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Multiband EEG Signatures of Openness to Experience: Exploratory Evidence from Resting-State Eyes-Open and Eyes-Closed Conditions

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ABSTRACT

Purpose: The present study aimed to investigate the correlated EEG indices of Openness to Experience by analyzing multiband resting-state EEG activity in 352 healthy adults.

Methods and Materials: The present research method is descriptive-correlational. The study population consisted of 352 healthy adult men and women from Tehran, selected through convenience sampling. The process of data collection and registration took place over two years, from 2022 to 2024. The research tools included the NEO Personality Inventory (NEO-PI-R) and EEG data recording using a 19-channel device (10-20 system) at the Parand Center. Four main indices (absolute power, relative power, peak frequency, and band ratios) were extracted across all frequency bands. Data analysis used scipy (1.14.x) for performing linear regression and statistical tests and matplotlib (3.10.x) for drawing EEG topological maps.

Findings: Results indicated that the transition from EC to EO showed the most robust effects, characterized by reduced alpha1 and increased beta and gamma power as a consistent tri-band profile. Similar, though weaker, associations appeared within EC and EO separately. Power-ratio analyses revealed state-dependent markers: alpha/beta ratios in EC and delta/alpha and theta/alpha ratios in EO. These findings suggest that Openness is associated not with a single oscillatory marker but with subtle interactions between alpha, slower rhythms (delta, theta), and faster activity (beta, gamma). Comparisons with pharmacological studies demonstrated overlap with psilocybin-induced reductions in alpha and increases in gamma, while the additional beta effect may help differentiate imaginative and creative aspects of Openness from hallucinatory experiences.

Conclusion: The present results suggest that Openness leaves a modest but detectable multiband trace in resting EEG, providing a foundation for replication and future machine-learning approaches in personality neuroscience.

Keywords: *Openness to Experience, Resting-state EEG, Alpha, beta, gamma rhythms, Personality neuroscience*

1. Introduction

Personality neuroscience seeks to identify the neural mechanisms underlying stable individual differences in personality by linking them to reliable and reproducible neural markers. Within the framework of the Five Factor Model (FFM), the dimension of Openness/Intellect reflects variations in imagination, curiosity, aesthetic sensitivity, and complex cognitive processing. Contemporary discussions differentiate "Openness" (associated with aesthetic and perceptual exploration) from "Intellect" (linked to abstract and semantic exploration), while acknowledging their shared higher-order substrate in exploration and cognitive engagement (Allen & DeYoung, 2017; DeYoung et al., 2007; Sassenberg et al., 2023).

From a neuroscience perspective, Openness has been associated with large-scale cortical networks, particularly the default mode network (DMN), as well as with neuromodulatory systems. Evidence suggests that dopamine and serotonin collaboratively contribute to exploratory cognition and aesthetic-perceptual experiences, with dopaminergic influences highlighted in theoretical models such as the Cybernetic Big Five Theory, which posits that dopamine facilitates curiosity, working memory, and cognitive exploration (Allen & DeYoung, 2017). Pharmacological EEG studies further indicate that dopaminergic changes can affect a wide range of oscillatory bands, especially in the alpha and beta ranges (Dimpfel, 2009). Additionally, the serotonergic system—particularly variations at the 5-HT$_2$A receptor—has been proposed as a biological correlate of Openness to Experience. Pharmacological research demonstrates that serotonergic modulation with psilocybin, a 5-HT$_2$A agonist, can enhance Openness scores and alter perception, self-referential processing, and resting neural dynamics (Carhart-Harris et al., 2012; Kometer et al., 2013). Collectively, these findings suggest that Openness arises from the interplay of dopaminergic and serotonergic modulation within large-scale networks such as the DMN.

Resting-state EEG, characterized by its high temporal resolution, is particularly well-suited for investigating oscillatory mechanisms linked to networks like the DMN. Alpha band dynamics correlate with DMN connectivity and the eyes closed/eyes open states, highlighting the importance of including both eyes closed (EC) and eyes open (EO) conditions in personality studies and analyzing their differences (CH = EC − EO) (Kropotov, 2010). Moreover, simultaneous EEG-fMRI studies have revealed that EEG-vigilance fluctuations—primarily driven by alpha activity—are strongly correlated with BOLD changes in DMN regions (Olbrich et al., 2009). These findings indicate that alpha oscillations in EEG are relevant not only at the electrophysiological level but also reflect large-scale network dynamics, providing further justification for analyzing both EC and EO conditions in EEG-based personality research.

However, findings regarding EEG-personality associations—particularly concerning Openness—are heterogeneous and sometimes contradictory. Large-sample studies have reported negligible predictions of Big Five traits from resting spectral power, and systematic reviews of resting alpha asymmetry highlight significant heterogeneity and limited trait specificity (Jach et al., 2020; Korjus et al., 2015; Vecchio & De Pascalis, 2020). More recent research suggests that EEG vigilance indices can exhibit small but detectable associations with Openness, emphasizing the importance of state-sensitive analyses and large sample sizes (Jawinski et al., 2021).

An additional complication is that resting EEG is heavily influenced by factors unrelated to personality. Medical conditions such as diabetes or thyroid dysfunction, along with pharmacological treatments, can significantly alter both absolute and relative power (Atli et al., 2023; Frøkjær et al., 2017). Psychiatric conditions also produce robust and characteristic changes, including increases in theta and beta activity or shifts in frontal alpha asymmetry, as observed in depression and anxiety (Koo et al., 2015; Wang et al., 2025). Consequently, spectral indices such as absolute power (AP) and relative power (RP) are highly susceptible to non-personality influences. In contrast, personality traits likely exert stable yet weak influences that manifest not as distinct, localizable markers, but as distributed and multiband patterns. This perspective aligns with the mixed results in the literature: while some studies have found relationships between Big Five traits and resting EEG spectra, others—particularly larger decoding studies—have reported only trait-specific or null effects, underscoring the challenge of detecting subtle personality-linked EEG signals at rest (Jach et al., 2020; Korjus et al., 2015; Vecchio & De Pascalis, 2020).

