An EEG-Based Neural Re-evaluation Index for Moral-Semantic Conflict

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ABSTRACT: Most studies of cognitive control rely on experiment-wide averages, failing to capture trial-by-trial neural adaptation essential for quantifying an individual's capacity for belief updating. Consequently, there is currently no standardized, survey-free EEG metric to operationalize re-evaluation readiness when individuals encounter conflicting information. This project aims to address this gap by developing the Neural Re-evaluation Index (NRI) to function as a physiological marker of cognitive re-evaluation capacity. The study utilized a publicly available BIDS-formatted EEG dataset with 31 participants that involved moral-semantic conflict. The frontal theta power and the theta–beta ratio (TBR) were extracted using a reproducible Python pipeline. The NRI was constructed by calculating the standardized modulation of these signals during incongruent "re-evaluation triggers" relative to baseline congruent trials and was validated using group-level statistical comparisons and Leave-One-Subject-Out (LOSO) cross-validated decoding. Results showed that incongruent stimuli displayed a higher frontal theta and TBR values at the group level, validating the NRI's sensitivity to conflict-related neural recruitment. The LOSO classifier achieved a modest AUC of 0.543, establishing a foundation for a discriminative signal for identifying belief-updating states while reflecting the inherent complexity of cross-subject neural decoding. These findings support theories of functional dissociation, where increased theta–beta dynamics indicate the active suppression of prior mental models. The utility of the NRI lies in its reproducible, EEG-only framework that bypasses the biases of self-report measures by capturing re-evaluation readiness at a neural level with broad applications for enhancing conceptual change in education and improving resistance to misinformation.

KEYWORDS: EEG, Bias, Neural Activity, Brain Waves, NRI.

Introduction

Electroencephalography, a non-invasive measurement of the brain's electric fields, is used to record the brain's electrical activity through electrodes, capturing brain waves.[1] Brain waves are oscillating electrical voltages in the brain, measuring just a few millionths of a volt.[2] These brain waves are classified by frequency into five bands: delta (0.5–4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (16–31 Hz), and gamma (36–90 Hz).[3] The five brainwave bands represented distinct ranges of neural oscillations, each associated with characteristic functional states of the brain, from deep sleep and relaxation to active cognition and heightened concentration.[4]

As a result of EEGs' millisecond-level temporal resolution and comparatively low cost to other neuroimaging modalities, it has been widely adopted in both clinical and research contexts worldwide.[1] Clinically, EEG is used to diagnose and monitor neurological conditions, while at the research level, it has become central to the study of cognition, perception, and adaptive behaviour.[5] Globally, EEG constitutes a standard diagnostic and monitoring tool in neurology for conditions such as epilepsy, sleep disorders, and encephalopathies.[6]

Moreover, EEG has also been extensively applied to the study of error processing and decision-making due to its ability to capture rapid neural responses to cognitive conflict and feedback. The growth of open-access neuroimaging repositories supported these advances.[7] In India, researchers at institutions like AIIMS Raipur and AIIMS Kalyani used EEG and ERPs to objectively identify subclinical cognitive impairment in PCOS patients by measuring markers such as increased theta-alpha ratios and reduced P300 amplitudes.[8] Another study employs high-density EEGs to demonstrate that faces act as more potent emotional distractors than words, activating neural circuits associated with saliency, conflict, and goal-directed behaviour.[9]

Research has consistently demonstrated that distinct EEG frequency bands were differentially involved in decision-making, evaluation, and self-referential cognition. For example, a study investigating intracranial activity found that cortical theta and beta oscillations in the lateral prefrontal cortex (LPFC) functionally dissociate during decision-making, with higher theta activity observed during impulsive choices and higher beta activity during non-impulsive decisions.[8] A paper on social dynamics revealed that low-dominance individuals exhibit larger Feedback-Related Negativity (FRN) amplitudes, indicating a heightened concern for performance evaluation and sensitivity to negative prediction errors.[10] The study defined low dominance using the Personality Research Form dominance subscale (PRF-d). Another investigation into memory recall demonstrated that recalling decisions linked to self-threatening negative feedback requires greater cognitive effort, manifesting as increased beta and gamma band activity.[11] Additionally, a study on motivation identified Frontal Alpha Asymmetry (FAA) as a key predictor of decision-making, where leftward

