Thinking out of the Box: Divergent Thinking Is Associated with Increased Aperiodic Neural Activity

Chenyan Zhang[1*], Weitao Zhang[1,2*], Christian Beste[3,4†], and Bernhard Hommel[3†]

Abstract

■ Creativity, the ability to produce novel and useful ideas, is a fascinating ability about which we know surprisingly little. Here, we asked how people manage to think "out-of-the-box"—how they generate truly novel ideas. We hypothesized that higher levels of aperiodic neural activity (often termed "neural noise") may facilitate overcoming the constraints of prior knowledge, thus supporting novel idea generation. Participants (n = 51) performed two classical creativity tasks tapping divergent (alternative uses task) and convergent thinking (remote associates task), respectively, while EEG was recorded. Aperiodic activity was estimated from the EEG power spectrum using the FOOOF (fitting oscillations and one-over-f) toolbox. We found that engaging in divergent, out-of-the-box thinking (but not convergent thinking) was associated with a significant increase of aperiodic activity, reflected in a decreased aperiodic exponent. Moreover, individuals with more increased aperiodic activity during divergent thinking generated more novel ideas. Our findings suggest that aperiodic, "noisy" brain dynamics play a functional role in supporting divergent thinking. Aperiodic activity, which is often neglected in neuroscientific research, may be an important mechanism of human cognition. ■

INTRODUCTION

Creativity, the ability to produce novel and useful ideas (Runco & Jaeger, 2012), is a particularly fascinating ability about which we know surprisingly little. Early studies considered creativity as a personality characteristic and creativity as something that creative people do (Mackinnon, 1965; Barron, 1955). More recent research into the functions underlying human creativity suggests a more continuous picture according to which everyone can be creative sometimes (Kaufman & Beghetto, 2009). This raises a fundamental question: What cognitive and neural processes support the ability to generate novel ideas?

One influential framework posits that creative performance draws on two cognitive processes: divergent thinking (DT) and convergent thinking (CT) (Runco & Acar, 2012; Eysenck, 2003; Guilford, 1967). DT involves generating novel ideas in the first place, often through associative exploration and flexible shifts in mental sets (Runco & Acar, 2012; Eysenck, 2003; Guilford, 1967). CT, in contrast, serves to narrow down ideas to find the best solution for a problem (Cropley, 2006; Guilford, 1967). Following Guilford (1967) and Mednick (1962), the alternative uses task (AUT) is widely used to access DT, as it encourages the generation of multiple novel ideas through associative thinking (Benedek & Fink, 2019; Runco & Acar, 2012; Guilford, 1967), whereas the remote associates task (RAT) is used as a measure of CT, because it emphasizes narrowing down to a single correct answer, making it more reflective of CT (Beaty, Benedek, et al., 2014; Lee et al., 2014; Mednick, 1962). Indeed, performance in these two tasks has often been dissociated. For instance, performance in AUT does not correlate with performance in RAT, and the latter correlates with intelligence whereas the former does not (Akbari Chermahini et al., 2012). Performing the two tasks affects emotions in opposite ways (Akbari Chermahini & Hommel, 2012), and performance is differently affected by meditation (Colzato et al., 2012), bilingualism (Hommel et al., 2011), and brain stimulation (Zmigrod et al., 2015). The two tasks rely on different control settings (Hommel & Colzato, 2017; Hommel, 2012), and they engage in different brain areas and neural activities (Zhang et al., 2020; Akbari Chermahini & Hommel, 2010). Logically, the two tasks are unlikely to represent pure measures of DT and CT, because both involve some degree of divergent search and convergent homing in on two solutions (Beaty, Silvia, et al., 2014; Nijstad et al., 2010). And yet, it makes sense to assume that AUT involves more divergent and the RAT involves more convergent processing. Accordingly, in this study, we adopted AUT and RAT as proxies for the dominant cognitive demands they are assumed to bias while acknowledging their complexity and overlap.

Both DT and CT processes have been linked to a broader cognitive control framework—metacontrol

[1]Leiden University, [2]Zhejiang University, [3]Shandong Normal University, [4]Technische Universität Dresden
*These authors contributed equally to this work.
†Shared senior authorship.

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(Zhang et al., 2020, 2025; Hommel, 2015). Within this framework, cognitive control is not conceived as a unidimensional construct of "more" versus "less" control, but rather as a bias between persistence- and flexibility-biased processing modes. Metacontrol refers to the ability to establish processing modes that favor either stable, goal-directed control or more flexible, exploratory processing in response to task demands (Hommel & Colzato, 2017). A flexibility bias, characterized by a greater reliance on bottom–up information and open processing of incoming information, promotes openness to weak associations and flexible switching between ideas, thereby supporting DT tasks such as the AUT (Zhang et al., 2020, 2025; Hommel, 2012, 2015). In contrast, a persistence bias, characterized by focused, selective processing guided by task goals, supports CT tasks such as the RAT (Zhang et al., 2020; Hommel, 2015). Although some experimental manipulations (like mood or meditation) were successful in introducing systematic biases toward flexibility or persistence (Nijstad et al., 2010; Dreisbach & Goschke, 2004), the mechanisms underlying changes in metacontrol are not yet understood, which also means that neither metacontrol states nor changes therein can be directly measured. Accordingly, we treat AUT and RAT as imperfect proxies that typically bias processing toward flexibility and persistence of metacontrol states, respectively.

Neuroscientific research has largely focused on periodic brain oscillations; however, recent studies have begun to recognize the cognitive role of aperiodic (1/*f*-like) neural activity in EEG power spectra (Ostlund et al., 2021; Donoghue et al., 2020; Voytek et al., 2015; He, 2014). This aperiodic activity appears approximately linear in log–log space, where the aperiodic exponent quantifies how rapidly power decreases with frequency (Donoghue et al., 2020). Aperiodic activity has long been neglected or regarded as "noise" with little physiological significance. Recent research, however, suggests that it reflects fundamental neural properties such as excitation–inhibition balance and may play a functional role in cognition (Lendner et al., 2023; Zhang et al., 2023; Ostlund et al., 2021; Donoghue et al., 2020; Gao et al., 2017; Voytek et al., 2015). Converging empirical evidence from well-established cognitive control paradigms, individual differences, and causal neuromodulation studies indicates that aperiodic activity systematically covaries with metacontrol modes, being higher during persistence mode and lower during flexibility mode (Gao et al., 2025; Prasad & Beste, 2025; Van Schependom et al., 2024; Zhang et al., 2023). Building on this evidence, we have considered the possibility that aperiodic activity may serve as a candidate marker of metacontrol states and that situation- or task-specific changes in aperiodic activity represent a possible neural mechanism that people use to adjust their cognitive-control style to current challenges (Gao et al., 2025; Pi et al., 2024; Van Schependom et al., 2024; Zhang et al., 2023). Rendering the brain less periodic would loosen its organization to some degree, which in turn may help the individual to neglect previously acquired knowledge, rules, and regulations—all possible obstacles to finding a truly novel idea or solution.