In line with this view, pharmacological and genetic studies suggest that neuromodulatory systems influence EEG rhythms across multiple frequency bands, rather than in a single narrow range. For example, dopaminergic modulation in both animal electropharmacology and human clinical studies has been associated with distributed effects

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spanning delta, theta, alpha, and beta activity. L-DOPA and D2 agonists in rodents produce delayed increases in delta and theta, alongside sustained decreases in alpha and beta power, highlighting the broad spectral footprint of dopamine. Likewise, alterations of dopaminergic tone in Parkinson's disease have been linked to prominent beta-band abnormalities, together with changes in slower oscillations (Dimpfel, 2009; Morelli & Summers, 2023). The serotonergic system shows a similarly multiband profile: psilocybin-induced activation of the 5-HT$_2$A receptor reduces occipital alpha power (Kometer et al., 2013), while genetic variation in the serotonin transporter has been associated with reduced gamma power in healthy participants (Lee et al., 2011). Together, these findings indicate that both dopamine and serotonin shape distributed oscillatory dynamics across multiple bands, providing a neurobiological rationale for examining all major and sub-bands when probing the neural correlates of Openness.

Direct evidence linking resting EEG to Openness has been inconsistent, with some studies reporting associations in selected bands or regions, and others—particularly those using larger samples and machine-learning approaches—reporting null results (Jach et al., 2020; Korjus et al., 2015; Vecchio & De Pascalis, 2020). At the same time, recent work using vigilance-based EEG indices has demonstrated small but reproducible effects of Openness, suggesting that personality–EEG associations may be subtle and state-dependent rather than robustly localized (Jawinski et al., 2021). Resting-state fMRI evidence further links Openness to thalamic structures, which are known as key generators of alpha oscillations, as well as limbic structures and hubs of the DMN (Kropotov, 2010; Kunisato et al., 2011), converging with EEG–fMRI findings that alpha and beta power covary with DMN connectivity (Hlinka et al., 2010). Together, these literatures point to the likelihood that EEG markers of Openness exist, but manifest as weak, distributed, and multiband patterns that are difficult to detect with conventional approaches.

This exploratory study was motivated by long-term QEEG experience in which individual resting maps showed stable, low-amplitude patterns across years. Based on these observations, we hypothesized that Openness would be reflected in weak yet spatially consistent EEG signatures, detectable only when evidence is aggregated across multiple electrodes, sub-bands, and conditions. To maximize sensitivity to such patterns, we adopted a simple regression approach without classical multiple-comparison correction, thereby avoiding the loss of subtle effects, while using an aggregation criterion to guard against chance findings. We further examined a broad set of spectral indices—including absolute power (AP), relative power (RP), peak frequency (PK), and power ratios—across all major and sub-bands, recorded in both eyes-closed (EC) and eyes-open (EO) resting states, as well as their difference (CH = EC − EO). This design allowed us to derive an initial topographic map of how the trait of Openness is reflected in resting-state EEG dynamics.

2. Methods and Materials

2.1. *Study Design and Participants*

This study was conducted using a quasi-experimental design with pretest, posttest, and a two-month follow-up with a control group, in order to control for confounding variables and increase the internal validity of the findings—an approach recommended in psychological intervention studies (Kazdin, 2017). The statistical population included all 11th- and 12th-grade female students in public schools in Isfahan during the 2023–2024 academic year, estimated at approximately 5,100 students based on data from the Department of Education. Using a multi-stage cluster sampling method, four high schools from the central and northern districts of Isfahan were randomly selected, and an initial screening was conducted using the Social Anxiety Scale for Adolescents (La Greca & Lopez, 1998) to identify students scoring above the clinical cutoff. Ultimately, 60 eligible students with a mean age of 17.8 years (SD = 0.64) were randomly assigned via block randomization to three groups (20 in the mindfulness group, 20 in the integrated group, and 20 in the control group) to ensure balance of characteristics across groups (Moher et al., 2010; Schulz et al., 2010).

Inclusion criteria were: (1) scoring above the cutoff point on the social anxiety scale, (2) parental presence and obtaining written informed consent from both parents and students, and (3) the ability to regularly attend in-person sessions. Exclusion criteria included taking psychiatric medications, concurrent psychological interventions, having another psychiatric disorder according to parental report, missing more than 2 out of the 8 sessions, and experiencing a major stressful life event during the study period. The enrollment and attrition process was accurately recorded and monitored according to CONSORT standards.

The interventions were delivered in person at the schools. Each intervention group (mindfulness and integrated) participated in eight 90-minute sessions (two sessions per week over four consecutive weeks). To ensure protocol adherence and intervention consistency, session manuals and monitoring checklists were reviewed and approved by two independent clinical psychologists.

The control group was placed on a waiting list and received no intervention other than participating in assessments, but after the follow-up stage, they were offered mindfulness training to observe ethical considerations. Attendance, active participation, and attrition were carefully recorded for each session, and homework assignments were designed and distributed to consolidate learning.

2.2. Measures

The Revised NEO Personality Inventory (NEO-PI-R): The inventory consists of a 240-item measure rated on a 5-point Likert scale, assessing five domains: Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness, each subdivided into six facets (for a total of 30 facets). In large normative samples from the U.S., the internal consistencies at the domain level are high ($\alpha \approx$ 0.86–0.92) (Costa & McCrae, 2010). In Iran, the Persian NEO-PI-R has demonstrated acceptable psychometric properties and has successfully recovered the five-factor structure, with facet alphas reported in the range of 0.34–0.77 (Joshanloo et al., 2010). Since item-level responses were not retained for the present dataset, we relied on these published Persian reliability indices instead of re-estimating internal consistency within our sample.

