Calorie-Dependent Differential Habituation to Repeated Food Cues Assessed via EEG Functional Connectivity

Aruna Duraisingam*, Daniele Soria†, Ramaswamy Palaniappan‡
Artificial Intelligence and Data Analytics Research Group
University of Kent
Canterbury, United Kingdom
Email: *ad727@kent.ac.uk, †d.soria@kent.ac.uk, ‡r.palani@kent.ac.uk

***Abstract*—Understanding how the brain responds and adapts to repeated exposure to food-related stimuli is critical for uncovering the neural mechanisms underlying attentional biases and eating behaviour. This study investigates within-session habituation to repeated high-calorie, low-calorie, and non-food visual stimuli using electroencephalography (EEG) based functional connectivity analysis. Connectivity was assessed using the Weighted Phase Lag Index (WPLI) across different frequency bands, a measure sensitive to phase synchrony between spatially distinct brain regions while minimising artefacts from volume conduction. Results revealed significant habituation effects for non-food (hammer) stimuli were observed in the theta band (4–8 Hz), indicated by a decline in frontoparietal connectivity across repeated trials. In contrast, low-calorie (apple) and high-calorie (pizza) stimuli exhibited sustained connectivity, suggesting persistent neural engagement. Linear trend analysis further confirmed that WPLI values decreased most rapidly for non-food stimuli, followed by low-calorie foods, with minimal decline observed for high-calorie stimuli. These findings support the hypothesis that energy-dense food cues elicit prolonged attentional responses, potentially impeding habituation mechanisms. This study highlights the utility of WPLI as a reliable metric for detecting changes in neural synchrony and offers insights into the role of caloric content in modulating attentional regulation. The results have implications for developing targeted neurocognitive interventions aimed at reducing attentional biases toward high-calorie foods, particularly among individuals at risk for overeating or obesity.**

***Index Terms*—Electroencephalogram Signal Processing, Functional Connectivity, Food Habituation, Repetition of Visual Stimuli, Neural Oscillations**

I. Introduction

Understanding the dynamics of neural communication remains a central focus in neuroscience. Even during rest, the brain exhibits coordinated activity, as observed in networks such as the default mode network (DMN) [1]. Effective cognitive processing depends on the interaction between functionally distinct brain regions [2]. These interactions, or neural connectivity patterns, can be assessed through neuroimaging techniques such as Magnetic Resonance Imaging (MRI) for anatomical structure [3], [4] or electroencephalogram (EEG) for functional and temporal coupling across distant brain areas [5]. EEG-based studies offer unique advantages due to their high temporal resolution, allowing for real-time exploration of functional interactions during cognitive and sensory tasks.

Functional connectivity (FC) and effective connectivity (EC) are the two major paradigms used to analyse brain network interactions. FC measures statistical dependencies between neural signals without implying causality, while EC attempts to infer directional influences. FC measures can be further classified into coherence-based, phase synchronisation, generalised synchronisation, and Granger causality-based metrics [6]. Within EEG research, phase synchronisation measures such as the Phase Locking Value (PLV), Phase Lag Index (PLI), and Weighted Phase Lag Index (WPLI) have gained prominence for their ability to detect synchrony between spatially distinct regions. Among these, WPLI has emerged as a particularly robust method for evaluating true neural connectivity, as it minimises the effects of volume conduction and familiar sources [7].

Phase synchronisation is defined by the stability of phase differences between oscillatory signals over time. If the instantaneous phase difference between two EEG signals remains consistent, phase synchronisation is said to occur. This phenomenon is often quantified using WPLI, which calculates phase lead-lag relationships by focusing on the imaginary component of the EEG cross-spectrum. Unlike PLV and PLI, WPLI enhances signal fidelity by reducing susceptibility to artefactual synchrony and improving statistical power, making it particularly suitable for detecting neural dynamics associated with complex behaviours.

Recent research has underscored the value of EEG-based functional connectivity for understanding altered brain activity in individuals with obesity and food addiction. Findings of increased frontal beta-band activity and altered WPLI patterns in response to high-calorie food cues suggest impaired inhibitory control and a heightened attentional bias toward palatable stimuli [9]–[11]. Building on this, earlier EEG investigations have also examined food cue reactivity and the effects of repeated exposure, showing how neural responses to food-related stimuli adapt over time. Geisler and Polich [12] showed P300 modulation with repeated exposure to food stimuli. In contrast, Loeber et al. [13] reported impaired inhibitory control in obese participants, reflecting persistent attentional bias toward high-calorie foods. More recently, Schmidt et al.