To test this hypothesis, participants completed the AUT and RAT while EEG signals were recorded. Aperiodic activity was then estimated using the FOOOF (fitting oscillations and one-over-*f*) algorithm (Donoghue et al., 2020). Given the "out-of-the-box" character of the AUT, we predicted that performing on AUT would be accompanied by more aperiodic activity (i.e., a lower FOOOF-estimated aperiodic exponent) than performing on the RAT. Moreover, since people are likely to differ with respect to the degree to which they increase aperiodic activity when working on out-of-the-box problems, we expected to see a positive correlation between aperiodic activity and performance in the AUT. Our next study question was related to the speed and context sensitivity of metacontrol adjustments. Given that the two creativity tasks were presented in separate blocks, participants might establish different metacontrol states that are maintained throughout each block. If so, they should differ in aperiodic activity even between trials (in the intertrial [IT] period, see below), that is, before the respective task stimulus would appear. However, recent research suggests that people can tailor their metacontrol states to the challenges at hand from 1 sec to the other (De Luca et al., 2022), suggesting that aperiodic activity might also, or even more substantially, differ between the two tasks after the respective task stimulus was presented.

METHODS

Participants

The present FOOOF analysis shared data with a planned report of the more conventional EEG parameters that were studied for other scientific purposes. The sample initially consisted of 58 healthy human volunteers. In this study, seven participants were excluded from the analysis based on two quality control criteria: (1) poor FOOOF model fits, defined as FOOOF spectra fits (R^2) or error of fits deviating by 2.5 standard deviations from the sample mean, and (2) extreme outliers in aperiodic parameter values, defined as aperiodic exponent/offset values deviating by more than 3 standard deviations from the group mean, to prevent disproportionate influence on group-level analyses. Thus, the final sample for analysis in this study included 51 participants, of whom 50 were female, aged between 18 and 25 years (mean = 19.84 years, SD = 1.78). All participants were right-handed and had no history of neurological or psychiatric disorders. The present study and the original study were approved by the Psychology research ethics committee of Leiden University. All participants provided written informed consent for their participation. The study was conducted in accordance with the Declaration of Helsinki.

Stimuli and Procedure

In the original study, participants completed an AUT and a RAT to induce and measure DT and CT, respectively. In addition, an object characteristics task and a vowel searching task were included as noncreative control tasks for AUT and RAT, respectively. The order of all tasks was counterbalanced across participants to control for potential order and carryover effects. For the current study, we focused only on the data collected during the AUT and RAT blocks to specifically examine neural activity associated with creative thinking.

AUT

The task required participants to generate as many possible uses for a common object (e.g., brick) as they could within a 30-sec time limit (Figure 1). Each trial began with a 5-sec fixation cross, followed by the presentation of an object on the screen. Participants were instructed to press the SPACE key every time they had one idea and verbally report their answer. Since participants often had multiple ideas for one object, they pressed the SPACE key multiple times during a single trial. Each participant completed 18 items in the AUT. The items of AUT were acquired from a previous study (Abraham et al., 2012) and translated into Dutch. Performance in the AUT was scored along three dimensions: fluency (the number of ideas generated), flexibility (the number of categories to which the ideas belong), and originality (the uniqueness of the ideas generated). Two trained raters separately scored the originality (from 1 to 5 according to the original level) of every idea, and then the scores were averaged after a good inter-rater reliability was confirmed using a two-way mix intraclass correlation coefficient (.95).

RAT

Participants were presented with three unrelated words (e.g., cocktail, dress, birthday) and instructed to generate a fourth word that was connected with all three stimuli (e.g., party; Figure 1). Each trial starts with a 5-sec fixation cross, followed by the presentation of stimulus words for maximum 30 sec. Once participants had identified a solution, they pressed the SPACE key and then verbally provided their answer within 3 sec. Once the participants pressed the button, the stimulus words disappeared, and the answer was recorded by microphone. Then, participants indicated whether they had solved the problem through insight by pressing the V key or without insight by pressing the N key within a maximum of 3 sec. The same instruction to explain insight from a previous study (Jung-Beeman et al., 2004) was translated into Dutch and used in this study. This insight judgment was included to preserve the standard implementation of the RAT and was not a focus of the present analyses. All trials with a recorded response were included regardless of insight experience. The RAT consisted of 65 items, which were selected by a pilot testing from a pool of 144 items invented by Dutch-native researchers. All RAT trials with a recorded response were included in the neural analyses, regardless of accuracy or insight experience, as the analysis targeted the convergent processing preceding the keypress.

