

Exploring the neural effects of lucid dreaming workshops: An EEG and HRV pilot study

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Summary. Lucid dreaming is characterized by the awareness of being in a dream while maintaining the sleep state. Empirical analyses of dream narratives reveal that lucid dreams exhibit enhanced self-referential cognition and volitional control compared to non-lucid dreams. This report presents an exploratory encephalography (EEG) analysis of a subgroup of participants from a randomized controlled trial, which found significant reductions in post-traumatic stress disorder (PTSD) symptoms following participation in lucid dreaming workshops. Data were collected using Muse-S headbands during brief guided meditations performed before and after the workshops, measuring EEG, heart rate (PPG), blood oxygen saturation (pulse oximetry), and movement (gyroscope and accelerometer). Data from 11 participants were included in the final analysis after excluding unusable recordings. Temporal alpha asymmetry showed a significant change from pre- to post-intervention (p = 0.032), shifting from left-dominant (0.049) to right-dominant (-0.045) alpha power after the workshop—an unexpected result given the usual association of left-dominance with well-being. However, this finding is constrained by the small sample size. No significant changes were observed in other EEG or heart rate variability (HRV) metrics, but these preliminary results provide a foundation for future studies exploring the neural effects of lucid dreaming interventions.

Keywords: Dreams, encephalography, alpha asymmetry, adults, quantitative survey

1. Introduction

The exact neural correlates of lucid dreaming remain incompletely understood. However, studies using EEG and fMRI have shown that lucid rapid eye movement (REM) sleep is associated with increased activation in cortical regions involved in metacognition, self-reflection, episodic memory, agency, and visual processing compared to non-lucid REM sleep (Dresler et al., 2012). Notably, lucid REM sleep has been linked to heightened activity in the prefrontal cortex, parietal lobes, and occipitotemporal regions (Dresler et al., 2012), as well as increased coherence in certain EEG frequency bands, particularly in the delta, theta, and gamma ranges, with gamma power peaking around 40 Hz in frontal regions (Voss et al., 2009). While these findings provide valuable insights into the neural dynamics of lucid dream-

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Submitted for publication: April 2025 Accepted for publication: September 2025 DOI: 10.11588/ijodr.2025.2.110366 ing, it remains unclear whether lucid REM sleep produces lasting neurophysiological changes beyond the dream state itself.

Recent neuroimaging research further supports the link between lucid dreaming and brain regions involved in metacognitive and self-reflective functions. For example, individuals who frequently experience lucid dreams (defined as three or more per week) show increased resting-state functional connectivity between the anterior prefrontal cortex and temporoparietal association areas, such as the angular and middle temporal gyri (Baird et al., 2018). This suggests that lucid dreaming may depend on enhanced communication between frontal and parietal networks, which are typically deactivated during non-lucid sleep. Supporting evidence from structural and functional MRI studies shows that individuals with higher self-reported dream lucidity also exhibit greater gray matter volume in the frontopolar cortex, a region activated during metacognitive tasks such as thought monitoring (Filevich et al., 2015). Together, these findings suggest that trait-level differences in lucid dream frequency may reflect stable neuroanatomical and neurofunctional profiles linked to introspective and self-monitoring capacities.

Theoretical frameworks propose that lucid dreaming may support trauma recovery by enabling emotional individuals to consciously reshape distressing dream content, therby



alleviating nightmares, while simultaneously fostering enhanced cognitive control and reflective processing that can generalize to waking life (Baird et al., 2019; Konkoly & Burke, 2019). In two of our recent studies, participation in a six-day live-video lucid dreaming workshop was linked to significant reductions in PTSD symptoms (Yount et al., 2023) (Yount et al., 2025). Building on these findings, we asked whether such workshops might also lead to measurable changes in the brain. This report presents an exploratory EEG analysis of a subset of participants (N = 11) from our larger randomized controlled study (Yount et al., 2025) by examining whether a lucid dreaming workshop might produce measurable neurophysiological changes outside of sleep. To test this, EEG and heart rate variability (HRV) were recorded during a standardized, audio-guided meditation before and after the lucid dream workshop intervention. . This secondary analysis focused on EEG frequency bands and hemispheric asymmetry, as well as HRV indices derived from linear and non-linear metrics to explore potential physiological correlates of the observed therapeutic effect.

