Metacontrol on Demand: Task-induced Shifts in Metacontrol States Reflected in Aperiodic Neural Activity

Xi Wang[1], **Christian Beste**[1,2], **and Bernhard Hommel**[1,2]

Abstract

■ Metacontrol refers to the dynamic regulation between persistence and flexibility, enabling adaptive behavior across varying task demand. This study investigated whether metacontrol states induced by two creativity tasks, Remote Associates Test to bias persistence and Alternate Uses Task to bias flexibility, would modulate behavioral and neural responses in a global/local perceptual task. We recorded EEG and analyzed aperiodic neural activity using the FOOOF (fitting oscillations and one-over-*f*) exponent as a marker of neural inhibition and variability. At the behavioral level, participants responded faster and more accurately to global than to local stimuli across sessions, consistent with a global processing advantage. EEG results revealed that differences in aperiodic exponent between local and global trials emerged only after stimulus onset. This supports a reactive model of metacontrol, where control states are not maintained but are adaptively recruited in response to task demands. The results highlight the context-sensitive nature of metacontrol and support the use of aperiodic exponent as a neural index of these cognitive dynamic adjustments. ■

INTRODUCTION

Cognitive control involves a set of cognitive processes that enable individuals to regulate their thoughts and actions effectively in pursuit of specific goals (Shenhav et al., 2024; Botvinick, Braver, Barch, Carter, & Cohen, 2001; Miller & Cohen, 2001; Gratton, Cooper, Fabiani, Carter, & Karayanidis, 2018; Diamond, 2013; Braver, 2012). These processes involve generating and maintaining task-relevant goals, suppressing irrelevant or competing goals, and dynamically adjusting attentional biases to optimize task performance. Such characteristics are essential for adaptive behavior, especially when faced with complicated, rapidly changing environments that demand not only sustained focus but also the flexibility to adjust strategies and responses appropriately (Dajani & Uddin, 2015; Goschke & Bolte, 2014). Traditionally, theories about cognitive control tended to focus mostly on persistence, which refers to the ability to remain concentrated, inhibit distractions, and maintain performance on goal-directed tasks despite challenges or competing demands (Gratton et al., 2018). However, more recent perspectives emphasize that effective cognitive control requires not just persistence but also flexibility. Being flexible refers to the capability of considering alternative goals, generating multiple creative solutions to problems, and selectively attending to stimuli or ideas that might initially seem irrelevant but are potentially beneficial for task outcomes (Cools, 2015; Hommel, 2015; Durstewitz & Seamans, 2008; Dreisbach & Goschke, 2004). Thus, based on current situations, dynamically switching between persistence and flexibility appears essential for adaptive and successful behavior in complex environments.

The metacontrol state model (MSM) addressed this balance, which conceptualized cognitive control not as a stable, single function, but as a dynamic balance between two different mental biases: persistence, which associated with the stable maintenance of task goals, and flexibility, which opens to alternative goals and novel solutions (Hommel & Wiers, 2017; Hommel, 2015). According to the MSM, cognitive control emerges from two separate dopamine pathways, the mesolimbic and nigrostriatal dopamine pathways, suggesting that these neural circuits mediate the shifting between persistence and flexibility through dopaminergic modulation (Hommel & Colzato, 2017). Critically, persistence and flexibility are not two independent constructs but opposites of a joint dimension, thus implying trade-offs in the sense that a stronger bias toward persistence implies less flexibility, and vice versa (Hommel, Colzato, & Beste, 2024). Empirical evidence from neurocognitive research supports this interdependence. For example, people diagnosed with obsessive-compulsive disorder, which is characterized by strong persistence, often show deficits in tasks requiring cognitive flexibility, while people with attention-deficit/hyperactivity disorder, which is characterized by excessive flexibility, display impairments in persistence-related tasks (Hommel et al., 2024; Colzato, Hommel, Zhang, Roessner, & Beste, 2022). Recent electroencephalographic findings

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[1] Cognitive Neurophysiology, Department of Child and Adolescent Psychiatry, Faculty of Medicine, TU Dresden, [2] Shandong Normal University, Jinan, China

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further suggest that metacontrol states operate by modulating cortical noise and brain variability, reinforcing the concept that cognitive control involves balancing between the persistent goal pursuit and flexible adaptation to a changing environment (Zhang, Stock, Mückschel, Hommel, & Beste, 2023). Thus, this metacontrol framework provides a comprehensive account for cognitive control and the dynamic interplay between persistence and flexibility to achieve adaptive human behavior.

Recent neurophysiological research on metacontrol underpinnings has highlighted the significance of aperiodic neural activity, which refers to broadband, nonoscillatory background fluctuations in the EEG power spectrum (Jia et al., 2024; Zhang et al., 2023; Donoghue et al., 2020). Empirical evidence demonstrates that variations in aperiodic neural activity correspond to changes in neural noise, which in turn reflects shifts in the excitation/inhibition balance (Jia et al., 2024; Donoghue et al., 2020). Specifically, higher aperiodic exponent represents a dominance of inhibitory processes and reduced neural noise, indicating a bias toward persistence, while a lower exponent value reflects more neural noise, indicating enhanced excitatory processes and a more flexible, explorative bias (Jia et al., 2024; Turri et al., 2023; Zhang et al., 2023).

Recent EEG studies provide support for aperiodic activity as a reflection or even neural mechanism of metacontrol states and biases therein (Gao et al., 2024, 2025; Jia et al., 2025; Yan et al., 2024). For example, Zhang et al. (2023) demonstrated that tasks demanding persistence, such as incongruent conditions in cognitive control paradigms that create response conflict, consistently elevated the aperiodic exponent. In contrast, conditions favoring flexibility resulted in a decreased exponent, suggesting enhanced neural noise and a more unconstrained processing mode. Pi et al. (2024) showed that trait-like differences in resting-state aperiodic activity predicted individual cognitive control styles, further corroborating the relevance of aperiodic neural dynamics as a robust neurophysiological marker for metacontrol biases. Additionally, studies using conflict-inducing tasks, such as the Flanker and go/no-go tasks, have found adjustments in aperiodic activity following high-conflict trials, emphasizing their role in conflict-driven metacontrol adaptations and proactive cognitive adjustments (Jia et al., 2024; Pi et al., 2024). Collectively, these findings suggest aperiodic activity as a neurophysiological marker or even the mechanism of metacontrol, reflecting the adjustments in the brain's cognitive control state in response to shifting environmental demands.

The current study aimed to investigate whether engaging in tasks that promote persistence or flexibility (the prime tasks) would induce metacontrol states that shape subsequent perceptual processing in another task (the probe task). Specifically, we examined whether and how these induced metacontrol states might influence both behavioral performance and aperiodic activity in an intermixed probe task. We used two creativity tasks as prime tasks (Wang et al., 2023). Tasks commonly used to assess creative thinking, such as Remote Associates Test (RAT) and Alternate Uses Task (AUT), differ in their cognitive demands, which makes them suitable for inducing metacontrol states (Ma & Hommel, 2020; Hommel & Colzato, 2017; Hommel, 2015). The RAT assesses convergent thinking, defined as the ability to generate a single, precise solution to a problem, emphasizing goal-oriented persistence, logical processing, and focused attention. In this task, participants receive a set of three seemingly unrelated words and need to identify a fourth word that can combine with each of the three stimulus words to form three new compound words (Wang et al., 2023; Hommel & Colzato, 2017; Hommel, 2015; Mednick, 1962). Research indicated that performance on RAT was enhanced by cognitive states oriented toward persistence because of its reliance on strong top–down control and focused cognitive processing (Colzato, Ritter, & Steenbergen, 2018; Hommel, 2015; Akbari Chermahini & Hommel, 2010). This persistence state aligns with the concept of proactive cognitive control, which is goal-directed and robust against distraction (Braver, 2012). Conversely, AUT assesses divergent thinking, which requires participants to generate multiple creative and novel uses for a common object. Divergent thinking is inherently flexible and characterized by cognitive processes that accommodate switching goals, consider alternative solutions, and creatively integrate information that may appear initially irrelevant (Wang et al., 2023; Hommel & Colzato, 2017; Guilford, 1967). Studies using AUT showed that flexible cognitive states enhance performance, which underscores the role of open-ended, explorative thought processes (Ma & Hommel, 2020; Ritter & Ferguson, 2017). As compared with persistence, flexibility reflects a more stimulus-driven, reactive control mode, allowing rapid shifting among various concepts and task demands (Hommel & Colzato, 2017; Hommel, 2015; Braver, 2012).

