Biological Psychology 202 (2025) 109170

Contents lists available at ScienceDirect

Biological Psychology

journal homepage: www.elsevier.com/locate/biopsycho

Aperiodic EEG activity as metacontrol marker predicts assimilative and accommodative coping strategies

Jimin Yan [a,b], Tanja Könen [c], Hongchi Zhang [a,b], Lorenza Colzato [a,b,*], Bernhard Hommel [a,b,*]

[a] Faculty of Psychology, Shandong Normal University, Jinan, China
[b] Shandong Provincial Key Laboratory of Brain Science and Mental Health, Jinan, China
[c] Department of Psychology, RPTU Kaiserslautern-Landau, Landau, Germany

ARTICLE INFO

Keywords:
Cognitive adaptivity
Metacontrol framework
Coping strategies
Structural equation modeling
Aperiodic EEG activity

ABSTRACT

Cognitive adaptivity—the capacity to adjust behavior in response to changing demands—is central to human functioning. The metacontrol framework describes this adaptivity as a dynamic balance between persistence (goal-directed stability) and flexibility (openness to change). Recent research links individual metacontrol biases to the aperiodic exponent of EEG activity, which reflects the brain's excitation/inhibition balance. Higher exponents indicate persistence-related control, while lower exponents reflect flexibility-oriented processing. This study investigated whether aperiodic EEG markers predict coping preferences—assimilative (persistence-based) vs. accommodative (flexibility-based)—in a large sample of Chinese university students. We used structural equation modeling to compare a trait-based model based on resting-state EEG with a task-based model that included dynamic EEG indices reflecting situational challenge. The task-based model offered stronger predictive power. Two EEG markers—rest-to-task exponent change and within-trial exponent change—formed a latent metacontrol factor. This factor negatively predicted assimilative coping (measured via a resilience scale) and positively predicted accommodative coping (measured via a culturally validated dialectical thinking scale). These opposite effects align with the theoretical distinction between the two coping styles. These findings suggest that dynamic shifts in aperiodic activity provide a sensitive neural marker of the control states that shape coping behavior and resilience.

1. Introduction

The probably most important and evolutionary most valuable cognitive skill of the human species is its ability to adapt to changing circumstances and challenges. But how does this adaptivity work? Increasing insight into the mechanisms underlying human adaptivity has been garnered from research on metacontrol (Goschke, 2000; Hommel, 2015; Hommel et al., 2024; Hommel & Colzato, 2017). The metacontrol concept refers to the ability to balance between two extreme cognitive-control styles. Traditionally, cognitive control is viewed as the human ability to overcome obstacles, realize goals even in the face of resistance, to concentrate on what is necessary for the current task and intention, and to ignore what is not (Braver, 2012; Hofmann et al., 2012). However, recent discussions have pointed out that this kind of persistence view of cognitive control covers only one side of the control coin. Indeed, in many situations, persisting on the current goals, and increasing effort and selectivity is highly counterproductive, as in the face of unsurmountable obstacles, unrealistic goals, and much more useful alternatives. In these cases, agents should open up to new options, consider as much information as possible, and consider new goals. In other words, while a cognitive-control style supporting persistence is indeed useful under many circumstances, others rather suggest a style that supports cognitive flexibility and openness. Accordingly, theorists have argued that truly adaptive control consists of more than just promoting persistence. Rather, adaptive behavior requires balancing between two extreme control styles: persistence and flexibility (Cools & D'Esposito, 2009; Durstewitz & Seamans, 2008; Goschke, 2000; Goschke & Bolte, 2014; Hommel, 2015; Hommel et al., 2024; Hommel & Colzato, 2017).

The metacontrol framework has been shown to be useful in predicting and explaining both individual and intraindividual differences. For instance, chronic individual biases towards metacontrol persistence or flexibility, and correspondingly good or poor performance in persistence-heavy or flexibility-heavy tasks, can be predicted to some

* Correspondence to: Faculty of Psychology, Shandong Normal University, No. 88 East Wenhua Road, Jinan, Shandong Province 250014, China.
E-mail addresses: colzato@bhommel.onmicrosoft.com (L. Colzato), bh@bhommel.onmicrosoft.com (B. Hommel).

https://doi.org/10.1016/j.biopsycho.2025.109170
Received 23 September 2025; Received in revised form 6 November 2025; Accepted 24 November 2025
Available online 25 November 2025

degree by genetic predisposition and cultural upbringing (for an overview, see (Hommel & Colzato, 2017). Intraindividual variability was shown to be driven by instructions and other task factors (Hommel & Colzato, 2017), suggesting that, on top of possible individual biases, people can respond to task challenges by increasing or decreasing their metacontrol persistence or flexibility. The neural underpinnings of metacontrol and changes therein are assumed to be associated with the prefrontal and the striatal dopaminergic pathway (Cools, 2015, 2016), but how dopaminergic changes mechanistically alter information processing according to metacontrol principles remained unclear.

Interestingly, more recent studies point to such a particular neural mechanism. More specifically, metacontrol biases toward persistence and flexibility have been systematically linked to a neural marker of cortical noise (Y. Gao et al., 2024, 2025; Pi et al., 2024, 2025; Yan et al., 2024; Zhang et al., 2023), as quantified using the FOOOF (Fitting Oscillations & One-Over-F) algorithm developed by Donoghue et al. (2020). This algorithm calculates the aperiodic FOOOF exponent, which measures the extent of aperiodic activity in EEG signals—representing neural fluctuations that remain after standard EEG frequency bands (alpha, beta, delta, gamma, and theta) are extracted. Aperiodic signal variations serve as key indicators of the excitation/inhibition (E/I) balance within the cortical network (R. Gao et al., 2017), with changes in the aperiodic exponent reflecting shifts in inhibitory and excitatory processes. A high exponent is associated with strong inhibitory neural activity, promoting cortical stability and improving neural signal fidelity, whereas a low exponent corresponds to increased excitatory dynamics, resulting in higher cortical noise and reduced information transmission efficiency (Lombardi et al., 2017). Specifically, a lower aperiodic exponent is linked to heightened cortical instability and neural interference, whereas a higher exponent indicates a more regulated and structured neural state, optimizing cognitive performance (Voytek & Knight, 2015). In other words, a metacontrol bias towards persistence might be achieved by systematically denoising one's own brain, which should be reflected by a high aperiodic exponent, whereas a metacontrol bias towards flexibility is achieved by systematically increasing the noise of one's brain, which should be reflected by a low aperiodic exponent.

Previous research has looked into cognitive adaptivity by studying the relationship between changing task requirements and corresponding changes in metacontrol biases. While demonstrating a systematic relationship between these two factors provides a solid basis for establishing the metacontrol framework, real-life challenges often go beyond small variations of the degree to which laboratory tasks benefit from persistence or flexibility. Successfully dealing with stress, threatening events, and an increasingly complex and hard to predict future call for more comprehensive and ideally more powerful coping strategies. Accordingly, the main goal of the present study was to see whether individual metacontrol biases, as expressed by the aperiodic exponent, would be able to predict individual coping strategies. Traditionally, research on coping can be characterized by what has been called an assimilative view of successful coping (Block, 1982; Hanfstingl et al., 2022). The distinction between assimilative and accommodative coping styles is based on the original concept of assimilation and accommodation introduced by Jean Piaget (1977). Assimilative coping involves efforts to alter external conditions in order to better achieve personal goals, which implies a persistence-dominated mode of control. This strategy is typically employed when individuals perceive situational demands as modifiable and maintain a strong commitment to goal attainment. While this is the more traditional and better-known approach to coping, it does reflect a Western, if not Western, educated, industrialized, rich, and democratic (WEIRD) (Muthukrishna. et al., 2020) cultural view, according to which successful coping is bound to the maximal realization of individual needs and life plans. In less individualistic countries, like China (Hofstede, 2001), where the present research was carried out, successful coping often implies a different approach, an approach that takes the social group and embedding into consideration, and that tries to negotiate individual intentions, needs and strategies with others. This approach is better captured by the concept of accommodative coping, which involves the flexible adjustment of personal goals and expectations in response to unchangeable constraints, which in turn implies a flexibility-oriented metacontrol mode. This style enables individuals to preserve emotional well-being and identity coherence when external modification is not feasible or considered to be too costly.

The main goal of the present study was, thus, to see whether preferences for a more assimilative or more accommodative coping style can be predicted from individual aperiodic exponents, our neurophysiological indicator of metacontrol biases. Given the evidence that variability of the aperiodic exponent can have both a trait-like character, as indicated by spontaneous variability of exponents taken from task-unrelated resting-state conditions, and a more state-like impact during the performance of a particular task (Donoghue et al., 2020), we considered both kinds of measures as predictors. To capture the interplay between metacontrol, its neural correlates, and assimilative and accommodative coping styles, we applied structural equation modeling (SEM) to a large sample of healthy young adults. We calculated individual aperiodic exponents under both resting-state conditions, to capture spontaneous, trait-like variability, and task conditions, to assess situational task-specific adjustments. Exponents from both measures were used as predictors of assimilative coping, as assessed means of a classical resilience scale (Carere-Comes, 2001), and accommodative coping. As of now, a culturally validated measure of accommodative coping has not been developed for use in China, accordingly, we made use of a dialectical thinking scale that has been validated within the Mainland China context (Julie Spencer-Rodgers. et al., 2004). Dialectic thinking is an integral part of schooling and university studies in China. In contrast to the binary Western logic developed from Greek philosophy, according to which mutually exclusive statements (like x = p and x = non-p) are taken as contradictions that cannot be true at the same time, Marxian dialectics as taught in China consider contradictions as calling for integration, so to reach the next level of insight and understanding (Mao, 1937). Given that dialectical thinking and flexible coping have been shown to be related (Carere-Comes, 2001; Cheng, 2010), and given that the three subscales of our measure (Contradiction, Cognitive Change, and Behavioral Change) address both cognitive and behavioral flexibility in the face of contradictions, we considered the tendency to think dialectically as a good proxy to an accommodative coping style.