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asymmetry serves as a proxy for withdrawal processes, while rightward asymmetry reflects an approach-oriented state.[12]

Technique-focused EEG research has emphasized the development of composite frequency-based indices to quantify cognitive states with greater precision. An example is the Theta-to-Alpha Ratio (TAR), which is a highly effective marker for measuring cognitive effort and workload during memory manipulation tasks.[12] In contrast, the Theta-Alpha-to-Beta Ratio (TA2BR) measured at temporal locations has emerged as a superior descriptor for assessing vigilance and fatigue states in tasks requiring sustained attention.[13] The Theta-Alpha-to-Beta Ratio (TA2BR) is calculated by summing the power of slow waves (theta and alpha) and dividing them by the power of fast waves (beta). Furthermore, advanced source localization methods, such as sLORETA, have identified the hyperactivity of the amygdala and the involvement of the dorsolateral prefrontal cortex as central to the reward-punishment processing loop.[14] Finally, multivariate modelling in high-stress environments has shown that lower beta-band activation in the frontal cortex correlates with better situational performance and reasoning, suggesting that high performance is underpinned by greater neural efficiency and reduced cognitive load.[15]

Overall, in previous research studies, there have been extensive investigations into EEG spectral biomarkers and event-related potentials (ERPs) to understand cognitive control, impulsivity, and feedback processing. The studies show that frontal theta activity is a central mechanism for action monitoring, and the theta-to-beta ratio is a biomarker for self-regulation and inhibition, while neural markers such as Feedback-Related Negativity (FRN) and the P3 component have been identified as critical indices for identifying prediction errors and updating internal models. However, there was a clear research gap. Firstly, Most studies collapse behavioral data across entire experiments, failing to capture the trial-by-trial adaptation necessary to quantify an individual's innate capacity for cognitive re-evaluation. Secondly, while EEG biomarkers of conflict and adaptation are well established, they have not been systematically integrated into a reproducible, survey-free framework that captures neural receptiveness to belief updating as a cognitive state. Publicly available EEG datasets, particularly those involving cognitive conflict and feedback, remain underutilized for identifying cross-task neural signatures that precede persuasion or conceptual change. As a result, there is currently no standardized EEG-based metric that operationalizes when the brain enters a “persuasion-ready” or re-evaluation state. Thus, it was hypothesized that individuals who exhibit stronger frontal theta reactivity, adaptive theta–beta ratio modulation, and sustained post-conflict neural adjustment across trials demonstrate greater neural receptiveness to belief updating. By analyzing open-access EEG datasets and integrating these spectral and adaptation features into a novel Neural Re-evaluation Index (NRI), this project aims to address the gap by providing a reproducible, EEG-only marker of cognitive re-evaluation capacity that generalizes across tasks and datasets.

Methodology

Data Collection.

To acquire data for analysis, public datasets of EEG data were searched, and an appropriate dataset was chosen from an open-access repository of neuroimaging data in November 2023, from the study 'Investigating the cognitive conflict triggered by moral judgement of accidental harm: an event-related potentials study' (Flora Schwartz, Radouane El-Yagoubi, Julie Cayron, Pierre-Vincent Paubel, and Bastien Tremoliere, n.d.). The data set consists of electroencephalography (EEG) data recordings of 31 healthy participants analyzed using event-related potentials (ERPs). The data set was originally collected as part of a controlled laboratory research program using a third-party task (N400). Participants heard stories that involved morally sensitive situations with deliberate or unintentional harm and had to indicate whether a final word displayed, and a statement below was congruous with the story by pressing a response button. The EEG findings were collected continuously and then divided into event-related potentials (ERPs), which were time-locked to the presentation of the target word. It consists of raw EEG records, event markers, and metadata about subjects and experimental conditions. Trials were explicitly labeled as either intentional or accidental, and congruent or incongruent, and condition-wise ERP comparisons were possible.