While RAT and AUT served as prime tasks to induce cognitive control biases toward persistence and flexibility, we adopted a global/local task as a probe task to assess how these states influence perceptual processing. In this task, participants respond to either the global or local features of hierarchical stimuli (Navon, 1977). Typically, processing global stimuli engages a broader perspective that is associated with flexibility because the performance is better when the attention is focused on the overall pattern instead of specific details. At the same time, local-level processing aligns with cognitive persistence because detailed attention to specific features, minimizing interference from broader contextual information, promotes performance (De Luca, Verschoor, & Hommel, 2022; Navon, 1977). Thus, the global/local task serves as a probe task for the effects of metacontrol on attentional breadth. Previous studies have shown a global effect, where global stimuli are processed faster and more accurately than local stimuli (De Luca et al., 2022; Navon, 1977). Overall, integrating creativity tasks (RAT and AUT) with the global/local processing paradigm provides a robust framework for inducing and assessing cognitive control states, offering insights into the flexible versus persistent cognitive strategies employed by individuals.

We had the following hypotheses. First, we predicted that the RAT session, which favors a persistence control style, would enhance performance on local trials of the global/local task and a neural signature of reduced neural noise, namely, a lower aperiodic exponent compared with global trials. Conversely, the AUT session, which encourages a more flexible control style, would facilitate global-level processing and lower the aperiodic exponent for global trials than local trials. Finally, by comparing neural and behavioral data from prestimulus and poststimulus intervals, we aimed to explore whether these control states affect prestimulus processing or are reflected in stimulus-enacted adjustments. By linking creative tasks engagement to both perceptual behavior and aperiodic neural dynamics, this study contributes to a more refined understanding of metacontrol as a dynamic mechanism that adapts cognitive control states to current demands.

METHODS

Participants

Forty-eight participants (mean age = 29.85 years, *SD* = 8.84; 32 women) were included in the study. Eight participants were excluded due to the following: misunderstood the task instruction ($n = 2$), withdrawal from the study ($n = 4$), EEG data quality ($n = 2$), resulting in a final sample of 40. Our sample size was comparable to previous EEG studies investigating aperiodic activity in the context of cognitive control (e.g., Gao et al., 2024; Yan et al., 2024; Pertermann, Mückschel, Adelhöfer, Ziemssen, & Beste, 2019). All participants had normal or corrected-to-normal vision and reported no history of neurological or psychiatric disorders. Informed consent was obtained before participation, and the study was approved by the ethics committee of the Faculty of Medicine of TU Dresden, and all relevant ethical regulations for human research were followed.

Task Procedure

Participants completed two separate sessions on different days, the RAT global/local session and the AUT global/local session. The order of sessions was counterbalanced across participants. Each session included two intermixed task trials, creativity task trials (RAT or AUT), and global/local trials. In both sessions, trials from the two tasks were fully intermixed in a randomized order, requiring participants to continuously switch between the creativity and global/local tasks. The first trial in each session was always a creativity task trial, a RAT trial in the RAT session, and an AUT trial in the AUT session to ensure that each session began with a metacontrol bias toward either persistence or flexibility.

The theoretical rationale behind this design is grounded in the MSM, which posits that cognitive control can flexibly shift between persistence and flexibility in response to contextual demands. Engaging in the RAT was assumed to induce a persistence-biased metacontrol state, leading participants to adopt a narrower, detail-focused processing style. As such, participants were expected to favor local-level perceptual processing, and performance should be better on local trials than on global trials within the RAT session. Conversely, engaging in the AUT was assumed to promote a flexibility-biased metacontrol state, encouraging a broader, more integrative processing style. Therefore, in the AUT session, performance was expected to be better on global trials than on local trials.

RAT

The RAT was designed to assess convergent thinking ability. Here, we adopted this task to induce the persistent metacontrol state. In each RAT trial, participants saw a triad of German cue words displayed at the center of the screen (e.g., in German, *Geheimnis–Note–Konto*; in English, "secret–note–account"). Their task was to identify a fourth word (e.g., Bank) that could logically combine with each of the cues to form familiar compound words (e.g., Bankgeheimnis, Banknote, Bankkonto). The answer word could sometimes be attached before the cue word as long as it consists of a legitimate German word. A total of 100 such triads, adapted from a validated German RAT database (Landmann et al., 2014), were used in the experiment. Each trial began with a 1-sec fixation cross, followed by the triad, which remained on screen for a maximum of 20 sec. Participants were instructed to press a response key (left Ctrl) as soon as they found a solution and then type in their answer. If they were unable to find a solution within the time limit, they proceeded to the next trial without input.

AUT

The AUT was originally designed to assess participants' ability to think creatively by generating unconventional uses for everyday objects. This task was used to induce a flexible metacontrol state because of the task's divergent attribute. Each trial began with a 1-sec fixation cross, after which an object name (e.g., in German, *leere Konservendose*; in English, "empty can") was shown at the center of the screen for 20 sec. During this time, participants were encouraged to think of as many creative uses for the object as possible. They were instructed to press the left Ctrl key each time a new idea came to mind, providing a temporal marker of idea generation. After the 20-sec idea generation phase, a response screen prompted participants to type in what they considered their most original or creative idea. Participants could take as much time as needed to enter their response. In total, 100 object names were used. These were drawn from a combination of sources, including the German AUT (Schoppe, 1979) and a translated selection of items from the Chinese AUT inventory (Ding et al., 2023; Wang et al., 2023). All non-German items were translated and culturally adapted by a native German speaker to ensure linguistic and contextual appropriateness.

Global/Local Task

In each of the RAT global/local and AUT global/local sessions, participants completed a total of 400 trials involving hierarchical visual stimuli, comprising 200 global trials and 200 local trials. These trials were fully intermixed with the RAT/AUT trials and presented in a randomized order. Each stimulus consisted of a compound image that conveyed letter identity at two hierarchical levels. In local trials, the overall shape was a large neutral circle, composed of many smaller letters ("H" or "S"). Participants were instructed to identify the small letters and respond accordingly with a left or right Ctrl key press. In global trials, the stimulus was a large letter ("H" or "S") constructed from many small neutral elements (unfilled circles). In this case, participants were instructed to respond to the overall shape, that is, the large letter formed by the arrangement of the small circles. Each trial began with the presentation of a central fixation cross for 1 sec, followed by the target stimulus, which was displayed for 1.2 sec. Participants responded by pressing the left or right Ctrl key on the keyboard to indicate whether the relevant letter (either local or global) was an "H" or an "S."