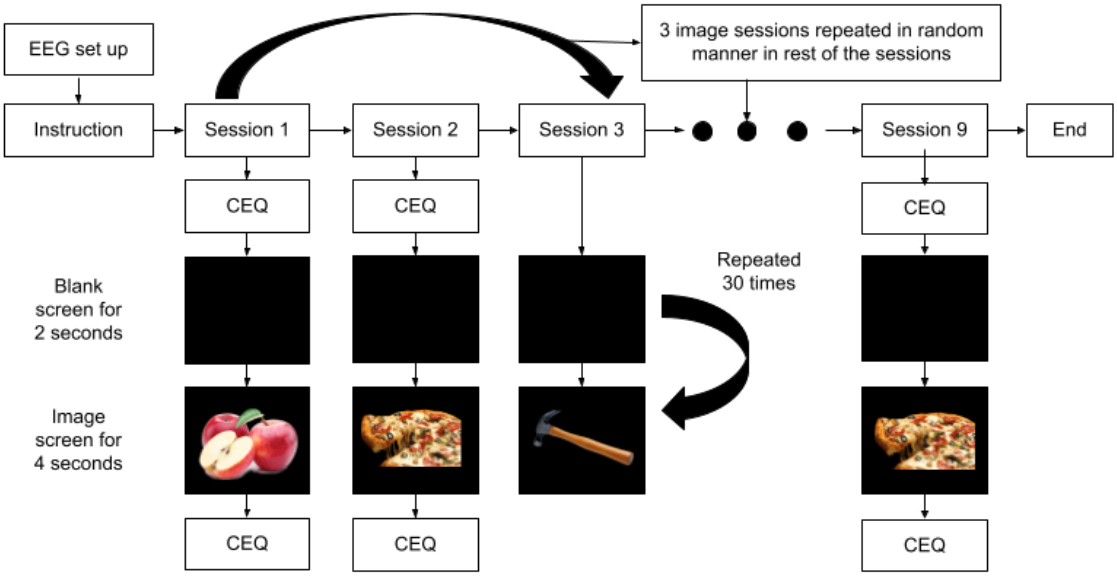


Fig. 1: Experimental design, EEG - Electroencephalogram, CEQ - Craving Experience Questionnaire (participants record their current craving intensity) [8]

[11] and Kössling et al. [10] observed altered EEG activity in children with overweight or obesity, reinforcing the influence of food salience on neural processing. Although most of these studies focused on ERP or spectral power, fewer examined inter-regional synchrony. By employing the WPLI, this study extends prior work by assessing connectivity dynamics across repeated exposures, providing a network-level perspective on how caloric content modulates attentional regulation and habituation.

Building on this foundation, the current pilot study examines within-session neural responses to repeated visual presentations of high-calorie, low-calorie, and non-food stimuli. Using the WPLI, the inter-regional functional connectivity was assessed to determine how brain networks adapt to repeated exposures and whether caloric content influences the rate and extent of adaptation. This connectivity-based approach, rarely applied in prior food cue research, offers a novel network-level perspective that extends beyond ERP and spectral measures. The insights gained may inform interventions to improve cognitive control in eating behaviours and contribute to a broader understanding of the neural mechanisms underlying food-related decision-making.

II. Methodology

A. Participants

A total of 26 participants were recruited through campus-wide advertisements. Participants were aged between 19 and 48 years (average age = 31.26±7.1 years), with BMI values ranging from 17.21 to 39.15 kg/m² (average BMI = 25.08±4.01 kg/m²). Among them, 12 participants (six females and six males) were classified as overweight or obese. Prior to the experimental sessions, participants rated their preference for apple and pizza using a six-point Likert scale (0 = extreme dislike; 5 = extreme like). Only individuals who rated both food items with a score of 3 or higher were included in the study. Participants with known neurological or eating disorders or those on medication that could influence cognitive processing were excluded. Due to excessive EEG signal noise, data from one male participant in the Low BMI group and one female participant in the High BMI group were discarded. As a result, EEG data from 24 participants were retained for analysis. All procedures were approved by the Faculty of Sciences Research Ethics Committee at the University of Kent. Written informed consent was obtained from all participants prior to their participation in the study.