Feature Engineering:

EEG processing was done using a pipeline in the Anaconda environment. The code compared the trial sequences to generate numerical features of different patients per event using ratios such as the theta-beta ratio. The theta–beta ratio (TBR) was calculated as the ratio of mean theta band power (4–7 Hz) to mean beta band power (16–31 Hz) for each epoch, and log-transformed for normalization before further analysis. The pipeline took data in BIDS structured EEG experimental data with sampling rates and metadata for events. Event onsets were identified based on the timestamp values that are stored in files in the BIDS events.tsv that contain the time when each stimulus was presented over the one-hour continuous EEG recording. These timestamps were used to segment the continuous EEG signal into epochs, segments of time of the signal surrounding an event. The raw EEG signals were bandpass filtered between 0.5 and 40 Hz to remove slow drifts and high-frequency noise. Ocular and movement-related artifacts were addressed using automated artifact rejection based on amplitude thresholds, and noisy epochs exceeding ±100 μV were excluded from further analysis. These epochs were time-locked to a definition with a discrete pre-event and post-event baselines. The analysis was limited to frontal EEG channels - Fz, FC1, FC2, AF3, and AF4. Each of the epochs was converted from the time domain to the frequency domain to look at the spectral content, which was the breakdown of the EEG signal into its underlying frequency components. Mean power in theta and beta in the oscillatory activity.

Neural Re-evaluation Index Building:

NRI is a composite EEG index that is based on frontal theta modulation during cognitive conflict. In this case, frontal theta is usually linked to the detection of conflict and the recruitment of one's cognitive control, and the TBR corresponds to the balance between cognitive control and good temporal stability. Through their combination, and together in NRI, the NRI provides a physiological measure of a person's readiness to update their internal representations when confronted with information that is incongruent or conflicting. In this paradigm, 'conflict' was used to refer to semantically incongruent (REVAL_TRIGGER) target words (compared to congruent (BASELINE) trials) with the preceding moral scenario. The NRI was the measure of the difference in the neural activity of the REVAL_TRIGGER and the BASELINE trials. It measured the reactivity with the amount of frontal theta activity increased immediately after a conflicting target word was presented, and the regulation balance with changes in TBR. Theta activity correlated with conflict detection and control engagement, but the beta activity was correlated with continued interpretations or cognitive stability. The activation of the TBR was reflected in how the brain changes between incorporating new information and storing existing information. Thus, using the combination of frontal theta reactivity and theta-beta dynamics, the NRI was able to capture both rapid detection of conflict and the possible updating of an initial interpretation.

Results

Input Features Used For NRI:

Neural features based on post-target EEG activity were used to operationalize the NRI. This consisted of two neural features (frontal theta reactivity and TBR reactivity) for several time windows in aggregate at the participant level. Frontal theta reactivity (4-7 Hz) was used as an indicator of the cognitive control engagement during the re-evaluation triggers. Incongruent target words were linked to more frontal theta power than congruent trials. Frontal theta reactivity was defined as the difference between theta power during REVALTRIGGER and BASELINE trials. The difference was able to isolate the increase in neural activity that was specifically associated with conflict and not general processing. A greater increase in frontal theta reflected a greater involvement of conflict detection and control-related processing. Frontal theta reactivity and TBR reactivity were used as indices of shifts between control-related processing associated with theta activity and maintenance-related processing associated with beta activity during re-evaluation. Therefore, the ratio reflected the relative dominance of updating-oriented to more stability-oriented neural dynamics. The TBR reactivity was calculated as the difference between the REVALTRIGGER and BASELINE trials. A larger increase in TBR was suggestive of a relative shift away from maintenance-related processing and increased participation of control-related mechanisms related to potential belief updating. Post-target activity was analyzed within a series of different short time windows, with the time window 0.0-0.8s after target onset being further divided into a series of smaller time intervals for distinguishing between early and later stages of neural modulation. The Theta and TBR values were both extracted separately for each window. Through the analysis of several windows, the index represents dynamic processing in the brain and not a single reaction. Due to differences in neural responses in individual trials, trial-level features were summarized into subject-level metrics. For every individual, the theta reactivity and TBR reactivity values were averaged between trials for each condition. This aggregation minimized variability over time and identified stable patterns of neural engagement. The number of trials was substantial for both the BASELINE and the REVALTRIGGER conditions, as shown in Figure 1.