Resilience and dialectical thinking can be meaningfully situated within the assimilative–accommodative coping framework because both represent adaptive manifestations of balancing persistence and flexibility in response to environmental demands. Empirical evidence suggests that resilient individuals tend to engage in both goal-directed persistence and flexible adjustment depending on situational controllability (Carver & Connor-Smith, 2010; Cheng et al., 2014). This dual capacity aligns with the metacontrol notion that adaptivity arises from dynamically regulating persistence and flexibility rather than maximizing one mode at the expense of the other (Goschke, 2000; Hommel & Colzato, 2017). In the present study, assimilative coping was operationalized via resilience scores, while accommodative coping was indexed by dialectical thinking. Although these measures do not capture situational coping behaviors directly, they provide validated trait-level proxies for persistence-oriented and flexibility-oriented coping strategies, respectively, allowing us to link underlying metacontrol biases to adaptive coping tendencies in a conceptually coherent manner. Dialectical thinking—a cognitive style characterized by tolerance for contradiction, expectation of change, and integrative reasoning (Spencer-Rodgers et al., 2009)—reflects accommodative flexibility at the cognitive level. It enables individuals to reinterpret conflicting information and maintain psychological balance under uncertainty, which parallels accommodative coping's emphasis on goal reappraisal and emotional equilibrium in uncontrollable contexts (Cheng et al., 2014). Empirical studies have shown that dialectical thinking is positively associated with emotional resilience, cognitive flexibility, and adaptive coping in East Asian samples (Hamamura et al., 2008; Spencer-Rodgers et al., 2009), supporting its functional correspondence to accommodative coping processes. Thus, resilience and dialectical thinking jointly embody the psychological and cultural mechanisms through which individuals sustain adaptive functioning—by integrating persistence (assimilative efforts) with flexibility (accommodative adjustments)—in line with the metacontrol model of adaptive behavior.

Given that metacontrol operates as a dynamic balance of persistence and flexibility, and that assimilative and accommodative coping styles reflect distinct psychological adaptation mechanisms, SEM provides an optimal analytical approach to quantify their interactions systematically (Kline, 2016). By using SEM, we were able to model multiple interrelated dependencies simultaneously rather than testing isolated relationships through traditional regression analyses (Kline, 2016). This approach allowed us to assess how underlying latent variables—such as cognitive persistence and flexibility—mediate the link between metacontrol biases, their neural correlates, and coping strategies. In sum, we applied SEM to investigate the predictive power of our neural metacontrol indicator (reflected by the aperiodic EEG activity) to favor assimilative and accommodative coping strategies.

2. Method

2.1. Participants

The study, of which the present investigation is a part of, initially recruited 160 undergraduate students (74 male, 68 female; $M_{age} = 19.79$ years, SD = 1.17) from the local university through campus advertisements. The study serves multiple scientific purposes and is documented on the Open Science Framework (OSF), providing a comprehensive dataset that encompasses a wide range of variables (see https://osf.io/5j4e2/ for the complete list of variables). All participants met the inclusion criteria of being right-handed, having normal or corrected-to-normal vision, and reporting no history of neurological disorders. Prior to data collection, each participant provided written informed consent in accordance with the Declaration of Helsinki and received 200 CNY as monetary compensation. No personal information from any participant is presented in this study. This study protocol was approved by the Institutional Review Board of Shandong Normal University School of Psychology (approval no. SDNU2023001) on November 3rd, 2023.

Electroencephalographic (EEG) data preprocessing resulted in the exclusion of 17 participants (10.63 % attrition) based on predefined quality thresholds: (a) persistent channel malfunction (>4 electrodes), (b) marker synchronization errors, and (c) excessive artifacts. Consequently, the final analytical samples comprised 143 participants for EEG analyses and the full cohort (N = 160) for behavioral and questionnaire measures.

2.2. Procedure

To control for circadian influences, all experimental procedures and psychometric evaluations were systematically administered between 08:00 and 18:00 local time. The testing session began with a resting-state EEG measurement. Right after the flanker task and simultaneous EEG recording, participants completed an assessment battery. In the current study, the data from the Dialectical Self Scale (Spencer-Rodgers et al., 2015) and Resilience Style Questionnaire (Mak et al., 2019) were analyzed, in addition to the behavioral and electrophysiological data from the flanker task and the electrophysiological data from the resting state measure.

2.3. Resting-State EEG

For six minutes, participants' open-eye resting EEG activity was monitored using 64 isometrically positioned Ag/AgCl electrodes, with a fixed cross continuously displayed on the screen. We acquired resting-state EEG data with eyes open to ensure participants remained awake and to capture brain dynamics under an externally-sensitized state; previous developmental work (e.g., Petro et al., 2022) has shown that eyes-open versus eyes-closed conditions yield distinct spectral profiles, particularly reflecting sensory and attention-related neural activity.

2.4. Flanker task

During EEG all participants performed the flanker task adapted from Konjusha et al. (2022), Mückschel et al. (2017) and Pscherer et al. (2020). The task conditions (Fig. 1.a) and procedure (Fig. 1.b) are shown in Fig. 1. As shown in Fig. 1b, each trial began with a fixation cross presented for 700–1000 ms, followed by a cue consisting of 2 vertically aligned triangles presented for 200 ms. The target triangle was then presented in the center of the cue for 300 ms, and then the response blank was presented until a response was made or a randomly varying interval of 700–1000 ms had elapsed. Participants completed 320 congruent and 160 incongruent Flanker trials (equally distributed to the left and right), presented in a randomized order. Participants were instructed to respond as quickly and accurately as possible with their right hand after the stimulus disappeared by pressing the J key if the central arrow was pointing to the right and the F key if the central arrow was pointing to the left. The experimental task was preceded by a practice block of 20 trials to ensure adequate understanding of the task. The experimental task consisted of 4 blocks of 120 trials each (480 trials in total).

2.5. Resilience Style Questionnaire

The Resilience Style Questionnaire (RSQ) is a reliable and valid tool for assessing resilience in Chinese and related groups (Mak et al., 2019). The RSQ is composed by two factors: Perseverance and Optimistic approach to life. The RSQ is a 5-point Likert-type scale ranging from 1 (never) to 5 (always), with higher scores indicating higher levels of resilience. The Cronbach's alpha in the current study was 0.87, indicating a good reliability of the questionnaire. We conducted a confirmatory factor analysis (CFA) to assess the construct validity of the RSQ. The results indicated that the RSQ demonstrated a well-fitting factor structure ($\chi^2_{(97)} = 193.14$, $p < 0.001$; RMSEA = 0.079, 90 % CI [0.062, 0.095]; CFI = 0.949; TLI = 0.936; SRMR = 0.058).

2.6. Dialectical Self Scale

The Chinese version of the Dialectical Self Scale (DSS; developed by Spencer-Rodgers et al. (2015), was used to assess dialectical thinking. The scale contains a total of 32 items with a 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree) to assess three dimensions: Contradiction (e.g., when I hear two sides of an argument, I often agree with both), Cognitive Change (e.g., I believe that my personality will remain the same throughout my life), and Behavioral Change (e.g., I am the same with my family as I am with my friends). The items of each dimension are listed separately, and 16 of the items are reverse scored. Cronbach's alpha in the current study was 0.67, indicating a reasonable reliability of the questionnaire. The confirmatory factor analysis (CFA) did not yield acceptable model fit ($\chi^2(461) = 948.69$, $p < 0.001$; RMSEA = 0.081, 90 % CI [0.074, 0.089]; CFI = 0.299; TLI = 0.246; SRMR = 0.110.), indicating limited construct validity. However, this finding is theoretically consistent with prior research on the DSS. Previous studies using the simplified Chinese versions of the DSS have also reported suboptimal Cronbach's α values (e.g., Cronbach's α =.67 in the preliminary study by Yang et al., 2015, and α =.68 in Lin and Wang, 2025). This pattern may arise from the nature of the construct itself: the dialectical self emphasizes tolerance for contradiction, change, and holism—features that inherently reduce inter-item correlations and complicate the factorial structure. Thus, lower internal consistency does not necessarily indicate measurement problems but may instead reflect