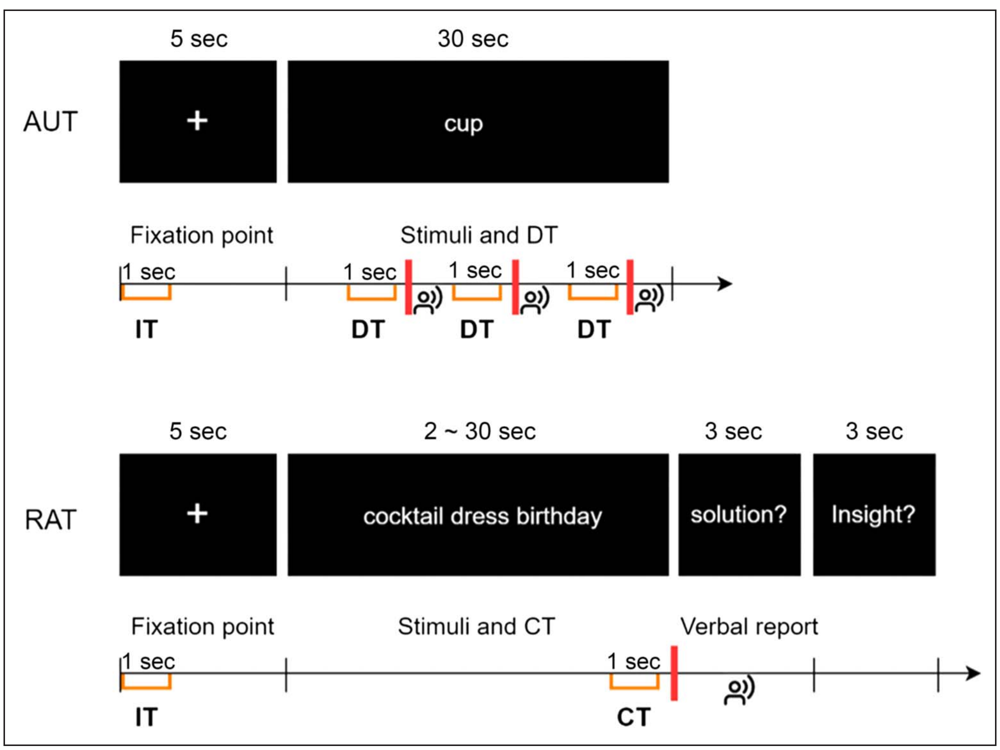

Figure 1. Creative thinking task schematic. Participants completed the AUT and RAT in counterbalanced order. In AUT, participants were required to generate as many possible uses for a common object (e.g., cup) as they could within a 30-sec time limit. Trials began with a 5-sec fixation cross, followed by stimulus presentation. Participants pressed the SPACE key every time they had one idea and then verbally reported their answer. In RAT, participants were presented with three unrelated words (e.g., cocktail, dress, birthday) and asked to generate a fourth word that connects all three stimuli. Each trial started with a 5-sec fixation cross, followed by the presentation of stimulus words for a maximum of 30 sec. Once participants had identified a solution, they pressed the SPACE key and then verbally reported their answer within 3 sec.

EEG Acquisition and Preprocessing

EEG data were acquired using a Biosemi ActiveTwo system with 64 electrodes positioned in accordance with the international 10–20 system. A reference electrode was placed on each mastoid. The EEG signal was recorded at a sampling rate of 512 Hz and preamplified at the electrode to enhance the signal-to-noise ratio. To identify and subsequently eliminate ocular artifacts from the EEG, the horizontal EOG was captured from electrodes located at the left and right outer canthi, while the vertical EOG was captured from electrodes located above and below the right eye. Monopolar recordings were referenced to the common mode sensor during data acquisition. Subsequently, the data were re-referenced offline to the average of the right and left mastoids.

All EEG data were analyzed in MATLAB 2018b (The MathWorks) using a combination of the EEGLAB toolbox (Delorme & Makeig, 2004) and custom in-house code, which followed a similar procedure as described in a previous study (van den Brink et al., 2021). All EEG data underwent a two-stage cleaning procedure. First, the data were high-pass filtered offline at 0.5 Hz, notch-filtered at 50 Hz, and segmented from −1.5 sec until +5.5 sec surrounding the onset of the fixation period and from −3 sec until +1 sec surrounding the response onset. Trials that contained artifacts were identified using an automatic algorithm, which relied on the following criteria: joint probability across channels (threshold: 5 standard deviations), kurtosis of each channel (threshold: 5), and absolute voltage deflections (2 mV). Next, we applied joint approximation diagonalization of eigen matrices independent component analysis (ICA) to detect eye movement and blink artifacts. The ICA weights were then saved and projected onto the raw, unfiltered, unsegmented data. Back projection was implemented with the aim of preventing ICA from solely accounting for the variance due to significant drifts in the unfiltered data, which could lead to incorrect identification of eye-blink-related components. This was done to ensure that trials would not be rejected as artifacts solely due to the presence of eye blinks. The data were then high-pass filtered and segmented, and the automatic artifact detection algorithm was applied again, this time with a more stringent absolute voltage deflection criterion (300 μV). The EEG data were current source density transformed and segmented separately for the task response period (−3 to +1 sec) and fixation/between-trial period (−1.5 to +5 sec).

Analysis of Behavioral Data

RAT and AUT were mainly used to induce CT/persistence state and DT/flexibility state, respectively. To investigate the possible relationship between aperiodic neural activity and behavioral performance, we used creativity behavioral scores, including RAT scores, AUT fluency scores, AUT flexibility scores, and AUT originality scores. RAT scores were obtained by summing the number of correct answers across all trials. Completing the RAT requires participants to find a single solution under highly constrained search conditions, relying mainly on the persistence of metacontrol (Zhang et al., 2020; Hommel, 2012, 2015). Participants with higher RAT scores were assumed to exhibit a stronger bias toward persistence of metacontrol than participants with worse performance (Zhang et al., 2020; Hommel, 2012). AUT fluency scores were calculated by summing the number of ideas generated, while AUT flexibility scores were obtained by summing the number of categories to which the ideas belong. Additionally, AUT originality scores were determined by averaging the originality scores from the two raters. As the higher AUT fluency and flexibility scores require switching between different ideas and considering multiple solutions, higher scores indicate a higher tendency toward the flexibility bias of metacontrol (Zhang et al., 2020; Hommel, 2012). To provide a general overview of behavioral performance, we also report the number of responses in both tasks and the RTs in the RAT.

EEG Data Analysis

Two segments of interest in each trial were selected for further analysis: IT period (0–1000 msec after the presentation of fixation cross) and creative thinking period (−1100 to −100 msec before the key press). In the AUT, where participants generated multiple ideas, neural activity in the creative thinking period was averaged across all responses to reflect a cognitive state dominated by DT. In the RAT, the same window was used to capture neural activity associated with CT processes leading up to each solution. We exclude −100 msec to key press as neural activity in this period could be dominated by the key pressing action preparation other than creative thinking. Power spectra were calculated using Welch's method (Welch, 1967; 250-ms Hamming window, 50% overlap) for all channels, trials, and across all segments, with zero-padding applied to increase frequency resolution (from 4 to 0.5 Hz).