EEG Data Acquisition and Preprocessing

EEG data were recorded throughout the experiment using 60 equidistant Ag/AgCl electrodes arranged in an elastic cap (EasyCap, Inc.). Recordings were made with BrainAmp amplifiers and BrainVision Recorder 2.1 (Brain Products GmbH). The reference electrode was placed at Fpz, and the ground electrode was located anterior to Fz (theta = 58, phi = 78). Signals were sampled at 500 Hz, and electrode impedances were kept below 10 kΩ to ensure data quality. Preprocessing was carried out offline using MATLAB R2022a (The MathWorks), combining tools from the Automagic toolbox (Pedroni, Bahreini, & Langer, 2019) and EEGLAB (Delorme & Makeig, 2004). The raw EEG data were first downsampled to 256 Hz. Any flat channels were removed prior to re-referencing the data to the average of all electrodes. The PREP pipeline (Bigdely-Shamlo, Mullen, Kothe, Su, & Robbins, 2015) and EEGLAB's *clean_rawdata()* function were used to remove 50-Hz line noise and exclude bad channels based on spectral and statistical properties. A high-pass finite impulse response filter was then applied with a cutoff of 0.5 Hz (order = 1286, stop-band attenuation = −80 dB, transition band = 0.25–0.75 Hz) to eliminate channels of flat-line, noisy, and outlier. To reduce muscle artifacts, a 40-Hz low-pass sinc filter (order = 86) was applied (Widmann, Schröger, & Maess, 2015). Eye-movement-related activity was corrected using subtraction methods based on Parra, Spence, Gerson, and Sajda (2005). Subsequently, independent component analysis was performed to identify and remove remaining artifacts, including those of ocular, muscular, and cardiac origin. Components were classified and rejected using the Multiple Artifact Rejection Algorithm (Winkler et al., 2014; Winkler, Haufe, & Tangermann, 2011) for further processing. Removed channels were interpolated using a spherical interpolation method. Afterward, the continuous EEG data were segmented for spectral analysis. For the RAT and AUT tasks, the signal was epoched into 4000-msec segments, time-locked to the key press, capturing neural activity from 4000 msec prior to each response. These response-locked epochs were used for power spectral density (PSD) estimation. For the global/local task, EEG data were segmented into 4000-msec epochs centered on stimulus onset, spanning from 2000 msec before to 2000 msec after stimulus presentation. The PSD was calculated separately for prestimulus and poststimulus windows. The prestimulus time window comprised 1000 msec before stimulus onset, and the poststimulus comprised 1000 msec after stimulus onset. Poststimulus power spectra were estimated from stimulus-locked epochs without explicit ERP subtraction. Although some studies remove the evoked component to isolate purely induced activity, previous work showed that ERP subtraction reduces the magnitude but preserves the overall pattern of aperiodic spectral changes (Kałamała et al., 2024; Gyurkovics, Clements, Low, Fabiani, & Gratton, 2022). We therefore followed the conventional approach of using the original epochs while acknowledging that both evoked and induced dynamics have a possibility to contribute to the observed aperiodic changes.

Parameterization of the Spectral Data

We computed the PSD for each electrode and participant using Welch's method, implemented in MATLAB. PSD estimates were calculated using a Hamming window of 0.25 sec with 50% overlap, a commonly used configuration that balances frequency resolution and noise reduction. For the global/local task, PSD was estimated separately for prestimulus and poststimulus time windows. The prestimulus window spanned the 1000 msec immediately preceding stimulus onset, while the poststimulus window covered the 1000 msec following stimulus presentation. For the RAT and AUT tasks, the PSD was computed from the 1000 msec prior to the participant's key press.

To acquire aperiodic ($1/f$-like) components of the EEG spectrum, we utilized the FOOOF (fitting oscillations and one-over-f) toolbox, Version 1.0.0 (https://fooof-tools.github.io/fooof/), which runs in Python. This algorithm models the power spectrum as the combination of a background aperiodic component and superimposed narrowband oscillatory peaks (Donoghue et al., 2020). Following previous studies (e.g., Jia et al., 2024; Zhang et al., 2023), we extracted the aperiodic exponent focusing on the

3–40 Hz frequency range. FOOOF was run using the following parameters: The aperiodic mode was set to "fixed," peak width limits were defined as [1, 8] Hz, the maximum number of detectable peaks was set to 8, and the minimum peak height was set to 0.05. All other settings were left at default. The spectral fitting was applied independently for each time window, condition, electrode, and participant. The average goodness-of-fit across all spectra was high, with a mean R^2 of .99. Across all task conditions, the average number of detected peaks ranged from 1.7 to 1.8 per spectrum, indicating that the model did not overfit the data.

Statistical Analysis

Behavior

Behavioral data from the global/local task were analyzed using SPSS Version 29.0 (IBM Corp.). Two performance measures, RT and error rate (ER), were considered. RT was calculated for correct trials only, while ER reflected the proportion of incorrect responses across all trials. The trials with RTs outside the time window of 200–1200 msec were excluded prior to analysis. To examine whether behavioral performance differed as a function of the metacontrol context, we conducted 2 × 2 repeated-measures ANOVAs separately for RT and ER. The analysis included two within-subject factors, Session Type (RAT session vs. AUT session) and Trial Type (local trials vs. global trials). This design allowed us to test whether engaging in tasks thought to promote persistence (RAT) or flexibility (AUT) modulated participants' efficiency and accuracy when processing information at the global or local level. All ANOVAs tested predefined hypotheses and therefore were not further corrected across models. Bonferroni adjustment was applied for exploratory post hoc comparisons. To complement these standard analyses, we conducted Bayesian repeated-measures ANOVAs in R (Version 4.5.1) using the BayesFactor package (Morey & Rouder, 2012; https://CRAN.R-project.org/package=BayesFactor). Bayes factors (BF_{10}) were computed to indicate the evidence for the alternative hypothesis relative to the null hypothesis.

Aperiodic Exponent

The aperiodic exponents were extracted for each participant and EEG channel using the FOOOF algorithm, resulting in a 60 (channels) × 40 (participants) data matrix. For statistical analysis, we focused on a global-level measure of aperiodic activity. To obtain this, the exponent values were averaged across all 60 electrodes for each participant within each condition. This approach was chosen based on previous studies showing that, in the absence of specific hypotheses about regional differences, a global average provides a stable and interpretable index of aperiodic dynamics (Jia et al., 2024; Zhang et al., 2023; Hill, Clark, Bigelow, Lum, & Enticott, 2022; Jacob, Roach, Sargent, Mathalon, & Ford, 2021).

We first conducted a 2 × 2 × 2 repeated-measures ANOVA with the within-subject factors Time Point (prestimulus vs. poststimulus), Session Type (RAT session vs. AUT session), and Trial Type (local trials vs. global trials) to examine how the global aperiodic exponent was modulated across cognitive conditions and time. Simple effect analyses were performed where the interaction effect is significant. All post hoc tests were Bonferroni-corrected. Bayesian statistics were also reported.

To further examine the spatial distribution of the aperiodic exponent effects, we performed additional cluster-based permutation tests. This nonparametric approach (Maris & Oostenveld, 2007) controls for multiple comparisons across electrodes by evaluating clusters of neighboring electrodes showing consistent effects. The analysis was conducted for conditions that showed significant effects at the global level in the repeated-measures ANOVA. For each contrast, t values were computed across participants for all electrodes, and clusters were formed by grouping adjacent electrodes exceeding a sample-level threshold of $p < .005$. The sum of t values within each cluster served as the cluster-level statistic. Significant clusters were obtained based on 1000 Monte Carlo random sampling using the .05 significance level.