EEG Acquisition and Preprocessing: Resting EEG was recorded using a 19-channel 10–20 cap (Fp1/2, F7/3/Z/4/8, T3/C3/Cz/C4/T4, T5/P3/Pz/P4/T6, O1/O2) with a linked-ears (LE) reference on a Mitsar 201 amplifier. Two three-minute resting blocks were acquired: one with eyes closed (EC) and the other with eyes open (EO), in rooms with stable white lighting and controlled acoustic conditions. Signals were recorded using a fixed clinical bandpass filter (0.5–50 Hz) and a notch filter (50 Hz), and then exported for QEEG processing. Automated artifact rejection was performed using NeuroGuide, followed by blind visual inspection by a trained technician. Datasets with fewer than 60 seconds of contiguous clean data per condition or with persistent artifacts were excluded. All features were computed from artifact-free segments.

EEG Indices and Tagging: We extracted four families of features: absolute power (AP), relative power (RP), peak frequency (PK), and power ratio (RAT). For AP and RP, we defined ten sub-bands: delta, theta, alpha1, alpha2, beta1, beta2, beta3, high beta, gamma, and high gamma. For PK, we identified seven bands: delta, theta, alpha, beta, high beta, gamma, and high gamma. For RAT, we calculated three ratios: alpha/beta, delta/alpha, and theta/alpha. Each feature was tagged with the condition (EC, EO, CH), index (AP, RP, PK, RAT), band, and electrode. In addition to analyzing EC and EO separately, we computed the "change" variable (CH = EC − EO) for each feature to capture state-dependent modulation associated with the opening of the eyes, along with related DMN/alpha shifts.

2.3. Interventions

The mindfulness-based intervention was adapted from the Mindfulness-Based Stress Reduction (MBSR) program developed by Jon Kabat-Zinn (1990) and tailored for adolescents (Zoogman et al., 2015; Hwang & Kearney, 2015). The content included training in mindfulness meditation, body scan exercises, mindful movement, acceptance of thoughts and emotions, and sustained present-moment attention practices. Over eight 90-minute sessions, participants progressed from introductory psychoeducation, body scan, and breathing exercises to mindful movement, labeling internal experiences, and cultivating self-compassion. They then practiced generalizing mindfulness skills to everyday life, engaging in self-monitoring, developing relapse prevention strategies, and concluded with feedback and posttest administration. Each session was designed to build progressively on previous skills and foster consistent daily practice.

The integrated intervention combined core mindfulness activities with elements of Cognitive Behavioral Therapy (CBT) based on the protocols of Hayes et al. (2011) and Strauss et al. (2014). This program incorporated mindfulness training alongside cognitive restructuring, graded exposure, and social skills training. Across eight 90-minute sessions, participants were introduced to the therapeutic framework through psychoeducation and treatment contracting, followed by mindfulness principles integrated with cognitive restructuring, construction of exposure hierarchies, relaxation strategies, and practical exposure exercises with attentional refocusing. Subsequent sessions emphasized building social self-efficacy, problem-solving, providing feedback on exposure tasks, and assertiveness training. The final session included summarizing learned skills, receiving feedback, and administering the posttest. The content was structured to balance both mindfulness and

E-ISSN: 2980-9681

CBT components while maintaining equal session duration and therapist workload.

2.4. Data Analysis

All EEG features were z-scored at the column level in the exported file, with no further normalization applied. For each index × band × electrode combination, we fitted simple linear regressions (Openness ~ EEG) with $\alpha = 0.05$ (two-sided). To avoid discarding weak but spatially and temporally extended EEG effects, we employed a cluster-inspired, pattern-level heuristic (Groppe et al., 2011; Maris & Oostenveld, 2007): candidate bins passed an uncorrected pointwise test (two-sided $p < .05$) and were interpreted only if they formed contiguous, sign-consistent patterns with coherent topographies that replicated across neighboring scalp regions. Therefore, inference is made at the pattern (cluster-like) level rather than at the individual bin level (Sassenhagen & Draschkow, 2019). Given the known pitfalls of parametric cluster-extent inference, we emphasize replication and transparency here and recommend using nonparametric cluster permutation/TFCE for confirmatory studies (Eklund et al., 2016; Smith & Nichols, 2009).

Several analytical choices were made to maximize sensitivity to subtle trait-linked EEG signatures for weak, distributed signals. First, all canonical bands and sub-bands were examined. Splitting alpha into alpha1 (8–10 Hz) and alpha2 (10–12 Hz) is supported by affective and clinical EEG research, which demonstrates that alpha sub-bands carry distinct information and that combining them can obscure opposing effects (Başar et al., 1997; Doppelmayr et al., 1998; Klimesch, 1999). Second, since EO/EC strongly modulates resting networks, including DMN-related connectivity, we modeled both states and their difference (CH). The EC–EO contrasts in EEG and resting-state fMRI provide convergent motivation for including CH as an informative index of state-dependent modulation (Jann et al., 2009; Moosmann et al., 2003; Yang et al., 2007). Third, instead of applying stringent multiplicity corrections, we combined conventional thresholding ($p < .05$) with a requirement for spatial–topographic consistency, similar to cluster- or extent-based logic (Maris & Oostenveld, 2007). This approach allows us to down-weight isolated hits while retaining patterns that are consistent across sites and bands

3. Findings and Results

The study included a total sample size of (N = 352) participants. The mean age of the participants was 33.88 years, with a standard deviation of 5.36 years, and their ages ranged from 20 to 61 years. In terms of gender distribution, 215 participants (61.1%) were male, while 137 participants (38.9%) were female.