To estimate aperiodic activity of EEG signals, we utilized the FOOOF toolbox, a Python-based software (Version 1.0.0, https://github.com/fooof-tools/fooof; Donoghue et al., 2020), to perform spectral parameterization analyses. This approach decomposes power spectra into aperiodic and periodic components, where the power spectrum is modeled as a linear combination of aperiodic activity [$L(f)$] and periodic (oscillatory) activity [$Gn(f)$], expressed as $PSD(f) = L(f) + \sum_n G_n(f)$, where f denotes frequency. The aperiodic component, $L(f)$, is fit as a function across the entire fitted frequency range and described by $L(f) = b - \log\,[f^x]$, where b represents the aperiodic offset reflecting the broadband power shift and x is the aperiodic exponent that corresponds to the slope of the line fitted to the power spectrum in a log–log space. The periodic (oscillatory) components are identified as

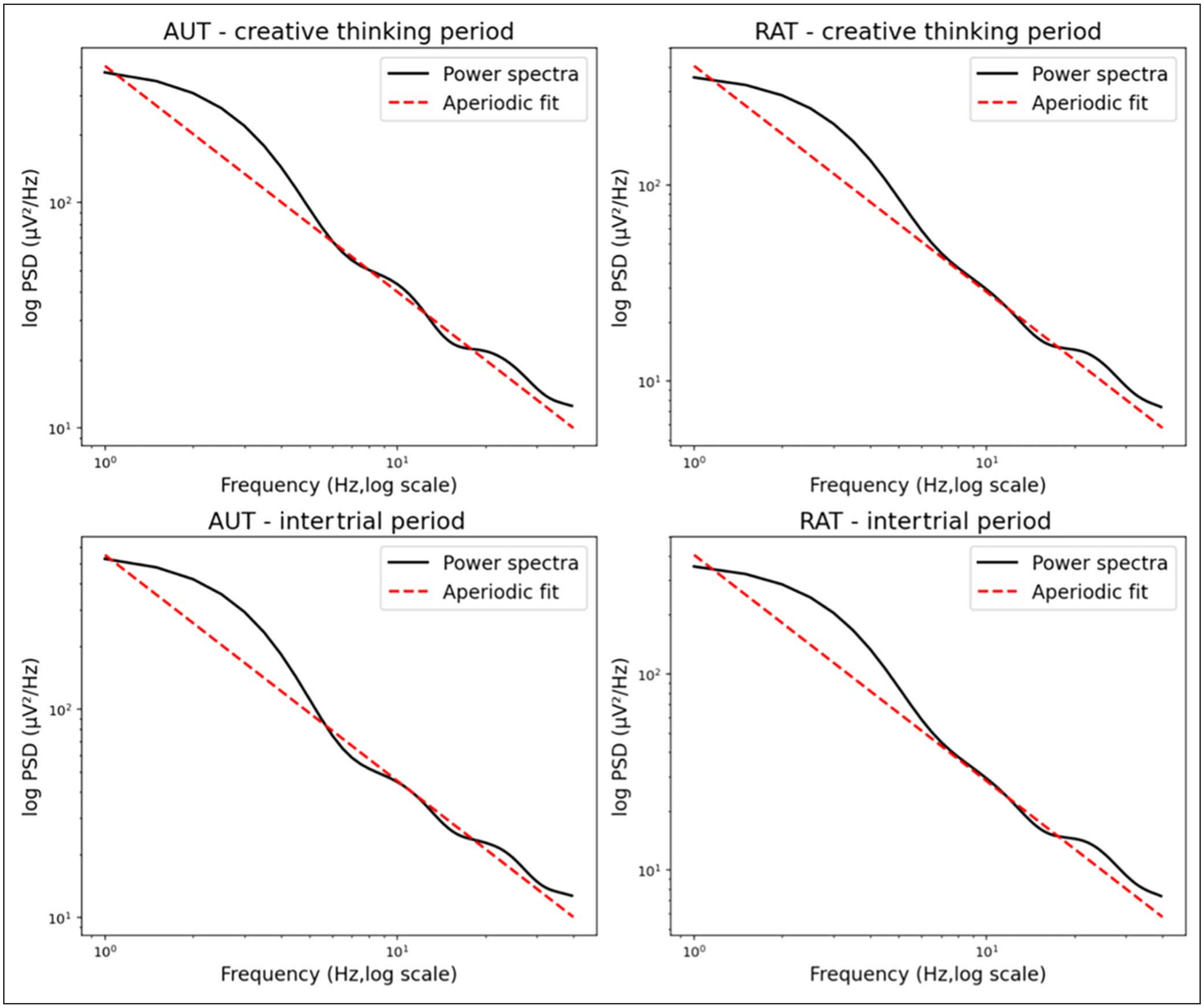

Figure 2. Power spectra and fitted aperiodic components for AUT and RAT during the creative thinking and IT periods. Top row: creative thinking period for AUT (left) and RAT (right). Bottom row: IT period for AUT (left) and RAT (right).

frequency regions of power that are above the aperiodic component. Each oscillatory component, also known as a *peak* is modeled with a Gaussian and characterized by three parameters that define a Gaussian. Specifically, each Gaussian fit can be written as $G_n(f) = a_n \exp\left[-\frac{(f-\mu_n)^2}{2\sigma_n^2}\right]$, where a_n denotes amplitude, μ_n denotes center frequency, and σ_n denotes bandwidth of each component.

The power spectra data were fit over a broad frequency range of 1–40 Hz, consistent with previous studies and recommendations in the FOOOF documentation (Zhang et al., 2023; Hill et al., 2022; Ostlund et al., 2021; Donoghue et al., 2020) to obtain a reliable estimation of the aperiodic component. As no prior assumptions were made regarding the scalp distribution of the aperiodic neural activity, the power spectra for the spectral parameterization analysis were averaged across all channels. The FOOOF algorithm was used with the following settings {peak width limits = [1, 8], maximum number of peaks = 8, minimum peak height = 0.05, aperiodic mode = "fixed," default settings otherwise}. Seven participants were excluded from further analyses due to R^2 or error of spectral fits 2.5 *SD* away from the mean. The power spectra were fit for each participant, each task condition (AUT vs. RAT), and each period (IT vs. task). The average R^2 of spectral fits for remaining participants in each task conditions was over .93, indicating good fits. Power spectra and corresponding aperiodic fits for each task condition and process period are shown in Figure 2. The aperiodic exponent was extracted from the aperiodic-only signal for each participant.

Statistical Analysis

We employed paired-samples *t* tests to compare aperiodic activity between the DT and CT, the IT period and DT period in AUT, the IT period and CT period in RAT, and the IT period in AUT and RAT. All t tests were two-tailed. Spearman correlation was used to assess the relationship between aperiodic activity and creativity task performance. We used two-way repeated-measures ANOVAs to examine whether changes in aperiodic activity are task-specific (IT period vs. task period) and process-specific (DT process vs. CT process). Bayesian statistics were reported for t tests and ANOVAs. The BF_{10} was reported to quantify the strength of evidence favoring the alternative hypothesis over null hypothesis. Additionally, BF_{incl} was calculated to evaluate the extent of evidence within the data for including a predictor (van den Bergh et al., 2020, 2022).

