion favoring k = 3, k = 5 was selected for subsequent analyses. This choice was motivated by the plateauing of the GEV curve beyond k = 4, indicating stable model performance, and the need for finer topographic differentiation, which is commonly reported in the microstate literature. Accordingly, k = 5 was considered an appropriate balance between parsimony and descriptive richness.

B. Temporal properties of global microstates

Following backfitting of the global microstate maps (k = 5), clear differences were observed in the temporal characteristics of individual microstates (see Fig. 5). Microstate 3 emerged as the dominant state, exhibiting the highest coverage (0.302), mean duration (93.21 ms), and occurrence rate (3.12 s^{-1}). Similarly, microstate 4 showed relatively strong engagement, with a coverage of 0.213, a mean duration of 89.67 ms, and an occurrence rate of 2.62 s^{-1}. In contrast, microstates 0, 1, and 2 demonstrated comparatively lower temporal dominance, with coverage values ranging from 0.097 to 0.128, mean durations between 58.30 and 65.23 ms, and occurrence rates between 1.53 and 1.88 s^{-1}.

Furthermore, a clear hierarchy of microstate dynamics was observed. Microstates 3 and 4 exhibited longer durations (approximately 90 ms) and higher coverage, indicating greater temporal stability and dominance. In contrast, microstates 0–2 were shorter in duration (approximately 60 ms) and less prevalent, suggesting more transient and rapidly switching activity. This pattern indicates that brain activity is not evenly distributed across states but is instead dominated by a subset of stable microstates, with the remaining states contributing more briefly.

TABLE III
RELATIONSHIP BETWEEN MICROSTATE DYNAMICS AND BEHAVIOURAL METRICES

Parameter	Effect Added	χ^2 (df)	p-value
Valence	State	0.00 (1)	1.000
	Coverage	0.02 (1)	0.887
	Mean Duration	4.40 (1)	0.036*
	Occurrence	4.17 (1)	0.041*
Arousal	State	0.00 (1)	1.000
	Coverage	2.88 (1)	0.090
	Mean Duration	0.26 (1)	0.610
	Occurrence	1.70 (1)	0.193

C. Statistical analysis

To disentangle the effects of experimental manipulations and subjective experience on microstate dynamics, the analyses were structured in two parts as explained below:

1) Effects of Experimental Conditions on Microstate Parameters

We first examined whether microstate properties were modulated by stimulation and location, explicitly excluding behavioural variables (Valence and Arousal) from these models (see Table II).

On microstate state distribution, no significant effects of stimulation were observed. However, a significant effect of location was observed. Adding location significantly improved model fit compared to the stimulation-only model ($\chi^2 = 6.06$, $df = 2$, $p = 0.048$).

On the mean duration, no significant effects of condition or location were observed (all $p > 0.36$) .

On the occurrence rate, a significant effect of location was found ($\chi^2 = 8.16$, $df = 2$, $p = 0.017$), while stimulation again showed no significant effect .

Overall, it was observed that location but not condition modulated microstate dynamics, specifically coverage and occurrence rate. Mean duration and state distribution remained unaffected.

2) Relationship Between Microstate Dynamics and Behavioural Variables

We next examined whether microstate parameters predict Valence and Arousal (see Table III). In contrast to the previous analysis, here behavioural variables were treated as dependent variables, and microstate parameters (state, coverage, mean duration, occurrence rate) were entered as

predictors. This reversal in model structure allows assessment of whether temporal properties of brain dynamics explain variance in subjective reports, rather than merely being influenced by external conditions.

Microstate parameters significantly contributed to explaining Valence ratings. It was observed that including mean duration significantly improved model fit ($\chi^2 = 4.40$, $p = 0.036$), and further inclusion of occurrence rate also yielded a significant improvement ($\chi^2 = 4.17$, $p = 0.041$). No significant contribution was observed for state or coverage alone.

Microstate parameters did not significantly contributed to explaining Arousal ratings. Although coverage showed a marginal trend ($p = 0.089$), inclusion of microstate parameters did not significantly improve model fit.

IV. Discussion

The present study reveals a functional dissociation between externally driven modulation and internally generated experiential states in microstate dynamics. By combining experimental manipulation with bidirectional modelling of behavioural variables, the findings provide converging evidence that microstates reflect both spatially specific neural processing and subjective experience.

A. Spatial Specificity Without Global Modulation

A key finding is that stimulation location influenced microstate coverage and occurrence rate, while the stimulus itself showed no significant effect. This suggests that microstate dynamics are spatially specific rather than globally driven. Consistent with prior work, microstates likely reflect brief activations of large-scale functional networks, each linked to distinct neural processes. The lack of a stimulus effect further indicates that the manipulation does not produce a uniform change in brain activity, but instead engages location-specific neural populations, in line with the localized nature of sensory processing.

B. Dissociable Roles of Microstate Parameters

The results reveal a clear functional dissociation across microstate parameters. While coverage and occurrence rate were sensitive to stimulation location, mean duration remained invariant. This dissociation is consistent with prior literature suggesting that different microstate parameters capture distinct aspects of neural dynamics (e.g., Khanna et al.; Michel and Koenig). In particular:

- Duration has been linked to the intrinsic stability of functional brain states
- Coverage and occurrence reflect the relative dominance and switching behaviour of these states

The present findings extend this framework by showing that external modulation selectively affects flexible properties (coverage, occurrence), while leaving intrinsic temporal stability (duration) unchanged. This supports the interpretation that duration reflects endogenous network constraints, whereas coverage and occurrence index task-dependent recruitment and reconfiguration.

C. Microstates Encode Subjective Experience

By reversing the modelling approach and using behavioural measures as outcomes, we show that microstate dynamics relate to subjective experience rather than simply mirroring stimulus features. Valence was linked to mean duration and occurrence rate, suggesting that the temporal organization of large-scale brain activity reflects affective experience. Notably, no such relationship was observed for Arousal, indicating that microstates may be more sensitive to the qualitative tone of experience than to its overall intensity. This aligns with evidence that Valence and Arousal are supported by partly distinct neural processes.

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