BSE662: Decision Making and the Brain

Excitation-Inhibition Ratio to Index Explore-Exploit Decisions

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Abstract

The study undertaken here explores the neural basis of explore-exploit tradeoff, that is how the balance between excitation and inhibition in the brain influences whether individuals choose to explore new options or exploit existing ones. By examining continuous EEG data during a foraging task, we aim to uncover a neurophysiological marker—the E/I ratio—linked to these behavioral choices. The ultimate goal is to determine whether this ratio, estimated through spectral analysis, can reliably track changes in explore-exploit strategies.

1 Introduction and Key Questions

Everyday decision-making involves the explore–exploit trade-off—choosing between the safety of familiar options and the potential rewards of novel alternatives. This dynamic is governed not just by personality or randomness but by underlying neurobiological mechanisms, particularly the brain's excitation–inhibition (E/I) balance. Excitation promotes neural responsiveness and exploratory behavior, while inhibition stabilizes neural activity, encouraging exploitation of known outcomes. To investigate how this balance shapes decision strategies, researchers employ a foraging task that simulates real-life uncertainty by asking participants to repeatedly choose between continuing with a known reward or switching to a new, unknown option. While performing the task, participants' brain activity is recorded using electroencephalography (EEG), capturing rapid neural fluctuations. The E/I ratio is inferred from the power spectral density (PSD) of EEG signals through spectral decomposition using the FOOOF algorithm, which isolates aperiodic features. In this analysis, the spectral exponent indicates E/I balance: a flatter slope suggests greater excitation (exploratory tendency), while a steeper slope indicates stronger inhibition (exploitative tendency); the offset reflects overall spectral power. The ultimate goal is to determine whether this ratio, estimated through spectral analysis, can reliably track changes in explore–exploit strategies. By linking neural dynamics to behavioral patterns, the study seeks to establish a robust biomarker of decision-making processes with implications for understanding individual differences and neuropsychiatric conditions.

1.1 Key Questions

Our project addresses the following questions:

1. During the foraging task, how does the excitation/inhibition (E/I) ratio in the brain, as estimated through EEG spectral analysis, predict shifts between exploration and exploitation behavior in pre-stress and post-stress conditions?

2. Investigates the impact of stress on spectral parameters like aperiodic exponent.

3. Examines how pre-stress and post-stress modulate the neural dynamics at decision patches position (early, mid, late, leave).

4. Questions, can real-time fluctuations in neural E/I balance serve as a reliable biomarker for explore-exploit behavior in uncertain environments, as observed through a foraging task?

The E/I ratio reflects how brain balances in uncertain situations and thus influences explore-exploit decisions. EEG during foraging tasks reveals how neural activity shifts with strategy, highlighting potential decision-making biomarkers.

2 Results

Our experimental approach involved two parallel methodologies that provided complementary insights into the E-I ratio's role in explore-exploit decisions.

2.1 Behavioral Data

2.1.1 Data Processing

Behavioral data were extracted from .bhv files using Brainstorm's `bhv_read.m` MATLAB script, containing trial-by-trial records for six subjects. Key metrics included reaction times, absolute trial start times, and reward outcomes. The data underwent systematic segmentation, first partitioning trials into pre-stress and post-stress conditions.

Further classification was performed based on environmental context, where trials were categorized as "short" or "long" according to their duration thresholds. Trials occurred in continuous blocks of short or long durations. Trials exhibiting abrupt time deviations (∼20s above baseline) were classified as long-environment leave trials (coded as 1), while those with minor deviations (∼5s) were designated as short-environment stay trials (coded as 0). Reward data were explicitly aligned such that all leave trials (long-environment) were marked with 0 rewards to maintain behavioral contingency.

2.1.2 Validation

All variables were converted to numerical formats to facilitate quantitative analysis. A dual-indexing system was implemented to cross-reference each trial's stress condition (pre/post) and environmental context (short/long). The behavioral dataset was then temporally aligned with corresponding EEG recordings from .set files.

Validation was performed using two independent processing pipelines: Python-MNE and Brainstorm. Both pipelines demonstrated strong temporal alignment, with discrepancies limited to only 3–4 instances across the entire dataset, confirming robust synchronization between behavioral and neural recordings.