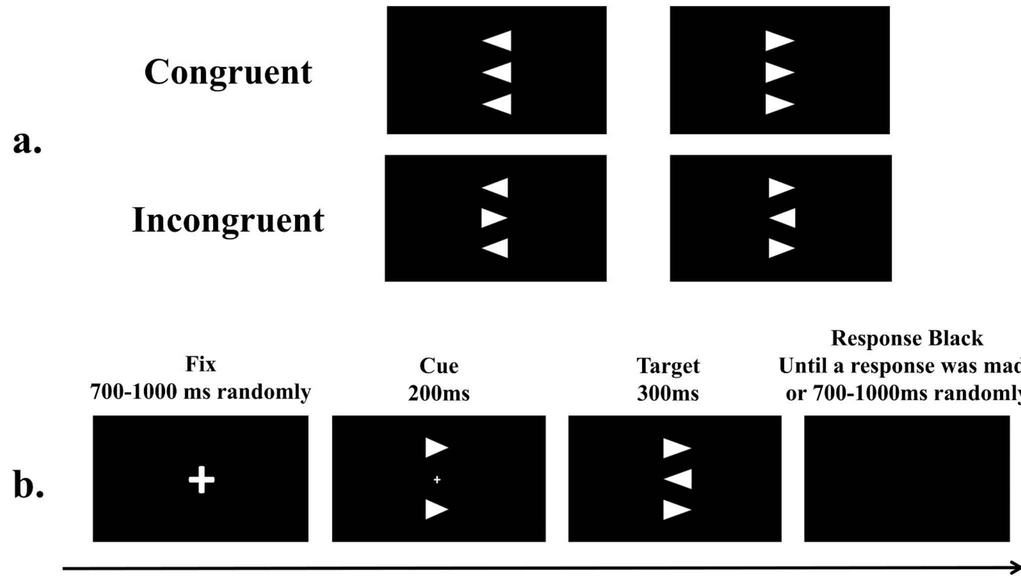

Fig. 1. Panel *a* depicts the congruent and incongruent task conditions, while panel *b* outlines the temporal sequence of experimental trials. The three triangles are positioned at coordinates (0, 80), (0, 0), and (0, −80) along the vertical axis.

the construct's complex, multifaceted, and culturally embedded nature. In line with this theoretical rationale, we retained the DSS in the present study, as it demonstrated sufficient theoretical relevance for assessing dialectical tendencies.

In addition, to test the discriminant validity of the optimistic approach to life (OA) in the RSQ and cognitive change (CC) in the DSS, a CFA was conducted to examine the factorial structure of these two dimensions. The CFA results indicated acceptable model fit: $\chi^2(132) = 180.998$, $p = 0.003$, RMSEA = 0.048 (90 % CI = 0.029–0.065), CFI = 0.848, TLI = 0.823, SRMR = 0.074. The latent correlation between OA and CC was 0.673 ($p < 0.001$), indicating a moderate relationship between the two constructs. While this supports their theoretical relatedness, the average variance extracted (AVE) values indicated insufficient discriminant validity: the AVE for both OA (0.268) and CC (0.145) was below the squared inter-factor correlation (0.452). In other words, these proxies may share variance and do not fully capture distinct assimilative and accommodative coping processes.

2.7. EEG recording and processing

Continuous EEG signals were recorded using a 64-channel Ag/AgCl electrode cap (equidistant montage) synchronized with the BrainVision Recorder software (Brain Products GmbH). Signals were digitized at a sampling rate of 500 Hz, with the ground electrode positioned at$\theta = 58^\circ$, $\varphi = 78^\circ$(spherical coordinate system). The first preprocessing step involved downsampling the raw data to a frequency of 256 Hz. Raw data were preprocessed using BrainVision Analyzer 2.2 (Brain Products GmbH), beginning with downsampling to 256 Hz to optimize computational efficiency. A zero-phase infinite impulse response (IIR) band-pass filter (0.1–50 Hz) was applied, accompanied by a 50 Hz notch filter to attenuate line noise interference. Subsequently, bad channels (electrodes with poor skin contact or that became disconnected) and bad trials (epochs contaminated by excessive muscle activity, large blinks/eye movements, motion artifacts, etc.) were removed from the data following visual inspection. Independent component analysis (ICA) was performed under manual supervision to remove common artifacts such as eye blinks and eye movements from the EEG data. All removed channels were interpolated using a spherical method. The remaining channels were re-referenced to the global average. Spherical spline interpolation was then applied to reconstruct discarded channels. A semiautomatic inspection was executed again: the maximal allowed voltage step was 50 μV/ms, the maximal allowed amplitude difference was 100 μV within 200-ms intervals, and the minimal allowed activity was 0.5 μV within 100-ms intervals. Segments violating any of these criteria (including 200 ms before and 200 ms after each detected event) were marked as bad and excluded following manual verification. On average, approximately 26.51 % ± 21.54 % of trials (range: 2.1 %–68.7 %) were removed per participant. To ensure adequate data quality and statistical power, each participant retained at least 50 trials per condition after artifact rejection. After the second artifact rejection, the EEG data were re-referenced to the average of all scalp electrodes. This average reference approach helps to reduce reference bias and ensures that all channels contribute equally to the measured scalp potentials, facilitating subsequent spectral and topographical analyses. Next, the pre-processed resting EEG data were split into fragments of 1000 ms fragments and the pre-processed Flanker EEG data were split into fragments of 3000 ms duration with the target stimulus onset serving as the locking point (1500 ms before the onset of the target stimulus and 1500 ms after the onset of the target stimulus). All the data were re-referenced to an average reference. Baseline correction using data 200 ms before each segment as reference. Finally, the data after pre-processing was exported to do the aperiodic analyses.

2.8. Parameterization of spectral data

We identified two specific time windows for analysis. The pre-trial period encompassed the time form −1000 to 0 ms before the stimulus, which represents a kind of task-specific baseline. The within-trial period spanned form 0–1000 ms after the target stimulus onset. Following Welch's (1967) method with a 250 ms Hamming window and 50 % overlap, power spectral density (PSD) estimates were computed using MATLAB R2023a's pwelch function. These analyses were conducted across four experimental dimensions: individual participants, task conditions (congruent vs. incongruent), and temporal phases (pre--trial/within-trial). EEG power spectra were subsequently analyzed using the FOOOF toolbox (v1.0.0; https://github.com/fooof-tools/fooof) as implemented in Python (Donoghue et al., 2020; Yan et al., 2024, 2025). FOOOF estimates the aperiodic slope and offset after removing the influence of oscillatory peaks, thereby yielding parameters that are statistically and conceptually independent of rhythmic activity. Consequently, it is unnecessary to include oscillatory power as a covariate in subsequent regression models, as the aperiodic exponent derived by FOOOF already reflects variance uniquely attributable to broadband neural dynamics. This analytic approach allows for the direct examination of the relationship between aperiodic neural activity and individual differences in metacontrol and coping tendencies without confounding from oscillatory processes. Specifically, this computational approach decomposes the spectral profile into two constituent elements: aperiodic components [*L(f)*] and periodic oscillatory activity [*Gn(f)*]. The FOOOF algorithm breaks down the power spectrum and expresses it as a linear combination of these two components, where f represents the frequency:

$$PSD(f) = L(f) + \sum_{n} G_n(f)$$

The power spectral density (PSD) is obtained by combining the aperiodic component, denoted *L(f)*, with a superposition of n Gaussian functions. To characterize the complete spectral profile, the aperiodic component *L(f)* is modeled as a continuous function spanning the full frequency range. This aperiodic element is mathematically defined as:

$$\mathrm{L(f)} = \mathrm{b} - \log[f^x]$$

Within this mathematical formulation, two key variables govern the aperiodic characteristics: the offset parameter 'b', which quantifies the broadband power baseline through vertical displacement, and the exponent 'x', determining the spectral slope's steepness when visualized on log-log axes. The model concurrently incorporates periodic oscillatory components emerging as localized power excesses above the aperiodic baseline, each spectral peak being mathematically represented by a Gaussian function parameterized through three distinct features - amplitude (α_n), central frequency (μ_n), and bandwidth (σ_n). These oscillatory elements combine with the aperiodic foundation through the relationship, collectively constituting the complete spectral decomposition framework:

$$G_n(f) = \alpha_n \exp\left[-\frac{(f-\mu_n)^2}{2\sigma_n^2}\right]$$

Following previous studies (Pi et al., 2025; Yan et al., 2024), spectral fitting within the 3–40 Hz frequency range was implemented with following parameter constraints: peak width limits (2–8 Hz), maximum peak allowance ($n = 8$), minimum peak amplitude threshold (0.05 μV^2/Hz), and fixed aperiodic optimization mode. Power spectra were parameterized between 3 and 40 Hz using FOOOF. This mid-band range was chosen to include the canonical theta/alpha/beta bands of interest while excluding very low-frequency drift/knee effects and high-frequency EMG/line noise that can distort aperiodic slope estimation (see Donoghue et al., 2020; Ostlund et al., 2022). This computational procedure generated aperiodic exponent estimates across multiple experimental dimensions including electrode topography, task condition (congruent/incongruent), participant variability, session-specific effects, and temporal phase (pre-/within-trial). The model demonstrated exceptional goodness-of-fit, achieving mean R^2 values > 0.94 across all 160 participants' spectral decompositions, thereby validating the robustness of our parameter estimation approach. Recent work by Zhang et al. (2023) identified a selective association between metacontrol states and the aperiodic exponent, while demonstrating negligible effects on the offset parameter. Consequently, we focused our investigation on characterizing this exponent. For each individual participant and electrode site, the exponent was derived from isolated aperiodic components using FOOOF-based decomposition. In the absence of a priori hypotheses regarding the topographic distribution of aperiodic activity, we adopted the methodological framework proposed by Hill et al. (2022), implementing the "global" exponent approach for cross-subject comparisons. This strategy aggregates scalp-wide aperiodic activity into a single representative metric, thereby mitigating spatial heterogeneity in statistical analyses. The average of the exponent values across 64 electrodes for each participant were calculated to observe the overall trend of variation at different periods. In sum, given the absence of a priori hypotheses regarding topographic localization of aperiodic changes related to coping tendencies, global averaging provided a trait-level index of metacontrol while maintaining statistical parsimony in the SEM framework. This approach also minimizes the risk of inflated Type I errors that would arise from conducting separate electrode-wise comparisons and reduces potential multicollinearity among highly correlated electrode-level predictors, ensuring robust and interpretable parameter estimates.