To analyze the scalp distribution of the aperiodic activity, we utilized a nonparametric cluster-based permutation test (Maris & Oostenveld, 2007). This approach enabled us to identify electrodes that differed between conditions across participants while circumventing the multiple comparison problem in high-dimensional EEG/MEG data. Clusters were formed based on the adjacency of thresholded sample-level t values ($\alpha = .005$), and the sum of t values in a cluster was used as the cluster-level statistics. To determine the significance of the clusters, 1000 Monte Carlo random samplings were performed using a .05 significance level.

Control Analysis: Spectral Decomposition Using Irregular Resampling Auto-spectral Analysis

To assess the robustness of our aperiodic activity findings across spectral decomposition methods, we conducted supplementary control analyses where irregular resampling auto-spectral analysis (IRASA) was used to estimate the aperiodic component. IRASA separates oscillatory from aperiodic components by irregularly resampling the neural signal using noninteger factors and estimating the aperiodic spectrum from the statistical summary of the resampled autopower spectra (for more details, see Wen & Liu, 2016). IRASA analyses were performed on the same preprocessed EEG data, time periods, channels, and trials as used in the main FOOOF-based analyses. Full methodological details and results are provided in the Supplemental Materials.

RESULTS

Behavioral Results

To provide an overview of participants' behavioral performance, we report the number of responses generated in each task and RTs in the RAT. In the AUT, participants generated an average of 62 responses across all trials ($SD = 21$; Figure 3A). In the RAT, participants generated an average

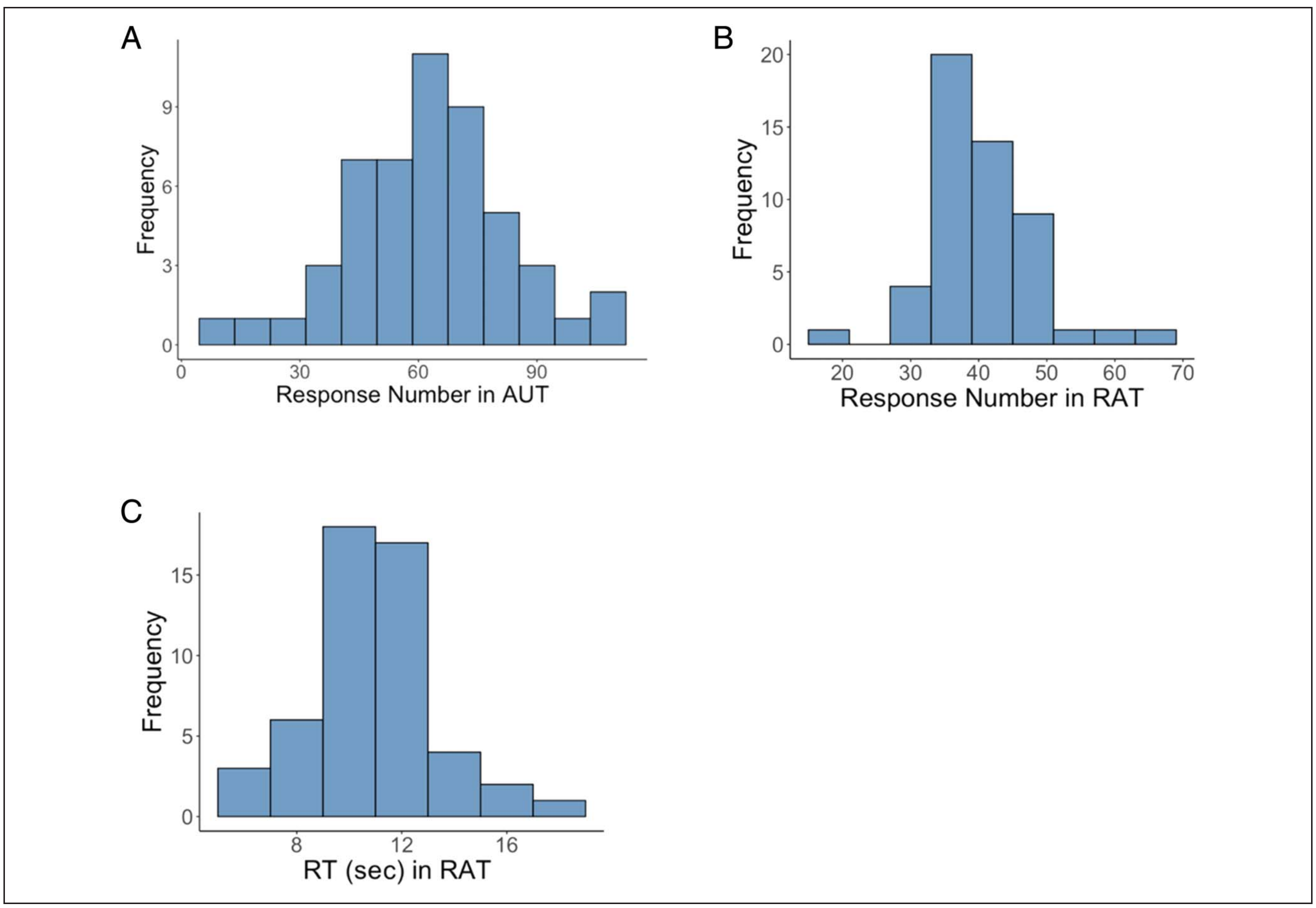

Figure 3. Behavioral performance in the AUT and RAT. (A) Distribution of the total number of responses generated in the AUT across participants. (B) Distribution of RAT trials with recorded responses. (C) Distribution of mean RTs (in seconds) per RAT item.

of 40 responses across all trials (SD = 8; Figure 3B), with a mean RT of 12 sec per item (SD = 2; Figure 3C).

Neurophysiological Results

Aperiodic Exponent Differences between DT and CT

To determine whether the different types of creative thinking are associated with different aperiodic exponents, we tested the difference in the mean aperiodic exponent across all electrodes between DT and CT. This difference was significant, $t(50) = 5.11, p < 0.001$, Cohen's $d = 0.60$, $BF_{10} = 3625.16$ (Figure 4A), with DT ($M = 1.00$) showing a lower aperiodic exponent (i.e., more aperiodic activity) than CT ($M = 1.15$). This pattern was as predicted, and it suggests that engaging in out-of-the-box thinking is accompanied by increasing one's aperiodic activity. A cluster-based permutation test (Methods) demonstrated that the difference in aperiodic exponent between DT and CT was evident in various electrodes above the frontal, central, temporal, and parietal regions (Figure 4B).

