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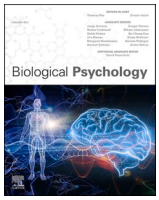

Neurophysiological mechanisms of fluid intelligence: Insights from ERP and aperiodic activity in adolescents

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ABSTRACT

To investigate the neurophysiological mechanisms of fluid intelligence (Gf), this study systematically examined neural activity differences between adolescents with high and low Gf using three core executive function (EF) tasks: inhibitory control (Flanker), working memory (4-back), and cognitive flexibility (task-switching), with a focus on event-related potentials (ERPs) and aperiodic activity. Electroencephalography (EEG) was recorded during both resting and task states, and the FOOOF algorithm was used to perform parametric spectral decomposition. The results revealed that the low-Gf group exhibited significantly larger P3 amplitudes across the Flanker, 4-back, and task-switching paradigms, a pattern consistent with the neural efficiency hypothesis and suggesting that Gf-related differences are primarily manifested in late-stage cognitive resource integration processes. Regarding aperiodic activity, group differences were task-specific. Notably, only in the Flanker paradigm did the high-Gf group exhibit a significantly larger aperiodic offset under the incongruent condition compared to the congruent condition, suggesting greater sensitivity in neural-state regulation when conflict demands increase. In contrast, the low-Gf group showed no significant difference in aperiodic offset between the two conditions, suggesting relatively limited condition-related adjustment of neural state across conflict conditions. By integrating conventional EEG measures with aperiodic components, this study provides multifaceted evidence for understanding the neural resource allocation and neural-state regulation associated with Gf and offers novel insights into the neurophysiological mechanisms underlying adolescent cognitive processing.

1. Introduction

Fluid intelligence (Gf) refers to an individual's ability to solve novel problems through reasoning, without relying on previously acquired knowledge and skills (Cattell, 1963). Higher levels of Gf are typically associated with superior cognitive performance in various domains, including verbal comprehension, mathematical reasoning, and cognitive control (Lynn & Yadav, 2015). Therefore, elucidating the neurophysiological mechanisms underlying Gf has become one of the central issues in cognitive neuroscience and is crucial for understanding the nature of intelligence.

According to Diamond's influential framework, executive functions (EFs)—especially its core components—working memory, cognitive flexibility, and inhibitory control—form the basis of higher cognitive functions such as planning, reasoning, and problem-solving (Diamond, 2020). These higher cognitive functions are, in turn, central to Gf. Specifically, inhibitory control helps individuals suppress irrelevant information to maintain goal-directed behavior (Eriksen & Eriksen, 1974); working memory is responsible for temporarily storing and manipulating information, serving as a prerequisite for complex reasoning (Jaeggi et al., 2008); and cognitive flexibility allows individuals to adapt to changing rules or situations, enabling switching between thought patterns (Buchler et al., 2008). These three core components collaborate, supporting the abstract reasoning and problem-solving abilities that Gf depends on. Therefore, systematically investigating the neurophysiological differences in these three core EF components across individuals with varying levels of Gf is of great theoretical significance for uncovering the neural basis of fluid intelligence.

Existing studies have employed task-based electroencephalography (EEG) techniques to investigate the neural activity differences during cognitive processing between individuals with different levels of Gf, although the findings remain inconsistent. Event-related potentials

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(ERPs), such as the P3 component, which is associated with attention resource allocation and working memory updating during task processing, are commonly used EEG measures in cognitive processing research (Hillman et al., 2012; Wessel, 2018). For instance, Luo et al. (2020) tested children with varying levels of Gf using the classical 2-back working memory paradigm and found that the high-Gf group exhibited larger P3 amplitudes during the task. In contrast, in adult individuals performing working memory tasks, the low-Gf group showed significantly larger P3 amplitudes (Jia et al., 2023; Wongupparaj et al., 2018). However, Wronka et al. (2013) found that in the three-stimulus oddball paradigm, the high-Gf group had larger P3a and P3b amplitudes, suggesting greater initial attention resource allocation and later-stage stimulus evaluation (Wronka et al., 2013). Lu et al. (2022) defined exploratory and exploitative tasks, proposing that high-Gf individuals use fewer cognitive resources for exploitative tasks but allocate resources according to task difficulty for exploratory tasks, as reflected in alpha and theta power differences. However, the paradigms used were not standardized and were biased toward spatial cues, which may have contributed to the observed gender differences and complicates the integration of these results into a unified neural framework (Lu, Bao, et al., 2022; Lu, Xi, et al., 2022).

We suggest that the inconsistencies observed in the literature arise from several factors: first, the age differences in the research groups are an important influence—children and adults have distinct neurodevelopmental stages, and their cognitive processing efficiency and neural response patterns differ significantly (Downes et al., 2017). Second, differences in research paradigms limit the robustness of comparisons across results and most studies have failed to systematically integrate neural measurements with the core cognitive processes that underpin Gf. Beyond the limitations of paradigm choices, another methodological limitation of traditional EEG analysis is the frequent treatment of aperiodic components (non-oscillatory neural activity, which follows a 1/f-like power distribution, where spectral power decreases exponentially with increasing frequency) as noise, leading to their correction or neglect (Gyurkovics et al., 2021).

Although the neurophysiological origins of aperiodic components are not yet fully understood, increasing evidence suggests that aperiodic components may reflect global brain excitability. Magnetoencephalography (MEG) studies have found that compared to oscillatory activity, task-related changes in aperiodic activity are more subtle, reflecting its importance as a stable feature of brain activity (Wainio-Theberge et al., 2022). Aperiodic activity is characterized by two key parameters: the aperiodic exponent (also referred to as the spectral slope) and aperiodic offset. The aperiodic exponent reflects the distribution pattern of power across different frequencies, indicating the steepness of the power spectral decay, while aperiodic offset reflects the broadband shift of power across all frequencies (Donoghue et al., 2020). Existing research indicates that the aperiodic exponent may reflect the excitation-inhibition (E/I) balance at the neuronal level (Waschke et al., 2021) and may serve as an index of neural population variability, representing the brain's ability to modulate neural activity according to task demands. Aperiodic offset, on the other hand, may reflect the firing activity of neural populations (Jacob et al., 2021). Aperiodic components are closely associated with various developmental, aging-related, and psychiatric conditions, including major depression, attention deficit hyperactivity disorder, and others (Hacker et al., 2025; McKeown et al., 2024; Peisch & Arnett, 2024; Pi et al., 2025; Satzer et al., 2025), and are implicated in perceptual, attentional, and cognitive control processes (Lu et al., 2024; Lu et al., 2025; Zhang et al., 2025). For example, Zhang et al. (2023) found that the aperiodic slope may relate to different cognitive control states, with higher values in tasks requiring sustained attention and lower values in tasks demanding greater cognitive flexibility (Zhang et al., 2023). Pi et al. (2024) found that resting-state aperiodic indices could predict cognitive control styles across different conditions, reflecting the brain's ability to adjust its neural activity patterns to accommodate environmental changes (Pi et al., 2024). These findings suggest that analyzing aperiodic activity offers a new way to understand the dynamic adjustment patterns of the brain during high-level cognitive processes and individual differences. Therefore, we hypothesize that individual differences in Gf are reflected not only in task-evoked neural responses but also in individual differences in these fundamental aperiodic activity patterns.