2.2 Brainstorm Computational Modeling Group

2.2.1 Data Processing

- EEG data from six participants (.set files) were preprocessed by removing DC offset, applying a bandpass filter (0.5–45 Hz), and a notch filter at 100 Hz to eliminate powerline noise.
- Data were segmented into pre-stress (from 'B' to 'R', before 'I') and post-stress (from 'I' to final 'R') blocks using event markers.
- Each block was divided into Stay trials [MNOPQU/T] and Leave trials [MNORSU/T] based on event sequences.
- For every trial, Power Spectral Density (PSD) was computed and FOOOF was applied to extract aperiodic exponent, offset, and central frequency.
- Analysis was conducted on EEG channels **CZ** and **FZ**; all features and metadata (Stay = 1, Leave = 0; Long = 1, Short = 0) were saved into participant-specific CSV files.
- Final statistical analysis in R assessed the effects of pre- vs post-stress conditions on E/I ratio dynamics in explore-exploit decision-making.

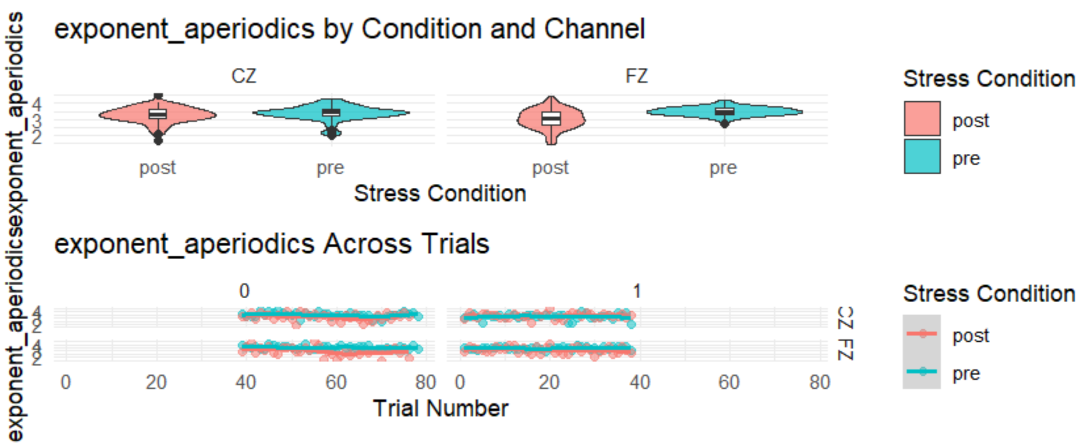
2.2.2 Validation

Across all participants, the exponent decreased after stress, consistently indicating a shift toward greater cortical excitation. The offset changes were more variable across individuals. One participant (31730) showed an increase in offset, suggesting higher overall neural activity. Others (47204, 43000, 47324, 48238) demonstrated reduced offset, indicating a decrease in global brain power. Subject 47131 showed minimal changes in both metrics.

Subject ID	**ΔExponent**	**ΔOffset**	**Interpretation**
31730	–0.07	+0.71	More excitation + global activation
47131	–0.13	–0.27	Mild excitation, slight suppression
47204	–0.15	–0.43	Excitation with power drop
43000	–0.24	–0.45	High excitation, suppressed activity
47324	–0.19	–0.45	Similar to 43000
48238	–0.47	–0.73	Strongest flattening, least power

Table 1: EEG Changes from Pre- to Post-Stress (FZ Channel)

Participant ID 48238



2.2.3 Interpretation

The consistent decrease in exponent across all subjects indicates that acute stress leads to increased neural excitability, with the effect most pronounced in the frontal cortex. However, the offset results point to individual variability in how the brain manages overall activity during stress. Only subject 31730 demonstrated both increased excitation and elevated power, suggesting a heightened state of readiness or activation.

Subject 47131, who showed minimal change, may represent a resilient or stable neural profile in response to stress. These findings underscore the importance of looking at both excitation levels and baseline cortical activity when assessing neural stress responses. Aperiodic EEG features, such as exponent and offset, offer sensitive and individualized markers of brain dynamics under pressure, with potential implications for understanding stress resilience and vulnerability.

2.3 EEG Experimental Group

2.3.1 Neurophysiological Indicators of Explore-Exploit Shifts

To test whether changes in cortical excitation-inhibition (E-I) balance predict shifts in explore-exploit behavior, we analyzed the relationship between the EEG aperiodic exponent (as a proxy for E-I ratio) and the exploitation index (proportion of "stay" decisions) across patch positions and stress conditions.