Aperiodic Exponent Correlates with DT

Spearman correlation tests revealed significant linear relationships between the aperiodic exponent for the AUT period and performance in the AUT for both fluency scores ($r = -.39$, $p = .004$) and flexibility scores ($r = -.28$, $p = .044$), but not for originality scores ($r = -.10$, $p = .476$; Figure 5). As anticipated, the correlation between the aperiodic exponent for the RAT period and performance in the RAT was not significant.

Considering that low exponent values indicate higher aperiodic activity, these findings confirm our prediction that individuals who are more successful in establishing a "noisier" metacontrol state perform better than others in out-of-the box thinking. The nonsignificant result for originality is rather common in correlational studies on interindividual differences in the AUT (Akbari Chermahini & Hommel, 2010), presumably due to two psychometric flaws of this measure: its low resolution (only three different scores) and the fact that it depends entirely on the current participant group (as the score reflects the uniqueness of the response).

Task- and Process-specific Aperiodic Exponent Changes

A 2 × 2 ANOVA with Time Period (IT vs. task) and Task (AUT vs. RAT) as within-participant factors yielded two significant main effects of Time Period, $F(1, 50) = 6.41$, $p = .015$, $\eta_p^2 = .11$, $BF_{incl} = 2.30$, and Task, $F(1, 50) = 18.06$, $p < .001$, $\eta_p^2 = .27$, $BF_{incl} = 263.84$, and a significant interaction, $F(1, 50) = 10.92$, $p = .002$, $\eta_p^2 = .18$, $BF_{incl} = 21.87$. t Tests revealed that the aperiodic exponents differed between AUT and RAT in both the task period (see above) and the IT period, $t(50) = 2.49$, $p = .016$, Cohen's $d = 0.28$, $BF_{10} = 2.50$, even though the Task effect was significantly larger in the task period, $t(50) = 3.31$, $p = .002$, Cohen' $d = 0.40$, $BF_{10} = 17.08$. As indicated in Figure 6A, the aperiodic exponent was lower in the AUT in general and further decreased considerably when actually engaging in DT. This was not the case in the RAT: The exponent changed significantly from IT to task period in the AUT ($M_{IT} = 1.08$, $M_{DT} = 1.00$), $t(50) = 5.68$, $p < .001$, Cohen's $d = 0.33$, $BF_{10} = 22911.13$ (Figure 6B), but not in the RAT ($M_{IT} = 1.15$, $M_{CT} = 1.15$), $t(50) = 0.02$, $p = .984$; $BF_{10} = 0.15$ (Figure 6C). This lack of any visible change of the aperiodic activity level in the RAT provides converging neural evidence for previous observations that interventions targeting creative thinking are more successful for DT than for CT (Matsumoto et al., 2022; Aga et al., 2021). Cluster-based permutation tests identified the spatial distribution of the observed differences in exponent values. Electrodes across a broad range of areas showed a difference in exponent values between IT and DT periods, while only a few electrodes in parietal and occipital areas showed a

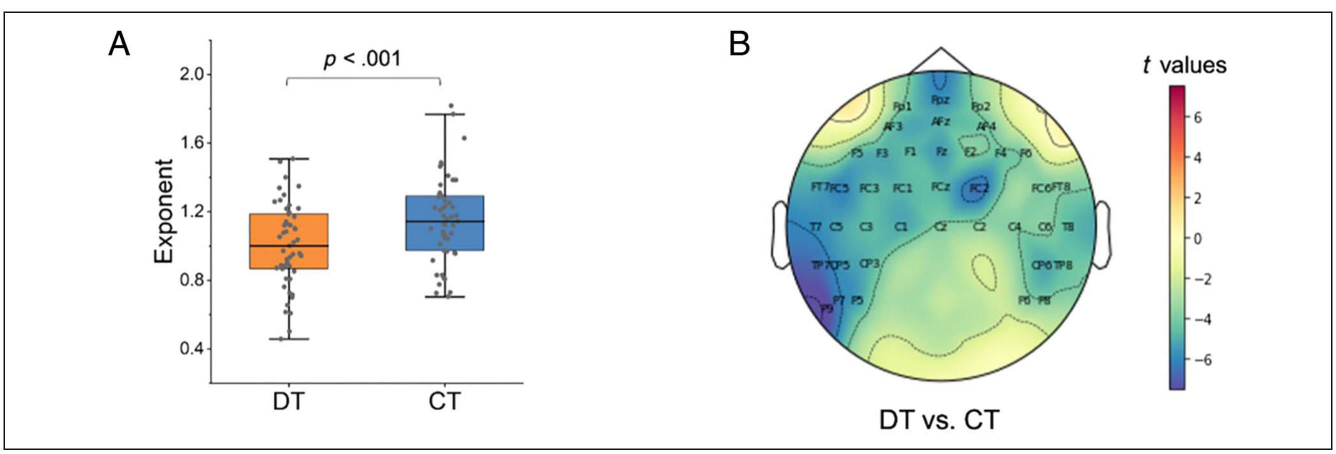

Figure 4. The comparison of aperiodic exponent between DT and CT. (A) Aperiodic exponent for DT and CT (two-tailed paired t test: $p < .001$). (B) Electrode sites and labels showing significant difference in aperiodic exponent between DT and CT processes. Significant electrodes were identified using the cluster-based permutation test.

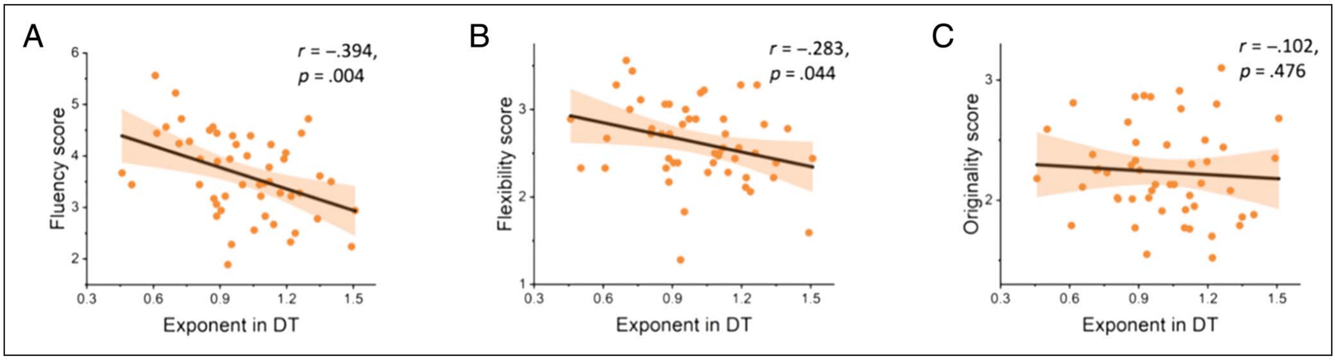

Figure 5. Correlation between aperiodic exponent and DT performance. (A, B, C) Correlation between aperiodic exponent during the DT process and fluency score (A), flexibility scores (B), and originality score (C). The shading indicates 95% CI.

difference in exponent values between IT and CT periods (Figure 6D). In summary, the outcome pattern provides evidence for both a general task effect (as evident from the IT period) and a process-specific effect (as evident from the increased task effect in the task period).