Building on the above considerations, this study aims to employ an integrated approach to systematically investigate the neurophysiological basis of Gf: namely, by examining both task-evoked neural potentials associated with the core components of EF and the aperiodic background activity that may underlie neural efficiency. Aperiodic activity is influenced by age and development, with a typical U-shaped developmental trajectory (Cross et al., 2025; Hill et al., 2022), and adolescence is a critical window for the development of Gf and related cognitive functions. Therefore, this study focuses on adolescents. We recruited adolescents with high and low Gf, recorded their resting-state EEG and task-based EEG signals during the completion of classic paradigms assessing working memory, inhibitory control, and cognitive flexibility. The Fitting Oscillations and One Over f (FOOOF) algorithm was used to parameterize the spectral decomposition of the EEG data (Donoghue et al., 2020), thereby extracting the key aperiodic parameters of exponent and offset. By integrating both ERP amplitudes and aperiodic parameters, this study aims to systematically characterize the neural activity patterns of the two groups across multiple levels of analysis. Based on the neural efficiency hypothesis (Haier et al., 1992), we propose two main hypotheses: First, we predict that, compared to the high-Gf group, the low-Gf group will exhibit larger P3 amplitudes across all three tasks, reflecting the need to allocate more cognitive resources to achieve comparable behavioral performance. Second, regarding aperiodic activity, given its role in reflecting neural excitability and the excitation-inhibition (E/I) balance, as well as its sensitivity to cognitive control demands, we hypothesize that high-Gf individuals will demonstrate more flexible and task-dependent modulation of aperiodic parameters. Specifically, we expect that, compared to the low-Gf group, the high-Gf group will exhibit greater condition-related variations in both offset and exponent.

2. Methods

2.1. Participants

Participants in this study were recruited from a rural high school in China. Gf was assessed using the Raven's Standard Progressive Matrices (RSPM) for all first-year students at the school (N = 415). Participants were given 40 min to complete the test. Based on their RSPM raw scores within the full school sample, students in the upper and lower quartiles were classified as the high-Gf and low-Gf groups, respectively. To further characterize the normative standing of the two groups, RSPM raw scores were additionally referenced to age-based RSPM norms appropriate for the study population (Zhang & Wang, 1989). Because the norm table provides discrete percentile cutoffs rather than exact percentile ranks for every possible raw score, descriptive percentile estimates were obtained using linear interpolation between adjacent percentile cutoffs and are reported in Supplementary Table S1. After obtaining full voluntary consent, 28 participants from the high-Gf group and 27 from the low-Gf group were included in the study. There were no significant gender differences between the two groups. This study was approved by the Ethics Committee of the Department of Psychology at Nanjing University. The participant characteristics (age and gender) are presented in Table 1. Sample size estimation for this study was performed using G*Power 3.1 software (Faul et al., 2009), setting the significance level $\alpha = 0.05$ and the desired statistical power $(1-\beta) = 0.8$. Using Cohen's (2013) guidelines for effect size and previous EEG studies on cognitive functions (Xiao et al., 2020; Zhang et al., 2024), a medium effect size ($f = 0.25$) was selected for calculation. The results indicated that the minimum required sample size was 34 participants (at least 17

Table 1
Grouping results and behavioral results (mean ± standard deviation).

	HFG(N = 28, 12male)	LFG(N = 27, 13male)	*t*	*p*
Age	15.67 ± 0.49	15.61 ± 0.37	0.496	0.622
Raw scores of RSPM	55.32 ± 1.47	44.41 ± 3.21	16.103	< 0.001
Flanker (mean ± standard deviation)				
	Congruent		**Incongruent**	
	RTs	**Accuracy**	**RTs**	**Accuracy**
HFG(N = 28)	438.01 ± 67.52	98.33%±2.38%	525.72 ± 71.74	83.51%±1.43%
LFG(N = 27)	423.94 ± 55.01	97.65%±4.65%	489.46 ± 53.97	89.44%±1.29%
4-back (mean ± standard deviation)				
	RTs		**Accuracy**	
HFG(N = 26)	361.47 ± 68.64		22.06%±17.81%	
LFG(N = 25)	367.50 ± 45.58		27.78%±17.47%	
Switch (mean ± standard deviation)				
	Non-switch		**Switch**	
	RTs	**Accuracy**	**RTs**	**Accuracy**
HFG(N = 27)	533.56 ± 92.25 ms	71.45 ± 11.80%	582.81 ± 122.12 ms	61.66 ± 11.32%
LFG(N = 27)	525.68 ± 77.81 ms	76.89 ± 9.17%	591.83 ± 111.83 ms	64.41 ± 7.21%

participants per group). The final sample included 28 participants in the high-Gf group and 27 in the low-Gf group, meeting the sample size requirement for the experimental design.

2.2. Experimental paradigms

Intelligence Testing: The Raven's Standard Progressive Matrices consists of 60 items, each composed of a 3 × 3 matrix with 8 options, where the lower-right element is missing. Participants are required to choose the appropriate figure from the options to complete the matrix, so that the matrix pattern is complete and logically consistent. The more correct answers completed within the 40-minute time limit, the higher the fluid intelligence score.

Resting-State Task: In the resting-state task, participants were instructed to open or close their eyes every minute based on auditory prompts. During the eye-opening phase, participants were required to focus on a " + " symbol presented at the center of the computer screen. The task lasted for 8 min.

Flanker Paradigm: This task was used to assess participants' inhibitory control abilities (Eriksen & Eriksen, 1974). A row of arrows was presented at the center of the screen, and participants had to quickly judge the direction of the central arrow. Each trial began with a fixation cross ("+") presented for 800–1200 ms, followed by a 1000 ms stimulus, and then a 1000 ms blank screen. The response window was 1000 ms. The practice block contained 20 trials, and the main experiment included 2 blocks, each consisting of 90 trials, with 30 incongruent trials and 60 congruent trials. Participants could rest between blocks.

N-back Paradigm: The classic 4-back number-matching paradigm was used in this study. Each trial began with a fixation cross ("+") presented for 800–1200 ms, followed by a 500 ms stimulus, and then a 1000 ms blank screen. The response window was 500 ms, resulting in typical accuracy rates below 50%. The practice block contained 30 trials, and the main experiment consisted of 2 blocks, each with 72 trials. Participants could rest between blocks.

Task Switching Paradigm: In this number-switching task, a series of numbers were presented at the center of the screen. Participants were required to judge the number (1–9, excluding 5); if the number was red, they compared it with 5, and if the number was green, they judged its parity. In the non-switch condition, participants only saw numbers of one color, while in the switch condition, they had to switch between the magnitude (larger/smaller than 5) and parity (odd/even) judgment rules (Buchler et al., 2008). Each trial began with a fixation cross ("+") presented for 800–1200 ms, followed by a 1000 ms stimulus, and then a 1000 ms blank screen. The response window was 1000 ms. The practice block contained 32 trials. In the non-switch condition, there were two blocks: one for size judgment and the other for parity judgment, with 48 trials in each block. In the switch condition, there were two blocks, each with 64 trials. The order of the three paradigms was randomized.

2.3. Data acquisition and analysis

EEG data were collected using a 64-channel Ag-AgCl electrode system (Scan4.5, Neurosoft Labs, Inc.) based on the international 10–20 system. The left mastoid was used as the reference electrode, and the AFz electrode was used as the ground. The bandpass filter was set to 0.05–100 Hz, with a sampling rate of 1000 Hz, and the electrode impedance was maintained below 10 kΩ.