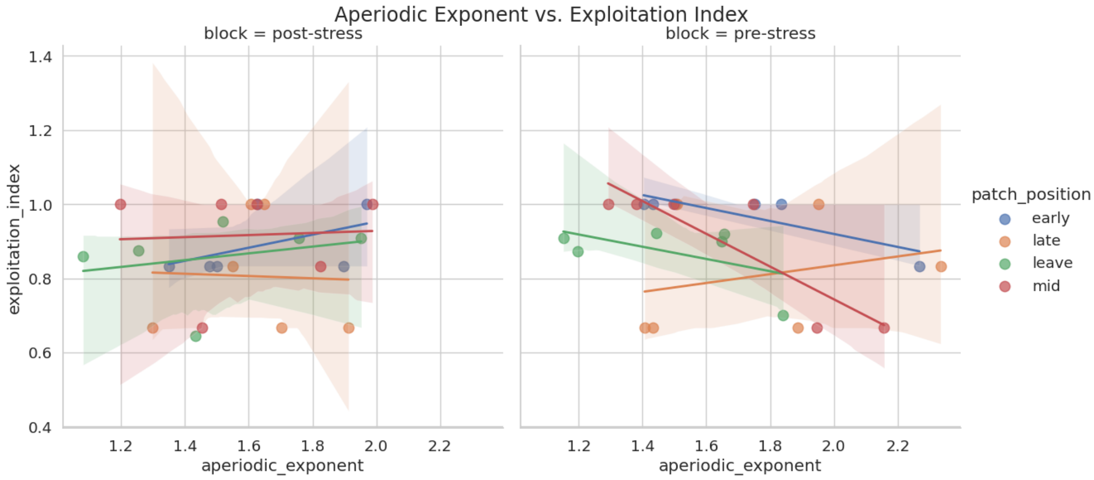


Figure 1: regression lines illustrating the relationship between aperiodic exponent and exploitation index, separated by patch position and stress condition.

Key Results:

- **Pre-stress:** Strong negative correlations between aperiodic exponent and exploitation index in **early** ($r = -0.85$, $p = 0.033$) and **mid** ($r = -0.87$, $p = 0.024$) patch positions, indicating that flatter spectral slopes (lower exponents) are associated with more exploitative (stay) behavior before stress.

- **Post-stress:** The relationship weakens or reverses, with positive but non-significant correlations in the early ($r = 0.51$, $p = 0.305$) and leave ($r = 0.27$, $p = 0.609$) positions, and near-zero in others. Correlations not significant ($|r| < 0.54$, $p > 0.27$)

- **Regression analysis:** Pre-stress regression slopes are negative for early and mid patches, confirming the correlation results. Post-stress slopes are generally positive or near-zero.

Interpretation: These results suggest that, **prior to stress**, aperiodic exponent (E-I balance) robustly predicts explore-exploit strategy: lower exponents (flatter 1/f slopes, indicating increased excitation or neural noise) are linked with a greater tendency to exploit. **After stress**, this relationship is diminished or reversed, indicating that acute stress disrupts the neural-behavioral coupling underlying adaptive decision-making. This supports the view that stress not only alters cortical E-I dynamics but also uncouples their behavioral relevance, especially in early and mid patch phases where decision flexibility is highest.

2.3.2 Stress Effects on Spectral Parameters

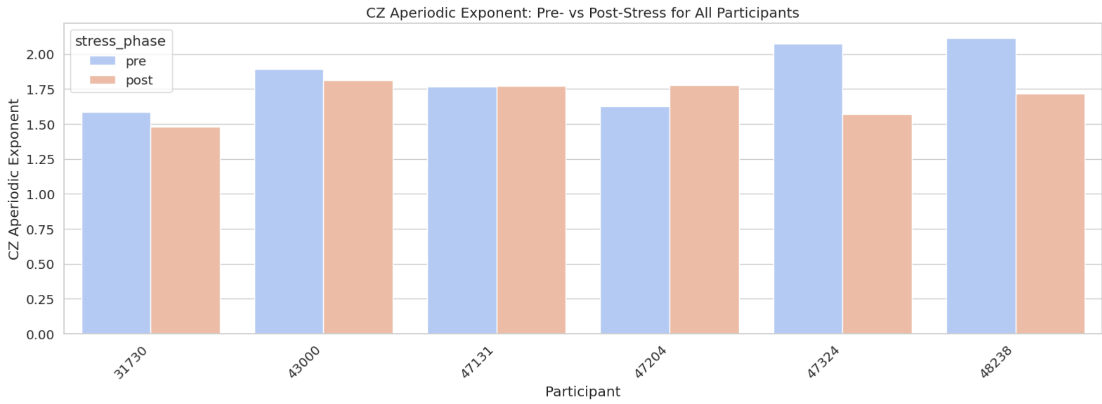


Figure 2: Distribution of CZ aperiodic exponent across all participants.