Neurophysiological Results in Control IRASA Analysis

IRASA control analyses largely replicated the main findings obtained with FOOOF. Specifically, aperiodic exponents were lower during DT compared with CT, $t(50) = 3.71$, $p < .001$, Cohen's $d = 0.59$, $BF_{10} = 51.36$, and reduced aperiodic exponents during DT were associated with higher behavioral fluency and flexibility scores of AUT (fluency: $r = -.43$, $p = .002$; flexibility: $r = -.40$, $p = .004$). A minor difference occurred in the IT period, where a small Task difference observed with FOOOF did not reach significance with IRASA. This difference likely reflects methodological distinctions between the two approaches rather than a substantive inconsistency. Full IRASA results are provided in the Supplemental Materials.

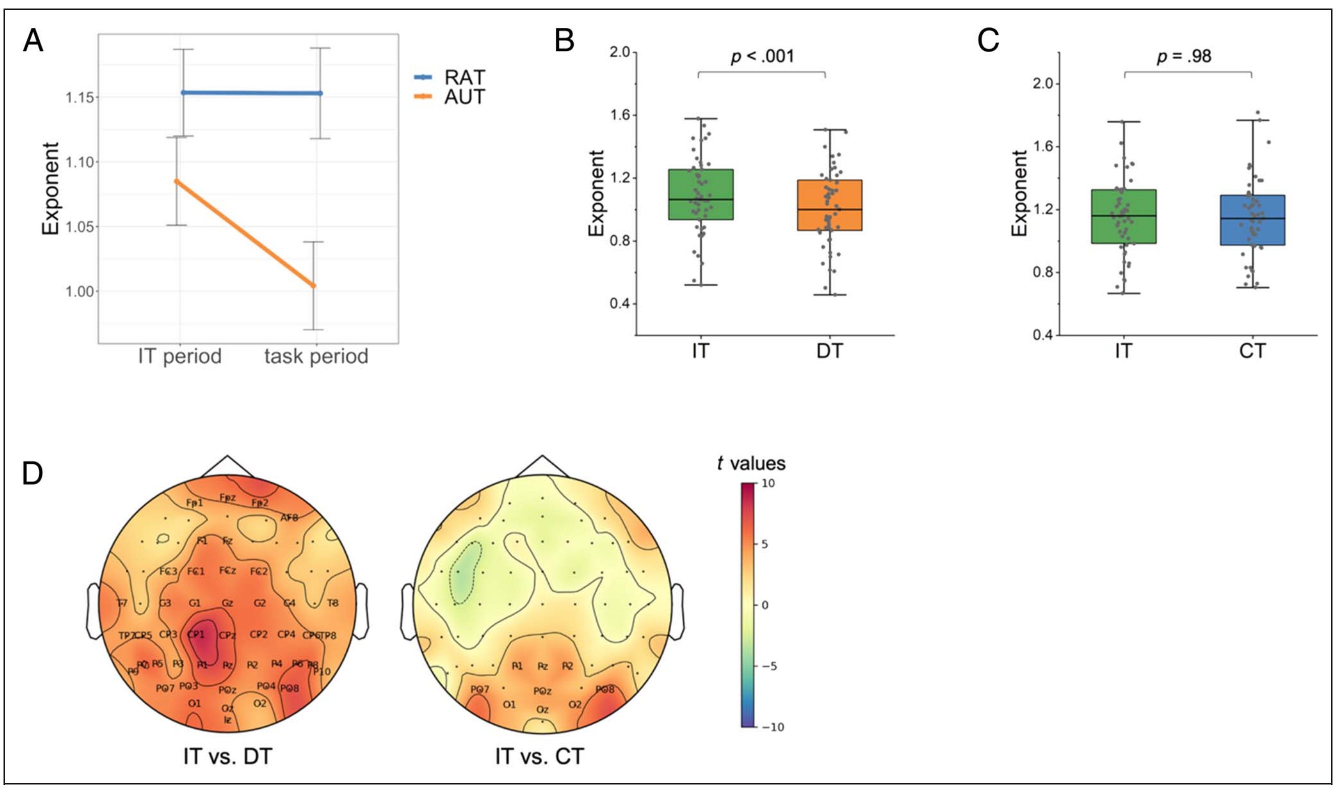

Figure 6. Aperiodic exponents for DT and CT as a function of time period. (A) The aperiodic exponent in different time period (IT vs. task) and task (AUT vs. RAT). (B) Aperiodic exponent for the IT period and DT period in the AUT (two-tailed paired t test: $p < .001$). (C) Aperiodic exponent for the IT period and the CT period in the RAT (two-tailed paired t test: $p = .98$). (D) Electrode sites and labels exhibiting significant difference in aperiodic exponent between IT period and DT period in AUT (left) and between IT period and CT period in RAT (right). Significant electrodes were identified using a cluster-based permutation test.

DISCUSSION

Here, we aimed to identify the neural mechanisms underlying creative, out-of-the-box thinking. We hypothesized that people may show increased aperiodic activity during DT, potentially reducing interference from past experience and overlearned routines in developing truly novel thoughts. Two of our findings provide strong support for this scenario: (1) engaging in DT, but not CT, was associated with a sharp drop of the aperiodic exponent (indicating increased aperiodic activity; Figure 4A) and (2) higher individual aperiodic activity (i.e., the aperiodic exponent) was associated with better performance on the DT task. Moreover, we found evidence for both a task-specific modulation of the aperiodic activity (in the IT period) and a process-specific modulation (restricted to the AUT period). This suggests that people can do both increase their aperiodic activity level throughout a given task and increase this level even further when solving a particular problem.