EEG data were processed using EEGLAB (Delorme & Makeig, 2004), down-sampled to 500 Hz, and re-referenced to both mastoids. Based on previous studies (Pi et al., 2025; Zhang et al., 2024), ERP analysis was performed using a bandpass filter of 0.1–30 Hz, while aperiodic components were analyzed using a 0.1–40 Hz bandpass filter. A notch filter was applied to remove 50 Hz power line interference. For resting-state analysis, the data were segmented into 2-second intervals with 50% overlap, and a 0.1–40 Hz bandpass filter was applied. For task-related data, EEG segments were extracted using a 1200 ms window (200 ms pre-stimulus to 1000 ms post-stimulus) and baseline-corrected using the pre-stimulus interval. Independent component analysis (ICA) was used to remove ocular and muscular artifacts, and segments with amplitude values exceeding ±150 μV were rejected. The valid data segments were then averaged.

Based on previous studies and visual inspection of the topographic maps (Gonzalez-Villar & Carrillo-de-la-Pena, 2017; Wei et al., 2022), the P3 amplitude was analyzed from the CPz electrode. For the Flanker task, the time window was selected as 300–600 ms, for the 4-back task, the window was 340–400 ms, and for the task-switching paradigm, the window was 300–600 ms. To comprehensively characterize neural activity across different stages of executive function, we also conducted exploratory analyses on the P1, N1, and N2 components of the Flanker paradigm, as well as the N2 amplitude of the 4-back and task-switching paradigms. The results are provided in the supplementary materials. Therefore, the subsequent analysis focused on the P3 component, which was considered a key indicator of late cognitive resource allocation.

Given that the execution of executive function tasks requires coordinated brain network involvement, no a priori assumptions were made regarding the scalp distribution of aperiodic components in this study. The global exponent and offset values were used for statistical analysis, which also helped avoid multiple comparisons across electrodes (Hill et al., 2022).

Aperiodic analysis followed previous studies (Pi et al., 2025; Zhang et al., 2024). For task-related EEG data, the baseline period was defined from −1000–0 ms before stimulus onset, and the response period was from 0 ms to 1000 ms after stimulus onset. Resting-state EEG data were categorized into eyes-open and eyes-closed conditions based on the

marked information during EEG recording. The "welch" function in Python was used to estimate the power spectral density (PSD) for each frequency in the baseline and response-trial intervals. Following similar studies (Pi et al., 2025; Welch, 1967), EEG data were computed using a 0.25-second Hanning window with 50% overlap. Aperiodic components were evaluated using the Fitting Oscillations and One Over f (FOOOF) toolbox (version 1.0.0; https://github.com/fooof-tools/fooof) (Donoghue et al., 2020). The power spectrum within the 3–40 Hz frequency range was parameterized to extract the aperiodic offset and exponent parameters. The FOOOF parameters were set as follows: peak width limit of 2–8 Hz, maximum number of peaks set to 8, minimum absolute peak height of 0.05, and the aperiodic mode set to fixed. Each trial was independently fitted, and the average aperiodic parameters for each condition were computed. The R^2 values for resting-state and task-related data were greater than 90%, indicating reliable fitting.

3. Results

All analyses of variance (ANOVAs) reported in this chapter were conducted using SPSS 26.0. Post-hoc comparisons and simple effects analyses for significant main effects and interactions were performed using the Bonferroni method for p-value correction.

3.1. Behavioral results

3.1.1. Flanker paradigm

Two-way mixed ANOVA was conducted with response time (RT) and accuracy (ACC) as dependent variables, task type (congruent vs. incongruent) as the within-subject factor, and Gf (high vs. low) as the between-subject factor.

For RT, the results showed a significant interaction between task type and Gf ($F(1, 53) = 9.583$, $p = .003$, $\eta p^2 = .153$). Further simple effects analysis revealed that under the congruent condition, there was no significant difference in RT between the high- and low-Gf groups ($F(1, 53) = 0.715$, $p = .402$, $\eta p^2 = .013$). However, under the incongruent condition, the high-Gf group exhibited significantly slower RTs than the low-Gf group ($F(1, 53) = 4.463$, $p = .039$, $\eta p^2 = .078$). The main effect of task type was significant ($F(1, 53) = 456.765$, $p < .001$, $\eta p^2 = .896$), with RTs being significantly longer under the incongruent condition compared to the congruent condition. The main effect of Gf was not significant ($F(1, 53) = 2.321$, $p = .134$, $\eta p^2 = .042$).

For accuracy, the results showed a significant interaction between task type and Gf ($F(1, 53) = 4.320$, $p = .043$, $\eta p^2 = .075$). Further simple effects analysis indicated the high-Gf group had significantly higher accuracy in the congruent condition than in the incongruent condition ($F(1, 53) = 44.219$, $p < .001$, $\eta p^2 = .455$), and the low-Gf group also showed significantly higher accuracy in the congruent condition, although the effect was smaller ($F(1, 53) = 13.083$, $p = .001$, $\eta p^2 = .198$). The main effect of task type was significant ($F(1, 53) = 52.417$, $p < .001$, $\eta p^2 = .497$), with accuracy being significantly higher in the congruent condition compared to the incongruent condition. The main effect of Gf was not significant ($F(1, 53) = 1.464$, $p = .232$, $\eta p^2 = .027$).

3.1.2. 4-back paradigm

Independent samples *t*-tests were conducted for RT and accuracy between the two groups. The results showed no significant differences in RT ($t(49) = -0.37$, $p = .714$, Cohen's d $= -0.10$) or accuracy ($t(49) = -1.16$, $p = .253$, Cohen's d $= -0.33$) between the groups.

3.1.3. Task switching paradigm

Two-way mixed ANOVA was conducted with RT and accuracy (ACC) as dependent variables, task type (non-switch vs. switch) as the within-subject factor, and Gf (high vs. low) as the between-subject factor.

For RT, the results showed no significant interaction between task type and Gf ($F(1, 52) = 1.636$, $p = .207$, $\eta p^2 = .031$). The main effect of task type was significant ($F(1, 52) = 76.357$, $p < .001$, $\eta p^2 = .595$), with RT being significantly longer under the switch condition compared to the non-switch condition. The main effect of Gf was not significant ($F(1, 52) < 0.001$, $p = .983$, $\eta p^2 < 0.001$).

For accuracy, the results showed no significant interaction between task type and Gf ($F(1, 52) = 1.117$, $p = .295$, $\eta p^2 = .021$). The main effect of task type was significant ($F(1, 52) = 76.538$, $p < .001$, $\eta p^2 = .595$), with accuracy being significantly higher under the non-switch condition compared to the switch condition. The main effect of Gf was not significant ($F(1, 52) = 2.864$, $p = .097$, $\eta p^2 = .052$).

The basic information of the participants and their RT and ACC data for each task are presented in Table 1.

3.2. Resting-state vs. task-state aperiodic components

3.2.1. Comparison of eyes-open and eyes-closed conditions

A two-way mixed ANOVA was conducted with the condition (eyes-open, eyes-closed) as the within-subject factor, and Gf (high vs. low) as the between-subject factor, with aperiodic exponent and aperiodic offset as dependent variables.

For the aperiodic exponent, the main effect of condition was significant ($F(1, 45) = 6.651$, $p = .013$, $\eta p^2 = .129$). Post-hoc comparisons indicated that the aperiodic exponent was significantly higher in the eyes-closed condition compared to the eyes-open condition. No significant interactions or main effects of Gf were found. For the aperiodic offset, the main effect of condition was significant ($F(1, 45) = 32.726$, $p < .001$, $\eta p^2 = .421$). Post-hoc comparisons showed that the aperiodic offset was significantly higher in the eyes-closed condition compared to the eyes-open condition. No significant interactions or main effects of Gf were found.