2.9. Cluster-based permutation test

A cluster-based permutation test was applied to examine the scalp distribution of aperiodic components. This nonparametric method, designed for high-dimensional EEG/MEG data, allows for statistical comparison across multiple electrodes while controlling for multiple comparisons (Maris & Oostenveld, 2007). The test was implemented using MNE-Python (https://mne.tools/stable/index.html). Clusters were formed based on spatial adjacency of electrodes exhibiting F-values exceeding a threshold corresponding to an alpha level of 0.05 at the sample level. Cluster-level statistics were computed by summing the F-values within each cluster. The significance of these clusters was assessed via a Monte Carlo approach with 1000 permutations, using a cluster-defining threshold of $p < 0.05$.

2.10. Statistical analysis

All statistical analyses were performed using SPSS software (IBM, version 27.0). Behavioral data were analyzed using paired-sample T-test. Only mean reaction times (RTs) and Percent error (PE) data from trials with correct responses were used as behavioral measures. For EEG measures, analyses of aperiodic activity were conducted using a whole-brain two-way repeated-measures ANOVA. The factors included were condition (congruent/incongruent) and time window (pre-trial/within-trial). Greenhouse–Geisser correction was used to adjust the ANOVA results, and Bonferroni correction was applied to post-hoc tests.

The main analysis was based on two structural equation models (SEM), latent variables were constructed to represent neural and behavioral responses to cognitive conflict. One model (Model 1) followed a trait-like approach, where we considered three indicators to capture the EEG factor of metacontrol: the mean of the aperiodic exponents across congruent and incongruent conditions (EEG_p_ci), the aperiodic exponent for the congruent condition (EEG_w_c), and the aperiodic exponent from the resting state measurement (EEG_rest). The other model (Model 2) was built to capture the task-specific adjustments participants made in order to respond to the stimulus-induced challenges. Here we used two components: the aperiodic exponent for the incongruent condition within the trial minus the exponent for the incongruent condition in the pre-trial period (EEG_wpi), and the aperiodic exponent for the incongruent condition within the trial minus the resting state exponent (EEG_rwi).

Behaviorally, the interference effect was captured by error_d (incongruent minus congruent error rate) and rt_d (incongruent minus congruent reaction time), together forming a latent construct representing conflict-processing efficiency. The scores on the subscales of the Dialectical Self Scale and Resilience Style Questionnaire were used as indicators of latent variables for accommodative and assimilative coping. Both models (Fig. 4) were calculated with *Mplus* 8.4, using full information maximum likelihood estimation (FIML). In line with Beauducel and Wittmann (2005), model-fit was evaluated with the χ^2-test, the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). For model identification, the first loading of a latent factor was fixed to 1. We considered all *p*-values below.05 to be significant. The significance of latent factor correlations was evaluated with likelihood ratio tests, which are more reliable than Z-tests (Gonzalez &

Griffin, 2001). Statistical power was evaluated post-hoc with an approach suggested by Jak et al. (2021), based on the work of Satorra and Saris (1985). We used the R-package *lavaan* combined with the app *power4SEM* (Jak et al., 2021) to estimate the power of the χ^2-test to reject exact model fit.

3. Results

3.1. Flanker task

Mean RTs and PEs are shown in Fig. 2. Paired-sample *t*-tests indicated a significant difference between the congruent and incongruent conditions on RT ($t_{(159)} = 25.42$, $p < 0.001$, $d = 2.45$, BF_{10} >1000) and PE ($t_{(159)} = 18.54$, $p < 0.001$, $d = 1.59$, $BF_{10} > 1000$). RT in the incongruent condition was significantly higher (359.00 ± 24.09) than in the congruent condition (302.14 ± 22.28). The PE was also significantly higher in the incongruent condition (22.18 ± 13.6) than in the congruent condition (4.24 ± 8.34).

3.2. Questionnaires

Descriptive statistics for all EEG measures, behavioral latent variables and questionnaires are presented in Table 1.

3.3. Aperiodic exponent (brain-wide)

Fig. 3 presents the power spectral density (PSD) results in log-log space across frequencies from 3 to 40 Hz for different experimental conditions during the within-trial and pre-trial periods. The results of the two-factor repeated measures ANOVA showed a significant main effect of time window ($F_{(1,\ 142)} = 867.49$, $p < 0.001$, $\eta_p^2 = 0.86$, $BF_{10} > 1000$) and a close-to-significant main effect of condition ($F_{(1,\ 142)} = 3.68$, $p = 0.057$, $\eta_p^2 = 0.025$, $BF_{10} = 1.19$). The aperiodic exponent was significantly lower in the pre-trial time window (1.16 ± 0.02) than in the within-trial time window (1.25 ± 0.02), and tended to be higher in the incongruent condition (1.21 ± 0.02) than in the congruent condition (1.19 ± 0.02). A significant time window × condition interaction emerged ($F_{(1,\ 142)} = 113.82$, $p < 0.001$, $\eta_p^2 = 0.45$, $BF_{10} > 1000$). Simple effect analysis revealed that the aperiodic exponent was significantly higher in the incongruent condition (1.27 ± 0.29) than in the congruent condition (1.24 ± 0.29) during the within-trial period, whereas no significant difference was found during the pre-trial period. Fig. 4 displays the aperiodic exponent profiles across experimental conditions and time windows.

Table 1
Descriptive statistics for the dependent measures used in the structural equation models.

	Mean	Std	Min	Max	Skewness	Kurtosis
Metacontrol EEG[a]						
EEG_c_pi	1.16	0.28	0.37	1.84	-0.21	-0.33
EEG_w_c	1.24	0.29	0.42	1.94	-0.34	-0.21
EEG_rest	1.30	0.29	0.17	1.84	-1.13	1.98
EEG_wpi	0.11	0.05	-0.05	0.25	-0.26	0.70
EEG_rwi	-0.03	0.22	-0.64	0.47	0.01	-0.11
Metacontrol Behavioral[b]						
PE_d	0.18	0.12	-0.04	0.55	0.87	0.29
RT_d	55.64	28.68	-88.00	119.00	-1.50	4.82
Resilience[b]						
Perseverance	31.96	5.55	14.00	45.00	-0.18	0.10
Optimistiv Approach to Life	26.11	3.84	15.00	35.00	-0.23	0.02
Dialectical Thinking[b]						
Contradiction	4.19	0.50	2.46	5.38	-0.20	0.19
Cognitive Change	3.87	0.60	2.00	5.09	-0.38	0.15
Behavioural change	4.07	0.57	2.50	5.63	-0.23	-0.03

EEG_p_ci = mean aperiodic exponent of the pre-time window from two conditions, EEG_w_c = aperiodic exponent in the congruent condition, EEG_rest = aperiodic exponent obtained during the resting state; EEG_wpi = within incongruent - pre incongruent; EEG_rwi = within incongruent - resting; PE_d = PE_incong - PE_cong; RT_d = RT_incong - RT_cong;
[a] N = 143; [b]N = 160

3.4. Cluster-based permutation test

An additional cluster-based permutation test was conducted to examine the scalp distribution of the aperiodic components. The results revealed a significant main effect of time window across the whole brain ($F_{(1142)} = 627.49$, $P < 0.01$, $\eta_p^2 = 0.03$). A significant main effect of condition on the aperiodic exponent was identified in four spatially distinct clusters spanning frontal, central, temporal, and occipital regions: cluster 1: P8, Fz, $F_{(1142)} = 20.97$, $P < 0.01$, $\eta_p^2 = 0.52$; cluster 2: Oz, FC1, FC2, CP1, $F_{(1142)} = 21.34$, $P < 0.01$, $\eta_p^2 = 0.40$; cluster 3: F2, C1, C2, $F_{(1142)} = 11.26$, $P < 0.05$, $\eta_p^2 = 0.37$; cluster 4: FT9, FT10, Fpz, Cpz, $F_{(1142)} = 20.46$, $P < 0.01$, $\eta_p^2 = 0.46$. Furthermore, a significant interaction effect between time window and condition was observed across the whole brain, forming five major clusters: (cluster 1: F4, C3, C4, P3, $F_{(1142)} = 36.12$, $P < 0.01$, $\eta_p^2 = 0.23$; cluster 2: O2, F7, F8, T7, T8, P7, P8, Fz, Cz, $F_{(1142)} = 38.06$, $P < 0.01$, $\eta_p^2 = 0.22$; cluster 3: Oz, FC1,