For the prime tasks (RAT and AUT), we conducted a paired-samples t test on the global exponent values to assess overall differences in broadband spectral characteristics between the two tasks. To localize spatial contributions, a nonparametric cluster-based paired permutation test was also performed for RAT and AUT.

To examine whether the neural control state induced by the prime tasks predicted the extent of control adaptation in the subsequent probe, we correlated each participant's aperiodic exponent difference between the RAT and AUT primes (ΔExponent_prime = RAT − AUT) with the global–local exponent contrast in the probe (ΔExponent_probe = Global − Local). For correlations we used Spearman's rho; 95% CIs were obtained via percentile bootstrap with 10,000 resamples.

RESULTS

Behavior

Prime Tasks

In the RAT (convergent) prime task, participants solved on average 34.5% of items (*SE* = 2.0%). In the AUT (divergent) prime task, participants generated on average 2.12 ideas per 20-sec trial (*SE* = 0.13). These task-specific measures confirm that participants engaged successfully with both prime tasks.

RT (Probe Task)

A 2 × 2 repeated-measures ANOVA was conducted on RT data, with Session Type (RAT session vs. AUT session) and Trial Type (local vs. global trials) as within-subject factors

(Figure 1A). The analysis revealed a significant main effect of Trial Type, $F(1, 39) = 155.24$, $p < .001$, $\eta^2 = .80$, $\mathrm{BF}_{10} = 1.04 \times 10^{10}$. Participants responded significantly faster on global trials ($M = 548$ msec, $SE = 7$ msec) than on local trials ($M = 581$ msec, $SE = 8$ msec), indicating a strong global processing advantage. The main effect of Session Type was not significant, $F(1, 39) = 0.43$, $p = .518$, $\eta^2 = .01$, $\mathrm{BF}_{10} = 0.23$, suggesting that overall reaction speed was not influenced by whether participants were in the RAT or AUT session. The interaction between session type and trial type also failed to reach significance, $F(1, 39) = 2.03$, $p = .162$, $\eta^2 = .05$, $\mathrm{BF}_{10} = 0.29$, indicating that the RT difference between global and local trials was similar across both sessions.

ER (Probe Task)

A 2 × 2 repeated-measures ANOVA was also conducted on ER data (Figure 1B). The analysis revealed a significant main effect of Trial Type, $F(1, 39) = 33.30$, $p < .001$, $\eta^2 = .46$, $\mathrm{BF}_{10} = 2.29 \times 10^6$, indicating that participants made more errors on local trials ($M = 0.03$, $SE = 0.003$) than on global trials ($M = 0.01$, $SE = 0.002$). The main effect of Session Type was not significant, $F(1, 39) = 0.67$, $p = .418$, $\eta^2 = .02$, $\mathrm{BF}_{10} = 0.23$, suggesting the ER was not affected by the RAT and AUT sessions. The interaction between Session Type and Trial Type was also not significant, $F(1, 39) = 0.21$, $p = .65$, $\eta^2 = .01$, $\mathrm{BF}_{10} = 0.27$.

To address concerns about appropriate statistical analysis of binary ERs, we additionally conducted a hierarchical logistic regression with session type (AUT vs. RAT) and trial type (global vs. local) as fixed effects, and participants and trials as random effects. The analysis revealed a significant main effect of Trial Type, $\chi^2(1) = 31.92$, $p < .001$. Participants demonstrated significantly higher ERs on local trials compared with global trials ($OR = 0.52$, 95% CI [0.41, 0.65]), indicating that local trials reduced the odds of a correct response by approximately 48%. There was no significant main effect of Session Type, $\chi^2(1) = 2.38$, $p = .123$, suggesting that ERs did not differ significantly between AUT and RAT sessions. Additionally, the Session Type × Trial Type interaction was not significant, $\chi^2(1) = 1.06$, $p = .303$, indicating that the effect of trial type on ERs was consistent across both session types.

Aperiodic Exponent

Figure 2 displays the PSDs within the 3–40 Hz frequency range for each experimental condition, shown separately for the prestimulus and poststimulus periods. The PSDs were averaged across all electrodes and participants. For completeness, condition-wise scalp maps of the aperiodic exponent for each time point (prestimulus, poststimulus), session (RAT, AUT), and trial type (local, global) are provided in Supplemental Figures S1 and S2.

To explore the neural correlates of metacontrol, a 2 × 2 × 2 repeated-measures ANOVA was conducted on the global aperiodic exponent, with Time Point (prestimulus vs. poststimulus), Session Type (RAT session vs. AUT session), and Trial Type (local trials vs. global trials) as within-subject factors. The three-way ANOVA revealed a significant main effect of Time Point, $F(1, 39) = 116.18$, $p < .001$, $\eta^2 = .75$, $\mathrm{BF}_{10} = 4.43 \times 10^9$, indicating that the exponent values were higher following stimulus onset ($M = 1.51$, $SE = 0.04$) than before ($M = 1.40$, $SE = 0.04$). This

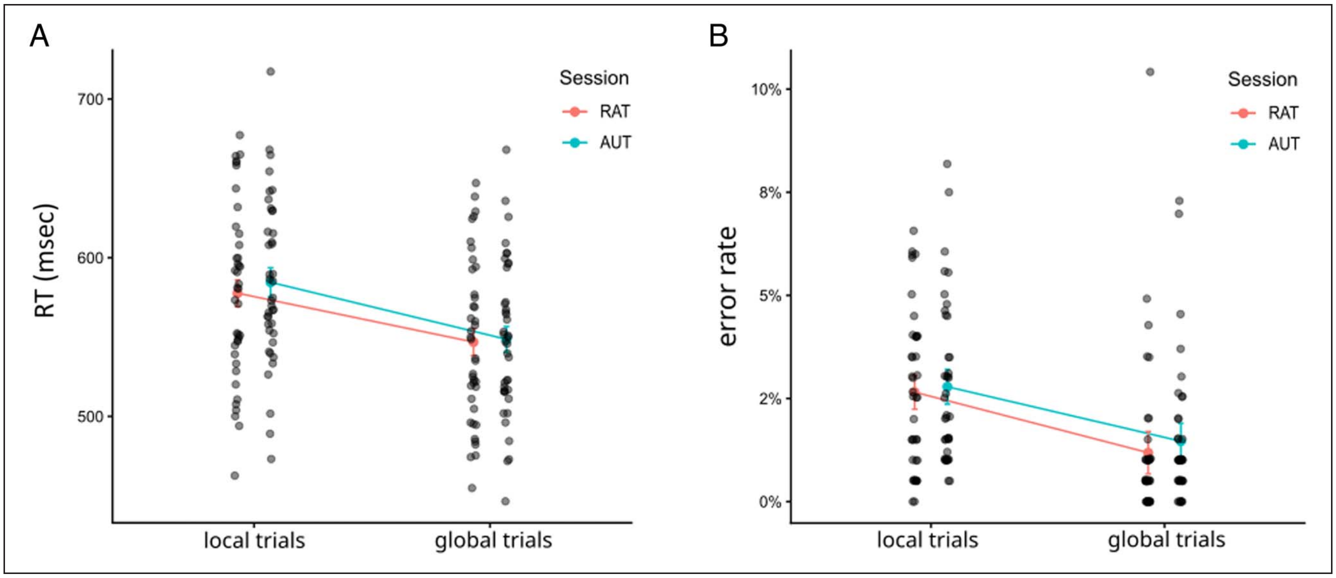

Figure 1. (A) 2 × 2 Repeated-measures ANOVA was conducted on RT data. Participants responded significantly faster on global than local trials. (B) 2 × 2 Repeated-measures ANOVA was conducted on ER data. Participants made more errors on local than global trials. Individual data points represent each participant, and error bars denote Cousineau–Morey within-subject 95% CIs.