3.2.2. Comparison with task-state aperiodic components

Given the differing number of valid participants after EEG preprocessing across tasks (see Supplementary Table S2), the data presented an unbalanced repeated-measures design. Linear mixed-effects models (LMEs) were used as they can effectively handle missing data and utilize all available observations for estimation. Task type (eyes-open resting-state, eyes-closed resting-state, Flanker, 4-back, task-switching) was included as the within-subject factor, and Gf (high vs. low) as the between-subject factor, with their interaction term. To account for the correlation among repeated measurements from the same participant, a random intercept for each participant (analysis_id) was included. Data were analyzed in R using the lmerTest package (Kuznetsova et al., 2017), with parameter estimation conducted via restricted maximum likelihood (REML), and the Satterthwaite method was used to estimate degrees of freedom. Type III ANOVA was conducted to test the significance of main effects and interactions. Post-hoc comparisons for significant main effects were performed using the emmeans package (Tukey correction). All statistical analyses used a significance level of $\alpha = 0.05$.

Model 1: Exponent ~ Group * Task + (1 | analysis_id)

Model 2: Offset ~ Group * Task + (1 | analysis_id)

Analysis of the aperiodic exponent showed a significant main effect of task type ($F(4, 187.7) = 2.46$, $p = .047$, $\eta p^2 = .050$), but no significant differences between task conditions were observed in post-hoc comparisons. No significant interactions or main effects of Gf were found.

Analysis of the aperiodic offset showed a significant main effect of task type ($F(4, 188.5) = 7.27$, $p < .001$, $\eta p^2 = .134$). Post-hoc comparisons (Tukey correction) revealed that the aperiodic offset in the eyes-closed resting-state was significantly higher than in the eyes-open resting-state ($p < .001$), Flanker ($p = .001$), and 4-back paradigms ($p = .004$). The aperiodic offset in the eyes-open resting-state was significantly lower than in the task-switching paradigm ($p = .035$). No significant differences were observed between other task conditions. The main effect and interactions for Gf were not significant. Figures of

the resting-state and task-state aperiodic components are presented in Fig. 1.

3.3. Flanker paradigm results

Due to excessive artifacts, one high-Gf participant was excluded from the ERP and aperiodic analyses.

3.3.1. EEG amplitude results

A two-way mixed ANOVA was conducted with task type (congruent vs. incongruent) as the within-subject factor, Gf (high vs. low) as the between-subject factor, and P3 amplitude as the dependent variable. The results showed no significant interaction between task type and Gf ($F(1, 52) = 2.000$, $p = .163$, $\eta p^2 = .037$). However, the main effect of task type was significant ($F(1, 52) = 5.747$, $p = .020$, $\eta p^2 = .100$), with significantly larger P3 amplitude under the incongruent condition compared to the congruent condition. The main effect of Gf was significant ($F(1, 52) = 4.583$, $p = .037$, $\eta p^2 = .081$), indicating that the low-Gf group exhibited significantly larger P3 amplitude than the high-Gf group. The ERP waveform and topographic map at the CPz electrode for this paradigm are shown in Fig. 2-a.

3.3.2. Aperiodic component results

Separate three-way mixed ANOVA was conducted for the aperiodic exponent and aperiodic offset, with the time window (baseline vs. response period) and task type (congruent vs. incongruent) as within-subject factors, and Gf (high vs. low) as the between-subject factor.

For the aperiodic exponent, the results showed a significant interaction between task type and time window ($F(1, 52) = 7.212$, $p = .010$, $\eta p^2 = .122$). Simple effects analysis indicated that there was no significant difference between task types in the baseline period ($F(1, 52) = 0.154$, $p = .697$, $\eta p^2 = .003$), but in the response period, the exponent was significantly larger under the incongruent condition than the congruent condition ($F(1, 52) = 13.946$, $p < .001$, $\eta p^2 = .211$). The main effect of task type was significant ($F(1, 52) = 6.739$, $p = .012$, $\eta p^2 = .115$), with the incongruent condition showing significantly higher exponent than the congruent condition. The main effect of time window was significant ($F(1, 52) = 113.302$, $p < .001$, $\eta p^2 = .685$), with the response period showing a significantly higher exponent than the baseline period. No significant main effects or interactions for Gf were found.

For the aperiodic offset, the results showed a significant interaction between task type and time window ($F(1, 52) = 9.593$, $p = .002$, $\eta p^2 = .156$). Simple effects analysis indicated that there was no significant difference between task types in the baseline period ($F(1, 52) = 0.102$, $p = .751$, $\eta p^2 = .002$), but in the response period, the offset was significantly larger under the incongruent condition compared to the congruent condition ($F(1, 52) = 18.589$, $p < .001$, $\eta p^2 = .263$). The interaction between task type and Gf was significant ($F(1, 52) = 4.849$, $p = .032$, $\eta p^2 = .085$), with further simple effects analysis showing that the high-Gf group had a significantly larger offset in the incongruent condition compared to the congruent condition ($F(1, 52) = 13.566$, $p < .001$, $\eta p^2 = .207$), whereas no significant difference was observed between task types for the low-Gf group ($F(1, 52) = 0.324$, $p = .572$, $\eta p^2 = .006$). The main effect of task type was significant ($F(1, 52) = 9.042$, $p = .004$, $\eta p^2 = .148$), with the incongruent condition showing a significantly larger offset than the congruent condition. The main effect of time window was significant ($F(1, 52) = 92.334$, $p < .001$, $\eta p^2 = .640$), with the response period showing a significantly larger offset than the baseline period. No significant main effect of Gf or other interactions involving Gf were found. The results for the aperiodic components in this paradigm are shown in Fig. 2-b.

3.4. 4-back paradigm results

Due to excessive artifacts, four high-Gf participants and one low-Gf participant were excluded from the ERP and aperiodic analyses.

3.4.1. EEG amplitude results

Independent samples *t*-tests showed that the low-Gf group had significantly larger P3 amplitude than the high-Gf group ($t(48) = 2.080$, $p = .043$, Cohen's d = 0.59). The ERP waveform and topographic map at the CPz electrode for this paradigm are shown in Fig. 3-a.

3.4.2. Aperiodic component results

Separate two-way mixed ANOVA was conducted for the aperiodic exponent and aperiodic offset, with the time window (baseline vs. response period) as the within-subject factor, and Gf (high vs. low) as the

