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Heterogeneous Decision-Making in ADHD: Computational Subtypes and Their Distinct Prefrontal Connectivity Patterns

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Abstract

Children with ADHD exhibit decision-making deficits characterized by lower efficiency in evidence accumulation and a preference for smaller, sooner rewards in intertemporal choices. This study aimed to explore subtypes of ADHD in children and to investigate differences in prefrontal functional connectivity between ADHD subtypes. A total of 94 children with ADHD and 63 typically developing children matched for gender, age, and IQ were included. All participants completed TCIP and the ADHD Symptom Rating Scale, and 43 children with ADHD underwent resting-state MRI scans. A hierarchical drift-diffusion model was applied to analyze TCIP task performance, followed by second-order cluster analysis to identify decision-making subtypes. Differences in prefrontal functional connectivity among ADHD decision-making subtypes were then compared. The ADHD group showed fewer square selections in the TCIP ($p < 0.001$), lower drift rates (pBayes < 0.001), and shorter non-decision times (pBayes = 0.002). The ADHD decision-making deficit subtype exhibited stronger functional connectivity between the left medial superior frontal gyrus and both the right middle frontal gyrus and the right postcentral gyrus, as well as between the right medial superior frontal gyrus and the right postcentral gyrus (all $p < 0.05$). Our results reveal that children with ADHD exhibit decision-making deficits during intertemporal choice, and these deficits show internal heterogeneity. Abnormal functional connectivity between the medial superior frontal gyrus and the middle frontal gyrus/postcentral gyrus may underlie these decision-making deficits.

Introduction

Attention-Deficit/Hyperactivity Disorder (ADHD) is characterized by significant inattention and hyperactivity-impulsivity, which has a prevalence of approximately 5.6%–7.6% among children and adolescents[1]. ADHD is associated with decision-making deficits[2]. Behaviorally, children with ADHD demonstrate a pronounced preference for smaller and sooner rewards during intertemporal choice[3]. Beyond that, their decision-making patterns are characterized by slower and more variable response times[4, 5].

For complex decisions such as intertemporal choice, integrating choice outcomes with response times through computational modeling can provide deeper insights into the underlying deficits[6]. The Drift Diffusion Model (DDM) offers a robust framework for quantifying these deficits. The DDM conceptualizes decision-making as a noisy process of evidence accumulation toward a threshold[7]. Its key parameters include the drift rate (v, reflecting the efficiency of evidence accumulation), decision threshold (a, indicating response caution), non-decision time (t, encompassing perceptual encoding and motor preparation), and bias (z, reflecting initial preferences)[8]. Applications of the DDM across various paradigms including continuous performance test[9], working memory task[10], stop signal task[11], and Go/No-Go task[12] converge on a core finding: children with ADHD exhibit a lower drift rate, which indicates less efficient evidence accumulation. In contrast to other DDM parameters, such as decision threshold and non-decision time, which show inconsistent results across studies[9, 11, 13], a low drift rate demonstrates notable cross-task stability and specificity.

The low drift rate of ADHD may be related to dysfunction of prefrontal cortex. First, studies indicate that evidence accumulation involves parietal and prefrontal regions, notably the dorsolateral prefrontal cortex (dlPFC)[14–16]. Second, the prevailing neurochemical theory of ADHD posits prefrontal dopamine deficiency, which could lower the neural signal-to-noise ratio and impair efficient evidence accumulation, manifesting as a low drift rate[2]. Finally, prefrontal regions such as the dlPFC, middle frontal gyrus, and inferior frontal gyrus are critically involved in exerting cognitive control and supporting self-control during intertemporal decision-making[17–20].

Taken together, current research has revealed that low drift rate may be a core feature of ADHD and may be related to the function of the prefrontal cortex. Direct research linking the hypothesized core feature of low drift rate of ADHD to PFC functional connectivity, particularly within the ecologically relevant context of intertemporal choice, is lacking. Filling this gap will help deepen understanding of the neuro-psychological characteristics of ADHD. The present study tests the following hypotheses: First, children with ADHD will exhibit a lower drift rate during the intertemporal choice task. Second, this lower drift rate will be associated with abnormal functional connectivity of the prefrontal cortex. Third, the drift rate will mediate the association between prefrontal functional connectivity and intertemporal choice preference.

Method

Participants and study design

This study included 94 children with ADHD aged 6 to 16 years and 63 typically developing (TD) children matched for age, gender, and Intelligence Quotient (IQ). Participants in the ADHD group were diagnosed by a psychiatrist at or above the attending physician level, meeting the DSM-5 diagnostic criteria for ADHD, with the diagnosis further verified using the K-SADS-PL-C DSM-5 interview[21]. Participants in the TD group were also assessed by a psychiatrist at or above the attending physician level to confirm the absence of any current or past psychiatric disorders or family history of psychiatric disorders. Furthermore, they had a total score of less than 4 on items rated as "often" or "always" on the Inattention and/or Hyperactivity-Impulsivity subscales of the ADHD-SRS. Exclusion criteria for both groups included: current severe physical illness; neurological abnormalities; impaired consciousness; severe psychiatric disorders such as childhood schizophrenia and intellectual disability; IQ below 70; inability to complete the study procedures for various reasons (e.g., severe visual impairment). For the ADHD group, additional exclusion criteria were: current use of any central nervous system stimulants, atomoxetine, antipsychotics, or antidepressants.