Table 1

Regression Outcomes by Condition and EEG Index (Openness)

Condition	Index	Total Bands	Valid Bands	Not Robust Bands	No Sig. Bands	Sig. Electrodes	Valid Electrodes	Non-Valid Regressions
CH	AP	10	1	2	7	10	8	2
CH	RP	10	4	3	3	27	24	3
CH	PK	7	3	2	2	37	34	3
EC	AP	10	1	2	7	6	2	4
EC	RP	10	3	3	4	35	28	7
EC	PK	7	0	3	4	6	0	6
EO	AP	10	0	1	9	1	0	1
EO	RP	10	1	4	5	13	7	6
EO	PK	7	2	1	4	27	25	2

Note. "Valid bands" = number of bands recognized as valid significant; "Not robust bands" = bands labeled as not robust; "No sig. bands" = bands with no significant regressions; "Sig. electrodes" = total electrodes with significant regressions; "Valid electrodes" = number of electrodes with validated regressions; "non-valid regressions" = number of regressions not recognized as valid. CH = change (EC − EO); EC = eyes closed; EO = eyes open; AP = absolute power; RP = relative power; PK = peak frequency.

This framework makes transparent how we applied an indirect, cumulative correction strategy: rather than eliminating effects with classical multiple-comparison adjustments (which risk discarding subtle but biologically

E-ISSN: 2980-9681

plausible signals), we preserved effects only when replicated across multiple electrodes or regions. This approach parallels procedures used in EEG/fMRI research to emphasize convergent, region-level patterns.

In brief, CH conditions yielded the highest number of validated bands and electrodes (e.g., four bands in CH–RP and three in CH–PK), while EC produced fewer but consistent regional effects (notably in RP-beta and gamma bands). EO showed the lowest number of validated bands, with most entries falling into the not robust or non-significant categories. Importantly, the counts demonstrate that single-site findings were never retained; every entry labeled "valid significant" reflects multi-site cumulative evidence.

Table 2

Regression Results (CH–AP, Absolute Power)

Band	Electrode	Region	β_std	r^2	p	Interpretation
Alpha1	F7	Left anterior	-0.1063	0.0113	0.0462	Significant (Valid)
Alpha1	F3	Left anterior	-0.1073	0.0115	0.0443	Significant (Valid)
Alpha1	FZ	Mid sagittal	-0.1172	0.0137	0.0279	Significant (Valid)
Alpha1	F4	Right anterior	-0.1104	0.0122	0.0384	Significant (Valid)
Alpha1	F8	Right anterior	-0.1111	0.0123	0.0373	Significant (Valid)
Alpha1	T4	Right central	-0.1291	0.0167	0.0154	Significant (Valid)
Alpha1	O1	Left posterior	-0.1171	0.0137	0.0281	Significant (Valid)
Alpha1	O2	Right posterior	-0.1083	0.0117	0.0423	Significant (Valid)
Delta	F4	Right anterior	-0.1088	0.0118	0.0414	Not Robust (1 site)
Gamma	O2	Right posterior	0.1141	0.0130	0.0323	Not Robust (1 site)

The table 2 shows that in the CH–AP condition, the alpha1 band was significant in 8 electrodes and was considered a Valid Band based on replication. In contrast, delta (F4) and gamma (O2) showed significance in only one electrode each and were classified as Not Robust Bands, likely false positives. Therefore, they were not included in the final topographic visualizations.

In the row labeled "CH‑AP," CH denotes the transition from eyes closed to eyes open (EC→EO), while AP refers to Absolute Power. In this condition, ten frequency bands were examined across 19 electrodes, with a separate regression analysis conducted for each band at each electrode. Among these bands, alpha1 exhibited significant associations with openness at 8 out of the 19 electrodes, qualifying it as a Valid Band based on the principle of replication. The details of the eight significant regressions for alpha1 include

F7 (left anterior): β_std = -0.106313, r^2 = 0.0113, p = 0.0462

F3 (left anterior): β_std = -0.107287, r^2 = 0.0115, p = 0.0443

FZ (mid sagittal): β_std = -0.117219, r^2 = 0.0137, p = 0.0279

F4 (right anterior): β_std = -0.110444, r^2 = 0.0122, p = 0.0384

F8 (right anterior): β_std = -0.111066, r^2 = 0.0123, p = 0.0373

T4 (right central): β_std = -0.129093, r^2 = 0.0167, p = 0.0154

O1 (left posterior): β_std = -0.117089, r^2 = 0.0137, p = 0.0281

O2 (right posterior): β_std = -0.108315, r^2 = 0.0117, p = 0.0423

Additionally, two other frequency bands demonstrated significant associations at a single electrode each; however, since these effects were not replicated in adjacent electrodes, they were classified as Not Robust Bands and treated as potential false positives, thus excluded from the topographic visualizations. These included

Delta at F4 (right anterior): β_std = -0.108761, r^2 = 0.0118, p = 0.0414

Gamma at O2 (right posterior): β_std = 0.114147, r^2 = 0.0130, p = 0.0323

Table 3 lists all bands and indices that showed nominally significant regressions, with condition, index, anatomical region, frequency band, and direction (positive/negative) specified. Thus, even single-site findings that did not reach cumulative regional support are included here. For example, under CH–AP delta, a single significant electrode was observed in the right anterior region; this appears in Table 3 but was labeled not robust in Figure 1 because it lacked replication. At the same time, cumulative effects can also be seen in this table.

E-ISSN: 2980-9681

For example, under CH–RP, alpha1 showed widespread negative correlations across frontal and central regions, while beta1 and beta2 displayed positive correlations over left anterior and midline sites. Under EC–RP, consistent negative associations were found for alpha1 across anterior and posterior regions, whereas beta3 and gamma bands yielded positive correlations in central–posterior sites. Under EO–PK, peak beta frequency showed a strong positive correlation across virtually the entire scalp. These regional patterns form the core interpretable outcomes, linking Openness to oscillatory dynamics in specific bands and topographies.