2. Method

2.1. Participants

This exploratory study drew its participant subgroup from a randomized controlled trial (Please see Yount et al., 2025 for full parent study details). Recruitment was conducted via print ads and social media (Facebook, Instagram). Eligible individuals were 18 or older, fluent in English, and self-reported PTSD symptoms (PCL-5 scores: 28–59). Exclusion criteria included pregnancy, regular use of sleeping pills, and any history of psychotic episodes (e.g., hallucinations). Notably, PTSD-related flashbacks were not considered hallucinations and did not disqualify participants. The study was approved by the Institute of Noetic Sciences' Institutional Review Board (IORG#0003743).

2.2. Procedure

2.2.1 Intervention: Lucid Dreaming Workshop

The intervention was an at-home immersive workshop designed to help people with PTSD symptoms transform trauma through engaging with their dream activity and thereby reduce their symptoms. The workshop spanned 22 hours of live instruction and group activities conducted via video conferencing over six days in January and April 2023. The content covered sleep neuroscience, mindfulness for relaxation, sleep hygiene, dream recall, dream planning, and various lucid dreaming induction techniques. Induction techniques were introduced sequentially, including reality checks, recognizing dream signs, mnemonic strategies, conscious sleep entry, and a wake-back-to-bed protocol with scheduled awakenings for dream recall, followed by audio reinforcement. A psychotherapist was present and available for participants throughout the study. Group activities included guided meditations, dream-sharing circles, and support from the instructor and psychotherapist in a nurturing group environment.

2.2.2 Electrophysiological Recording

Electrophysiological data were collected immediately before and after the lucid dreaming workshop during a guided

meditation task chosen as a controlled, replicable activity that induces a state of relaxation and heightened internal focus. This was a seven-minute guided meditation audio track designed to relax the mind and cultivate a deeper sense of present awareness. This approach was chosen to provide a reproducible mental state across participants, reducing variability in baseline activity. A classic resting-state, especially in home-based recordings, can be more susceptible to differences in spontaneous thought, alertness, and environmental distractions. Although guided meditation introduces cognitive and attentional demands, there is no perfect control for this type of intervention. It offers a consistent mental state across sessions while fostering focused attention and internal awareness, which are central to lucid dreaming training. Unlike traditional eyes-closed resting-state recordings, guided meditation aligns with the intervention's aims and allows examination of physiological changes under relevant conditions. Also, lucid stream and meditation are altered mental states that likely share common neural and psychological processes, including enhanced self-awareness and emotional integration (Filevich et al., 2015). This connection is further supported by research showing that long-term meditators experience more lucid dreams than those not engaging in such practices (Baird et al., 2019). Measuring EEG during meditation allows for the comparison of neural changes potentially related to emotional regulation and cognitive processing. During the meditation task, participants were asked to find a quiet location where they would be undisturbed. The meditation task was loaded into the participants' Muse app specifically for this study. Each person was instructed to close their eyes, sit still, and listen to the audio instructions, which included a guided meditation with ambient rainforest sounds playing. Wearing headphones was optional and up to the discretion of each participant.

EEG measurements were collected using a personal brainwave detection headband designed to be worn while sleeping (Muse S, Interaxon). The flexible headband contains EEG sensors to monitor brain activity. Additional sensors detected by the headband include PPG for heart rate monitoring, pulse oximetry for blood oxygen saturation, and a gyroscope and accelerometer to detect movement. Participants received training via online videos with the study team to learn how to properly use the device.

2.2.3 Data Analysis

All preprocessing was done using MATLAB 2024a (Mathworks, Inc.). Raw data were saved as .csv files on Google Cloud. Custom MATLAB code was used to find the match for each pre- and post-workshop for each participant. EEG data were filtered using EEGLAB's default filter (EEGLAB v2024; zero-phase noncausal FIR filter) to remove low-frequency drifts and high-frequency noise: high pass filter at 1Hz (order 846, transition bandwidth 1 Hz, cutoff frequency 0.5 Hz, passband edge 1 Hz, -6 dB attenuation) and lowpass filter at 50 Hz (order 68, transition bandwidth 12.4 Hz, passband edge 50 Hz, cutoff frequency 56.2 Hz, -6 dB attenuation). EEG electrode locations were set based on their names using the standard 10-10 Boundary Element Model (BEM) template available in EEGLAB. All EEG channels were hardware-referenced to FPz, and no offline re-referencing was applied. While posterior channels did not require rereferencing, re-referencing frontal channels to linked mastoids would have required consistently high-quality signals



from both posterior electrodes (a condition not met in all participants), which could have introduced inconsistent signal characteristics across subjects. Artifacts and abnormal channel activities were detected and removed using trained classifiers and 5-s sliding windows, and at least 50% of files were flagged as bad before considering the whole channel as bad. The remaining EEG artifacts were removed using artifact subspace reconstruction methods so that segments could be rejected instead of the whole channel to reduce data loss (Processing code available upon request).