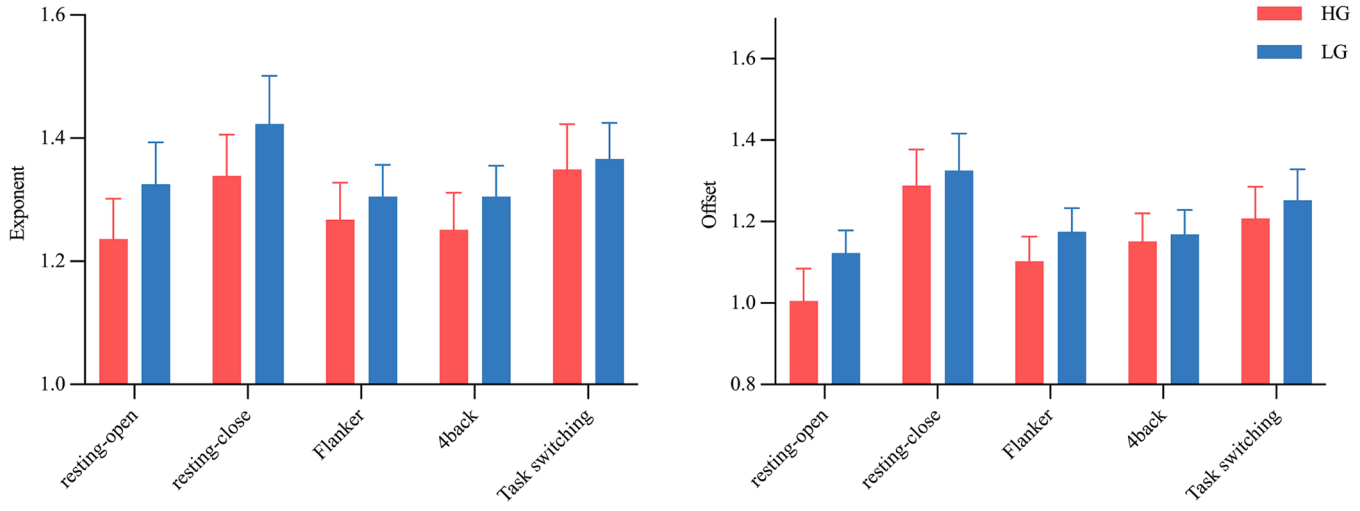

Fig. 1. Comparison of aperiodic components across resting-state and task-state conditions. Group means for the aperiodic exponent and offset are shown for the high-Gf (HG) and low-Gf (LG) groups during resting state (eyes-open and eyes-closed) and across each EF task (Flanker, 4-back, task-switching). Error bars indicate the standard error of the mean (SEM). For the aperiodic exponent, the main effect of task type was significant ($p = .047$), but post-hoc comparisons revealed no significant differences between any task pairs (all $p > .05$). For the aperiodic offset, the main effect of task type was significant ($p < .001$). Post-hoc comparisons (Tukey corrected) indicated that offset in the eyes-closed resting state was significantly higher than in the eyes-open resting state ($p < .001$), the Flanker task ($p = .001$), and the 4-back task ($p = .004$); offset in the eyes-open resting state was significantly lower than in the task-switching paradigm ($p = .035$). No other task comparisons reached significance (all $p > .05$).

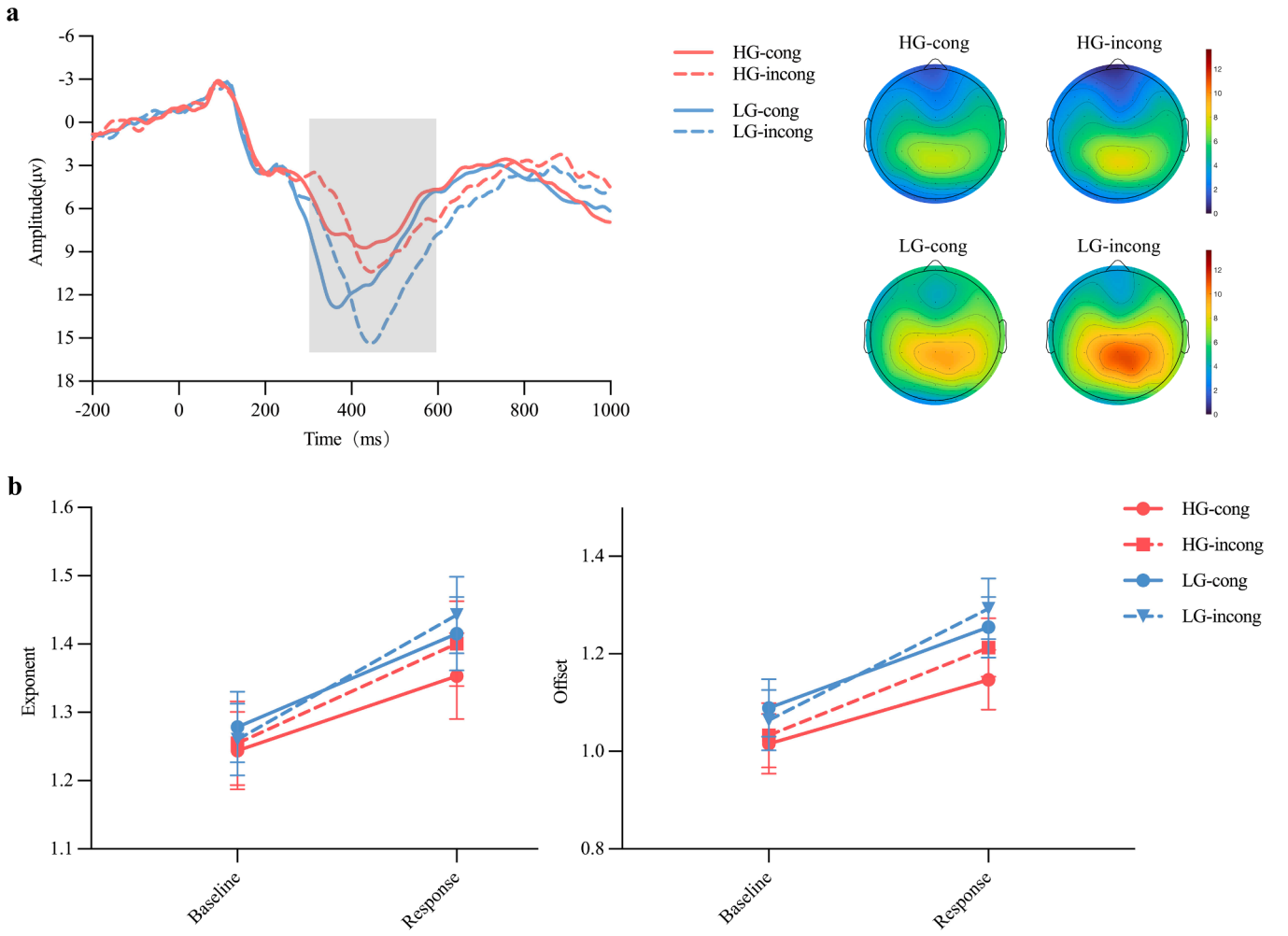

Fig. 2. Flanker task results. (a) Event-related potential (ERP) waveforms at the CPz electrode for the high-Gf (HG) and low-Gf (LG) groups under congruent and incongruent conditions. The shaded region denotes the P3 analysis window (300–600 ms). Topographic maps show the distribution of P3 amplitudes for each group and condition within this window. (b) Aperiodic component results. Line plots show the mean aperiodic exponent and offset during the baseline (−1000–0 ms) and response (0–1000 ms) periods for congruent and incongruent conditions in the HG and LG groups. Error bars indicate SEM. Statistical Summary: Both the exponent and offset showed significant increases from baseline to response period ($p < .001$). A significant task type × group interaction was found for the offset ($p < .05$). Simple effects analysis revealed a significant increase in offset from congruent to incongruent conditions specifically within the high-Gf group ($p < .001$).

between-subject factor.

For the aperiodic exponent, the main effect of time window was significant ($F(1, 48) = 43.653$, $p < .001$, $\eta p^2 = .476$), with the response period showing a significantly higher exponent than the baseline period. No significant main effects or interactions for Gf were found.

For the aperiodic offset, the main effect of time window was significant ($F(1, 48) = 38.001$, $p < .001$, $\eta p^2 = .442$), with the response period showing a significantly higher offset than the baseline period. No significant main effects or interactions for Gf were found. The results for the aperiodic components in this paradigm are shown in Fig. 3-b.