In this project, children with ADHD and typically developing children completed the TCIP task and underwent the ADHD-SRS assessment. Among them, 43 children with ADHD participated in the fMRI scan.

Measures

ADHD symptoms ADHD Symptom Rating Scale (ADHD-SRS) is a well-validated and reliable parent-rated scale used to assess the severity of ADHD symptoms. It employs a 4-point Likert scale and consists of two subscales: Inattention (IA) and Hyperactivity-Impulsivity (HI), each containing 9 items. Higher scores indicate greater severity of ADHD symptoms[22].

Intertemporal choice task The Two Choice Impulsivity Paradigm (TCIP) has been widely used in research involving children, adolescents, and adults[23, 24]. This intertemporal choice task comprised 50 choice trials. In each trial, a circle and a square appeared randomly on either the left or right side of a white screen. If participants chose and clicked the circle, they had to wait for 5 seconds. The circle then flashed, and a second click was required within the 2-second flashing period to earn 5 points. If participants chose and clicked the square, they had to wait for 15 seconds. The square then flashed, and a second click was required within the 2-second flashing period to earn 15 points. Participants were instructed to accumulate as many points as possible over the 50 trials. The reaction time for each choice and the number of squares selected were recorded.

fMRI Data Acquisition Resting-state fMRI data were acquired using a GE Discovery MR-750 3.0 T scanner with a standard head coil for radiofrequency transmission and signal reception. Scanning parameters for resting-state fMRI were as follows: An 8-minute resting-state functional scan was obtained using a gradient-recalled echo single-shot echo-planar imaging (GRE-SS-EPI) sequence with the following parameters: repetition time (TR) = 2000 ms, echo time (TE) = 30 ms, flip angle (FA) = 90°, slice thickness = 3.2 mm with no gap, matrix size = 64×64, field of view (FOV) = 220×220 mm², 43 axial slices, 240 volumes. To improve localization and co-registration of the fMRI images, high-resolution anatomical images were acquired using a T1-weighted gradient-echo sequence (180 sagittal slices, TR = 6.66 ms, TE = 2.93 ms, inversion time = 450 ms, FA = 8°, slice thickness = 1.0 mm with no gap, matrix size = 256×256, FOV = 256×256 mm²).

Statistical Analysis

Statistical analyses were performed using IBM SPSS Statistics 31 for between-group comparisons, correlation analyses, multiple linear regression, ANOVA, and two-step cluster analysis. Mediation analysis was conducted using PROCESS Model 4. $p < 0.05$ was considered statistically significant.

Statistical Analysis of Behavioral Results The Hierarchical Drift Diffusion Model (HDDM) version 1.0.1RC was used for parameter estimation of TCIP outcomes. Markov Chain Monte Carlo methods were employed to estimate the posterior distributions of the model parameters[7]. Prior to modeling, outlier data and trials with excessively short reaction times (less than 0.2 seconds) were excluded from the task data[25]. Model parameters were generated from 10,000 samples of the posterior distribution, with the first 5,000 samples discarded as burn-in to improve model convergence[26]. It was assumed that 5% of the data consisted of outliers unrelated to the drift-diffusion process, and these outliers were excluded to improve goodness of fit[13]. Eight different models with parameters varying by condition were constructed, as shown in Table 1. Model 5 (with drift rate, decision threshold, and non-decision

time varying by condition), which had the lowest Deviance Information Criterion (DIC) value, was retained for subsequent analysis. The Gelman-Rubin statistics (R_hat) for Model 5 were examined to ensure convergence; the maximum R_hat was 1.029, which is below the acceptable threshold of 1.1[27]. Model 5 demonstrated good fit as evidenced by posterior predictive checks[28]. Bayesian hypothesis testing was then performed on the group differences in the posterior means of each parameter, with pBayes ≥ 95% or pBayes ≤ 5% considered statistically significant[29]. A two-step cluster analysis was conducted using the drift rate parameter, resulting in two decision-making subtypes. ANOVA was performed to compare these subtypes across groups. For post-hoc multiple comparisons, the Bonferroni method was used when variances were homogeneous, and Tamhane's T2 method was applied when variances were heterogeneous.

Table 1
DIC of Different HDDM Models

MODEL1	**Model parameter settings**	**DIC**
	v was allowed to change under different conditions	**25289.88**
MODEL2	v and a were allowed to change under different conditions	25287.07
MODEL3	v and t were allowed to change under different conditions	25286.96
MODEL4	v and z were allowed to change under different conditions	25288.46
MODEL5	v, a and t were allowed to change under different conditions	25285.17
MODEL6	v, a and z were allowed to change under different conditions	25290.21
MODEL7	v, t and z were allowed to change under different conditions	25288.61
MODEL8	v, a, t and z were allowed to change under different conditions	25288.87