Table 3

Retained and Nominally Significant Bands by Condition, Index, and Region (Openness)

Condition	Index	Band	N (pos)	Regions (pos)	N (neg)	Regions (neg)
CH	AP	alpha1	0		8	LeftAnterior LeftPosterior MidSagittal RightAnterior RightCentral RightPosterior
CH	AP	delta	0		1	Right Anterior
CH	AP	gamma	1	RightPosterior	0	
CH	RP	alpha1	0		12	Left Anterior LeftCentral MidSagittal RightAnterior RightCentral RightPosterior
EC	AP	alpha1	0		3	Left Posterior RightAnterior RightCentral
EC	AP	gamma	2	LeftAnterior RightAnterior	0	
EO	RP	alpha2	0		7	LeftCentral Left Posterior MidSagittal RightAnterior RightCentral RightPosterior
EO	PK	beta	12	Left Anterior LeftCentral LeftPosterior MidSagittal RightAnterior RightCentral RightPosterior	0	

Note. Regions are grouped according to the 10–20 system. CH = change (EC − EO); EC = eyes closed; EO = eyes open; AP = absolute power; RP = relative power; PK = peak frequency.

Figures 1 visualize the retained regressions for each condition, using red to denote negative associations and blue for positive associations.

Figure 1 (CH): Highlights validated alpha1 negativity in frontal and occipital regions, PK-alpha positivity, and RP-beta positivity. In addition, peak gamma showed positive correlations in left posterior regions, whereas high-gamma peak frequency displayed negative correlations across posterior and left-hemisphere sites. This combined pattern suggests a noteworthy dissociation between gamma sub-bands under the change condition.

E-ISSN: 2980-9681

Figure 1

Topographic Maps of Openness Regressions Under the Change Condition (CH = EC − EO)

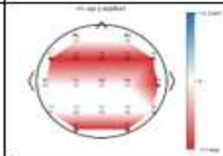
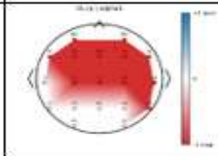
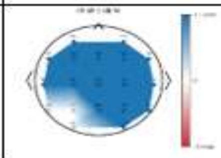
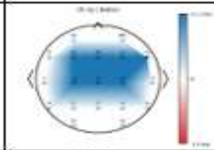
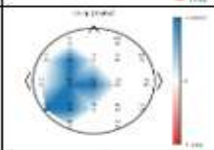
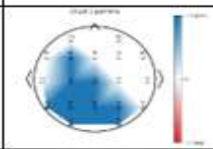
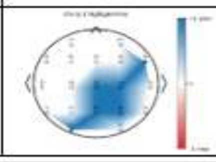
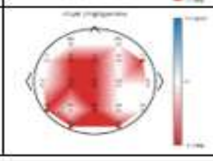
EEG Indices / FrequencyBands		Absolute power	Relative power	Peak frequency
Delta		not robust	No significant results	No significant results
Theta		No significant results	No significant results	not robust
Alpha	Alpha1			
	Alpha2	No significant results	not robust	
Beta	Beta1	No significant results		not robust
	Beta2	No significant results		
	Beta3	No significant results	not robust	
HighBeta		No significant results	No significant results	No significant results
Gamma		not robust	not robust	
HighGamma		No significant results		

Figure 2 (EC): Shows RP-alpha1 negativity in frontal, central, and right temporal regions; RP-beta3 positivity in frontal and central regions; and RP-gamma positivity in frontal, central, and parietal regions.

E-ISSN: 2980-9681

Figure 2

Topographic Maps of Openness Regressions Under the Eyes-Closed (EC) Condition

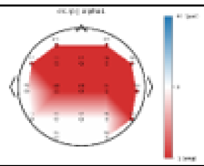
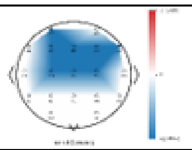
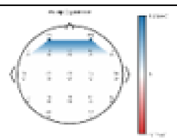
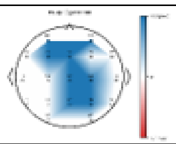
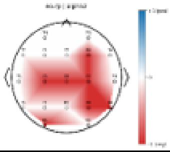
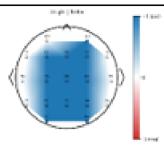
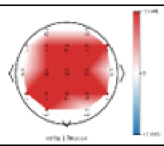
<table>
<tr><th colspan="2">EEG Indices / FrequencyBands</th><th>Absolute power</th><th>Relative power</th><th>Peak frequency</th></tr>
<tr><td colspan="2">Delta</td><td>No significant results</td><td>not robust</td><td>No significant results</td></tr>
<tr><td colspan="2">Theta</td><td>not robust</td><td>No significant results</td><td>not robust</td></tr>
<tr><td rowspan="2">Alpha</td><td>Alpha1</td><td>not robust</td><td></td><td rowspan="2">No significant results</td></tr>
<tr><td>Alpha2</td><td>No significant results</td><td>No significant results</td></tr>
<tr><td rowspan="3">Beta</td><td>Beta1</td><td>No significant results</td><td>No significant results</td><td rowspan="3">No significant results</td></tr>
<tr><td>Beta2</td><td>No significant results</td><td>not robust</td></tr>
<tr><td>Beta3</td><td>No significant results</td><td></td></tr>
<tr><td colspan="2">HighBeta</td><td>No significant results</td><td>not robust</td><td>No significant results</td></tr>
<tr><td colspan="2">Gamma</td><td></td><td></td><td>not robust</td></tr>
<tr><td colspan="2">HighGamma</td><td>No significant results</td><td>No significant results</td><td>not robust</td></tr>
</table>

Figure 3 (EO) depicts PK-beta positivity across widespread regions and RP-alpha2 negativity in central and right-hemisphere regions. In addition, PK-gamma displayed broad negative correlations across nearly the entire scalp.

E-ISSN: 2980-9681

Figure 3

Topographic Maps of Openness Regressions Under the Eyes-Open (EO) Condition

EEG Indices / FrequencyBands		Absolute power	Relative power	Peak frequency
Delta		No significant results	not robust	No significant results
Theta		No significant results	No significant results	No significant results
Alpha	Alpha1	No significant results	No significant results	No significant results
	Alpha2	not robust		
Beta	Beta1	No significant results	not robust	
	Beta2	No significant results	No significant results	
	Beta3	No significant results	not robust	
HighBeta		No significant results	not robust	not robust
Gamma		No significant results	No significant results	
HighGamma		No significant results	No significant results	No significant results

These visualizations confirm that the validated associations correspond to coherent, topographically distributed patterns rather than isolated sites.