3.5. Task switching paradigm results

Due to excessive artifacts, four high-Gf participants were excluded from the ERP and aperiodic analyses.

3.5.1. EEG amplitude results

A two-way mixed ANOVA was conducted with task type (non-switch vs. switch) as the within-subject factor, Gf (high vs. low) as the between-subject factor, and P3 amplitude as the dependent variable. The results showed no significant interaction between task type and Gf ($F(1, 49) = 0.558$, $p = .459$, $\eta p^2 = .011$). However, the main effect of task type was significant ($F(1, 49) = 8.362$, $p = .006$, $\eta p^2 = .146$), with the non-switch condition showing significantly larger P3 amplitude than the switch condition. The main effect of Gf was significant ($F(1, 49) = 5.642$, $p = .021$, $\eta p^2 = .103$), with the low-Gf group having significantly larger P3 amplitude than the high-Gf group. The ERP waveform and topographic map at the CPz electrode for this paradigm are shown in Fig. 4-a.

3.5.2. Aperiodic component results

Separate three-way mixed ANOVA was conducted for the aperiodic exponent and aperiodic offset, with the time window (baseline vs. response period) and task type (non-switch vs. switch) as within-subject factors, and Gf (high vs. low) as the between-subject factor.

For the aperiodic exponent, the results showed a significant main effect of time window ($F(1, 49) = 175.624$, $p < .001$, $\eta p^2 = .782$), with the response period showing a significantly higher exponent than the baseline period. No significant interactions or main effects for task type or Gf were observed.

For the aperiodic offset, the results showed a significant main effect of time window ($F(1, 49) = 171.846$, $p < .001$, $\eta p^2 = .778$), with the response period showing a significantly higher offset than the baseline period. No significant interactions or main effects for task type or Gf were observed. The results for the aperiodic components in this paradigm are shown in Fig. 4-b.

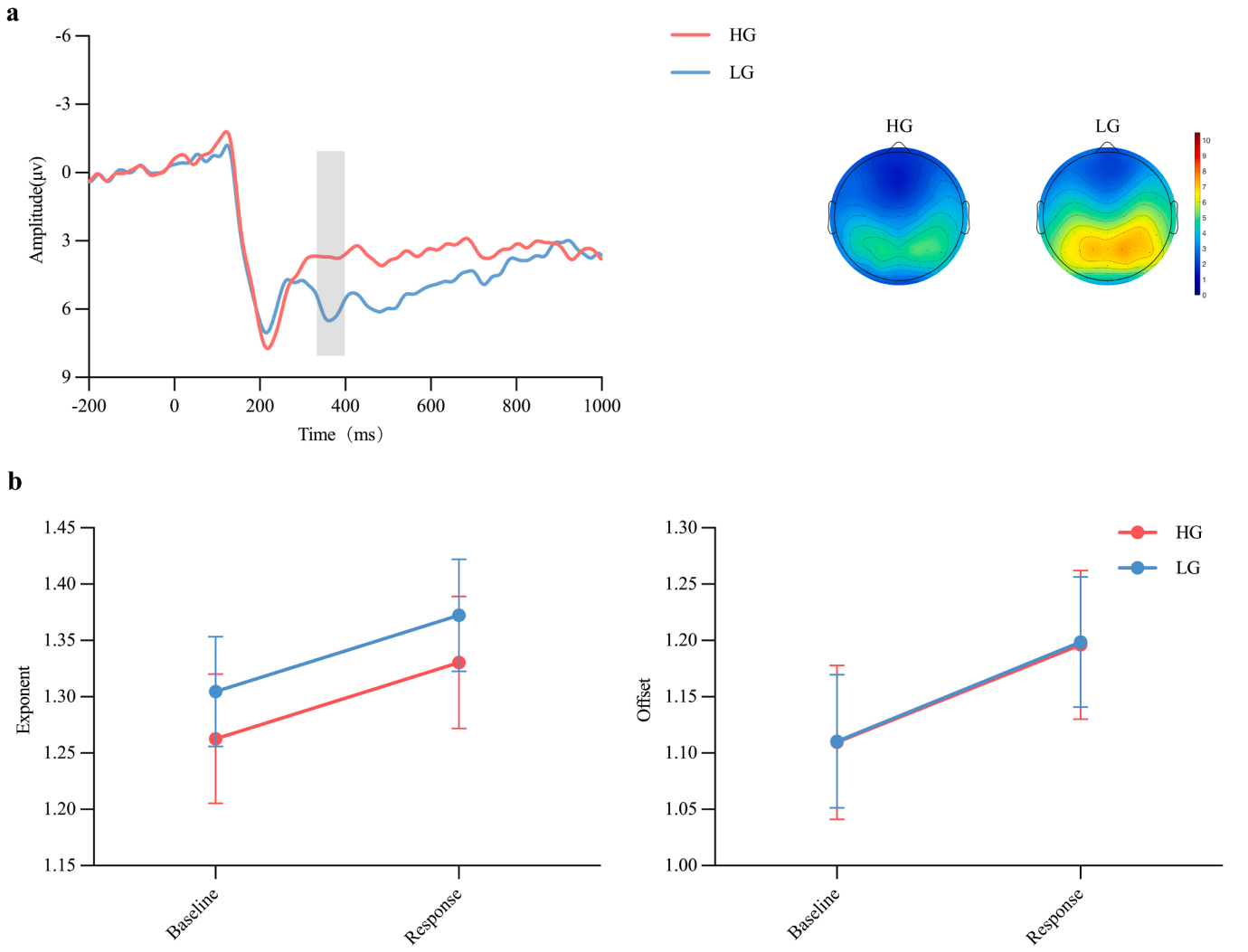

Fig. 3. 4-back task results. (a) ERP waveforms at the CPz electrode for the HG and LG groups. The shaded region denotes the P3 analysis window (340–400 ms). Topographic maps show the distribution of P3 amplitudes for each group within this window. (b) Aperiodic component results. Line plots show the mean aperiodic exponent and offset during the baseline (−1000–0 ms) and response (0–1000 ms) periods in the HG and LG groups. Error bars indicate SEM. Statistical Summary: The P3 amplitude was significantly larger in the low-Gf group ($p < .05$). For aperiodic components, both exponent and offset were significantly higher during the response period compared to the baseline period (both $p < .001$). No other significant effects involving group were observed.

4. Discussion

Based on a multi-task paradigm encompassing the core components of executive functions, this study systematically characterizes distinct neurophysiological activity patterns in adolescents with high versus low Gf. First, the event-related potential (ERP) results showed that the low-Gf group exhibited larger P3 amplitudes in the Flanker, 4-back, and task-switching paradigms. However, no significant differences were found between the two groups in the early components (P1, N1) and conflict monitoring components (N2). These findings suggest that the differences in fluid intelligence primarily manifest in the later stages of cognitive resource allocation, rather than in early perceptual processing or conflict detection. Second, regarding aperiodic neural activity, which reflects the brain's baseline excitability, the study found that only in the Flanker task did the high- and low-Gf groups exhibit different dynamic regulation trajectories of the aperiodic offset, while no significant group differences were observed in the 4-back and task-switching paradigms.