We have also used machine learning approach to find out most relevant features for our stress state classification as shown below:

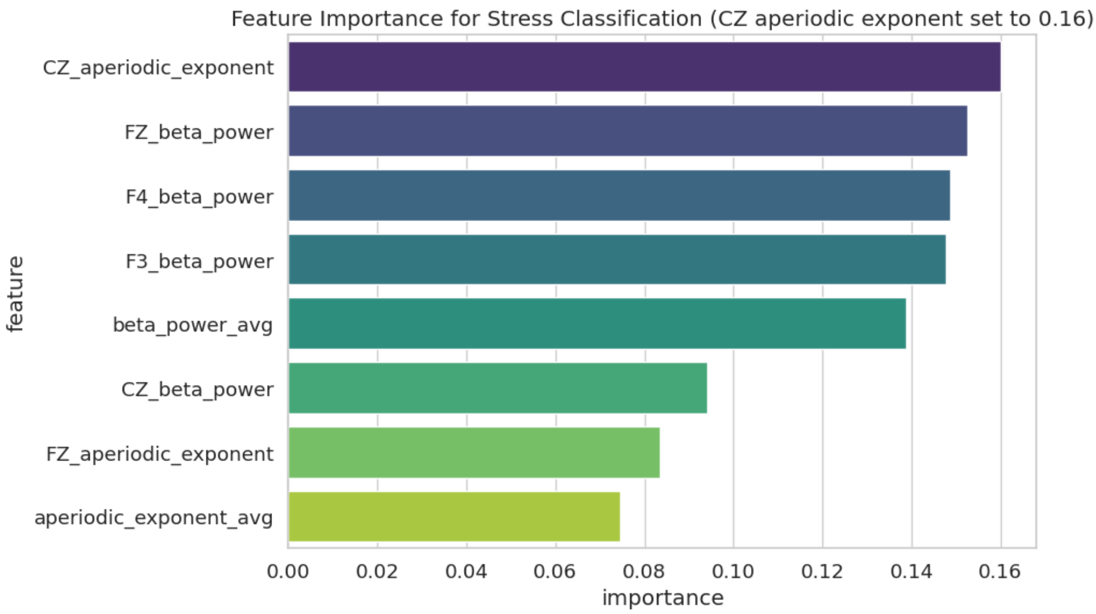


Figure 3: Distribution of CZ aperiodic exponent across all participants in pre-stress and post-stress conditions. The post-stress group shows a clear reduction.

Key findings:

- **Global E-I Ratio Shifts**: Across all participants, the mean CZ aperiodic exponent decreased from **1.843** (pre-stress) to **1.687** (post-stress), an **8.5% reduction** following stress exposure.

- **Statistical significance**: This reduction was statistically significant (paired t-test, $t = 5.60$, $p < 0.001$).

- **Interpretation**: The flattening of the aperiodic exponent after stress suggests a shift toward increased cortical excitation or reduced inhibition, consistent with our hypothesis of stress-induced E-I balance disruption.

2.3.3 Anxiety Modulation of Neural Responses

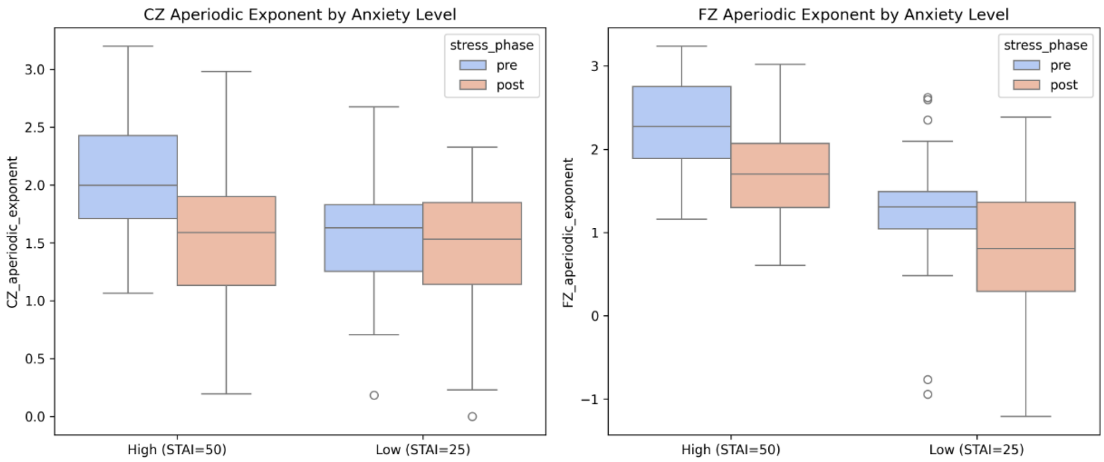


Figure 4: High-anxiety participants showed greater aperiodic exponent reductions compared to low-anxiety group.