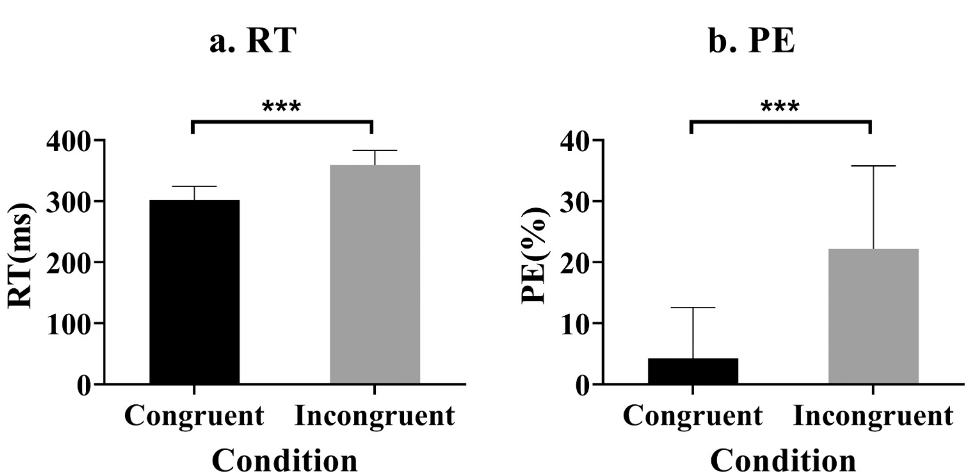

Fig. 2. Behavioral data results. Panel a: Reaction time (RT) results in different conditions. Panel b: Percent error (PE) results in different conditions. Error bars represent SEM, ***p < 0.001.

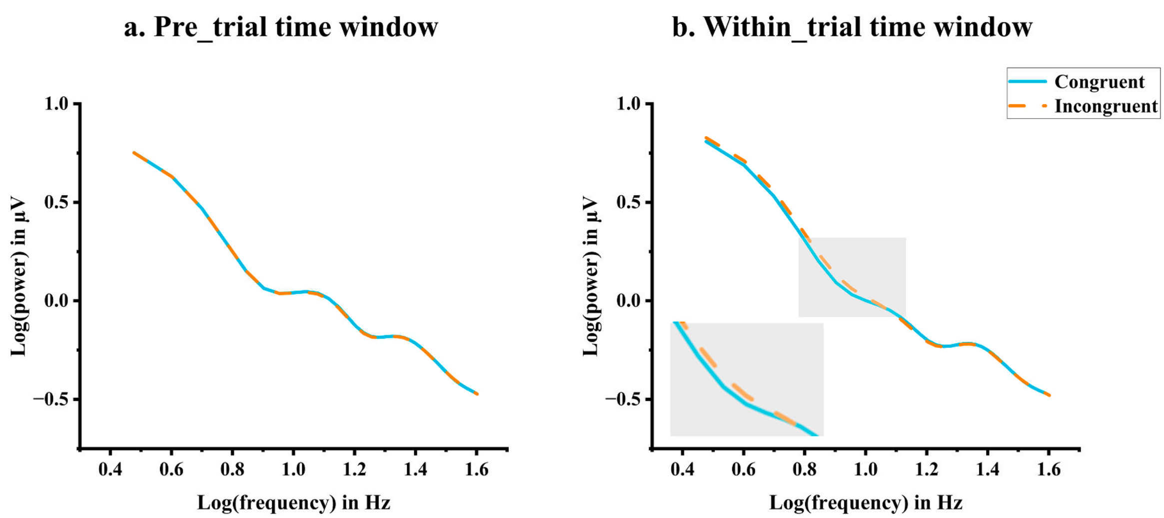

Fig. 3. Log-log transformed power spectral densities averaged across electrodes and participants. Panel a shows PSDs in the pre-trial period; panel b displays PSDs in the within-trial period.

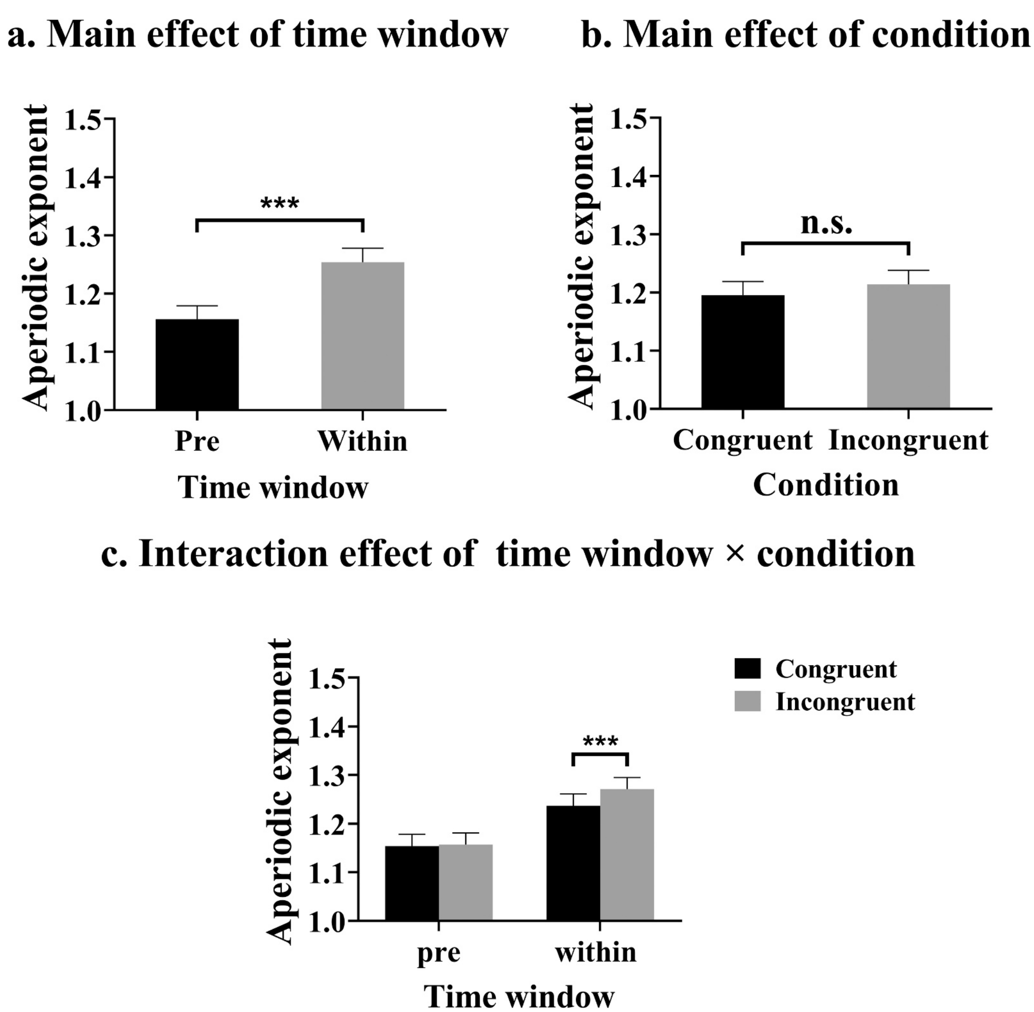

Fig. 4. Aperiodic exponent data results. Panel a: Aperiodic exponent in different time windows; Panel b: Aperiodic exponent in different conditions; Panel c: The interaction effect of time window × condition. Error bars represent SEM, n.s. means marginally significant, ***p < 0.001.

FC2, CP1, CP2, FC5, FC6, CP5, CP6, TP9, TP10, POz, F1, F2, C1, C2, P1, P2, AF3, AF4, FC3, FC4, CP3, $F_{(1142)} = 70.11$, $P < 0.01$, $\eta_p^2 = 0.12$; cluster 4: PO3, PO4, F5, F6, C5, $F_{(1142)} = 26.83$, $P < 0.01$, $\eta_p^2 = 0.33$; cluster 5: P5, P6, AF7, AF8, FT7, FT8, TP7, TP8, PO7, PO8, FT9, FT10, Fpz, CPz, $F_{(1142)} = 66.36$, $P < 0.01$, $\eta_p^2 = 0.21$). The scalp topography of the aperiodic exponent is presented in Fig. 5.