Statistical Analysis of Functional Connectivity Functional connectivity (FC) analysis was performed using SPM12 and RESTplus[30] for preprocessing and statistical analysis. The preprocessing steps included: discarding the first 10 time points; slice timing correction; head motion correction (four children with ADHD were excluded due to excessive head motion exceeding the quality control criteria, i.e., translation > 3 mm or rotation > 3°); spatial normalization using the DARTEL approach; spatial smoothing with a 6 mm full-width at half-maximum isotropic Gaussian kernel; linear detrending; nuisance covariate regression (including the 6 head motion parameters, white matter signal, and cerebrospinal fluid signal); and band-pass filtering (0.01–0.08 Hz) to obtain the BOLD time series. Following preprocessing, regions of interest (ROIs) were defined based on the Automated Anatomical Labelling Atlas 3 (AAL3)[31], ROI including the left/right dorsolateral superior frontal gyrus (MNI coordinates: -20, 36, 36; 22, 34, 38), left/right middle frontal gyrus (MNI coordinates: -36, 32, 30; 38, 32, 30), and left/right medial superior frontal gyrus (MNI coordinates: -6, 48, 30; 8, 50, 28). For each ROI, whole-brain voxel-wise FC values were computed as the Pearson's correlation coefficient between the ROI's mean time series and the time series of every other voxel. The resulting FC maps were then

converted to z-scores using Fisher's z-transformation to obtain zFC maps. Subsequently, multiple regression analyses[32] were conducted with the zFC maps as the dependent variable and the model parameters (drift rate, decision threshold, and non-decision time) as independent variables. This data-driven approach was used to identify functional connections between brain regions associated with the drift rate. Multiple comparison correction was applied using the family-wise error rate (FWE) correction at a cluster level (voxel-level threshold $p < 0.001$, cluster-level threshold $p < 0.05$). Finally, the FCs were compared between the ADHD decision-making subtypes.

Result

Sample characteristics

This study included 94 children with ADHD and 63 TD children. There were no significant differences in gender, age, and IQ between the ADHD group and the TD group. The IA, HI, and total scores of ADHD-SRS in the ADHD group were significantly higher than those in the TD group, and the results are shown in Table 2.

Table 2
Sample characteristics of ADHD group and TD group

N(male%)	**ADHD**	**TD**		
	94(61.7%)	**63(52.4%)**	**χ^2 = 1.345**	***p* = 0.246**
Age	8.93 ± 1.94	8.59 ± 1.51	*t* = -1.169	*p* = 0.244
Intelligence Quotient	112.21 ± 16.96	113.01 ± 11.79	*t* = 0.347	*p* = 0.729
ADHD-SRS				
IA	28.07 ± 4.13	16.06 ± 4.58	*t* = -17.113	*p* < 0.001***
HI	22.13 ± 6.18	15.70 ± 4.55	*t* = -7.071	*p* < 0.001***
Total scores	50.20 ± 8.38	31.76 ± 8.46	*t* = -13.463	*p* < 0.001***
* *p* < 0.05;**p < 0.01***p < 0.001				

Intertemporal choice preferences

The number of squares in the TCIP for the ADHD group were 23.03 ± 16.98, and for the TD group, it were 36.33 ± 11.45. The number of squares in the ADHD group were less than that in the TD group ($t = 5.861$, $p < 0.001$).

The multiple regression model was shown in Table 3. Collinearity statistics indicated that multicollinearity was not a concern (VIF 1.028–1.838, tolerance 0.544–0.973). The predictor variables could explain 12.3% of the variance in the number of squares (adjusted $R^2 = 0.123$, $F = 5.359$, $p < 0.001$).

Gender and IA had significant independent predictive effects on the number of squares, while the other variables had no significant predictive effects on the number of squares.

Table 3
the number of squares multiple regression analysis model

Outcome variable	the number of squares		
	b	***β***	***p***
Constant	21.363		< 0.001***
Sex	5.959	0.181	0.019*
Age	0.422	0.046	0.567
IQ	0.090	0.083	0.281
ADHD-SRS			
IA	-0.815	-0.364	< 0.001***
HI	0.187	0.073	0.472
* $p < 0.05$;** $p < 0.01$***$p < 0.001$			

HDDM parameters

- The drift rate and non-decision time in the ADHD group were significantly lower than those in the TD group [drift rate: v(ADHD) = -0.07 ± 0.08, v(TD) = 0.54 ± 0.09, pBayes(ADHD > TD) < 0.001; non-decision time: t(ADHD) = 0.81 ± 0.03, t(TD) = 0.92 ± 0.03, pBayes(ADHD > TD) = 0.002]. There was no statistically significant difference in the decision threshold between the two groups [threshold: a(ADHD) = 3.05 ± 0.08, a(TD) = 3.02 ± 0.10, pBayes(ADHD > TD) = 0.401] (Fig. 1).

- For the significant differences in the drift rate and non-decision time between the two groups, we conducted multiple regression analysis. Collinearity statistics indicated that multicollinearity was not a concern (VIF 1.028–1.838, tolerance 0.544–0.973). The predictor variables explained 16.2% of the variance in the drift rate (adjusted $R^2 = 0.162$, $F = 7.050$, $p < 0.001$). Gender and IA had significant independent predictive effects on the drift rate, while the other variables had no significant independent predictive effects on the drift rate. When the non-decision time was used as the dependent variable, the predictor variables explained 17.8% of the variance in the non-decision time (adjusted $R^2 = 0.178$, $F = 7.741$, $p < 0.001$). Gender, age, IQ, and IA had significant independent predictive effects on the non-decision time, and HI had no significant independent predictive effect on the non-decision time. Full results of the multiple linear regression analyses are shown in Table 4.