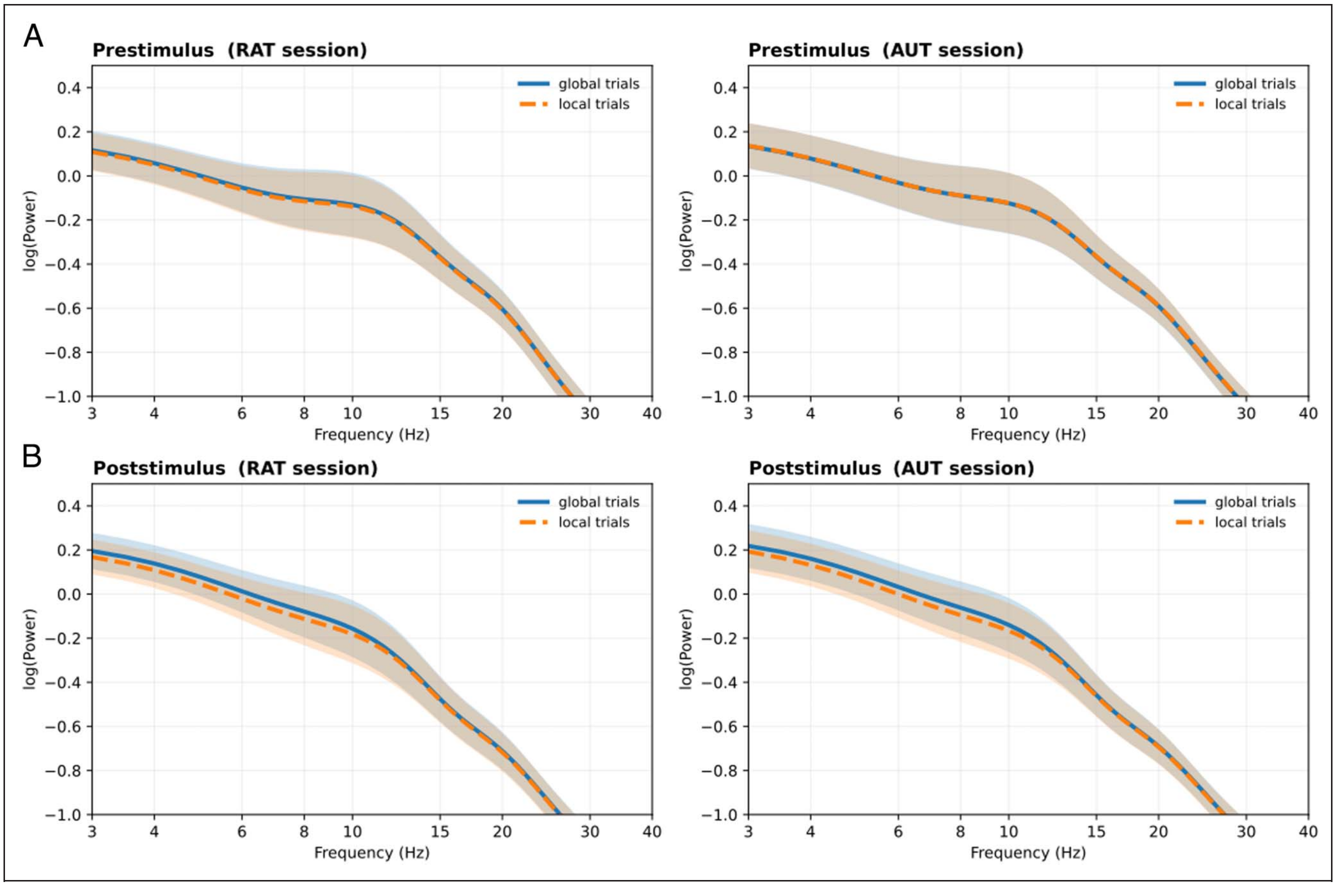

Figure 2. Log–log-transformed PSDs averaged across all electrodes and participants. (A) The top panel shows PSDs from the pretrial period (−1000 to 0 msec), and (B) the bottom panel shows PSDs from the posttrial period (0–1000 msec). Within each panel, PSDs are displayed separately for the RAT session (persistence bias) and AUT session (flexibility bias). Blue lines represent global trials, and orange dashed lines represent local trials. Shaded areas denote ±95% CIs across participants.

indicates that the aperiodic exponent increased after stimulus onset across all conditions. There was also a significant main effect of Trial Type, $F(1, 39) = 32.74, p < .001, \eta^2 = .46, \mathrm{BF}_{10} = 0.20$, with higher exponents observed for global trials ($M = 1.46$, $SE = 0.04$) than for local trials ($M = 1.45$, $SE = 0.04$), suggesting that global processing demands were associated with greater aperiodic activity. Importantly, the Time Point × Trial Type interaction was also significant, $F(1, 39) = 19.28$, $p < .001$, $\eta^2 = .33$, $\mathrm{BF}_{10} = 0.24$. Post hoc comparisons showed that this interaction was driven by a significant difference between global and local trials in the poststimulus window ($M = 1.52$, $SE = 0.04$ vs. $M = 1.49$, $SE = 0.04$, $p < .001$), whereas no significant difference was found in the prestimulus window ($M = 1.40$, $SE = 0.04$ vs. $M = 1.40$, $SE = 0.04$, $p = .081$). This indicates that global–local differences in aperiodic activity emerged only after stimulus presentation. The session type main effect and other interactions were not significant. Figure 3 illustrates the 2 × 2 × 2 repeated-measures ANOVA results for aperiodic exponent.

To examine the scalp distribution of aperiodic activity, cluster-based permutation tests were conducted to identify electrode sites contributing to significant differences between task conditions. The analysis focused on the poststimulus period since no significant effects were detected in the prestimulus interval. The scalp topographies of the aperiodic exponent are shown in Figure 4. For the Time Point × Trial Type interaction, two significant clusters were identified. Cluster 1 encompassed mainly posterior electrodes (P3, P7, O1, P9, O9, CP6, P4, PO2, TP8, P8, O2, OZ, P10, O10, IZ), whereas Cluster 2 included anterior–frontal electrodes (F1, FC3, AFZ, AF3, F5, FC5, FP1, AF7, AF4, F6, FC6, FP2, AF8, FT8). The Time Point main effect (post vs. pre) revealed a broad cluster covering frontal, central, parietal, and occipital regions, including electrodes Cz, FCz, FC1, CP1, Fz, F1, FC3, C3, CP3, P1, AFz, AF3, F5, FC5, C5, CP5, P3, PO1, Fp1, AF7, FT7, T7, TP7, P7, O1, FT9, TP9, P9, O9, FC2, CP2, CPz, F2, FC4, C4, CP4, P2, Pz, AF4, F6, FC6, C6, CP6, P4, PO2, Fp2, AF8, FT8, T8, TP8, P8, O2, Oz, FT10, TP10, P10, O10, and Iz, suggesting a widespread increase in exponent values following stimulus onset. For the Trial Type comparison (global vs. local), significant posterior clusters emerged exclusively during the poststimulus period. One cluster involved posterior–occipital electrodes (P3,