B. Experimental Design and Procedure

Participants were exposed to three visual stimuli presented on a computer monitor positioned approximately one meter from the viewing point. The stimuli consisted of images of an apple (low-calorie food), a pizza (high-calorie food), and a hammer (non-food object). Each participant completed a total of nine sessions on the same day. In each session, a single image, randomly selected from the three categories, was displayed for 4 seconds, followed by a 2-second inter-stimulus interval (ISI). This image presentation cycle was repeated 30 times per session, resulting in 30 trials per session. To evaluate subjective food cravings, the Craving Experience Questionnaire (CEQ) was administered at the beginning and end of each session, followed by a rest period of five minutes. A rest period of five minutes was provided between sessions to reduce cognitive fatigue. A schematic overview of the experimental paradigm is shown in Fig. 1.

Prior to participation, written informed consent was obtained, and all individuals completed a screening questionnaire to confirm eligibility in accordance with the inclusion and exclusion criteria. To standardise event-related potential (ERP) responses and reduce the confounding effects of hunger,

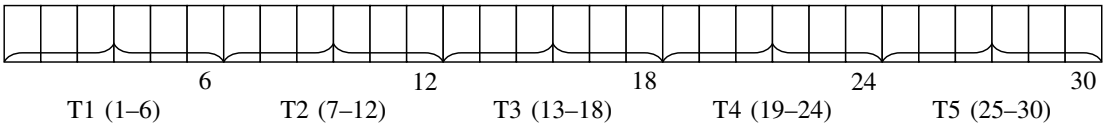


Fig. 2: Schematic of trial grouping. Each stimulus condition comprised 30 trials, sequentially divided into five trial groups (T1–T5), where T denotes a trial group, with each group containing six trials to enable assessment of habituation across repetitions.

participants were instructed to consume a substantial breakfast and refrain from eating for at least three hours before the experiment [12]. All experimental sessions were conducted at noon. Upon arrival, participants first completed the Dutch Eating Behaviour Questionnaire to understand the participants' eating behaviour. Following this, EEG electrodes were affixed, and participants were briefed on the experimental procedure. Visual stimuli were presented using the Psychtoolbox framework. If requested, a test trial was provided to ensure familiarity with the procedure. Participants then proceeded to complete the remaining sessions, each lasting approximately five minutes, during which continuous EEG recordings were obtained.

C. EEG Recording and Data Processing

EEG data for this study were recorded using the Neuroelectrics StarStim 32-channel system, with electrode placement conforming to the international 10-10 system. The sampling rate was set at 500 Hz, and reference and ground signals were collected via an ear clip using the Common Mode Sense (CMS) and Driven Right Leg (DRL) electrodes. Data preprocessing and analysis were conducted using MATLAB (R2023a), incorporating EEGLAB (v2023.1) and FieldTrip (v20231220) toolboxes. Preprocessing steps included high-pass filtering at 0.5 Hz ($-6\,\mathrm{dB}$ cutoff, Hamming-windowed sinc FIR filter) and low-pass filtering at 30 Hz, implemented via the EEGLAB FIR filter. Noisy channels were identified, removed, and subsequently interpolated.

Independent Component Analysis (ICA) was performed on the cleaned data, and non-neural artefacts such as ocular, cardiac, line noise, and channel noise were identified using the ICLabel plugin. Components with a classification probability exceeding 75% were excluded from further analysis. The data were then epoched from -100 ms to 1000 ms relative to stimulus onset.

MATLAB was further employed to extract 30 trials per participant across 24 individuals. These trials were grouped and averaged according to the corresponding image category session. To investigate within-session neural habituation to repeated visual presentations of food and non-food stimuli, the 30 trials were sequentially divided into five consecutive groups, each consisting of six trials. These were denoted as trial groups (T1–T5; see Fig. 2). The averaged trial groups were subsequently subjected to statistical evaluation using a cluster-based permutation test for each visual stimulus. This approach enabled the examination of functional connectivity dynamics across brain regions over time and facilitated statistical comparisons between food and non-food conditions.