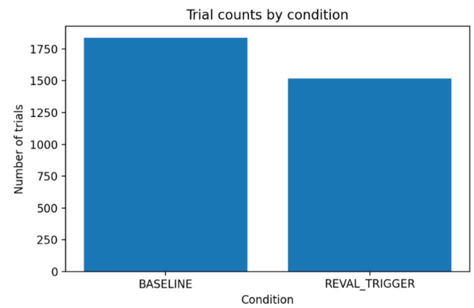

Figure 1: A bar graph of the number of trials for each condition. The x-axis is the quantity of the sum of the number of trials of the analysis (BASELINE and REVALTRIGGER), and the y-axis is the quantity of trials included. The blue bars are the aggregate trial count of the trials of all participants for each condition. The graph indicates a moderate imbalance in trial counts, with more trials in the BASELINE condition compared to the REVAL_ TRIGGER condition.

Labelling Of The Re-evaluation Trigger:

Using predefined labels, which are specified in the BIDS event files of the dataset, the target events were systematically grouped into two conditions (BASELINE and REVALTRIGGER). It indicated whether each target trial was a congruent condition or an incongruent condition to the previous scenario. Those re-evaluation moments, including a semantic inconsistency between the scenario and the final target word, were REVELTRIGGER. If the following target word was incongruent, it did not match this established representation, and a measurable prediction error was created at the moment of word presentation. Therefore, REVALTRIGGER trials were the control trials in which re-evaluation was experimentally induced and measured in terms of neural differences, evidenced by the increased frontal theta and theta-beta reactivity (Figures 2,3). All condition assignments were made directly from the standardized metadata that was provided in the dataset by filtering events based on predefined condition labels specified in the dataset metadata, and can be reproduced using the same condition mapping, strengthening the reliability of the NRI construction process.

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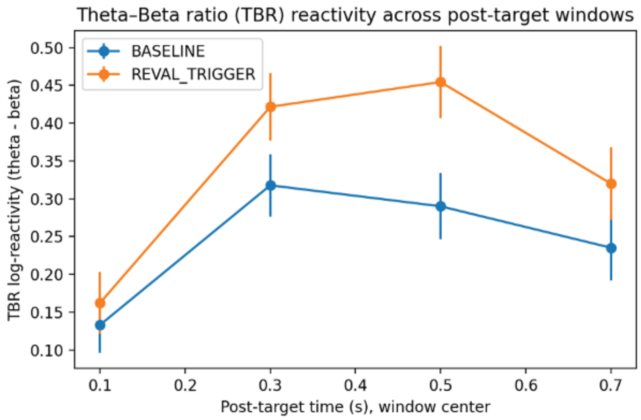

Figure 2: A line graph of Theta-Beta Ratio (TBR) reactivity across windows. Post-target time windows (0.1-0.7 s) are shown on the x-axis, and log TBR reactivity (theta - beta) is shown on the y-axis. The color blue is used to represent the BASELINE (congruent) trials, and the color orange is used to represent the REVALTRIGGER (incongruent) trials. Points indicate mean values across participants, error bars represent +/- standard error. TBR reactivity is consistently higher in the REVAL_TRIGGER condition than in the BASELINE condition across all time windows, with the largest differences observed around 0.3–0.5 s.

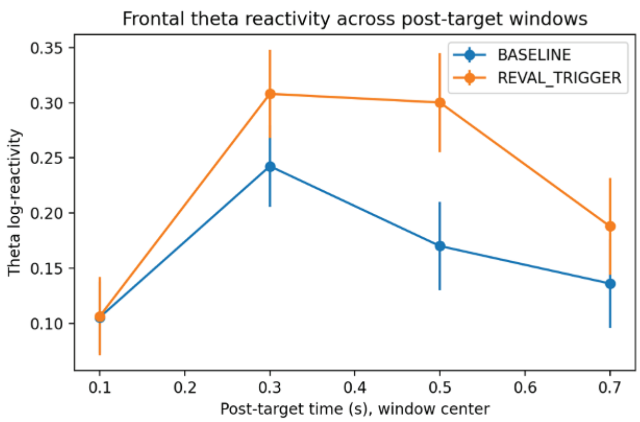

Figure 3: A line graph for Frontal theta reactivity over post target windows. The x-axis is post-target time windows (0.1 - 0.7 s); the y-axis is log frontal theta reactivity (4 to 7 Hz). The color blue stands for baseline (congruent) trials, and orange stands for REVALTRIGGER (incongruent) trials. Points indicate mean values across participants, error bars represent +/- standard error. Frontal theta reactivity is higher in the REVAL_TRIGGER condition than in the BASELINE condition across most time windows, with the largest differences observed around 0.4–0.5 s.