To clarify RP effects (Table 3; Figure 4) In Figures 2 and 3, relative power (RP) patterns showed that, in the eyes-closed (EC) condition, alpha1 correlated negatively with Openness while beta and gamma correlated positively; in eyes-open (EO), alpha2 exhibited negative correlations. Because RP indexes a band relative to the total spectrum, we introduced band-specific power ratios (RAT) to determine which pairwise contrasts best accounted for these RP effects—specifically, alpha relative to other bands (e.g., α/β, α/θ, α/δ).

The key RAT findings are summarized in Table 3 and illustrated in Figure 4. Under EC, the alpha/beta ratio showed a negative association with Openness, with 10 of 19 electrodes reaching significance; other alpha-to-band ratios did not show comparably strong or widespread effects. This indicates that the EC RP pattern is primarily captured by the α/β contrast, consistent with simultaneous lower alpha1 and higher beta power in higher-Openness individuals.

Under EO, two slow-wave contrasts dominated: delta/alpha was positively associated with Openness at 13 of 19 electrodes, and theta/alpha was positively associated at 8 of 19 electrodes (note that in these expressions alpha appears in the denominator). By contrast, an EO alpha/beta effect was not retained as robust. Together, these results suggest that the EO RP pattern is better explained by alpha's relative decrease vis-à-vis slow bands (δ, θ), whereas the EC RP

E-ISSN: 2980-9681

pattern is better explained by alpha's contrast with faster beta activity.

Table 4

Power-Ratio (RAT) Regressions with Openness by Condition

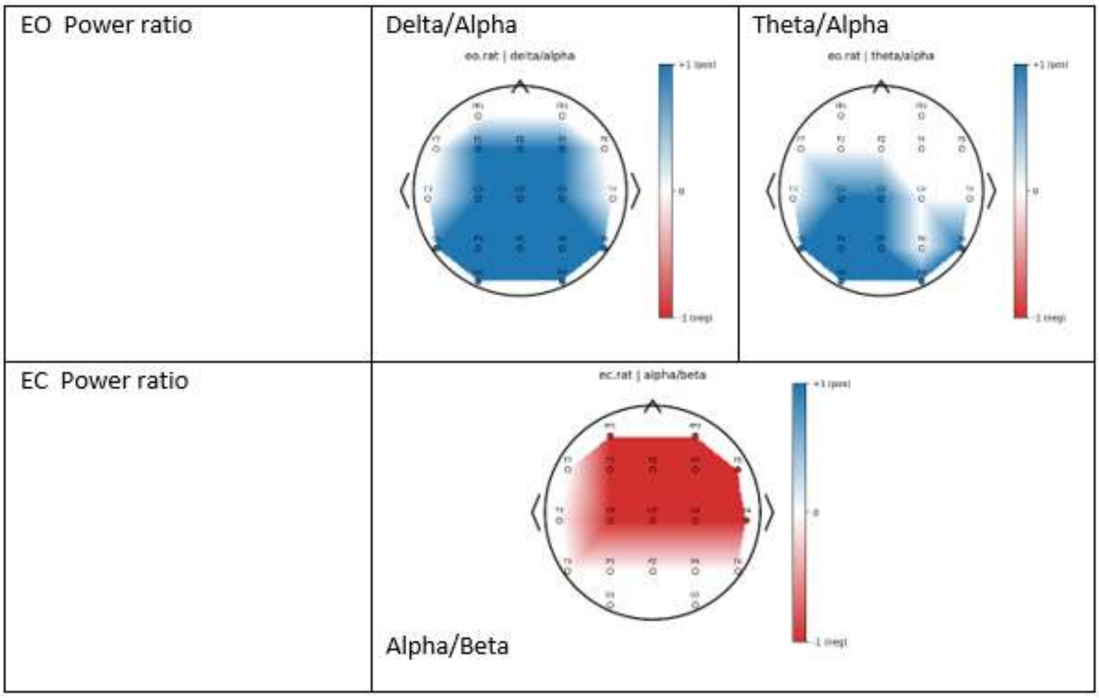
Condition–Index	Frequency Band	Total Electrodes	Sig. Regressions	Pos. Sites (N)	Neg. Sites (N)	Sites List
EC.RAT	alpha/beta	19	10	10		fp1, fp2, f3, fz, f4, f8, c3, cz, c4, t4
EO.RAT	delta/alpha	19	13	13		f3, fz, f4, c3, cz, c4, t5, p3, pz, p4, t6, o1, o2
EO.RAT	theta/alpha	19	8	8		c3, cz, t5, p3, pz, t6, o1, o2

Note. RAT = power ratio. Sites are electrode names based on the 10–20 system. EC = eyes closed; EO = eyes open.

Topographically, Figure 4 recapitulates these condition-specific contrasts: EC α/β negativity appears predominantly over frontal–central sites, while EO δ/α and θ/α positivity extends across central and posterior regions, in line with the site counts in Table 3. These complementary EC vs. EO profiles is consistent with alpha's state-sensitive coupling to resting networks and highlight a nuanced interplay between alpha and both fast (beta) and slow (delta/theta) rhythms in relation to Openness.

Figure 4

Topographic Maps of Power-Ratio (RAT) Regressions with Openness



Scalp maps depicting retained RAT effects by condition: EC α/β (negative; red) and EO δ/α and θ/α (positive; blue). Colors indicate direction (red = negative, blue = positive). Spatial patterns mirror Table 3 counts, with EC α/β negativity concentrating over frontal–central regions and EO δ/α and θ/α positivity spanning central–posterior sites.