III. Statistical assessment

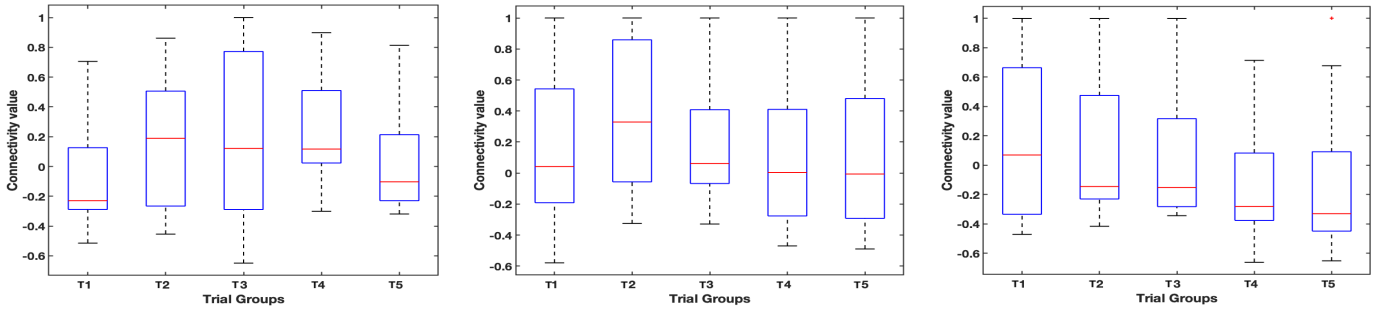
Statistical analyses were conducted to examine habituation effects and functional connectivity changes across trial groups (T1–T5) and image categories, high-calorie, low-calorie, and non-food, with a focus on midline EEG channels (Fz, Cz, Pz, and Oz). Functional connectivity was assessed using channel pair combinations (Fz–Cz, Fz–Pz, Fz–Oz, Cz–Pz, Cz–Oz, Pz–Oz), targeting brain regions associated with sensory processing, attentional regulation, and cognitive integration. The analysis encompassed five frequency bands: Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–14 Hz), Beta (15–30 Hz), and Gamma (30–60 Hz), each associated with distinct cognitive and neural functions. WPLI values were extracted as the connectivity metric, reflecting phase synchrony between electrode pairs. These values were computed for each participant, trial group, image category, and frequency band, creating a comprehensive dataset for subsequent statistical evaluations.

A non-parametric Friedman test, serving as an alternative to repeated-measures ANOVA, was employed to assess overall differences in functional connectivity across trial groups, independently for each channel pair, frequency band, and image type. This test was chosen due to its robustness against violations of normality, which is often the case in EEG-derived connectivity data. The Friedman test indicated significant group-level differences; post hoc Wilcoxon signed-rank tests were conducted to identify specific transitions between consecutive trial groups (T1 vs. T2, T2 vs. T3, etc.). A Bonferroni correction was applied to control for multiple comparisons, adjusting the significance threshold to $p < 0.0125$. This two-tiered statistical approach enabled a detailed investigation of connectivity modulation over time, revealing the temporal progression of habituation and highlighting when significant reductions in inter-regional synchrony occurred.

IV. Results

The repeated-measures Friedman test was conducted to analyse differences in functional connectivity (WPLI values) across the trial groups (T1–T5) for the three image categories: apple (low-calorie), pizza (high-calorie), and hammer (non-food), as well as across different frequency bands.

The results revealed that significant differences were observed in the theta band, with overall effects found for the low-calorie apple image and the non-food hammer image. No significant effect was observed for the high-calorie pizza image. Pairwise comparisons between consecutive trial groups (T1/T2, T2/T3, T3/T4, T4/T5) showed a habituation effect for the non-food hammer image in the frontal (Fz) and parietal



(a) Apple (b) Pizza (c) Hammer

Fig. 3: Boxplot of functional connectivity values (WPLI) across trial groups (T1, T2, T3, T4 and T5) in the theta band for different image categories

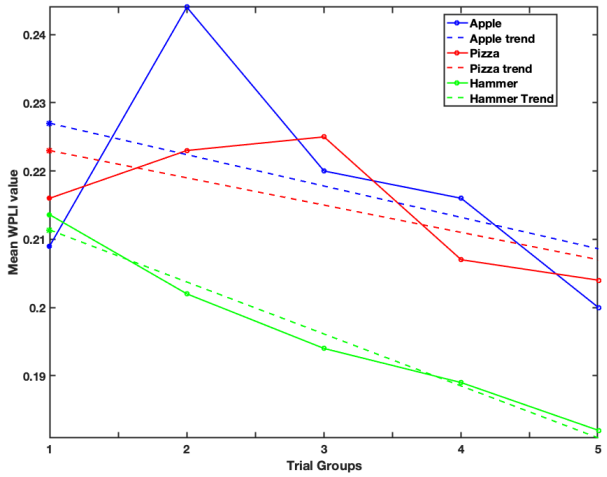


Fig. 4: Connectivity value (WPLI) and its linear trend for various images and trial groups for Fz-Pz channel combination in theta band