Subject-level Aggregation:

For the subject-level aggregation, the mean frontal theta power and TBR values were computed for all the BASELINE trials and separately for all the REVALTRIGGER trials. This led to four main condition-specific averages for each subject: mean thetabaseline, mean thetatrigger, mean TBRbaseline, and mean TBRtrigger. The result of aggregation at this stage was that random trial-to-trial fluctuations were reduced and a more stable, condition-specific estimate was obtained for each participant. The values of Frontal theta modulation were the increase in frontal theta specifically related to the incongruent stimuli. The distribution of the scores of modulations at the subject level is shown in Figure 4. The score reflects a change in the regulatory balance in conflict and non-conflict conditions. Z-score normalization was used between participants because these measures are on different numerical scales. The neural responses were compared based on what happened in the previous trial to see if conflict in one trial affected neural activity in the next trial. This sequence-based measure presents trial-by-trial adjustment in cognitive control following recent conflict.

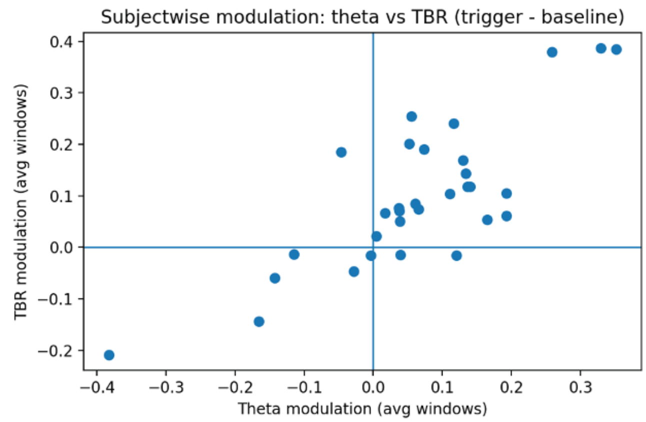

Figure 4: Subject-Level Modulation of Frontal Theta and Theta-Beta Ratio (TBR). The x-axis is the mean frontal theta modulation, and the y-axis is the mean TBR modulation (REVALTRIGGER, BASELINE), averaged on post-target windows. Each dot represents a single participant, and the reference lines at zero represent no modulation relative to baseline; positive values indicate increased activity during REVALTRIGGER trials. The figure shows positive modulation in both theta and TBR, with a general positive association between the two measures.

Normalization, scaling, and the final NRI formula:

The frontal theta modulation and TBR modulation were measured on different numerical scales, which led to each subject-level component being standardized before combination. Z-score normalization was performed across participants to ensure comparability of neural measures on a common scale. For each of these features, the group mean was subtracted from each participant's value and divided by the group standard deviation. After normalization, the NRI composite score was computed by synthesizing the average of standardized frontal theta modulation, standardized TBR modulation, and standardized adaptation component to generate one index value for each participant. This led to less reliance on any single feature, which portrayed a more general pattern of conflict-related neural involvement. The formula was kept deliberately simple so as not to lose conceptual clarity. The index was kept simple to grasp and associated with the underlying neural features (by not having complex weighting or multi-step transformations). NRI ensured that differences in neural re-evaluation readiness are examined quantitatively and proportionally, consistent with the interpretation of the index, and with the graded nature of neural responses.

Validation of NRI:

Internal validation of the NRI was done by testing whether the index was grounded in conflict processing. The incongruent trials would elicit higher theta and TBR values for the incongruent trials than the congruent trials. This pattern was indicative of a higher level of engagement of neural systems