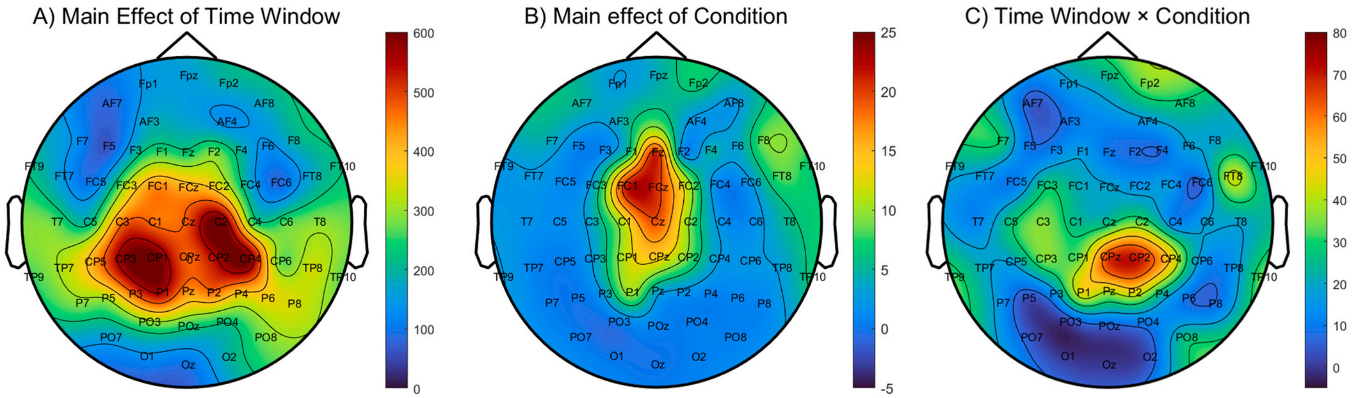

Fig. 5. Scalp distributions of the aperiodic exponent. The figures show electrode sites with a significant main effect of time window, condition and the interaction effect of time window × condition respectively in the aperiodic exponent (this corresponds to the subheading in the figure). Colors indicate cluster-level summed F-values.

3.5. SEM

Descriptive statistics can be found in Table 1, the main finding in Fig. 6. We constructed two models, one with a trait-like approach in mind (Model 1) and the other (Model 2) to capture the task-specific adjustments participants made in order to respond to the stimulus-induced challenges. Both models fitted the data well (notes on Fig. 6), but Model 2 turned out to be considerably more informative.

The fit of Model 2 to the data was good (Fig. 6), as well as the power of the χ^2-test of model fit ($1 - \beta = 0.99$; with $N = 160$, noncentrality parameter $\lambda = 40.33$, $df = 21$, and $\alpha = 0.05$). The model included four well-defined factors with significant factor loadings, indicating that all factors captured systematic common variance. Metacontrol dynamic EEG and Metacontrol behavioral correlated substantially ($r = 0.50$), as well as accommodative coping and assimilative coping ($r = -0.48$), indicating related but differentiable factors. Notably, only Metacontrol dynamic EEG (but not Metacontrol behavioral) was related to accommodative ($r = 0.33$) and assimilative coping ($r = -0.36$). To compute the amount of variance explained by Metacontrol dynamic EEG, we estimated a statically equivalent model (having exactly the same model fit) with three correlation coefficients replaced by regression coefficients. The model showed that Metacontrol dynamic EEG predicted Metacontrol behavioral ($\beta = 0.50$, $p = 0.003$; $R^2 = 0.25$), accommodative coping ($\beta = 0.33$, $p = 0.032$; $R^2 = 0.11$), and assimilative coping (β

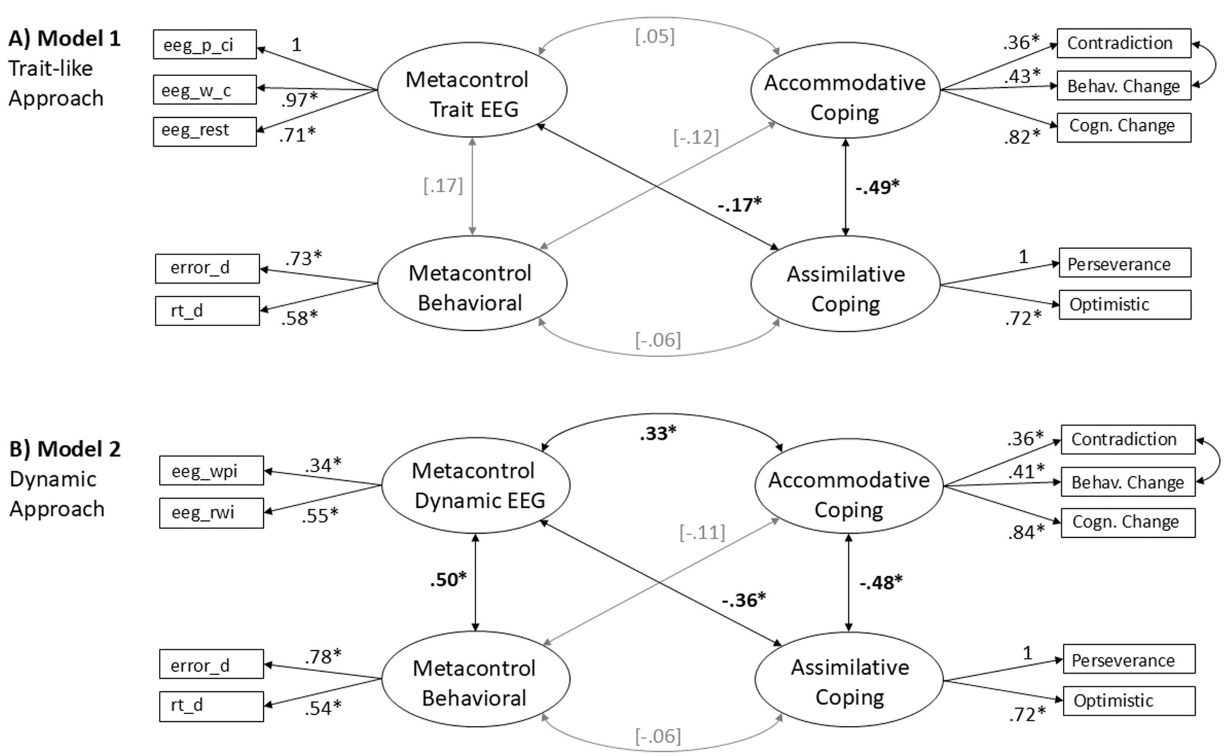

Fig. 6. Panel A depicts Model 1, which was based on a trait-like approach. The fit of Model 1 to the data was good [$\chi^2(30) = 42.76$, $p = .06$; CFI = .98; RMSEA = .05 (90 % CI = 0–.08); SRMR = .06; $k = 35$, $N{:}k = 4.57$]. Panel B depicts model 2, which was based on task-specific adjustments to stimulus-induced challenges. The fit of Model 2 to the data was good [$\chi^2(21) = 28.98$, $p = .11$; CFI = .97; RMSEA = .05 (90 % CI = 0–.09); SRMR = .05; $k = 33$, $N{:}k = 4.85$]. All parameters are standardized. The correlations and factor loadings displayed in black were significant at $p < .05$. The squares represent observed variables and the circles represent latent variables. EEG_p_ci = mean aperiodic exponent of the pre-time window from two conditions, EEG_w_c = aperiodic exponent in the congruent condition, EEG_rest = aperiodic exponent obtained during the resting state, EEG_wpi = within incongruent - pre incongruent; EEG_rwi = within incongruent aperiodic exponent – resting aperiodic exponent; PE_d = incongent percent error -congruent error; RT_d = incongruent reaction time - congruent reaction time.

= −0.36, $p = 0.018$; $R^2 = 0.13$). Moreover, these findings were robust when controlling for the effects of participants' gender and age.

Model 1 also showed a good fit (notes on Fig. 6) but was less informative. Metacontrol trait EEG predicted assimilative coping (r = - 0.17) but not Metacontrol behavioral or accommodative coping. This highlights the advantage of a dynamic approach (Model 2) compared to a trait approach (Model 1).

4. Discussion

In view of the substantial empirical evidence that metacontrol has an impact on how people deal with task-specific challenges (Hommel & Colzato, 2017), and that the aperiodic exponent reflects metacontrol biases towards persistence or flexibility (Y. Gao et al., 2024, 2025; Pi et al., 2024, 2025; Yan et al., 2024; Zhang et al., 2023), we tested whether trait-like and task-specific metacontrol biases would be able to predict preferences for particular coping styles. While previous studies (Pi et al., 2025; Yan et al., 2024, 2025) focused primarily on task-related variations in aperiodic neural activity related to metacontrol, the present study extends this work by linking trait- and state-level aperiodic exponents to individual differences in coping strategies. By integrating neural metacontrol dynamics with the assimilative–accommodative coping framework, this approach moves beyond laboratory tasks to examine how intrinsic neural control parameters predict ecologically relevant adaptive behavior, providing a novel bridge between neurophysiological mechanisms and psychological coping processes.

While even the trait-inspired Model 1 was able to predict coping to some degree, the task-specific Model 2 turned out to be much more effective. We considered both assimilative and accommodative coping styles by means of resilience and dialectical-thinking scales. Let us first consider the two electrophysiological predictors of Model 2. EEG_rwi reflects the difference between spontaneous aperiodic activity, as assessed in the resting-state condition, and the aperiodic activity under maximal task-specific challenge, namely, in the incongruent condition. The corresponding value thus assesses the degree of adaptivity of the individual, the degree to which the individual can adjust his or her cortical noise level to the situational challenge at hand. EEG_wpi also assesses some kind of adaptivity, but this is strictly task-specific. In particular, it reflects the degree to which individuals can adjust to the particular condition that is signaled by the stimulus, as compared to the pre-stimulus phase. Interestingly, both measures contribute to the overall Metacontrol dynamic EEG factor, which fits with our previous assumptions that trait-like and task-specific metacontrol biases jointly operate to determine the processing style (Hommel & Colzato, 2017). This also fits with the observation that Model 1 was not entirely unsuccessful either.