(Pz) brain regions in the theta band. However, this effect was not evident for either the low-calorie apple or the high-calorie pizza image. Figure 3 presents the boxplot of functional connectivity values (WPLI) across the trial groups in the theta band for the different image categories.

For the apple image, the Friedman test yielded p-value = 0.0160, indicating a statistically significant difference in functional connectivity across trial groups. However, pairwise comparisons between consecutive trial groups did not reach significance, with p-values of 0.626, 0.250, 0.987, and 0.276 for T1/T2, T2/T3, T3/T4, and T4/T5, respectively (see Table I). These results suggest that while an overall effect is present, it may not be attributed to specific trial transitions. For the pizza image, the Friedman test resulted in p-value = 0.2138, indicating no significant differences across trial groups. Similarly, pairwise comparisons did not reveal any significant changes, with p-values of 0.774, 0.323, 0.314, and 0.997, respectively, implying no observable habituation in response to the high-calorie stimulus.

In contrast, for the hammer image, the Friedman test returned a p-value = 0.011, indicating a significant difference in connectivity across trial groups. Pairwise comparisons revealed statistically significant differences between T1/T3 (p-value = 0.0012), T2/T3 (p-value = 0.0094), and T3/T4 (p-value = 0.0104), with a marginal difference between T4/T5 (p-value = 0.0119), particularly between the Fz–Pz channels (refer to Table I). These findings support a clear habituation pattern for the non-food hammer image, with a progressive decrease in connectivity between the frontal and parietal regions.

Figure 4 illustrates the mean WPLI connectivity values between Fz and Pz across the five trial groups for each image type, along with corresponding linear trends. The results show a marked linear decrease in connectivity for the hammer image, indicating significant habituation. In contrast, the apple and pizza images did not exhibit any consistent linear decline, suggesting minimal or absent habituation effects. Additionally, the slope analysis revealed a faster rate of habituation for the hammer image. Between the food stimuli, the apple image demonstrated a slower habituation rate than the pizza image. The calculated slope and intercept values for all three image categories are presented in Table II, offering quantitative insight into how calorie content and stimulus type influence neural habituation dynamics.

TABLE I: Functional Connectivity - Pairwise comparison between consecutive trial groups

Compare Trial Groups (p-Value)	Apple	Pizza	Hammer
Trial Group 1 /Trial Group 2	0.626	0.774	**0.0012**
Trial Group 2 /Trial Group 3	0.250	0.323	**0.0094**
Trial Group 3 /Trial Group 4	0.987	0.314	**0.0104**
Trial Group 4 /Trial Group 5	0.276	0.997	**0.0119**

TABLE II: Functional Connectivity - Habituation rate details for different images in theta band.

Image	Slope	Intercept
Apple	-0.0046	0.232
Pizza	-0.0040	0.227
Hammer	-0.0076	0.219

V. Discussion

Prior EEG research has largely focused on ERP modulation and spectral power changes during food cue processing and repeated exposure [10]–[13]. In contrast, this study applied a WPLI-based approach to capture inter-regional synchrony, highlighting how connectivity patterns evolve across repetitions. The findings revealed that connectivity changes were most evident in the theta band, where non-food and low-calorie stimuli showed signs of adaptation, while high-calorie cues maintained stable engagement. Notably, only the non-food condition demonstrated a clear habituation pattern, with connectivity between frontal and parietal regions declining across exposures. The absence of a comparable effect for food stimuli suggests that calorie-related salience sustains neural attention, consistent with prior evidence that energy-dense foods activate reward networks and delay disengagement [13]. By emphasising connectivity dynamics rather than ERP amplitudes or spectral power alone, this work extends existing literature and provides a network-level perspective on how different stimulus categories shape attentional regulation during repeated exposure.