Our study supports previous claims that aperiodic activity may not be mere "noise" in the brain or the data that should be neglected, but rather represents a brain state that may serve important cognitive functions, especially creative thinking. Previous work suggests that the aperiodic exponent reflects variations in the balance of excitation and inhibition in the brain (Gao et al., 2017). A decrease in the aperiodic exponent, indicating increased aperiodic activity, may reflect greater neural variability, with neurons firing in less predictable, more dynamic patterns (Deodato & Melcher, 2024; Waschke et al., 2021; Voytek & Knight, 2015). This variability may disrupt the stability of well-established neural circuits that support habitual thought patterns, reducing the automatic retrieval of overlearned responses and freeing cognitive resources to consider less conventional ideas. Our data demonstrate that DT, but not CT, involves increased aperiodic activity, indicating that DT relies on heightened neural variability to reduce interference from overlearned routines and facilitate the generation of novel ideas. The observed association between higher aperiodic activity and improved performance in DT further supports this, highlighting that greater aperiodic neural activity enables individuals to explore a wider range of ideas and associations, thereby facilitating the generation of truly novel ideas. Our findings align with theories that link creativity to the ability to bypass overlearned habitual thought patterns, allowing for spontaneous and associative ideation (Beaty et al., 2016; Gabora, 2010; Mednick, 1962).

Moreover, our data are consistent with the idea that aperiodic neural activity may indicate particular metacontrol states (Zhang et al., 2023). DT is assumed to benefit from a metacontrol state biased toward flexibility, whereas CT is supported by a metacontrol state biased toward persistence (Zhang et al., 2020; Hommel, 2012). The increased aperiodic activity observed during DT compared with CT in our study aligns with prior research, which associates higher EEG aperiodic activity with a bias toward flexibility and lower activity with a bias toward persistence (Jia et al., 2024; Pi et al., 2024; Zhang et al., 2023). This means that aperiodic activity may serve as a direct measure of both individual metacontrol biases and the neural mechanism that realizes them.

This study's findings also integrate with the dual-process models of creativity, which distinguish between the DT and CT (Nijstad et al., 2010; Mednick, 1962; Guilford, 1956). Our results align with studies suggesting that DT involves decreased top–down prefrontal control and greater engagement of the default mode network, which is known to facilitate internal exploration and associative thinking (Beaty et al., 2016; Jung et al., 2013). By contrast, CT relies more on prefrontal control to maintain focus and suppress irrelevant information (Beaty & Schacter, 2018; Zmigrod et al., 2015). This distinction is further supported by our findings: Higher aperiodic activity during DT reflects the flexibility required for generating novel ideas, whereas lower aperiodic activity during CT reflects the persistence and goal-oriented processing needed for arriving at a single correct solution.

In addition to these task-specific findings, we observed two distinct patterns of aperiodic activity modulation: a general task-level increase during the IT period and a more focused, process-specific increase during the AUT period. More aperiodic activity during the IT period in AUT compared with RAT may indicate that individuals establish different metacontrol states at the block level, potentially preparing their cognitive systems for the demands of each task. Moreover, the process-specific increase during AUT periods reflects a more targeted, adaptive adjustment of aperiodic activity when actively engaging in DT. This targeted increase in aperiodic activity suggests that individuals not only establish distinct baseline metacontrol states for different tasks but also dynamically adjust these states in response to specific task demands. Such findings align with recent research suggests that people can tailor their metacontrol states to the challenges at hand from 1 sec to the other (De Luca et al., 2022).

Recent work indicates that aperiodic neural activity shows relative stability across time and individuals (Wainio-Theberge et al., 2022). Although stability was not assessed here, the association between aperiodic exponent and DT performance suggests that individual differences in aperiodic activity are behaviorally meaningful. Moreover, our results indicate that such stability can coexist with systematic state-dependent modulation. In the current study, the IT versus task period comparisons parallel evidence that aperiodic activity mediates transitions from prestimulus to poststimulus neural states (Wainio-Theberge et al., 2021). The present findings further suggest that such transitions may be task-specific, with DT associated with a more pronounced modulation of aperiodic activity. More broadly, scale-free neural dynamics have been linked to conscious processing (Klar et al., 2023) and shown to track the temporal statistics of external inputs, with higher spectral exponents reflecting stronger stimulus-driven alignment across individuals (Klar et al., 2025). In the present study, the reduced aperiodic exponents observed during DT may reflect a shift away from externally structured or stimulus-driven dynamics toward a more intrinsic, exploratory processing mode. Such relative decoupling from external temporal structure may benefit out-of-the-box thinking, as it reduces the influence of shared or overlearned representations and allows internally generated ideas to unfold more freely.

While this exploratory study provides novel insights into the relationship between aperiodic neural activity and different modes of creative thinking, several limitations should be noted. Our theoretical claims concern DT and CT as constructs, whereas the AUT and RAT are necessarily imperfect operationalizations. Although the AUT and RAT are widely used tasks for inducing DT and CT states, respectively, these tasks differ in several other dimensions—including linguistic demands, reliance on internal attention, and imagination. This construct–measure gap, together with task-specific differences, could contribute to the observed effects. Furthermore, the sample consisted primarily of young female participants, limiting the generalizability of the findings. Future research should replicate these findings in more diverse populations and further investigate how task-specific factors and individual differences influence the neural dynamics of creative thinking. In addition, other measures of the aperiodic component (e.g., intercept, R^2, critical edge) may provide additional insights into the functional role of aperiodic activity and warrant systematic investigation in future work.

Overall, our study highlights that aperiodic activity of EEG signals is associated with high-level cognitive functions in humans, including different creative processing, metacontrol processing, and task engagement. We therefore emphasize the importance of aperiodic activity as a neural indicator of human cognition.

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Corresponding author: Bernhard Hommel, School of Psychology, Shandong Normal University, East Wenhua Road 88, 250014 Jinan, Shandong Province, China, e-mail: bh@bhommel.onmicrosoft.com.

Data Availability Statement

Data, analysis scripts, and task stimuli used in this study are available via the Open Science Framework (OSF): https://osf.io/trza4/?view_only=84af48b9d1f040a6a23e9b653708da4c. Supplemental Material can be accessed on this article's homepage: https://doi.org/10.1162/JOCN.a.2521.

Author Contributions

Chenyan Zhang: Conceptualization; Formal analysis; Methodology; Software; Visualization; Writing—Original draft; Writing—Review & editing. Weitao Zhang: Data curation; Formal analysis; Investigation; Writing—Review & editing. Christian Beste: Methodology; Writing—Review & editing. Bernhard Hommel: Conceptualization; Funding acquisition; Supervision; Writing—Original draft; Writing—Review & editing.

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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 = .706; W/M = .157; M/W = .059; W/W = .078.

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