Another interesting observation is that the Metacontrol dynamic EEG factor successfully predicts the Metacontrol behavioral factor. Even though this seems to be a trivial finding, given our assumption that the aperiodic exponent has an impact on behavior, previous observations suggest that matters are a bit more complicated. In particular, Jia et al. (2024) showed that congruent and incongruent stimuli can drive both behavior and the aperiodic exponent in parallel, but the latter does not necessarily need to directly affect the former. In fact, changes in aperiodic exponents often affect only the behavior in the next trial, which suggests that metacontrol changes may often take too long to materialize to still have an impact on the ongoing trial. Accordingly, metacontrol changes may often mainly serve to prepare the processing system for the next trial according to the degree of conflict experience in the present trial—a scenario as envisioned by Holroyd and Coles (2002). This suggests that ongoing response selection and metacontrol changes engage in a horse race, which in turn suggests that whether or not metacontrol can affect response selection in the present trial depends on the relative speed of the two types of processes. If so, the fact that we found a significant impact of present metacontrol changes on present response selection, as expressed in overt behavior, might indicate that response selection was slow enough and/or metacontrol fast enough to generate interactions between the two types of processes at least in a substantial number of trials. However, the number of trials where such interactions took place might not have been substantial enough for behavior to predict coping strategies.

Most importantly, however, we found a strong impact of our electrophysiological indicator of metacontrol, the aperiodic exponent that is, on coping strategies. More specifically, the Metacontrol EEG factor fueled by the two aperiodic exponent measures negatively predicts assimilative coping, as assessed by the resilience scale, but it positively predicts accommodative coping, as assist by the dialectical thinking scale. The fact that one prediction is positive and the other is negative fits with the negative correlation between the two coping styles and with the opposite approach to challenges that these two styles imply. Accordingly, we take our findings as considerable support for both the distinction between assimilative and accommodative coping styles and the existence of considerable individual variability regarding the preference for one or the other coping style. Given that we were exposing participants to just one particular task and one particular challenge, our findings do not speak to possible task- and/or challenge-specific strategy preferences. Hence, it may well be that the same individual sometimes prefer a more assimilative coping strategy and sometimes a more accommodative coping strategy. However, to some extent, the fact that all more trait-related aperiodic measures made a contribution to the predictive effect suggests that strong individual preferences are not unlikely.

While post-hoc model fit indices and sample-to-parameter ratios indicated adequate statistical power for the SEM, we acknowledge that future research should include more diverse samples and preregistered power analyses. Moreover, incorporating demographic and psychosocial covariates such as socioeconomic status, stress exposure, and family background would provide a more comprehensive understanding of how contextual factors influence coping tendencies and metacontrol dynamics. Furthermore, although the Resilience Style Questionnaire (RSQ) demonstrated strong internal consistency ($\alpha = 0.87$), the Dialectical Self Scale (DSS) showed only borderline reliability ($\alpha = 0.67$) in our sample. Confirmatory factor analysis indicated that the hypothesized factor structure of the DSS did not achieve acceptable fit, suggesting limited construct validity. Furthermore, analyses of discriminant validity revealed substantial overlap between resilience and dialectical thinking, indicating that these proxies may not fully capture distinct assimilative and accommodative coping processes. Consequently, interpretations regarding the differential prediction of assimilative versus accommodative coping should be made with caution. Future studies should consider more robust, behaviorally anchored, or situational measures of coping to strengthen construct validity and allow for clearer differentiation between these related constructs.

As no cross-cultural or moderation analyses were conducted, the current findings should not be interpreted as evidence of cultural differences per se, but rather as culturally situated observations that may reflect how dialectical thinking and metacontrol dynamics manifest within this specific sociocultural setting. The cultural focus of the sample thus enhances ecological validity while highlighting the need for future cross-cultural research directly comparing Eastern and Western populations to elucidate how cultural value systems shape the neural substrates of adaptive coping.

In any case, we can conclude that preferences for coping styles can be predicted to some degree, and that the aperiodic exponent exhibits predictive effects on it. Accordingly, individual metacontrol biases, as expressed in variability of the aperiodic exponent, can be assumed to play a considerable role in determining how people deal with everyday challenges.

Author contributions statement

Study design: B.H., L.C.; data collection and analysis: J.Y., T.K., H.Z.;

writing of the manuscript: J.Y., L.C., B.H., All authors reviewed the manuscript.

CRediT authorship contribution statement

Bernhard Hommel: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Jimin Yan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis, Data curation. **Tanja Könen:** Writing – review & editing, Visualization, Validation, Supervision, Methodology. **Hongchi Zhang:** Investigation, Data curation. **Lorenza Colzato:** Writing – review & editing, Writing – original draft.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors declare that no content of this manuscript was generated by AI or AI-assisted technologies in a manner that replaces authorship. All text, analyses, interpretations, and conclusions were developed and verified by the authors. The authors take full responsibility for the integrity, accuracy, and originality of the manuscript.

Funding

The study was funded by the "One case, one policy" grant from Shandong Province (China) awarded to BH.

Declaration of Competing Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and publication of this article.

Acknowledgements

We thank all the participants who took part in the study.

Data availability

Data will be made available on request.

References

Beauducel, A., & Wittmann, W. W. (2005). Simulation Study on Fit Indexes in CFA based on data with slightly distorted simple structure. *Structural Equation Modeling: A Multidisciplinary Journal, 12*(1), 41–75. https://doi.org/10.1207/s15328007sem1201_3

Block, J. (1982). Assimilation, accommodation, and the dynamics of personality development (JSTOR) *Child Development, 53*(2), 281–295. https://doi.org/10.2307/1128971.

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences, 16*(2), 106–113. https://doi.org/10.1016/j.tics.2011.12.010

Carere-Comes, T. (2001). Assimilative and accommodative integration: The basic dialectics. *Journal of Psychotherapy Integration, 11*(1), 105–115. https://doi.org/10.1023/A:1026633125774

Carver, C. S., & Connor-Smith, J. (2010). Personality and coping. *Annual Review of Psychology, 61*, 679–704. https://doi.org/10.1146/annurev.psych.093008.100352

Cheng, C. (2010). Dialectical thinking and coping flexibility: A multimethod approach. *Journal of Personality, 77*. https://doi.org/10.1111/j.1467-6494.2008.00555.x

Cheng, C., Lau, H.-P. B., & Chan, M.-P. S. (2014). Coping flexibility and psychological adjustment to stressful life changes: A meta-analytic review. *Psychological Bulletin, 140*(6), 1582–1607. https://doi.org/10.1037/a0037913

Cools, R. (2015). The cost of dopamine for dynamic cognitive control. *Current Opinion in Behavioral Sciences, 4*, 152–159.

Cools, R. (2016). The costs and benefits of brain dopamine for cognitive control. *Wiley Interdisciplinary Reviews-Cognitive Science, 7*(5), 317–329. https://doi.org/10.1002/wcs.1401

Cools, R., & D'Esposito, M. (2009). Dopaminergic modulation of flexible cognitive control in humans. *Dopamine handbook*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195373035.003.0017

Donoghue, T., Haller, M., Peterson, E. J., Varma, P., Sebastian, P., Gao, R., Noto, T., Lara, A. H., Wallis, J. D., & Knight, R. T. (2020). Parameterizing neural power spectra into periodic and aperiodic components. *Nature Neuroscience, 23*(12), 1655–1665.

Durstewitz, D., & Seamans, J. K. (2008). The dual-state theory of prefrontal cortex dopamine function with relevance to catechol-O-methyltransferase genotypes and schizophrenia. *Biological Psychiatry, 64*(9), 739–749. https://doi.org/10.1016/j.biopsych.2008.05.015

Gao, R., Peterson, E., & Voytek, B. (2017). Inferring synaptic excitation/inhibition balance from field potentials. *Neuroimage, 158*, 70–78. https://doi.org/10.1016/j.neuroimage.2017.06.078

Gao, Y., Koyun, A. H., Roessner, V., Stock, A. K., Mückschel, Moritz, Colzato, L., Hommel, B., & Beste, C. (2025). Transcranial direct current stimulation and methylphenidate interact to increase cognitive persistence as a core component of metacontrol: Evidence from aperiodic activity analyses. *Brain Stimulation, 18*(3), 720–729. https://doi.org/10.1016/j.brs.2025.03.024

Gao, Y., Roessner, V., Stock, A.-K., Mückschel, M., Colzato, L., Hommel, B., & Beste, C. (2024). Catecholaminergic modulation of metacontrol is reflected by changes in aperiodic EEG activity. *International Journal of Neuropsychopharmacology, 27*(8), Article pyae033. https://doi.org/10.1093/ijnp/pyae033

Gonzalez, R., & Griffin, D. (2001). Testing parameters in structural equation modeling: Every" one" matters. *Psychological Methods, 6*(3), 258. ⟨https://psycnet.apa.org/doi/10.1037/1082-989X.6.3.258⟩.

Goschke, T. (2000). Intentional reconfiguration and involuntary persistence in task-set switching. *Control of Cognitive Processes: Attention and Performance XVIII, 331*(2000), *18. -355*.