Although the low-Gf group did not show clear overall behavioral disadvantages, this group exhibited larger P3 amplitudes across all three tasks. Previous studies have suggested that P3 amplitude generally reflects the allocation of attentional resources to task-relevant information and the inhibition of task-irrelevant information (Fonken et al., 2020). Therefore, the present findings are consistent with the neural efficiency hypothesis (Haier et al., 1992), which posits that individuals with lower Gf require more cognitive resources to achieve comparable behavioral performance. In this sense, the larger P3 amplitudes observed in the low-Gf group may reflect greater late-stage cognitive resource allocation, whereas the smaller P3 amplitudes in the high-Gf group may indicate relatively more efficient neural resource recruitment during task processing. However, studies on children have shown that high-Gf children exhibit larger P3 amplitudes in cognitive tasks (Luo & Zhou, 2020). We believe this may reflect developmental differences in intelligence: fluid intelligence follows an inverted U-shaped trajectory across the lifespan, peaking around the age of 20 and gradually declining after the age of 30 (Kent, 2017). Children's neurophysiological functions and cognitive abilities have not yet fully matured, which may result in differences in the neural efficiency patterns of cognitive processing when compared to adolescents (Sumich et al., 2012; van Dinteren et al., 2014). Specifically, children's neural networks and cognitive strategies are still developing, which increases the subjective difficulty of cognitive tasks and necessitates greater cognitive resource engagement. Consequently, higher fluid intelligence in children may manifest as a heightened capacity for resource mobilization, leading to larger P3 amplitudes in high-Gf children. For example, in the study by Rico-Picó et al., high-Gf

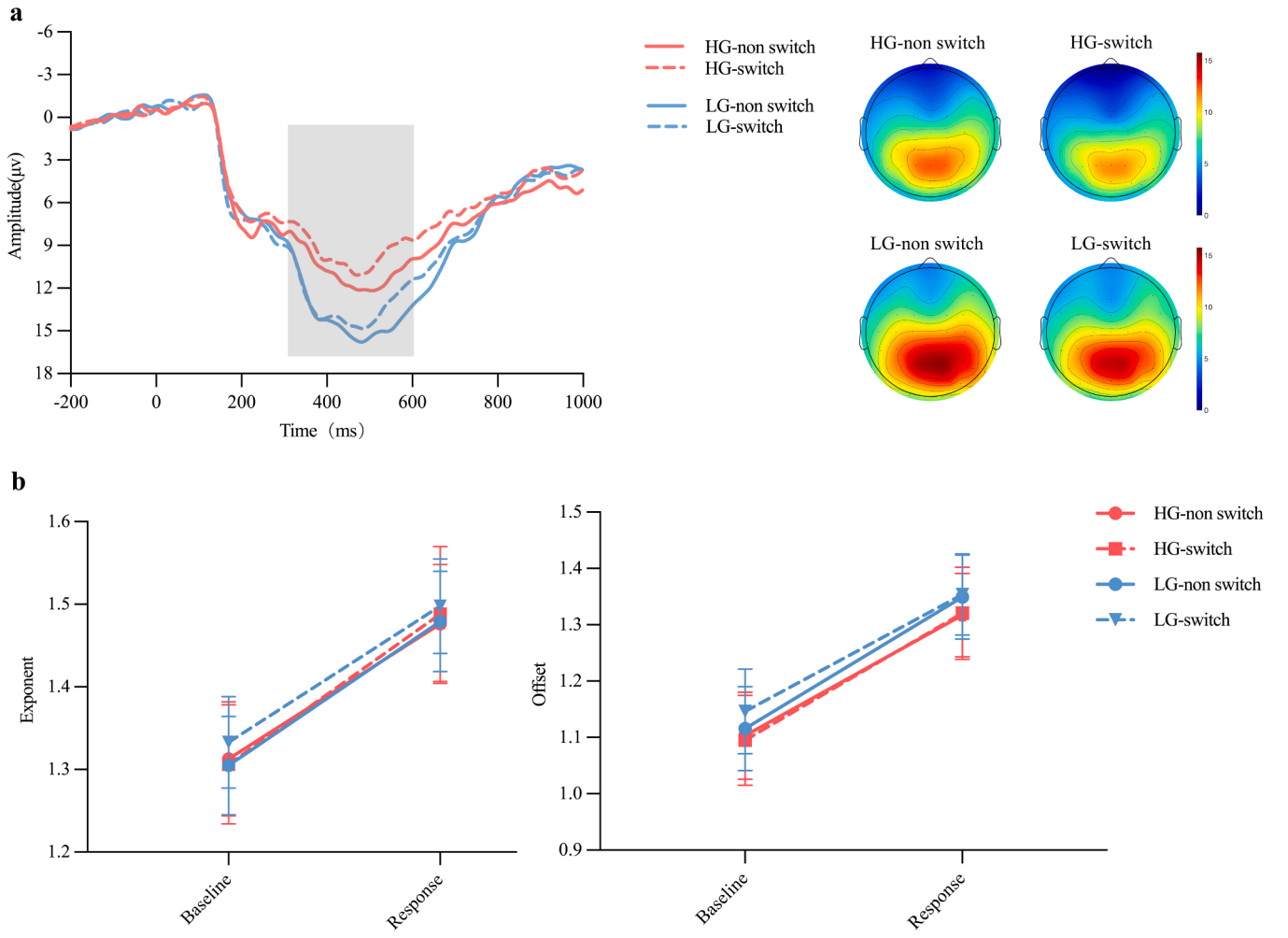

Fig. 4. Task-switching paradigm results. (a) ERP waveforms at the CPz electrode for the HG and LG groups under non-switch and switch conditions. The shaded region denotes the P3 analysis window (300–600 ms). Topographic maps show the distribution of P3 amplitudes for each group and condition within this window. (b) Aperiodic component results. Line plots show the mean aperiodic exponent and offset during the baseline (−1000–0 ms) and response (0–1000 ms) periods for non switch and switch conditions in the HG and LG groups. Error bars indicate SEM. Statistical Summary: P3 amplitude was significantly larger in the low-Gf group ($p < .05$) and during non switch trials ($p < .01$). For aperiodic components, both exponent and offset were significantly higher during the response period compared to the baseline period (both $p < .001$). No significant effects involving group were observed.

children exhibited larger P3 amplitudes in the reactive NoGo condition of an active control task (Rico-Picó et al., 2021). In contrast, adolescents' neural networks and cognitive strategies are more mature, and higher fluid intelligence is more likely to manifest as more efficient resource allocation, resulting in smaller P3 amplitudes in high-Gf adolescents. This is consistent with findings in adult populations (Jia et al., 2023; Wongupparaj et al., 2018). In addition, consistent with previous research (Goffaux et al., 2006), the results of this study show that P3 amplitude in the non-switch condition of the task-switching paradigm is larger than in the switch condition. This may be because task rules are more stable in the non-switch condition, allowing participants to allocate more cognitive resources, reflecting the dynamic allocation of resources within specific task contexts.

Neural noise refers to the random, background electrophysiological fluctuations within the central nervous system, i.e., aperiodic activity (Dave et al., 2018). The aperiodic exponent is considered a reflection of the excitatory-inhibitory balance of neurons: a higher excitation-inhibition (E/I) ratio is associated with a shallower aperiodic exponent, whereas a larger exponent reflects a lower E/I ratio (Gao et al., 2017; Lombardi et al., 2017). According to the neural noise hypothesis, the aperiodic exponent serves as a proxy for the level of intrinsic noise in neural circuits (Dave et al., 2018). Synchronized neuronal firing increases the aperiodic exponent and improves the signal-to-noise ratio (SNR), while asynchronous neuronal firing lowers the aperiodic exponent and reduces the SNR (Voytek et al., 2015). Aperiodic offset is often considered an indicator of neuronal excitability or broadband firing activity, with lower offset values reflecting increased excitability of neuronal populations (Manning et al., 2009).