Table 4
Multivariate regression model for drift rate(v) and non-decision time(t)

Outcome variable	**v**			**t**		
	b	***β***	***p***	**b**	***β***	***p***
Constant	-0.04		0.950	1.401		< 0.001***
Sex	0.280	0.183	0.015*	0.074	0.188	0.011*
Age	0.040	0.095	0.229	-0.035	-0.323	< 0.001***
IQ	0.003	0.058	0.438	-0.002	-0.161	0.031*
ADHD-SRS						
IA	-0.043	-0.410	< 0.001***	-0.005	-0.197	0.046*
HI	0.006	0.052	0.601	0.001	0.031	0.544
* $p < 0.05$;** $p < 0.01$***$p < 0.001$						

Cluster Analysis Based on Drift Rate

- A two-step cluster analysis was performed based on the drift rates of 157 participants. The average silhouette coefficient was 0.70, indicating good clustering quality. Cluster 1 included 101 participants (64.3%) with a drift rate of -0.30 ± 0.46 and was defined as the “decision-making defect subtype”, comprising 70 participants with ADHD and 31 typically developing (TD) participants. Cluster 2 included 56 participants (35.7%) with a drift rate of 1.02 ± 0.33 and was defined as the “decision-making normal subtype”, comprising 24 participants with ADHD and 32 TD participants.
- The IA score was 28.09 ± 4.38 in the ADHD decision-making defect subtype, 28.04 ± 3.36 in the ADHD decision-making normal subtype, 16.77 ± 4.49 in the TD decision-making defect subtype, and 15.38 ± 4.62 in the TD decision-making normal subtype. One-way ANOVA revealed a significant main effect of group[$F(3, 153) = 97.950$, $p < 0.001$]. Post hoc analyses showed that both TD decision-making subtypes had significantly lower IA scores than the two ADHD decision-making subtypes, whereas no significant differences were observed between the two ADHD subtypes or between the two TD subtypes (Fig. 2).The HI score was 22.51 ± 6.31 in the ADHD decision-making defect subtype, 21.00 ± 5.76 in the ADHD decision-making normal subtype, 15.87 ± 4.27 in the TD decision-making defect subtype, and 15.53 ± 4.87 in the TD decision-making normal subtype. One-way ANOVA also revealed a significant main effect of group[$F(3, 153) = 17.053$, $p < 0.001$]. Post hoc analyses indicated that both TD decision-making subtypes had significantly lower HI scores than the two ADHD subtypes, whereas no significant differences were found between the two ADHD subtypes or between the two TD subtypes (Fig. 2).

The number of squares were 15.00 ± 10.88 in the ADHD decision-making defect subtype, 46.46 ± 6.49 in the ADHD decision-making normal subtype, 26.23 ± 6.80 in the TD decision-making defect subtype, and 46.13 ± 4.05 in the TD decision-making normal subtype. One-way ANOVA revealed a significant main effect of group[$F(3, 153) = 141.404$, $p < 0.001$]. Post hoc analyses showed that the ADHD decision-making defect subtype exhibited the lowest number of square. In addition, the TD decision-making defect subtype had fewer square than both the ADHD decision-making normal subtype and the TD decision-making normal subtype, whereas no significant difference was observed between the latter two groups (Fig. 3).

Figure 3 Group differences in the number of squares among the decision-making subtypes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Functional connectivity analysis results

Multiple regression analysis revealed several FCs between brain regions that were negatively correlated with the drift rate (FWE-corrected), as shown in Fig. 4a. After controlling for gender, age, and IQ, these negative correlations remained significant (all $p < 0.01$).

Among the 39 children with ADHD included in the FC analysis, 27 were classified as the ADHD decision-making defect subtype, and 12 as the ADHD decision-making normal subtype. There were no significant differences in gender, age, and IQ between the two groups (gender: $\chi^2 = 1.551$, $p = 0.213$; age: $t = -0.524$, $p = 0.603$; IQ: $t = -1.768$, $p = 0.085$). We then compared the FCs of the regions identified above between the two subtypes, as shown in Fig. 4b. The ADHD decision-making defect subtype exhibited stronger FC between the left medial superior frontal gyrus and both the right middle frontal gyrus and the right postcentral gyrus, as well as between the right medial superior frontal gyrus and the right postcentral gyrus (all $p < 0.05$).

After controlling for sex, age, and IQ, the number of squares were negatively correlated with the FC between the left medial superior frontal gyrus and the right middle frontal gyrus ($r = -0.424$, $p = 0.010$), the FC between the left medial superior frontal gyrus and the right postcentral gyrus ($r = -0.489$, $p = 0.002$), and the FC between the right medial superior frontal gyrus and the right postcentral gyrus ($r = -0.481$, $p = 0.003$).