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that are involved in conflict detection and control allocation. The finding of the expected increase in the REVALTRIGGER conditions supported the construct validity of the NRI. It showed that the neural features that were used to construct the index were sensitive to experimentally caused conflict. Computational validation of the NRI was performed by means of a Leave-One-Subject-Out (LOSO) decoding strategy. A logistic regression classifier with default L2 regularization was used for decoding, implemented using standard machine learning libraries in Python. The classifier resulted in the Area Under the Curve (AUC) value of 0.543 as shown in Figure 6. A total of theta, beta, and TBR features extracted across multiple post-target time windows were used as input to the classifier. Feature importance analysis gives information about the features that contributed most to classification as part of the neural components. As can be seen in the feature coefficient plot, LOSO folds were associated with theta and TBR features in early-to-mid post-target windows, theta0p40p6 and tbr0p4_0p6. These windows are associated with the period in which the strongest group-level modulation was observed, indicating that neural activity during the 0.4-0.6 s period contributed most to the discrimination of whether or not conflict occurred in comparison to the baseline trials. Although the classification performance across all cases was modest, the robustness of the contribution of these features suggests that there is something in the conflict-related neural modulation that can be generalized across individuals. A positive association between NRI and RT cost suggested that people who show more neural engagement of conflict were also more prone to a behavioral slowing during re-evaluation triggers. Behavioral effects were not always found to be consistent across paradigms, and response timing was observed. In tasks where the accuracy was high or the timing of response was a constraint, RT differences may be small even when neural differences were robust. Therefore, a poor or non-existent behavioral correlation does not necessarily invalidate the NRI.

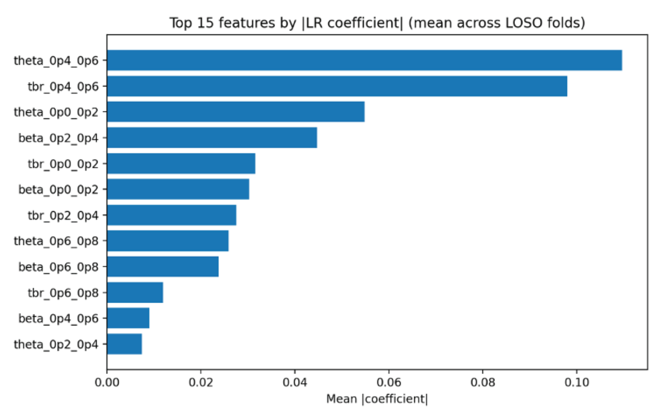

Figure 5: Top features ranked by Mean Absolute Logistic Regression Coefficient (LOSO). The x-axis represents the average (across Leave-One-Subject-Out, LOSO) of the absolute value of logistic regression coefficients. The y-axis is the list of top features in terms of importance, taken from specific time windows after targeting. Theta and TBR features, particularly in later time windows (e.g., 0.4–0.6 s), show the highest coefficients and therefore contribute most strongly to classification performance.

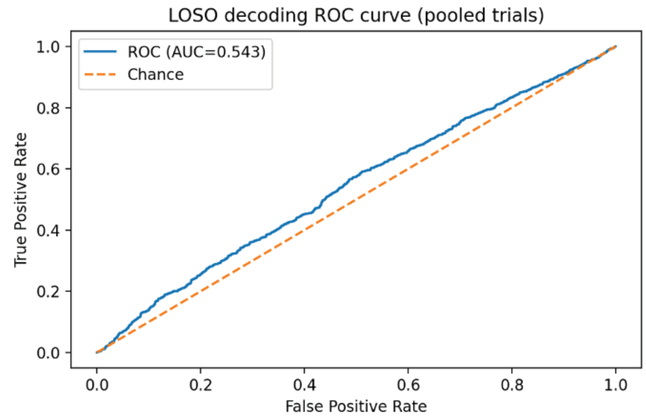

Figure 6: Leave-One-Subject-Out (LOSO) decoding Receiver Operating Characteristic (ROC) curve. On the x-axis is the false positive rate, and on the y-axis is the true positive rate. The solid blue line shows the classifier performance (AUC=0.543) and the dashed orange line shows the chance level performance (AUC=0.50). The ROC curve is a grouped curve of the trial predictions based on LOSO folds. The classifier performs only slightly above chance (AUC = 0.543), indicating limited discriminative ability between conditions.