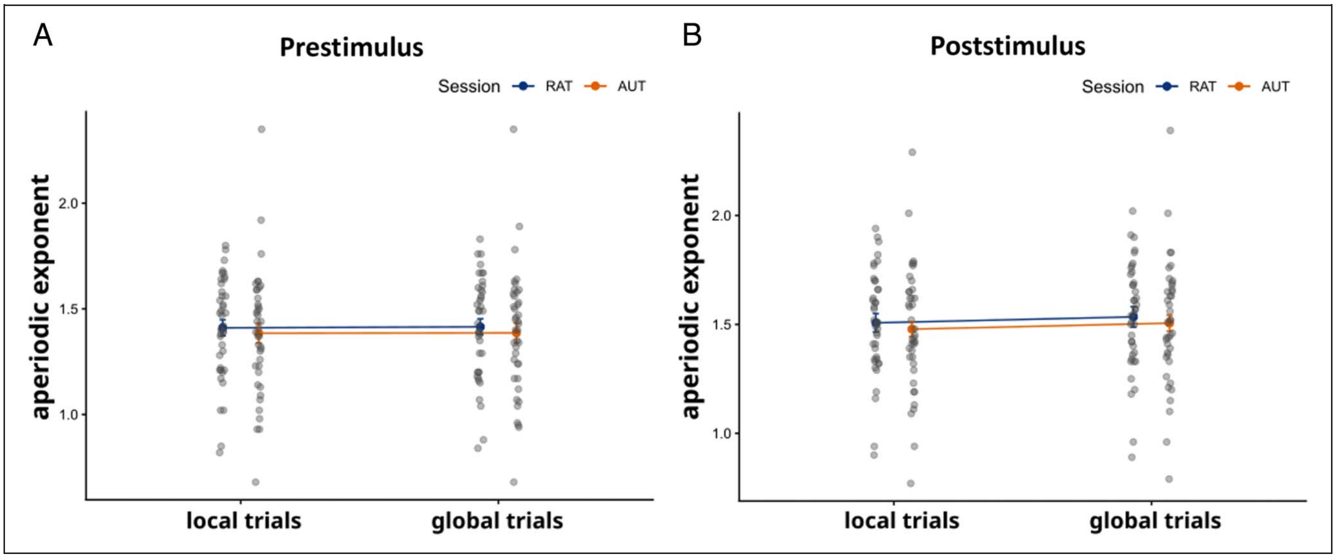

Figure 3. Aperiodic exponent results from the 2 × 2 × 2 repeated-measures ANOVA. (A) Prestimulus interval. (B) Poststimulus interval. Exponent values were significantly higher in after stimulus onset compared with prestimulus period and higher for global than local trials. A significant Time Point × Trial Type interaction showed that global–local differences emerged only after stimulus presentation. Individual data points represent each participant, and error bars denote Cousineau–Morey within-subject 95% CIs.

PO1, P7, O1, P9, O9, CP6, P4, PO2, TP8, P8, O2, Oz, P10, O10, Iz), while another encompassed anterior–frontal regions (Fz, F1, FC3, AFz, AF3, F5, FC5, Fp1, AF7, F2, AF4, F6, FC6, Fp2, AF8, FT8). No significant clusters were identified during the prestimulus period.

Figure 5 shows the PSDs within the 3–40 Hz frequency range for RAT and AUT trials. The AUT showed slightly higher broadband power (i.e., flatter slope) than the RAT. In the metacontrol framework, this pattern suggests that the divergent thinking demands of AUT are associated with a more flexible control mode characterized by reduced inhibition and a higher excitation–inhibition (E/I) ratio. By contrast, the RAT, requiring convergent thinking demands, showed a relatively steeper spectral slope indicative of stronger inhibitory control and a more persistent processing state. A paired-samples t test showed that aperiodic exponents were indeed higher in RAT (M = 1.50, SD = 0.23) than AUT (M = 1.41, SD = 0.31), $t(39) = 2.18$, $p = .036$, Cohen's $d = 0.34$, 95% CI [0.02, 0.66], indicating a medium within-subject effect. A cluster-based permutation test was conducted to identify electrode sites contributing to significant differences

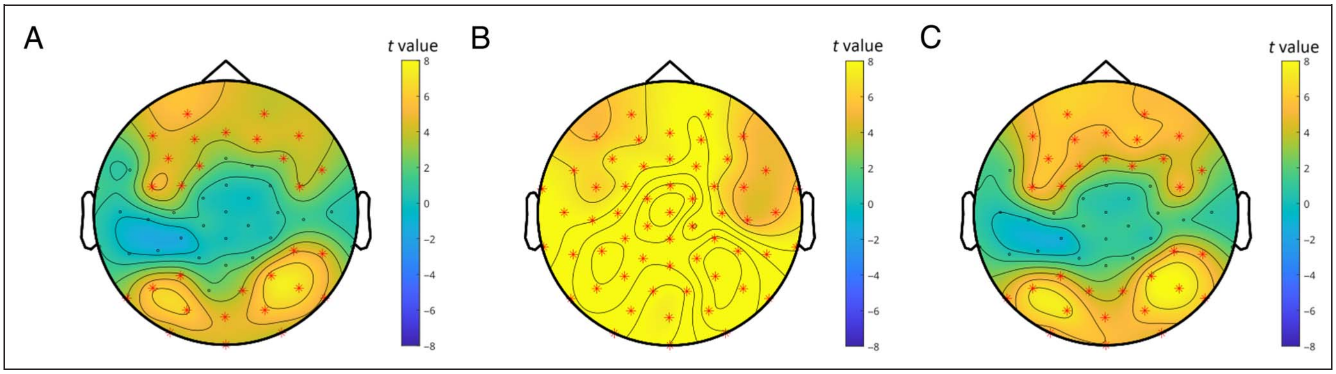

Figure 4. Scalp distributions of the aperiodic exponent during the poststimulus period. (A) Topography of the Time Point × Trial Type interaction. The map shows t values from a cluster-based paired permutation test on the difference-of-differences contrast: $(\text{Global} - \text{Local})_{\text{post}} - (\text{Global} - \text{Local})_{\text{pre}}$, collapsed across sessions. Positive t values indicate that the global–local difference was larger poststimulus than prestimulus. (B) Topography of the time point main effect (post vs. pre). The map shows t values from a cluster-based paired permutation test on the contrast Post − Pre, collapsed across trial type and session. Positive t values indicate higher exponents poststimulus. (C) Topography of the trial type main effect (global vs. local, poststimulus). The map shows t values from a cluster-based paired permutation test comparing global and local trials during the poststimulus window, collapsed across sessions. Positive t values indicate higher exponents for global than local trials. Red asterisks mark electrodes belong to cluster-corrected significant clusters (two-sided, cluster forming $\alpha = .005$, 1000 permutations, cluster level $\alpha = .05$).