Goschke, T., & Bolte, A. (2014). Emotional modulation of control dilemmas: The role of positive affect, reward, and dopamine in cognitive stability and flexibility. *Neuropsychologia, 62*, 403–423. https://doi.org/10.1016/j.neuropsychologia.2014.07.015

Hamamura, T., Heine, S. J., & Paulhus, D. L. (2008). Cultural differences in response styles: The role of dialectical thinking. *Personality and Individual Differences, 44*(4), 932–942. https://doi.org/10.1016/j.paid.2007.10.034

Hanfstingl, B., Arzenšek, A., Apschner, J., & Gölly, K. I. (2022). *Assimilation and accommodation: A systematic review of the last two decadesassimilation and accommodation: A systematic review of the last two decades* (pp. 320–337). Hogrefe Publishing. https://doi.org/10.1027/1016-9040/a000463

Hill, A. T., Clark, G. M., Bigelow, F. J., Lum, J. A., & Enticott, P. G. (2022). Periodic and aperiodic neural activity displays age-dependent changes across early-to-middle childhood. *Developmental Cognitive Neuroscience, 54*, Article 101076.

Hofmann, W., Schmeichel, B. J., & Baddeley, A. D. (2012). Executive functions and self-regulation. *Trends in Cognitive Sciences, 16*(3), 174–180. https://doi.org/10.1016/j.tics.2012.01.006

Hofstede, G. H. (2001). Culture's consequences: Comparing values, behaviors, institutions and organizations across nations. *Behaviour Research and Therapy, 41*(7). https://doi.org/10.1177/031289620202700105

Holroyd, C. B., & Coles, M. G. H. (2002). The neural basis of human error processing: Reinforcement learning, dopamine, and the error-related negativity. *Psychological Review, 109*(4), 679–709. https://doi.org/10.1037/0033-295X.109.4.679

Hommel, B. (2015). Chapter Two - Between Persistence and Flexibility: The Yin and Yang of Action Control. In A.J. Elliot (Ed.), *Advances in Motivation Science* (Vol. 2, pp. 33–67). Elsevier. https://doi.org/10.1016/bs.adms.2015.04.003.

Hommel, B., Colzato, L., & Beste, C. (2024). No convincing evidence for the independence of persistence and flexibility. *Nature Reviews Psychology, 3*(9), 638. https://doi.org/10.1038/s44159-024-00353-6

Hommel, B., & Colzato, L. S. (2017). The social transmission of metacontrol policies: Mechanisms underlying the interpersonal transfer of persistence and flexibility. *Neuroence Biobehavioral Reviews, 81*(Pt A), 43–58. https://doi.org/10.1016/j.neubiorev.2017.01.009

Jak, S., Jorgensen, T. D., Verdam, M. G. E., Oort, F. J., & Elffers, L. (2021). Analytical power calculations for structural equation modeling: A tutorial and Shiny app. *Behavior Research Methods, 53*(4), 1385–1406. https://doi.org/10.3758/s13428-020-01479-0

Jia, S., Liu, D., Song, W., Beste, C., Colzato, L., & Hommel, B. (2024). Tracing conflict-induced cognitive-control adjustments over time using aperiodic EEG activity. *Cerebral Cortex, 34*(5). https://doi.org/10.1093/cercor/bhae185

Spencer-Rodgers, Julie, Peng, Kaiping, Wang, Lei, & Hou, Yubo (2004). Dialectical self-esteem and East-West differences in psychological well-being. *Personality and Social Psychology Bulletin, 30*(11), 1416–1432. https://doi.org/10.1177/0146167204264243

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed). The Guilford Press. pp. xvii, 534.

Konjusha, A., Colzato, L., Mückschel, M., & Beste, C. (2022). Auricular transcutaneous vagus nerve stimulation diminishes alpha-band-related inhibitory gating processes during conflict monitoring in frontal cortices. *The International Journal of Neuropsychopharmacology, 25*(6), 457–467. https://doi.org/10.1093/ijnp/pyac013

Lin, & Wang, Fengyan (2025). Reliability and validity of the simple version of the Analysis-Holism Scale in Chinese college students. *Chinese Journal of Clinical Psychology, 33*(04), 686–690. https://doi.org/10.16128/j.cnki.1005-3611.2025.04.006

Lombardi, F., Herrmann, H., & de Arcangelis, L. (2017). Balance of excitation and inhibition determines 1/f power spectrum in neuronal networks. *CHAOS, 27*(4). https://doi.org/10.1063/1.4979043

Mak, W. W., Ng, I. S., Wong, C. C., & Law, R. W. (2019). Resilience style questionnaire: Development and validation among college students and cardiac patients in Hong Kong. *Assessment, 26*(4), 706–725. https://doi.org/10.1177/1073191116683798

Mao, Z. (1937). On contradiction. *Selected Works of Mao Tse-Tung*. Foreign Languages Press. Vol. 1.

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG-and MEG-data. *Journal of Neuroscience Methods, 164*(1), 177–190.

Muthukrishna, Michael, Bell, Adrian V., Henrich, Joseph, Curtin, Cameron M., Gedranovich, Alexander, McInerney, Jason, & Thue, Braden (2020). Beyond Western, Educated, Industrial, Rich, and Democratic (WEIRD) psychology: Measuring and mapping scales of cultural and psychological distance. *Psychological Science, 31*(6), 678–701. https://doi.org/10.1177/0956797620916782

Mückschel, M., Chmielewski, W., Ziemssen, T., & Beste, C. (2017). The norepinephrine system shows information-content specific properties during cognitive control – Evidence from EEG and pupillary responses. *NeuroImage, 149*, 44–52. https://doi.org/10.1016/j.neuroimage.2017.01.036

Ostlund, B., Donoghue, T., Anaya, B., Gunther, K. E., Karalunas, S. L., Voytek, B., & Pérez-Edgar, K. E. (2022). Spectral parameterization for studying neurodevelopment: How and why. *Developmental Cognitive Neuroscience, 54*, Article 101073.

Petro, N. M., Ott, L. R., Penhale, S. H., Rempe, M. P., Embury, C. M., Picci, G., Wang, Y.-P., Stephen, J. M., Calhoun, V. D., & Wilson, T. W. (2022). Eyes-closed versus eyes-open differences in spontaneous neural dynamics during development. *NeuroImage, 258*, Article 119337.

Pi, Y., Pscherer, C., Mückschel, Moritz, Colzato, L., Hommel, B., & Beste, C. (2025). Metacontrol-related aperiodic neural activity decreases but strategic adjustment thereof increases from childhood to adulthood. *Scientific Reports*. https://doi.org/10.1038/s41598-025-00736-6

Pi, Y., Yan, J., Pscherer, C., Mückschel, M., Colzato, L., Hommel, B., & Beste, C. (2024). Interindividual aperiodic resting-state EEG activity predicts cognitive-control styles. *Psychophysiology*. https://doi.org/10.1038/s41598-025-00736-6

Piaget, J. (1977). La naissance de l'intelligence chez l'enfant. FeniXX.

Pscherer, C., Bluschke, A., Prochnow, A., Eggert, E., Mückschel, M., & Beste, C. (2020). Resting theta activity is associated with specific coding levels in event-related theta activity during conflict monitoring. *Human Brain Mapping, 41*(18), 5114–5127. https://doi.org/10.1002/hbm.25178

Satorra, A., & Saris, W. E. (1985). Power of the Likelihood Ratio Test in covariance structure analysis. *Psychometrika, 50*(1), 83–90. https://doi.org/10.1007/BF02294150

Spencer-Rodgers, J., Boucher, H. C., Mori, S. C., Wang, L., & Peng, K. (2009). The dialectical self-concept: Contradiction, change, and holism in East asian cultures. *Personality Social Psychology Bulletin, 35*(1), 29–44. https://doi.org/10.1177/0146167208325772

Spencer-Rodgers, J., Srivastava, S., Boucher, H. C., English, T., Paletz, S., & Peng, K. (2015). Dialectical Self Scale. *Personality and Social Psychology Bulletin*. https://doi.org/10.1037/t75704-000

Voytek, B., & Knight, R. (2015). Dynamic network communication as a unifying neural basis for cognition, development, aging, and disease. *Biological Psychiatry, 77*(12), 1089–1097. https://doi.org/10.1016/j.biopsych.2015.04.016

Welch, P. D. (1967). The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. *15*(2), 70–73 *IEEE Trans Audio Electroacoust, AU-15, 70–73*. https://doi.org/10.1109/TAU.1967.1161901.

Yan, J., Colzato, L., & Hommel, B. (2025). Code conflict in an event file task is reflected by aperiodic neural activity. *NeuroReport, 36*(7), 337–341. https://doi.org/10.1097/WNR.0000000000002156

Yan, J., Yu, S., Mückschel, M., Colzato, L., Hommel, B., & Beste, C. (2024). Aperiodic neural activity reflects metacontrol in task-switching. *Scientific Reports, 14*(1), Article 24088. https://doi.org/10.1038/s41598-024-74867-7

X.-L., Yang, H.-L., Yan, & L., Liu (2015). The relationship between bicultural identity integration and psychological adaptation: The mediating role of dialectical self. *Journal of Psychological Science, 38*(06), 1475–1481. https://doi.org/10.16719/j.cnki.1671-6981.20150628

Zhang, C., Stock, A., Mückschel, M., Hommel, B., & Beste, C. (2023). Aperiodic neural activity reflects metacontrol. *Cerebral Cortex, 33*(12), 7941–7951. https://doi.org/10.1093/cercor/bhad089