In the mediation analyses controlling for sex, age, and IQ, drift rate (v) was included as the mediator. The FC between the left medial superior frontal gyrus and the right middle frontal gyrus significantly negatively predicted v (β = -2.081, SE = 0.596, $p = 0.001$, 95% CI [-3.292, -0.870]), and v significantly positively predicted the number of squares (β = 21.125, SE = 1.732, $p < 0.001$, 95% CI [17.601, 24.650]). After including the mediator, the direct effect of the FC between the left medial superior frontal gyrus and the right middle frontal gyrus on the number of squares was no longer significant (β = 5.949, SE = 7.015, p = 0.403, 95% CI [-8.323, 20.222]), the indirect effect was significant (BootSE = 11.506, 95% bootstrap CI [-66.232, -19.531]).The FC between the left medial superior frontal gyrus and the right postcentral gyrus also significantly negatively predicted v (β = -2.440, SE = 0.578, $p < 0.001$), and v significantly positively

predicted the number of squares (β = 21.390, SE = 1.831, $p < 0.001$). After including the mediator, the direct effect of the FC between the left medial superior frontal gyrus and the right postcentral gyrus on the number of squares was not significant (β = 7.222, SE = 7.612, $p = 0.350$), the indirect effect remained significant (BootSE = 10.975, 95% CI [-79.587, -35.277]).Similarly, the FC between the right medial superior frontal gyrus and the right postcentral gyrus significantly negatively predicted v (β = -2.934, SE = 0.669, $p < 0.001$), and v significantly positively predicted the number of squares (β = 21.880, SE = 1.828, $p < 0.001$). After including the mediator, the direct effect of the FC between the right medial superior frontal gyrus and the right postcentral gyrus on the number of squares was not significant (β = 12.259, SE = 8.924, $p = 0.179$). The indirect effect was significant (BootSE = 14.968, 95% CI [-103.588, -42.015]).

Discussion

This study employed hierarchical drift diffusion modeling to quantify intertemporal choice in children with ADHD. We utilized cluster analysis to identify computational subtypes based on decision-making within the ADHD and explored their associated neuropsychological profiles and neural correlates.

Consistent with prior meta-analytic findings[3], children with ADHD demonstrated a stronger preference for smaller, sooner (SS) rewards. This preference may reflect a combined influence of delay aversion and an impulsive drive for immediate reward[33]. Notably, the severity of attention-deficit symptoms was the primary correlate of this SS preference in our task, aligning with findings from study using the MIDA paradigm[34].

By using HDDM, this study revealed a significantly lower drift rate in children with ADHD, indicating less efficient evidence accumulation during decision-making[8]. This finding is consistent with results across various other cognitive tasks[9–12, 35], supporting the view that low drift rate may represent a core cognitive feature in ADHD[6]. The drift rate was specifically associated with attention-deficit symptoms, a correlation also reported in another study[36]. Developmental research indicates that improvements in drift rate with age are linked to reductions in attentional problems[37]. We hypothesize that spontaneous attentional fluctuations, potentially related to default mode network dysregulation, may disrupt efficient evidence accumulation[9]. Furthermore, children with ADHD exhibited shorter non-decision time, suggesting faster motor initiation or perceptual encoding stages[8], which was also related to attention deficits. Poor motor coordination may lead to prolonged non-decision time, as we found that older age is associated with shorter non-decision time, indicating developmental improvements in motor and perceptual processes[13, 37].

Cluster analysis delineated two distinct decision-making subtypes characterized primarily by high versus low drift rate. The ADHD decision-making defect subtype showed the most pronounced preference for small-soon (SS) rewards, indicating internal heterogeneity in ADHD at the behavioral level of decision-making. Functional connectivity analysis revealed that, compared to the ADHD decision-making normal subtype, the ADHD decision-making defect subtype exhibited specifically enhanced between the

left/right superior frontal gyrus and the right postcentral gyrus, as well as enhanced FC between the left medial superior frontal gyrus and the right middle frontal gyrus. Moreover, these functional connectivities were negatively correlated with drift rate. Notably, we found that the association between these functional connectivities and preference for SS rewards was fully mediated by drift rate. Given the role of the prefrontal cortex in cognitive control[38] and the role of the postcentral gyrus in primary somatosensory processing[39], this hyper-connectivity may reflect ineffective filtering of task-irrelevant sensory information. Such neural noise could interfere with evidence accumulation, leading to a lower drift rate[7]. Similarly, altered functional connectivity within the prefrontal network may disrupt the integrative processes necessary for decision-making. These findings align with evidence implicating the prefrontal cortex as a key node in the evidence accumulation network[14–16]. We propose that in ADHD, enhanced FC between the left/right superior frontal gyrus and the right postcentral gyrus, as well as enhanced FC between the left medial superior frontal gyrus and the right middle frontal gyrus, interferes with the evidence accumulation process during decision-making, thereby leading to a stronger preference for SS rewards.

Limitations and future research

Decision-making was assessed using a single task. Future studies should employ multiple decision-making paradigms to provide a more comprehensive characterization. The neuroimaging analysis was based on a relatively small sample of 39 children with ADHD, which may affect the generalizability and reliability of the FC findings[40]. Replication in larger samples is essential in the future. Our FC analysis was restricted to selected prefrontal regions. A whole-brain exploratory approach in future research could provide a more systematic understanding of the neural circuitry underlying decision-making deficits in ADHD.