Theta-band oscillations (4–8 Hz) have been widely associated with attentional control, sensory processing, and cognitive regulation during habituation tasks [14], [15]. In line with this, the current findings demonstrated a significant habituation effect in the theta band for non-food stimuli, evidenced by a marked reduction in WPLI connectivity between frontal (Fz) and parietal (Pz) channels across repeated exposures. This supports the hypothesis that frontoparietal theta-band synchrony reflects the neural mechanism of attentional disengagement from repetitive stimuli [16]. The connectivity analysis revealed that food cues did not exhibit this reduction in synchrony, suggesting a resistance to habituation, which may be driven by the activation of reward circuitry.

Further examination of the connectivity matrices across five trial groups (T1–T5) illustrated how functional connectivity evolved over time. For the non-food image, there was a progressive decline in WPLI values between Fz and Pz, indicating reduced synchrony with repeated presentation. In contrast, WPLI values remained stable for the low-calorie food and high-calorie pizza image, reinforcing previous findings that food images maintain sustained neural attention due to their hedonic value [17]. These differences in neural adaptation emphasise the role of stimulus type in modulating attentional processes.

The rate of habituation, as assessed through linear trend analysis of WPLI values across trial groups, provided additional insights. The hammer image exhibited the steepest decline in connectivity, indicating rapid habituation. The apple image showed a slower but evident decline, while the pizza image demonstrated minimal change over time. These trends support the notion that high-calorie foods resist habituation due to their higher motivational salience. Such findings are consistent with previous literature showing that high-calorie stimuli elicit prolonged engagement of frontal cortical areas, which may contribute to reduced attentional disengagement and increased food cravings [9], [18].

These results hold significant implications for understanding eating behaviours and developing targeted interventions. The pairwise comparison of trial groups showed specific reductions in connectivity for the hammer image but not for the food image, highlighting the brain's slower adaptation to food stimuli. Frontal-parietal connectivity in the theta band, which underlies cognitive control and inhibitory regulation, appears less responsive to repetition when food images are involved [7], [16]. This suggests that attentional retraining interventions could benefit from incorporating connectivity metrics such as WPLI to monitor changes in attentional bias. Additionally, individuals with higher BMI may be especially vulnerable to the sustained neural engagement elicited by high-calorie foods, reinforcing the need for personalised strategies to mitigate habitual overconsumption [10], [19].

VI. Conclusion

This study examined the neural mechanisms of habituation to food and non-food stimuli using EEG-based functional connectivity measured with the WPLI. The results showed a significant decline in theta-band connectivity between frontal and parietal regions during repeated exposure to non-food images, indicating effective habituation. In contrast, both high-calorie (pizza) and low-calorie (apple) cues maintained stable connectivity, reflecting sustained engagement and resistance to habituation. These findings suggest that food-related stimuli, particularly high-calorie cues, elicit prolonged attentional and reward-related responses that may interfere with the brain's natural adaptation processes. The novelty of this work lies in its use of WPLI to capture connectivity dynamics across repeated exposures, providing a network-level perspective that extends beyond traditional ERP and spectral measures.

Furthermore, the findings also point to practical applications in healthcare communication and digital health interventions. Persistent neural engagement with high-calorie cues could serve as a biomarker for identifying individuals at risk of overeating or reduced dietary self-regulation. Incorporating such measures into mobile health apps, neurofeedback platforms, or cognitive retraining tools could enable personalised feedback and attentional bias modification to promote healthier food choices. By linking connectivity-based neural markers to behavioural interventions, this work highlights how EEG-informed approaches may inform scalable, tailored strategies for behaviour therapy and public health messaging.

While this study provides novel insights into food-related habituation using EEG-based functional connectivity, several limitations should be noted. The modest sample size may limit statistical power and generalizability, underscoring the need for replication with larger and more diverse cohorts. The controlled laboratory setting with static visual stimuli ensured consistency, but it does not fully capture the multisensory and dynamic nature of real-world food environments. Individual factors such as hunger state, dietary habits, and BMI group differences may also have influenced neural responses despite

standardised protocols. Moreover, as the analysis relied solely on EEG, WPLI measures remain correlational and do not imply causality; future multimodal approaches (e.g., combining EEG with fMRI or behavioural tasks) could provide a more comprehensive account. Finally, the focus on within-session habituation and a limited set of stimuli constrains ecological validity, suggesting that broader stimulus categories and longitudinal designs are needed. These considerations should be taken into account when interpreting the results, but also point to important directions for extending this line of research.

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