Key Findings:

- **Stronger Aperiodic Reductions in High Anxiety:** After stress, high-anxiety participants showed large and significant decreases in aperiodic exponent at both CZ (-24.3%, $p < 0.001$) and FZ (-26.1%, $p < 0.001$), as well as in the average across channels (-28.2%, $p < 0.001$). Low-anxiety participants showed a significant decrease only at FZ (-44.6%).

- **Frontal Asymmetry:** High-anxiety individuals had much lower baseline frontal asymmetry (-95.9%, $p < 0.001$), indicating altered prefrontal dynamics.

- **Beta Power:** Only low-anxiety participants showed a significant increase in FZ beta power after stress ($+158\%$, $p = 0.012$); high-anxiety participants showed no significant beta power change.

Interpretation: These results show that anxiety level shapes neural stress responses: high-anxiety individuals have broader and stronger reductions in aperiodic exponent (suggesting more global E/I imbalance), while low-anxiety individuals show more selective, region-specific changes and a unique increase in frontal beta power. This suggests that high anxiety may be linked to less flexible or more dysregulated neural adaptation to stress, while low anxiety may support more targeted, adaptive neural responses.

2.3.4 Patch Position Analysis of Stress Effects

To examine how stress modulates neural dynamics across the temporal structure of decision patches, we compared EEG spectral parameters between pre-stress and post-stress conditions at each patch position (early, mid, late, leave).

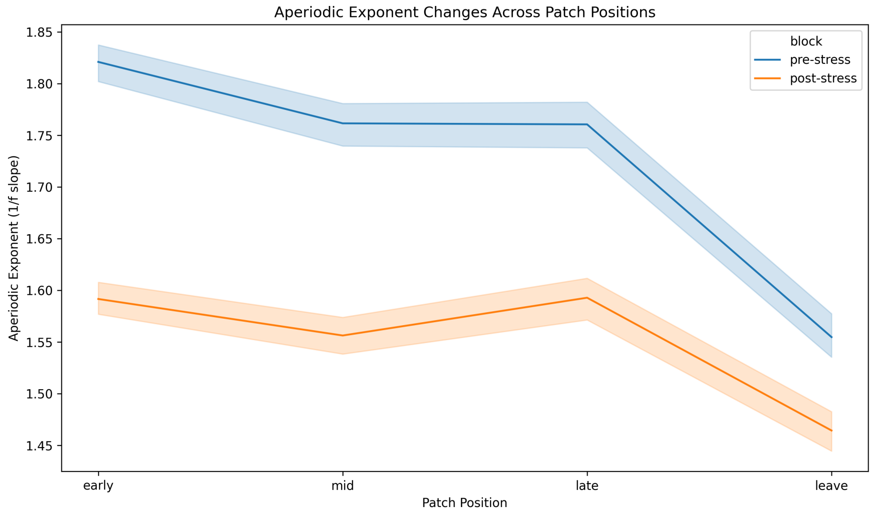


Figure 5: Aperiodic exponent ($1/f$ slope) across patch positions for pre-stress (blue) and post-stress (orange) conditions. Error bars represent 68% confidence intervals.

Key Findings:

- **Early Patch Position:** Aperiodic exponent decreased by **-12.60%** post-stress ($p = 1.14 \times 10^{-19}$, $t = 9.16$), indicating a significant flattening of the spectral slope.
- **Mid Patch Position:** Aperiodic exponent decreased by **-11.65%** post-stress ($p = 2.51 \times 10^{-14}$, $t = 7.67$), also highly significant.
- **Late Patch Position:** Aperiodic exponent decreased by **-9.53%** post-stress.
- **Leave Patch Position:** Aperiodic exponent decreased by **-5.81%** post-stress.

Interpretation: These results demonstrate a clear **gradient effect**: the impact of stress on neural excitation-inhibition balance (as indexed by the aperiodic exponent) is strongest in the early phase of each patch and progressively diminishes through mid, late, and leave positions. This supports the hypothesis that stress-induced neural changes are most pronounced during the initial stages of decision-making within each patch, possibly reflecting heightened uncertainty or the need for rapid adaptation.