Conclusion

This study found that children with ADHD demonstrate a preference for smaller, sooner rewards and lower efficiency in decision evidence accumulation during intertemporal choices. There is heterogeneity in decision-making deficits among children with ADHD. Abnormal functional connectivity between the medial superior frontal gyrus and the middle frontal gyrus/postcentral gyrus may underlie decision-making deficits in children with ADHD.

Declarations

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Ethical Information Ethics approval for this study was granted by the Peking University Sixth Hospital Review Board on November 26, 2022. Parents or guardians gave written informed consent, and

adolescents provided assent to participate.

Data availability statement The data from this study are available from the corresponding author upon reasonable request.

Declarations The authors have declared that they have no competing or potential conflicts of interest.

Author contributions HHH, LL, and QJQ conceived and designed the study. HHH, ZYY, and HML performed data collection, data curation and statistical analyses. HHH wrote the main manuscript. ZYY, YFW, LL, and QJQ edited the manuscript. YFW, LL, and QJQ co-supervised this project. All authors read and approved the final manuscript.

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Figures

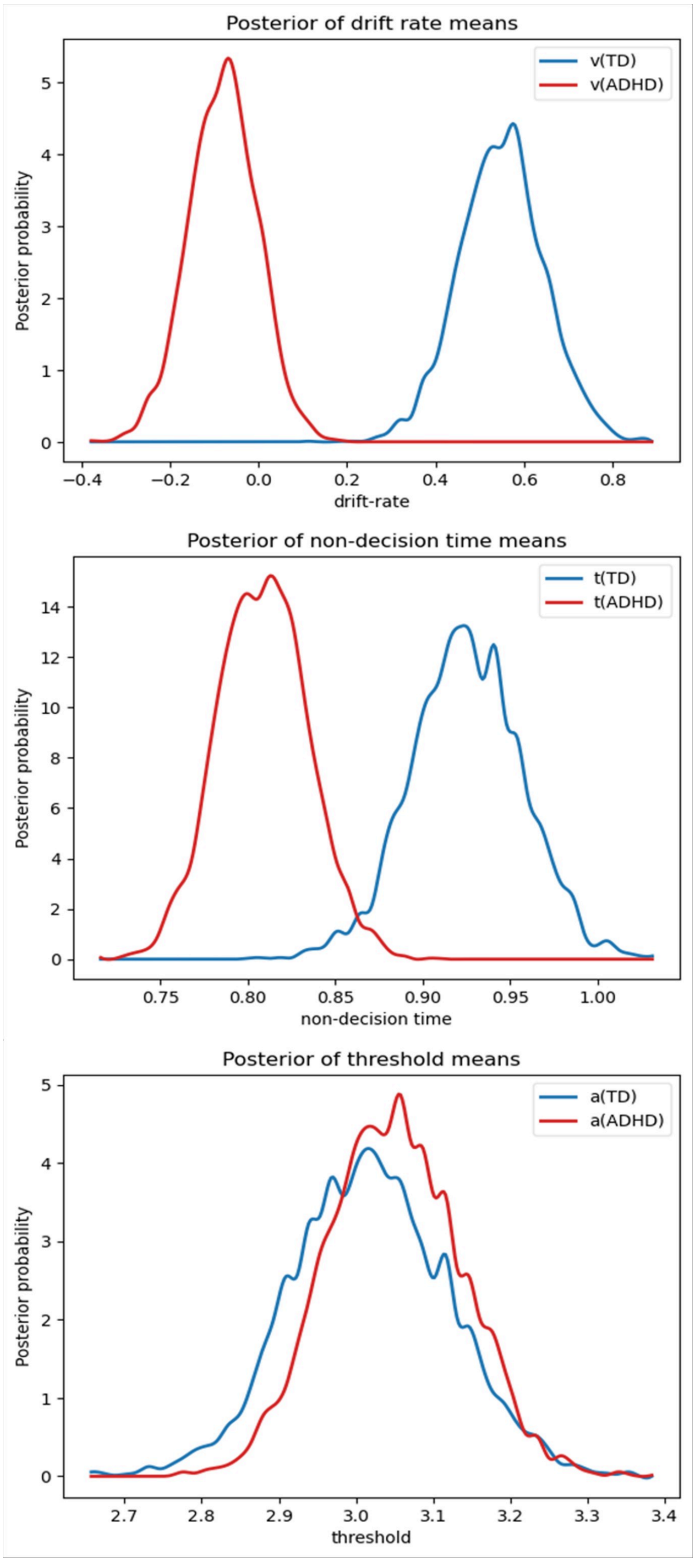


Figure 1

Posterior probability of HDDM parameters for the ADHD group and the TD group

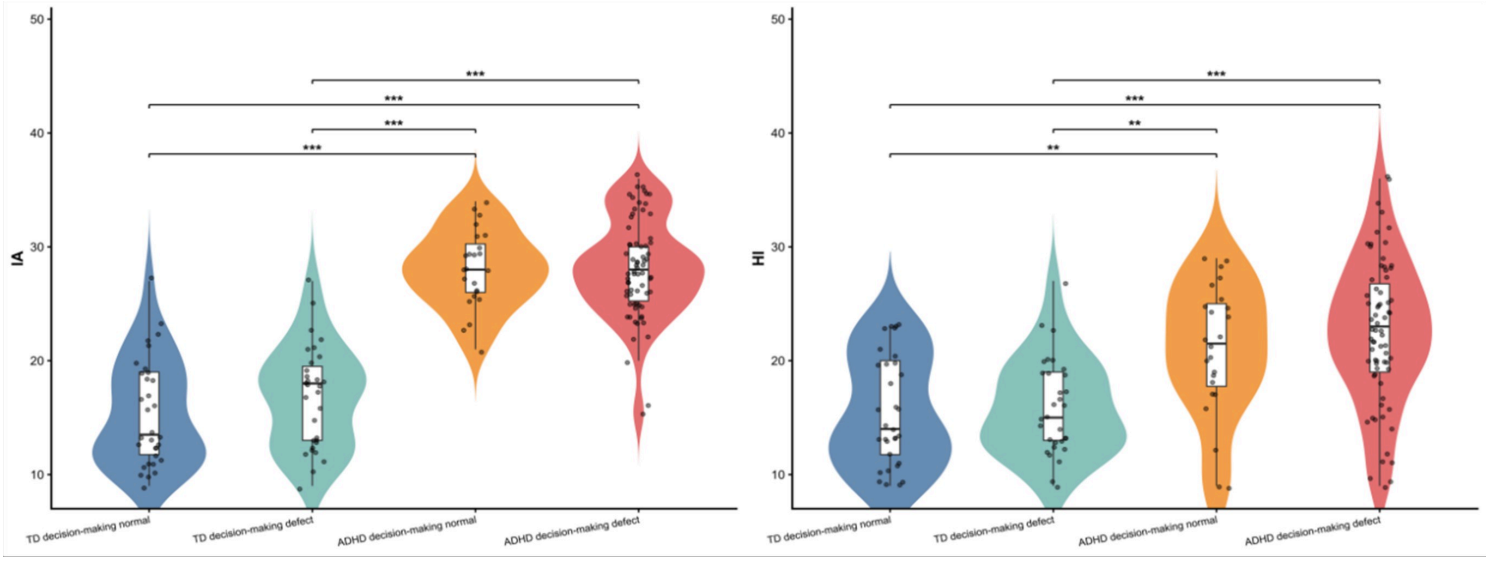


Figure 2

Group differences in ADHD-SRS scores among the decision-making subtypes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