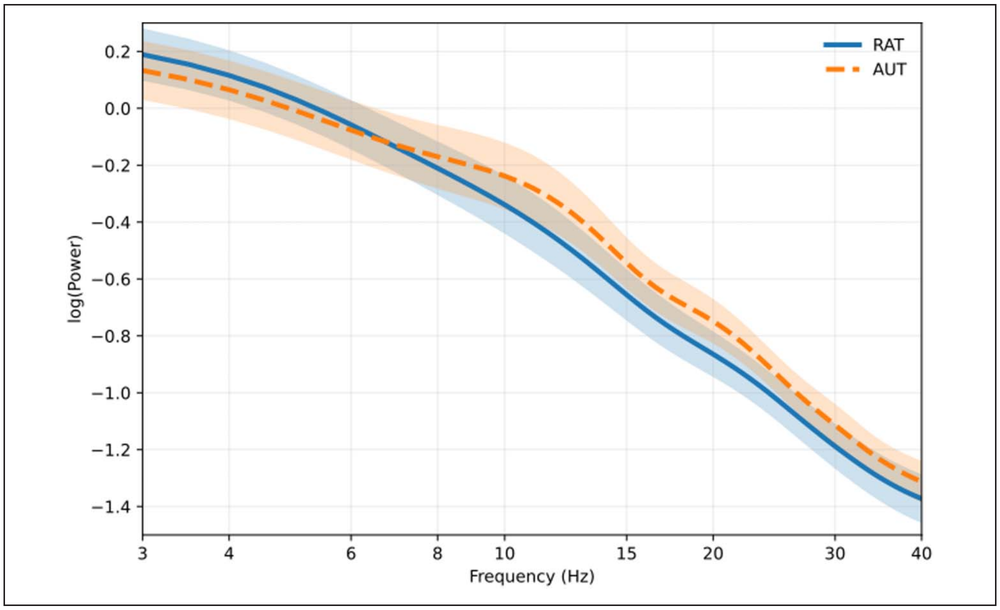

Figure 5. Log–log-transformed PSDs averaged across all electrodes and participants in the time window of 1000 msec prior to key-press. Blue lines represent RAT trials, and orange dashed lines represent AUT trials. Shaded areas denote ±95% CIs across participants.

between RAT and AUT. The scalp topographies of the aperiodic exponent are shown in Figure 6. One significant cluster was identified, including mainly frontal electrodes (Cz, FCz, FC1, FC3, FC2).

We tested whether the prime-induced exponent difference (ΔExponent_prime) predicted the probe exponent contrast (ΔExponent_probe). In the RAT session, the association was positive and moderate, rho = .37, 95% bootstrap CI [.05, .63], p = .019, indicating that participants who showed a stronger RAT–AUT exponent difference during the primes also showed a larger global–local exponent difference during the probe. In the AUT session, no reliable association was found, rho = .08, 95% bootstrap CI [−.24, .39], p = .622. Thus, prime-induced neural states showed measurable carryover to the probe only in the convergent (RAT) session.

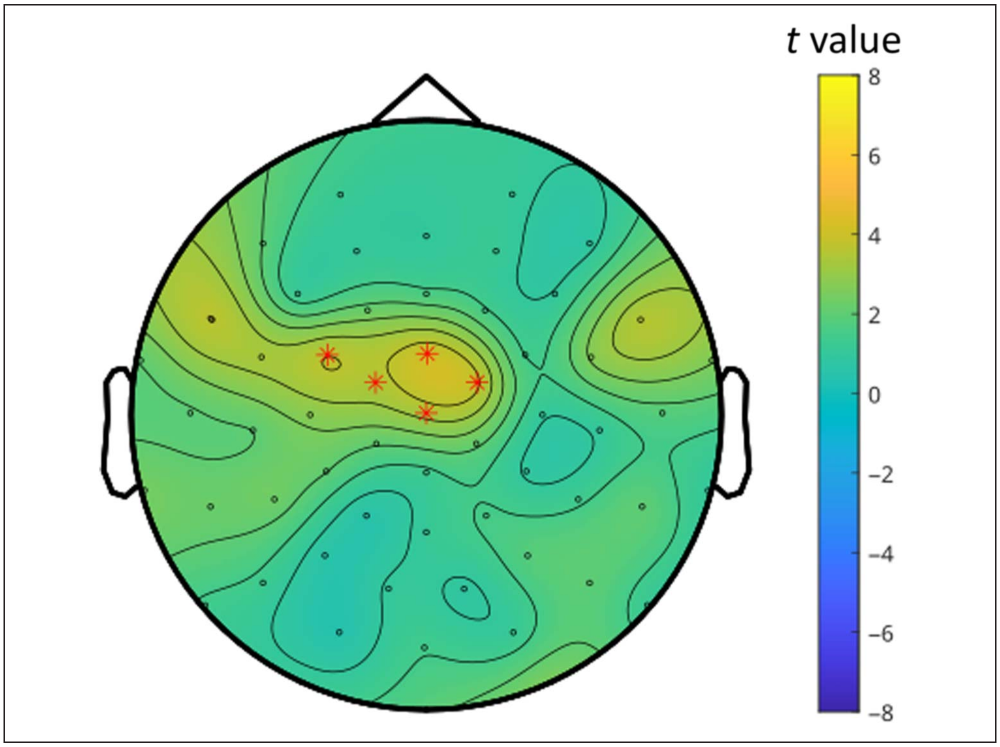

Figure 6. Scalp distributions of the aperiodic exponent of the RAT–AUT contrast. Positive *t* values indicate higher exponents for RAT than AUT. Red asterisks mark electrodes belong to cluster-corrected significant clusters (two-sided, cluster forming α = .005, 1000 permutations, cluster level α = .05).

DISCUSSION

The primary aim of the current study was to examine whether engaging in different creativity tasks to bias participants toward persistence or flexibility metacontrol states could influence behavioral performance and neural signatures in an intermixed RAT/AUT global/local tasks. At the behavioral level, participants demonstrated significantly faster and more accurate responses on global trials compared with local trials, a finding consistent across both the RAT and AUT sessions. However, the overall performance was not affected by session type, indicating that engaging in persistence- or flexibility-inducing tasks did not modulate behavioral responses in the global/local probe tasks. This pattern suggests that metacontrol biases induced by the prime tasks did not generalize to overt performance instead remained task-specific.

Regarding neural measures, EEG analyses revealed a significant main effect of trial type on the aperiodic exponent for poststimulus intervals, with local trials exhibiting lower exponents than global trials. Importantly, no significant differences emerged in the prestimulus intervals, highlighting that metacontrol adjustments were dynamically recruited in response to task demands rather than maintained as sustained preparatory states. Specifically, the aperiodic exponent did not differ between trial types before the stimulus onset, even though participants had just completed creativity tasks designed to induce distinct control states. Instead, the significant differences between global and local processing only emerged after stimulus presentation, with local trials consistently showing lower exponents than global trials. This suggests that participants did not maintain a general metacontrol bias in anticipation of the task but rather adjusted their control settings reactively once the specific demands of the trial became clear. This interpretation aligns with the "dual mechanisms of control" theory, which distinguishes between proactive control, where individuals prepare and maintain task-relevant goals in advance, and reactive control, which involves stimulus-driven adjustments (Braver, 2012). Our results support the reactive mode. That is, control states were not generally preactivated by prior task context but were recruited in real time when required (Dignath, Eder, Steinhauser, & Kiesel, 2020; Hommel, 2015; Braver, 2012)—they act as "prepared reflexes" (Hommel, 2000). In particular, studies using conflict-inducing tasks such as the Flanker task and go/no-go task have shown that the aperiodic exponent increases following the onset of high-conflict stimuli, but not before (Jia et al., 2024; Zhang et al., 2023). Another study from De Luca et al. (2022) showed that global/local processing modes only carried over to new tasks when there was substantial similarity. Moreover, our findings also relate to the "affective signaling hypothesis" of conflict monitoring, which suggests that control adjustments reflect not only cognitive demands but also motivational relevance (Dignath et al., 2020). This pattern of a higher aperiodic exponent in global trials than in local trials supports the idea that global processing might be the default (Kimchi, 1992; Navon, 1977), while local processing requires more flexible, effortful engagement, reflected in reduced neural inhibition and greater variability (Zhang et al., 2023; Donoghue et al., 2020; Gao, Peterson, & Voytek, 2017).