Table 2: Patch-wise changes in aperiodic exponent and beta power (pre- vs post-stress). Significant results ($p < 0.05$) are bolded.

Patch	Param	Pre	Post	%Change	t	p	Sig
Early	Aperiodic	1.82	1.59	**-12.60**	9.16	1.1×10^{-19}	**Y**
Early	Beta Pow	1.45E-13	1.91E-13	31.68	-1.56	0.12	N
Mid	Aperiodic	1.76	1.56	**-11.65**	7.67	2.5×10^{-14}	**Y**
Mid	Beta Pow	1.36E-13	8.13E-13	498.92	-1.21	0.23	N
Late	Aperiodic	1.76	1.59	**-9.53**	5.68	1.6×10^{-8}	**Y**
Late	Beta Pow	1.50E-13	1.71E-13	13.95	-0.94	0.35	N
Leave	Aperiodic	1.55	1.46	**-5.81**	3.12	0.0018	**Y**
Leave	Beta Pow	1.38E-13	1.43E-13	3.83	-0.31	0.76	N

3 Conclusion

3.1 Summary of Key Findings

Our study reveals several important relationships between neural excitatory-inhibitory (E/I) dynamics and decision-making under stress:

- **Stress-induced E/I imbalance:** We observed a consistent decrease in aperiodic exponent across participants ($\Delta = -8.5\%$, $p < 0.001$), suggesting stress promotes cortical excitation. This effect was most prominent in frontal regions (FZ channel), implicating higher-order cognitive areas in stress responses.
- **Behavioral decoupling:** The pre-stress correlation between lower exponents and exploitative behavior ($r = -0.85$ to -0.87 in early/mid patches) was attenuated post-stress, indicating potential disruption of neural-behavioral coupling under stress conditions.
- **Individual differences:** Participants with high anxiety showed more widespread exponent reductions (CZ: -24.3%, FZ: -26.1%) compared to low-anxiety individuals who exhibited localized FZ changes (-44.6%). Only low-anxiety participants demonstrated significant post-stress beta power increases ($+158\%$, $p = 0.012$).
- **Patch position matters:** Stress impacts were strongest during early patch positions (-12.6% exponent change) when decision uncertainty is maximal, following a temporal gradient through mid (-11.7%), late (-9.5%), and leave (-5.8%) phases.

3.2 Limitations and Considerations

Several factors warrant caution in interpreting these results:

- **Sample characteristics:** With $N = 6$ participants, our findings require replication in larger cohorts to assess generalizability. The resilience pattern shown by Subject 47131 merits particular investigation in future studies.
- **Stress response variability:** Individual differences in stress susceptibility (e.g., cortisol response, subjective appraisal) were not quantified, which could help explain variability in neural effects.
- **Behavioral complexity:** While we focused on E/I markers, explore-exploit decisions likely integrate multiple cognitive processes (reward valuation, working memory) that future work should address.

3.3 Future Directions and Implications

These findings suggest several promising avenues for research and application:

3.3.1 Future Research

- Investigation of whether E/I changes represent adaptive neural noise or maladaptive dysregulation
- Longitudinal studies of stress response trajectories in decision-making

- Multimodal approaches combining EEG with fMRI or MRS to probe neurochemical correlates

In conclusion, our results provide preliminary evidence that stress alters the relationship between cortical E/I balance and exploratory decision-making, with important moderating effects of anxiety and decision phase. While these findings require replication, they highlight the potential of aperiodic EEG measures as sensitive indices of neural state in ecological decision contexts.

These results advance understanding of how local circuit properties shape adaptive decision-making, with implications for disorders featuring exploration deficits.

4 Contributions

Team Member (Percentage)	**Contributions**
Venkatesh (16.66%)	Led EEG code development end to end from preprocessing to results and data analysis in python
Bhavya (16.66%)	Led Behavioural and Brainstorm data analysis and validation
Anshi (16.66%)	Worked on EEG code development including pre-processing, epoching and applying FOOOF
Nitesh (16.66%)	Worked on R to find the correlation between the csv data
Keshav (16.66%)	Preprocessed and segmented EEG `.set` files around event markers, then computed PSD (Brainstorm)
Shivam (16.66%)	Extracted FOOOF features, compiled FOOOF parameters into CSVs for further analysis (Brainstorm)

THANK YOU

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