4. Discussion and Conclusion

The aim of this study was to identify associations between EEG indices and frequency bands related to the trait of Openness to Experience, as well as to categorize and map these relationships. To achieve this, we computed four EEG

E-ISSN: 2980-9681

indices—absolute power, relative power, peak frequency, and power ratios—across all frequency bands in both eyes-open (EO) and eyes-closed (EC) conditions, as well as during the transition between them. We then examined their associations with Openness scores from the NEO personality inventory. The findings indicate the strongest associations between Openness and resting EEG during the transition from eyes-closed to eyes-open, particularly in the alpha1 band, with additional effects observed in the beta, gamma, and high-gamma ranges. Weaker but partly similar patterns were noted in both EC and EO conditions separately, while absolute power, relative power, and peak frequency showed no consistent relationships with delta, theta, and high-beta activity. These findings converge with prior EEG studies linking Openness to alpha and gamma rhythms. Notably, pharmacological evidence suggests that psilocybin reduces occipital alpha power and modulates gamma-band activity through 5-HT_2A receptor activation (Kometer et al., 2013). Additionally, research has shown that psilocybin induces changes in DMN integrity alongside sustained increases in Openness (Carhart-Harris et al., 2012; MacLean et al., 2011). Our results are also consistent with EEG–fMRI studies reporting that alpha and beta dynamics covary with DMN connectivity (Hlinka et al., 2010). In contrast, our findings diverge from large-scale investigations that reported null findings for Openness or associations limited to other traits, such as Agreeableness (Jach et al., 2020; Korjus et al., 2015). In the following sections, we will examine these results in greater detail.

In our results, three frequency bands showed significant associations with Openness: reduced alpha activity, increased gamma activity, and increased beta activity. The first two findings parallel EEG changes observed under psilocybin, specifically decreased alpha and increased gamma power. However, in the case of Openness, an additional increase in beta activity was also observed. Pharmacological and personality neuroscience converge on the observation that serotonergic psychedelics such as psilocybin can be associated with increases in Openness, sometimes persisting beyond the acute drug state (Allen & DeYoung, 2017; MacLean et al., 2011). At the neural level, EEG studies consistently report that psilocybin reduces occipital alpha-band power while gamma-band power often shows upward modulation (Kometer et al., 2013; Nikolic et al., 2024; Tylš et al., 2014). In contrast, beta effects have not been consistently reported in the literature. These findings illustrate that psilocybin interventions can produce large-scale, state-dependent oscillatory changes that extend into longer-lasting shifts in the trait of Openness. Medical and neurological conditions exert strong effects on EEG, while psychiatric disorders such as depression and anxiety show moderate but reliable influences. In contrast, personality-related differences in resting oscillations are expected to be weaker and more widely distributed. Psychedelic states therefore offer a useful proof-of-concept: they amplify a personality dimension that typically leaves only subtle electrophysiological traces, making the underlying neurobiological mechanisms easier to detect. From this pattern, we infer both similarities and differences between heightened Openness and psilocybin states. Psilocybin experiences—marked by the alpha–gamma combination—are typically characterized by hallucinations, an intensified sense of unity, psychotic-like phenomena, and vivid sensory experiences. Notably, the association of gamma activity with hallucinatory percepts has been confirmed in prior research (Behrendt & Young, 2004; Hirano et al., 2015; Mulert et al., 2011). By contrast, Openness to Experience—as reflected in our findings with an alpha–beta–gamma tri-band signature—is associated with imagination, fantasy, heightened aesthetic sensitivity, and creativity. Importantly, fantasy in Openness represents a flexible and adaptive form of imaginative engagement, whereas hallucination under psilocybin reflects an uncontrolled perceptual distortion. Given the known functions of the beta band in attentional processes, working memory, and top-down executive control across perceptual tasks (Gola et al., 2013; Schmidt et al., 2019; Spitzer & Haegens, 2017), beta activity may serve a regulatory role in Openness. It balances the intense and unregulated experiential features linked to psilocybin with higher-order executive and cognitive control processes. In this sense, beta may help organize the spectrum of Openness, delineating the boundary between creativity and psychotic-like features, aesthetic appreciation and overwhelming sensory-emotional states, and fantasy and hallucination.

Jawinski et al. emphasized that EEG-vigilance, a composite index combining delta, theta, and alpha activity, provides a more sensitive marker of arousal than alpha power alone (Jawinski et al., 2021). In conjunction with Olbrich et al., who linked vigilance fluctuations to DMN activity (Olbrich et al., 2009), these studies suggest that multiple low-frequency bands may jointly shape the association between Openness and large-scale resting networks. Inspired by this perspective, we extended our analyses beyond simple relative alpha power to examine power ratios. Our analysis revealed that in the eyes-open condition, the most consistent associations of Openness with alpha were captured by delta/alpha and theta/alpha ratios. Conversely, in the eyes-closed condition, alpha/beta ratios were found to be the most predictive. This pattern indicates a complexity in how relative alpha power reflects trait–EEG associations: under eyes-closed rest, when DMN activity is known to increase, concurrent alpha and beta dynamics may specifically reflect DMN-related processes. In contrast, under eyes-open conditions, relative alpha suppression appears to be more strongly influenced by its balance with slower rhythms (delta, theta), possibly reflecting the recruitment of additional large-scale networks. Prior studies have linked delta and theta activity to Extraversion, suggesting that low-frequency dynamics may more broadly index approach-related traits beyond Openness (Allen & DeYoung, 2017; Kropotov, 2010; Tran et al., 2006). Taken together, these findings highlight that EEG correlates of Openness are multifaceted and context-dependent, reflecting both alpha's interactions with faster beta activity during eyes-closed rest and its relations to slower oscillations in eyes-open states.