Interpretation of NRI In The Context of The Research Question:

NRI can be interpreted as a neural indicator of cognitive re-evaluation capacity, which reflects the degree to which an individual's brain recruits conflict-related control mechanisms when faced with information that contradicts prior expectations, with a high NRI value indicating a higher degree of neural modulation during conflict. This indicates a more intensive activation of systems that are responsible for discrepancy monitoring and internal representation adjustment. The NRI, therefore, is a physiological index of readiness to change existing representations according to new information. It also allows for millisecond-level temporal resolution, which enables researchers to see neural responses at the time when conflicting information was encountered. These responses are often made before a conscious decision is made or verbally expressed. As a result, the NRI may be able to capture states related to pre-conscious readiness, that is, early neural indications that a person is allocating cognitive resources to processing and perhaps updating information. The NRI is an objective measure of belief revision efforts, and therefore could indicate whether or not a correction has been successful in getting the brain's regulatory circuitry to kick in through TBR modulation or if the correction has been turned away at a pre-conscious level.

Discussion

This project constructed a neural metric, the NRI, designed to quantify how strongly individuals engage neural mechanisms associated with conflict detection and cognitive re-evaluation. A publicly available EEG dataset involving moral scenarios followed by congruent or incongruent target words was utilized. By using the metadata and makers in the dataset, the frontal theta activity and the theta–beta ratio were extracted as neural markers of conflict processing. The calculated differences in these signals between incongruent and congruent trials were used to construct the NRI, which was then evaluat-

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ed using statistical comparisons and cross-validated decoding analyses. The results confirmed that incongruent stimuli elicit a significantly higher theta and TBR value at the group level.

The methodology of the contracted NRI aligns with recent advancements in technique-focused EEG research. A previous study demonstrated that frontal-midline theta oscillations serve as a real-time marker of cognitive control during the resolution of conflicting interpretations.[16] This project utilized theta-band activity to capture the brain's response to semantic mismatch. Furthermore, the usage of the theta–beta ratio as a core component of the NRI mirrors another study, which found that frequency ratios such as the TAR and TA2BR are superior descriptors of cognitive effort and vigilance compared to single-frequency bands alone.[13] By adopting a trial-by-trial aggregation approach rather than collapsing data across the entire experiment, this project follows the dynamic statistical modelling proposed by a research study on frontal alpha asymmetry, predicting subsequent social decision-making, allowing for a more nuanced observation of how neural states shift in response to specific feedback.[17]

In terms of results, the NRI modulation patterns support the "functional dissociation" theory observed in prior decision-making studies. As explored in a previous study, there is a documented split where theta activity is linked to impulsive choice and beta activity to cognitive control.[18] Similarly, this paper's findings suggest that an increased TBR occurs during moments requiring the suppression of an initial mental model. However, some studies have found that individual traits like social dominance significantly modulate the Feedback-Related Negativity (FRN) in response to uncertainty; the NRI focuses on a broader, task-agnostic indicator of "re-evaluation readiness."[10]

The primary limitation of the project is the relatively small sample size of 31, which may limit statistical power and the generalizability of the findings. This could improve the classifier, which showed only a modest discriminative performance, suggesting that the current feature set captures conflict-related neural signals only partially. As a future scope of this study, additional studies would be examined for the behavioral validity of the NRI by correlating NRI values with reaction time (RT) costs and accuracy differences between conflict and baseline trials. The framework would also be tested on established paradigms such as the Stroop and Flanker tasks to evaluate if the NRI reflects a task-agnostic measure of conflict processing. Further validation across paradigms will help determine whether the index can predict adaptive trust calibration in human and AI interaction contexts.

Conclusion

In conclusion, this project addresses a critical research gap by capturing dynamic and trial-by-trial neural signatures of cognitive re-evaluation by moving beyond static mode. A basic structure for an objective, persuasion-ready metric was achieved in the combination of frontal theta reactivity and TBR modulation into a combined index. The low performance of 0.543 obtained by the classifier is reflective of how hard it is to identify belief-updating states across individuals. A steady modulation in the neural activity during conflict triggers suggests that the NRI acquired meaningful involvement of cognitive control processes. The utility of this study is that it has developed a reproducible EEG-only framework, which avoids the limitations of traditional self-report surveys. The NRI provides one way of quantifying "re-evaluation readiness" on a pre-conscious level. This approach provides a process-level index of how people identify and deal with conflicting information, which may have applications in the literature of conceptual change, misinformation resistance, and adaptive human-AI interaction. Overall, the NRI provides a reproducible and objective EEG-based framework for quantifying neural readiness for cognitive re-evaluation, offering potential applications in understanding adaptive decision-making and resistance to misinformation.

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