A battery of EEG metrics was calculated using the EEGLAB BrainBeats plugin v1.5 (Cannard et al., 2024). In brief, power spectral density (µV²/Hz) was estimated via the Welch method (2 s Hamming window, 50% overlap) and normalized to decibels, and mean power was computed for delta (1-3 Hz), theta (3-7 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-40 Hz) bands. Individual alpha frequency (IAF) was derived with the alpha center-of-gravity method (Corcoran et al., 2018), using Savitzky-Golay filtering, derivative-based alpha-band boundary detection, and centroid calculation across qualifying channels. Alpha asymmetry was calculated for homologous left-right pairs (AF7-AF8 and TP9-TP10) as $\ln(\text{left } \alpha \text{ power} + \epsilon)$ – $ln(right \alpha power + \epsilon)$, following guidelines (Allen et al., 2004). Alpha asymmetry was computed only for electrode pairs that remained available after preprocessing. Fuzzy entropy (Azami & Escudero, 2016; with m = 2, $r = 0.15 \times SD$, n = 2, τ = 1), and fractal votality was estimated using normalized box-counting and slope fitting. See Cannard et al. (2024) for more details.

PPG data were filtered using the default EEGLAB FIR filter at 1-5 Hz (order 212, transition bandwidth 1 Hz, attenuation -6 dB, cutoff frequencies 0.5 and 5.5 Hz)and cleaned with the same custom ASR algorithm described above (except 'burstrejection' variance cutoff = 100). R. RR intervals were detected from the PPG signal using the EEGLAB BrainBeats plugin v1.5, which implements the PhysioNet gppg algorithm (Vest et al., 2018) with a 5 s learning period, minimum threshold = 5, eye-closing period = 0.65 s, expected period = 5 s, slope window = 0.3 s, and buffer length = 4096 samples (all other parameters at default). RR artifacts were detected and corrected using BrainBeats default settings (removal of intervals < 0.375 s or > 1.5 s, spline interpolation of gaps, and correction of outliers or abrupt spikes > 20% change from the local median) to obtain the normal-to-normal (NN) intervals for computing reliable HRV metrics.

The HRV metrics (SDNN, heart rate, LF/HF ratio, entropy, and fractal dimension) were computed on the cleaned NN intervals series using the EEGLAB BrainBeats plugin v1.5 using default parameters (for more details, see Cannard et al., 2024), with default parameters. In brief, frequency-domain measures were calculated with the normalized Lomb–Scargle periodogram on 25%-overlapping sliding windows of minimum recommended lengths for each band: low frequency (LF) band = 0.04–0.15 Hz, \geq 125 s; high-frequency (HF) band = 0.15–0.40 Hz, \geq 34 s. With power expressed in ms² and LF/HF as the ratio of mean LF to HF power. Fuzzy entropy and fractal were computed the same as for EEG above.

2.2.4 Statistics

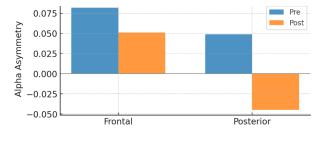
Each variable was checked for missing values and variance homogeneity. When heteroscedasticity was present, a Welch t-test was used, otherwise, a paired t-test. When

required, corrections for multiple comparisons were applied to control for type 1 errors using the false discovery rate (FDR) method (Benjamini & Hochberg, 1995).

3. Results

Twenty-five pre-workshop and 18 post-workshop files were recorded. Of these, 18 participants had files from both time points. The above cleaning method excluded seven participants for one or both of their files, resulting in 11 participants being included in subsequent analyses. An average of 0.7 EEG channels (SD = 0.9) were removed due to artifacts (see Methods), with 19.1% of the signal excluded as artifacts on average (SD = 12.8%). For each pre- and post-measurement, the resulting average data length for EEG recordings was 10 minutes (SD = 1.4 minutes). For PPG data, 2.2% of the signal was removed via ASR on average (SD = 3.3%), leaving an average data recording length of 12.3 minutes (SD = 2.2 minutes).

Temporal alpha asymmetry between electrodes TP9 and TP10 of the Muse was significantly different after FDR multiple comparison correction (p=0.032, t=2.53, 95% Cl: [0.010, 0.178], df=9; Figure 1). The average alpha asymmetry pre-workshop recording was 0.049, reflecting greater left-than-right alpha power. Conversely, the average alpha asymmetry post-workshop was -0.045, reflecting greater right-than-left alpha power following the workshop.