We examined the scalp distribution for aperiodic exponent using the cluster-based permutation test and identified two significant clusters over the scalp for the global effect. One is over the anterior–frontal regions, and another is over the posterior–occipital areas. This pattern suggests that reactive metacontrol adjustments recruit both higher-order executive networks involved in top–down regulation and posterior perceptual regions that integrate visual information (Jones & Graff-Radford, 2021; Xu, 2018; Gazzaley & Nobre, 2012; Li, Gratton, Yao, & Knight, 2010). The widespread cluster found for the prestimulus and poststimulus contrast indicated that stimulus onset broadly increased cortical inhibition across frontal, central, and posterior regions, consistent with a global adjustment of excitatory–inhibitory balance. These topographical results reinforce the view that metacontrol adjustments are distributed rather than localized, reflecting coordinated engagement of multiple cortical systems during adaptive control (Jia et al., 2024; Zhang et al., 2023).

Beyond the timing of metacontrol engagement, our findings also suggest that control states induced by the creativity tasks (RAT and AUT) did not generalize to the global/local task. Specifically, we observed no evidence that these induced states influenced pretrial aperiodic activity. This lack of transfer supports the idea that metacontrol adjustments are tied to task-specific representations. This aligns with the concept of episodic integration proposed by Spapé and Hommel (2008), which demonstrated that cognitive control adaptations can become integrated into task-specific event files that incorporate representations of stimuli, responses, and control states (Hommel, 2004). Control settings from one task do not automatically transfer to another unless the two tasks are very similar. In our study, even though participants just completed the RAT/AUT trial, the global/local trial likely initiates a new task set with different representational demands; therefore, direct transfer of the prior control state might be prevented. According to another study, control adjustments depend not only on conflict but also on the relevance and meaningfulness of the task context (Dignath et al., 2020). Although RAT and local trials both require focused attention, their differences likely prevented the transfer of persistence. Similarly, flexibility induced by AUT may not be carried over because there might not be enough overlap with the global trials that can be perceived. Overall, whether a control bias is reinstated depends on the perceived overlap in goals, structure, and processing mode, supporting the view that metacontrol adaptations appear to be flexible and selectively engaged when representational overlap justifies their retrieval.

The creativity prime tasks exhibited distinct spectral characteristics. Specifically, the aperiodic exponent was significantly higher in the RAT than in the AUT, suggesting stronger inhibitory processes and a more persistent control mode during convergent thinking, whereas the flatter spectral slope during the AUT indicates increased neural noise and a predominance of excitation over inhibition, which represents a more flexible processing state (Turri et al., 2023). Notably, the difference was most pronounced over frontal electrodes, consistent with the pFC's role in maintaining goal-directed control (Miller & Cohen, 2001). To examine whether these induced neural states carried over to subsequent perceptual processing, we correlated the exponent difference between the prime tasks (RAT–AUT) with the exponent difference between the probe tasks (global–local). The correlation was significantly positive for the RAT session, but not the AUT session. This finding suggests that a persistence-biased neural state, as induced by RAT, can exert a measurable carryover effect on subsequent control engagement, whereas flexibility-biased state induced by AUT may be less tangible to capture. The partial transfer in the persistence condition supports the notion that stability-oriented control state may have a longer lasting impact on cortical dynamics (Gao et al., 2025; Hommel, 2015). In contrast, flexibility-oriented state may entail greater neural variability and rapid contextual adaptation, which could hinder their transfer across tasks (Pi et al., 2024; Hommel & Colzato, 2017).

Taken together, our findings highlight three key insights: (1) Metacontrol adjustments were primarily reactive rather than preactive, emerging only after stimulus presentation (Hommel, 2000). (2) Persistence-biased neural states induced by convergent thinking task showed partial carryover to subsequent control processing, whereas flexibility-biased state did not, supporting that persistence involves more stable cortical configurations. (3) Control states are tied to specific task contexts and do not generalize unless representational demands match (De Luca et al., 2022). (4) Aperiodic exponent provides a sensitive neural index for these dynamic and context specific control adaptations, capturing both the transient engagement of control within tasks and the limited cross-task generalization of metacontrol state (Jia et al., 2024; Pi et al., 2024). Understanding how metacontrol adapts to changing task demands provides insight into how the brain dynamically allocates resources in real time, which is essential for navigating complex environments.

While the present study provides novel evidence for task-induced and reactive adjustments in metacontrol reflected in aperiodic neural activity, several limitations should be noted. First, although we used creativity tasks (RAT and AUT) to induce distinct metacontrol states, the lack of transfer to the global/local task suggests that the induced control biases may be highly task-specific. Future studies could extend this design by using tasks with greater representational overlap or by employing transfer paradigms that explicitly test the boundaries of metacontrol generalization. Combining behavioral and neural measures across multiple tasks could help determine whether persistence and flexibility biases can become more stable traits under certain training or motivational contexts. Second, regarding the spectral analyses, we estimated poststimulus power spectra from stimulus-locked epochs without explicit ERP subtraction. Frelih, Matkovič, Mlinarič, Bon, and Repovš (2025) highlighted that ERPs may contain both transient-evoked activity and induced changes of the ongoing signal. Because evoked transients can alter the spectrum without indicating a shift in ongoing background activity, ERP subtraction can be used to isolate induced aperiodic changes. Previous studies show that ERP subtraction reduces the magnitude of aperiodic effects but preserves their overall pattern, indicating that these effects reflect genuine induced modulations of ongoing background activity rather than solely evoked transients (Kałamała et al., 2024; Gyurkovics et al., 2022). Future research could complement the current approach with ERP subtraction to further disentangle their relative contributions. Such work would help clarify to what extent exponent increases primarily reflect induced shifts in cortical excitation–inhibition balance. Third, although the global averaging of the aperiodic exponent provides a robust summary index, it precludes insight into possible regional differences in metacontrol-related neural dynamics. Future studies using source-level analyses may help specify the cortical networks contributing to these adjustments.

Corresponding author: Xi Wang, Cognitive Neurophysiology, Department of Child and Adolescent Psychiatry, Faculty of Medicine, TU Dresden, Schubertstraße 42, 01307 Dresden, Germany, e-mail: Xi.Wang@ukdd.de.

Data Availability Statement

Data supporting the article can be found in OSF https://osf.io/jhzc6. Supplemental Material can be accessed on this article's homepage: https://doi.org/10.1162/JOCN.a.2524.

Author Contributions

Xi Wang: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Visualization; Writing—Original draft; Writing—Review & editing. Christian Beste: Conceptualization; Methodology; Resources; Supervision; Writing—Review & editing. Bernhard Hommel: Conceptualization; Methodology; Supervision; Writing—Review & editing.

Diversity in Citation Practices

Retrospective analysis of the citations in every article published in this journal from 2010 to 2021 reveals a persistent pattern of gender imbalance: Although the proportions of authorship teams (categorized by estimated gender identification of first author/last author) publishing in the *Journal of Cognitive Neuroscience* (*JoCN*) during this period were M(an)/M = .407, W(oman)/M = .32, M/W = .115, and W/W = .159, the comparable proportions for the articles that these authorship teams cited were M/M = .549, W/M = .257, M/W = .109, and W/W = .085 (Postle and Fulvio, *JoCN*, 34:1, pp. 1–3). Consequently, *JoCN* encourages all authors to consider gender balance explicitly when selecting which articles to cite and gives them the opportunity to report their article's gender citation balance. The authors of this paper report its proportions of citations by gender category to be: M/M = .595; W/M = .190; M/W = .119; W/W = .095.

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