Consistent with previous studies (Hill et al., 2022), the results of this study show that the aperiodic exponent and offset values in the closed-eye condition were significantly higher than those in the open-eye condition. This state-dependent change validates the effectiveness and sensitivity of aperiodic parameters as indicators of the brain's baseline neurophysiological state. LMMs were used to compare the aperiodic exponent and offset values in open-eye and closed-eye resting states and task states. The results revealed that the aperiodic offset was significantly higher in the closed-eye resting state than in the open-eye resting state, Flanker, and 4-back task states. The offset in the task-switching paradigm was significantly higher than in the open-eye resting state. While the main effect of task type on the aperiodic exponent was significant, post hoc comparisons showed no significant differences between task conditions, which may be due to the aperiodic exponent reflecting the overall excitatory-inhibitory balance in the brain. Therefore, it may be more influenced by resting state or global neural activity and less sensitive to task-specific neural activities. However, no significant main effect differences were found between the

high- and low-Gf groups in the resting-state aperiodic exponent or offset, indicating that, under baseline conditions without task intervention, the brain's overall excitatory-inhibitory balance and population firing activity are not significantly different between the groups of adolescents with high and low fluid intelligence.

Further analysis of the baseline and response periods across all tasks was consistent with previous studies (Zhang et al., 2023). Aperiodic activity during the response period was significantly higher than in the baseline period for all tasks, indicating a close link between aperiodic activity and task state and its capacity for dynamic adjustment according to cognitive demands. Results from both resting and task states reveal the multi-level dynamic characteristics of aperiodic activity as an indicator of the brain's baseline neurophysiological state: it reflects both the global change of the overall state and the specific modulation induced by task demands (Monchy et al., 2024). Moreover, this study found group differences in the Flanker paradigm: under the incongruent condition, the high-Gf group showed a significantly larger aperiodic offset than under the congruent condition. However, the behavioral results showed that, in the Flanker task, the high-Gf group had slower RTs than the low-Gf group under the incongruent condition, whereas the accuracy results did not provide clear evidence of a reliable behavioral advantage for either group. Accordingly, within the present study, this condition-related offset modulation in the high-Gf group may be better understood as a task-specific neural-state adjustment to increased conflict demands, whose functional significance requires further investigation. In contrast, the low-Gf group did not show significant differences between conditions, suggesting relatively limited condition-related adjustment of neural state across conflict conditions.

It is noteworthy that this intelligence-related offset difference was observed only in the Flanker paradigm and not in the 4-back or task-switching paradigms. This phenomenon may be related to the varying dependence of different tasks on the excitation–inhibition balance. Current research shows that aperiodic activity is closely associated with cortical excitation–inhibition balance (Waschke et al., 2021; Gao et al., 2017). Inhibitory control tasks directly involve the suppression of irrelevant information, requiring a higher degree of regulation of the excitation–inhibition balance, and thus more easily reveal individual differences in neural excitability regulation. Working memory (4-back) and cognitive flexibility (task-switching) tasks involve more complex cognitive processes, including information updating, rule switching, and the collaboration of various neural mechanisms, beyond just inhibition control. Therefore, group and condition differences in aperiodic activity may be less apparent in these tasks. This study calculated the correlations between the two variables for each group and task condition (see Supplementary Table S2). The results showed a strong positive correlation across all conditions. However, the primary focus of this study was on discussing the role of aperiodic offset in task modulation and group differences, while the similar change patterns in the exponent did not reach significance. This result may suggest that, within the framework of this study, aperiodic offset is more sensitive to Gf-related neural-state regulation differences in specific cognitive processes. Alternatively, it may reflect differences in the degree of association between the neural physiological processes represented by the exponent and offset and fluid intelligence.

This study also has several limitations: First, as a cross-sectional study, it primarily focused on the adolescent group. However, the neural physiological basis of fluid intelligence may change with age and developmental stage, exhibiting a unique developmental trajectory. Therefore, future research could expand to include children and adult populations to explore neural activity differences across different age stages and their relationship with fluid intelligence. Second, the sample in this study comes from a single regional background, with a high degree of homogeneity in terms of socio-economic and cultural background. Future studies could further examine the robustness of these findings in more diverse demographic samples. Third, the behavioral significance of the observed neural differences should be interpreted with caution, as the behavioral results did not consistently show superior performance in the high-Gf group. This may partly reflect the limited sensitivity of task-level behavioral indices to RSPM-defined Gf differences, as well as task-specific constraints related to task difficulty. Future studies could combine neural measures with model-based analyses of behavioral performance to clarify how Gf-related neural modulation relates to task performance. Fourth, Lamichhane et al. (2020) used fMRI to investigate changes in brain activity with varying N-back load levels. They found that higher N-back load levels (4−6), rather than the commonly used lower levels (1−3), were more sensitive in detecting differences in brain activity patterns and behavior between individuals. Therefore, this study selected an N-back load of 4 to maximize the differences between high- and low-Gf individuals. However, the behavioral results for the 4-back task in this study exhibited a floor effect, indicating that this difficulty level may have been too high for the adolescent group, potentially masking the true differences in working memory performance between the high- and low-Gf groups. Previous studies have demonstrated that even with low accuracy in high-load N-back paradigms, neural responses such as P3 amplitude can still distinguish between load conditions, suggesting that participants maintain cognitive engagement (Scharinger et al., 2017). However, the impact of task difficulty should be further considered, and future research could adopt a gradient difficulty design to systematically examine how working memory load modulates neural activity in individuals with different levels of fluid intelligence across a broader range of task demands. Finally, integrating brain imaging techniques to explore the spatial distribution and functional networks of neural activity will help provide a more comprehensive understanding of the key brain regions and networks involved in the aperiodic regulation and neural resource allocation related to fluid intelligence.

5. Conclusion

In conclusion, the present study provides the following principal findings: High- and low-Gf adolescents exhibit reliable differences in neural resource allocation during executive function tasks, as evidenced by larger P3 amplitudes in the low-Gf group across the Flanker, 4-back, and task-switching paradigms. These findings are consistent with the neural efficiency hypothesis, with Gf-related differences primarily localized to the later stages of cognitive resource integration. Second, aperiodic neural activity differences between groups are task-specific, with the high-Gf group demonstrating greater condition-related modulation of aperiodic offset specifically during inhibitory control tasks. This suggests that aperiodic offset may serve as a sensitive index of the neural-state tuning mechanisms that support inhibitory control. By integrating ERP amplitude and aperiodic activity, this study provides a systematic, multi-faceted characterization of the relationship between fluid intelligence and the neurophysiological representations of executive function in adolescents. These findings offer new evidence and perspectives for understanding the neural resource allocation and neural-state regulation associated with fluid intelligence.

CRediT authorship contribution statement

Haohao Dong: Formal analysis, Data curation. **Yuhui Zhang:** Formal analysis, Data curation. **Renlai Zhou:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Funding acquisition, Conceptualization. **Mingmei Gao:** Writing – original draft, Formal analysis, Data curation. **Yiming Men:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation. **Fang Wang:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation.

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

All content in this paper was independently produced by the authors without the use of any generative AI or AI-assisted technologies. The design, data collection, analysis, and writing of this research were conducted solely by the authors to ensure the accuracy and reliability of the findings.

Declaration of Competing Interest

None.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.biopsycho.2026.109330.

Data availability

Data will be made available on request.

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