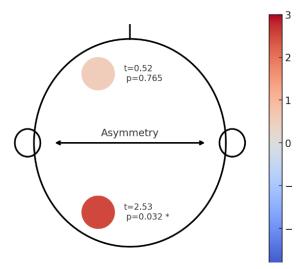


Figure 1. Top: alpha asymmetry scores averaged across the group for each region (AF7-AF8 and TP9-TP10) and session (Pre- and Post-intervention). Bottom: Statistical results of the alpha asymmetry, showing a significant difference in the posterior regions (p = 0.032; t-value = 2.53; 95% Cl: [0.010, 0.178]; df = 9) was observed between the two distributions.



No other significant effects were observed post-FDR: Frontal alpha asymmetry (p = 765; t-value = 0.52; df = 9), EEG entropy frontal (p = 0.671; df = 7), temporal (p = 0.445; df = 10); EEG fractal dimension frontal (p = 0.847; df = 7), temporal (p = 0.975; df = 10). SDNN (p = 0.90; df = 10), heart rate (p = 0.723; df = 10), LF/HF ratio (p = 0.793; df = 10), entropy (p = 0.709; df = 10), and fractal dimension (p = 0.71; df = 10).

4. Discussion

Understanding the healing impacts of lucid dreaming is an emerging area of interest, particularly as lucid dreaming workshops gain popularity. In this study, we explored whether participating in a week-long lucid dreaming workshop intended to be a healing experience for people living with PTSD could lead to observable neurophysiological changes. We observed a mild shift from left- to right-dominant alpha activity. We observed a small shift in temporal-parietal alpha asymmetry from greater right cortical activation (lower right alpha power, higher left alpha power) pre-workshop to greater left cortical activation (lower left alpha power, higher right alpha power) post-workshop. Under the inhibition-timing framework (Klimesch et al., 2007; Jensen & Mazaheri, 2010), this suggests relatively reduced engagement of right TP cortical processes and a concomitant release of inhibition over left-hemisphere functions. The right TP region is implicated in attentional reorienting, self-related perspective taking, and processing of novel or emotionally salient stimuli, whereas the left TP is more associated with language, narrative construction, and logical-analytical integration of experiences. A shift toward greater left-hemisphere cortical activation could reflect a workshop-related enhancement in narrative integration or verbal-cognitive framing of internal experiences, potentially relevant to the re-appraisal and restructuring of dream content. In therapeutic contexts such as lucid dream training for trauma-related nightmares, integrating dream experiences into coherent narratives is thought to help reduce distress and promote adaptive meaning-making (Holzinger et al., 2015; Harb et al., 2019). While preliminary, our findings may point to an increased capacity for such integrative processing following the intervention, complementing the role of right-hemisphere engagement often highlighted in creative and imagery-based aspects of lucid dreaming.

However, these findings must be interpreted cautiously due to the study's exploratory nature, the small sample size, and the use of a dry wearable EEG headset, all of which limit generalizability. Individual differences in EEG responses, prior meditation experience, or familiarity with dream practices could all influence the observed effects. Also, the use of a real-world wearable EEG system, in which a substantial proportion of recordings were of insufficient quality for analysis; future studies could mitigate data loss by employing systems with more electrodes, allowing retention of partial datasets when some channels fail. Furthermore, while our results suggest promising neurophysiological adaptations, they do not directly link these changes to improvements in clinical outcomes such as reduced PTSD symptoms or enhanced mental well-being.

To build on these findings, future research can integrate subjective reports, use larger and more diverse samples, and include longer follow-up periods to assess these changes' persistence and functional relevance. At the same time, this progress must be balanced with careful attention to po-

tential risks, including disrupted sleep quality and blurred reality-fantasy boundaries, especially for vulnerable groups (Soffer-Dudek, 2019). A thoughtful exploration of both benefits and risks will help clarify lucid dreaming's therapeutic potential as an innovative intervention. Furthermore, although EEG and HRV both index aspects of brain–heart interaction, the present analyses did not explicitly assess their dynamic coupling; future studies could examine this using approaches such as heartbeat-evoked potentials (HEPs) or EEG–HRV coherence metrics to determine whether the intervention alters coordinated central–autonomic activity.

Despite these limitations, the study represents an important first step toward implementing real-world EEG and PPG measurements with remote support in the context of a week-long intervention. As research into dream-based therapies advances, it will be important to situate lucid dreaming within existing clinical and neuroscientific frameworks. This study provides early support for its potential role in promoting neural and psychological flexibility, but clinical integration requires a deeper understanding of mechanisms, individual differences, and long-term outcomes.

Conflict of Interest

The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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