The results of this study indicate that the association between the trait of Openness to Experience and EEG can be reliably observed across widespread brain sites in multiple EEG indices—such as relative power, peak frequency, and various power ratios—within the alpha, beta, and gamma bands. These findings are consistent with previous long-term observations regarding the ability of EEG to carry personality traits (Kropotov, 2010) and with our clinical experience with EEG and QEEG, which motivated the present exploratory work. However, some investigations have struggled to identify reliable associations between Openness and resting EEG spectra. For example, Korjus et al. applied machine-learning approaches to resting-state EEG in nearly 300 participants and found that none of the Big Five traits, including Openness, could be predicted from spectral power—although the same algorithms robustly classified eyes-open versus eyes-closed states (Korjus et al., 2015). Similarly, Jach et al. used multivariate pattern analysis and reported that only Agreeableness could be consistently decoded, while Openness and other traits yielded null results (Jach et al., 2020). These findings highlight that trait–EEG associations are extremely subtle and easily obscured when relying on conventional indices such as absolute or relative power. Moreover, common statistical correction methods may further suppress such weak effects.

On the one hand, the research literature shows that EEG variance is strongly influenced by factors unrelated to personality traits, such as medical conditions, medication use, and psychiatric disorders. On the other hand, the activity of neural networks involved in the processing of personality traits generates electrical oscillations—albeit subtle—that still carry personality-related information in EEG signals. To reduce the risk of overlooking such weak but potentially meaningful effects, we examined multiple EEG indices across each frequency band. We also avoided applying conventional statistical corrections that might eliminate small but spatially consistent effects, and instead emphasized the spatial replicability of significant results. While this approach represents a limitation of the present study—since it prioritizes sensitivity over strict control of false positives—it can also be considered a methodological strength. By allowing subtle but consistent trait-related signals to emerge, this strategy provides a more realistic window into the weak and distributed nature of personality–EEG associations. Based on these considerations, our results indicate that in personality EEG research, when the aim is to detect and aggregate subtle effects, interpretable results may emerge. Conversely, when only large effects are targeted and small variances disregarded, null findings are the more likely outcome. Following the same logic, for predicting personality traits using machine-learning algorithms, guided input features may be preferable to unguided ones, as they help reduce variance stemming from non-personality factors. For example, focusing on features derived from the alpha, beta, and gamma bands may improve prediction of Openness to Experience.

Several limitations of the present study should be acknowledged: Although our final sample of 352 participants is relatively large compared to many EEG-personality investigations, it remains modest given the high dimensionality of EEG data. Detecting subtle trait-related effects across multiple electrodes, bands, and indices necessitates even larger samples to ensure stability and generalizability.

We relied on the NEO PI-R and commonly used EEG indices (absolute power, relative power, peak frequency, and power ratios) to maximize comparability with existing literature. While this choice enhances the interpretability and reproducibility of our findings, it may obscure finer distinctions within the Openness/Intellect domain. Future research would benefit from employing the Big Five Aspect Scales (BFAS), which separately score the Openness and Intellect facets. This approach may reveal more precise electrophysiological signatures of each facet and clarify the heterogeneity observed in prior work.

E-ISSN: 2980-9681

Our exploratory regression strategy prioritized sensitivity over strict control of multiple comparisons, emphasizing aggregation across sites and indices. Although this approach successfully uncovered distributed patterns, it calls for replication in larger samples and with complementary analytic strategies. One promising direction is to use our results as guided input features for large-scale machine learning studies (n > 1000) aimed at predicting Openness from EEG. Such efforts could help establish whether the subtle, context-dependent patterns we identified scale reliably across populations.

Future studies may also benefit from integrating multimodal measures (e.g., simultaneous EEG-fMRI or EEG-MEG) to directly map oscillatory signatures onto large-scale networks such as the DMN. Additionally, longitudinal designs could be employed to test the stability of trait-related EEG motifs over time. By addressing these limitations, future research can provide a more nuanced understanding of the relationship between EEG dynamics and personality traits like Openness.

Taken together, the present findings suggest that Openness to Experience is reflected in subtle but consistent EEG signatures that emerge most clearly when considering state-dependent contrasts and multiple spectral indices. The strongest associations were observed during the transition from eyes-closed (EC) to eyes-open (EO) conditions, characterized by reduced alpha1, increased beta, and increased gamma power, forming a tri-band profile. This pattern partially overlaps with the alpha–gamma signature associated with psilocybin but is distinguished by the additional beta component, which may provide top-down regulation that separates the imaginative, aesthetic, and creative aspects of Openness from hallucinatory or psychotic-like phenomena.

While vigilance studies have emphasized that combined indices incorporating delta, theta, and alpha provide more sensitive markers of brain state than alpha power alone (Jawinski et al., 2021; Olbrich et al., 2009) and have linked vigilance fluctuations to DMN activity, our results both converge with and diverge from this perspective. In both EC and EO conditions, we observed relative alpha power associations with Openness. However, when power ratios were considered, different dynamics emerged: in the eyes-open condition, alpha's associations were most consistently expressed through its balance with delta and theta (delta/alpha, theta/alpha), whereas in the eyes-closed condition, these slow-wave ratios were less relevant, and alpha/beta ratios proved to be more predictive.

Thus, our findings suggest that Openness-related alpha effects are context-dependent. They align with vigilance accounts in highlighting the importance of multi-band interactions linked to large-scale networks such as the DMN, but differ in the specific patterns that emerge across EC and EO states. This divergence may reflect the recruitment of partially distinct networks in each resting state or the differential expression of Openness and Intellect facets within the broader Openness/Intellect domain. At the same time, large-scale studies reporting null or trait-specific results highlight that such effects are weak and easily overlooked with conventional analyses (Jach et al., 2020; Korjus et al., 2015). By combining exploratory regressions with spatial and spectral aggregation, our study demonstrates that Openness leaves a detectable, multiband electrophysiological trace—one that is modest in size, context-sensitive, and embedded in the dynamic interplay of alpha with both slower and faster oscillatory activity.

Authors' Contributions

All authors significantly contributed to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this study, to observe ethical considerations, participants were informed about the goals and importance of the research before the start of the study and participated in the research with informed consent.

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