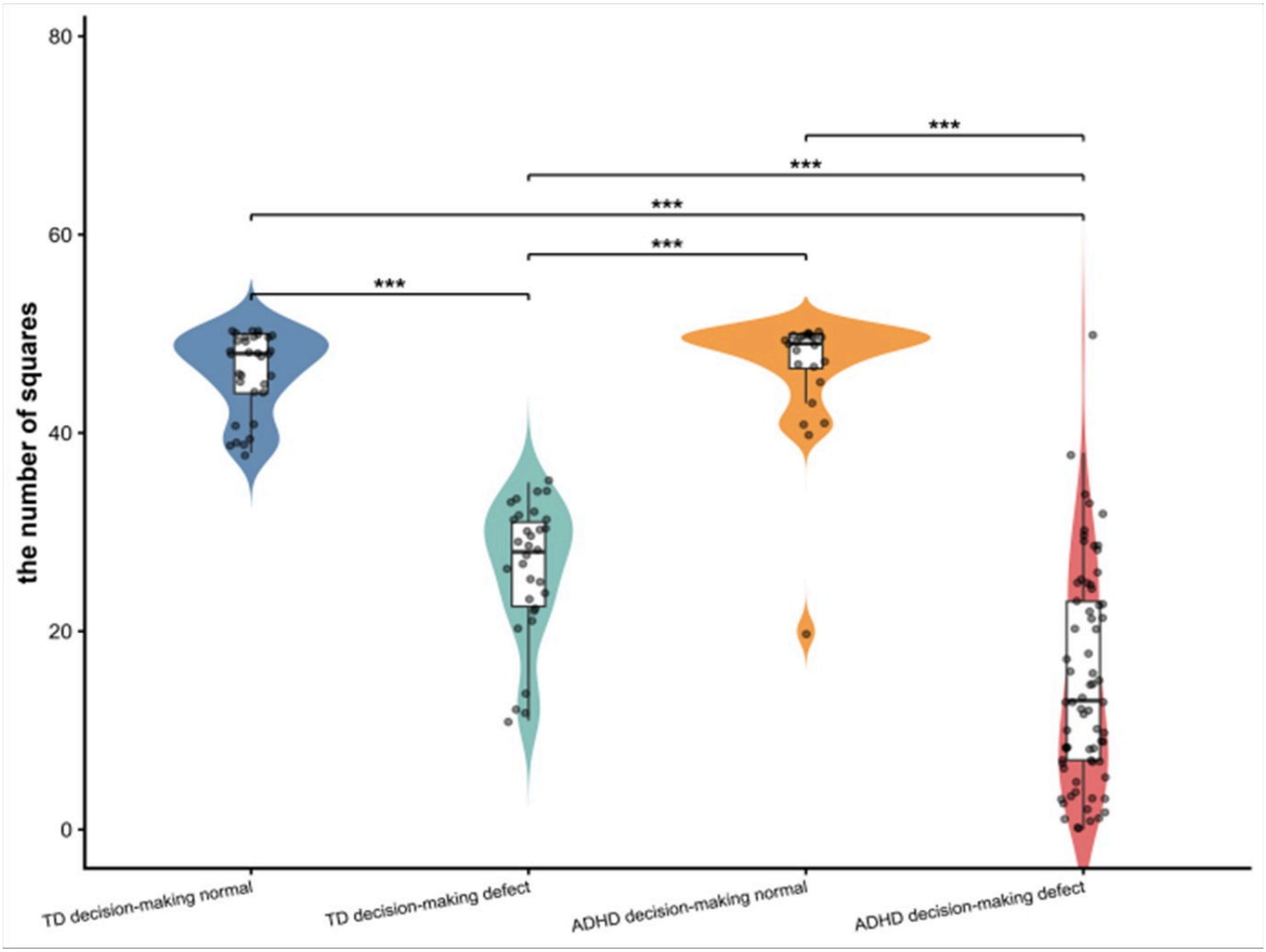


Figure 3

Group differences in the number of squares among the decision-making subtypes. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

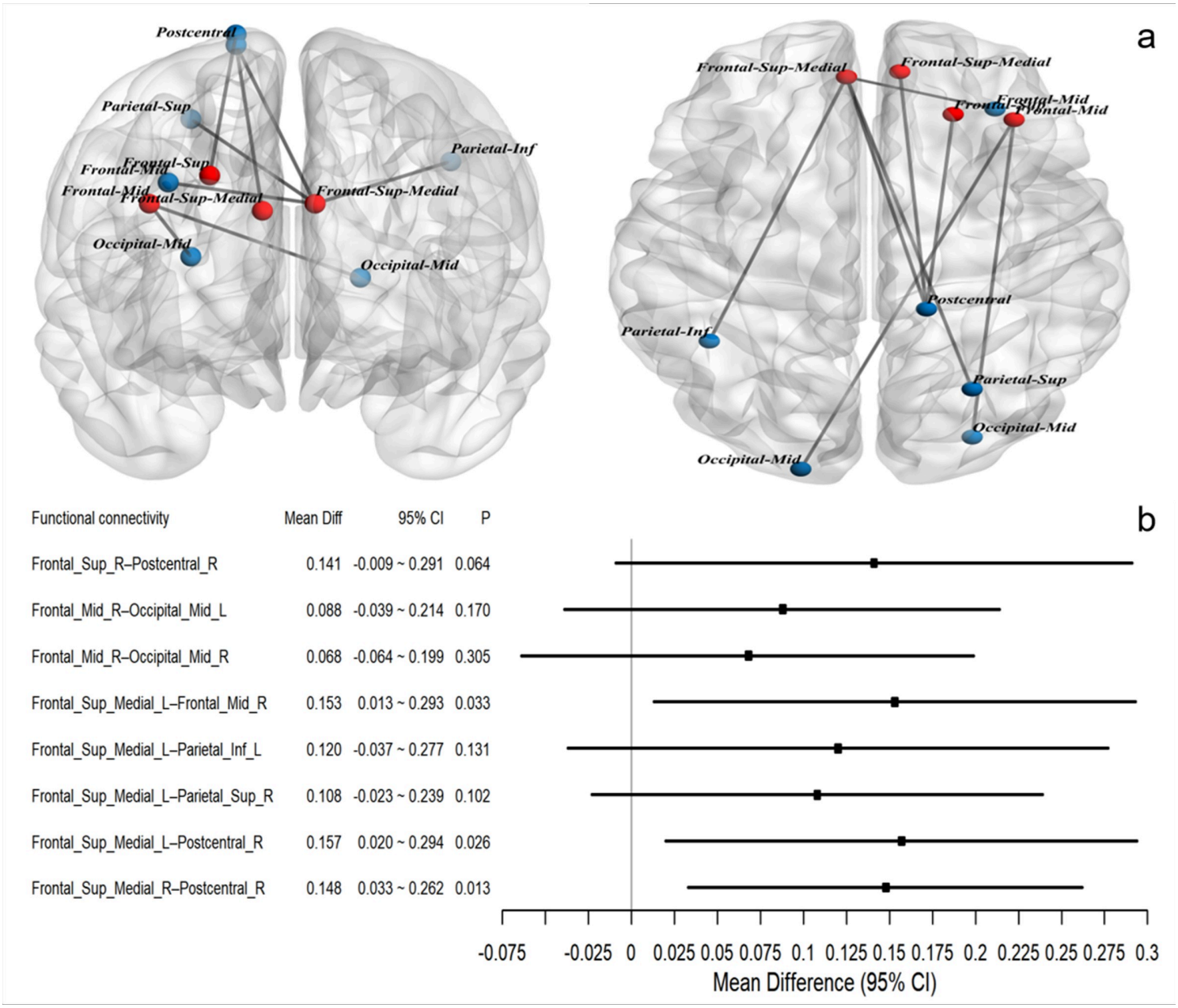


Figure 4

(a): The FCs correlated with the drift rate. The red areas represent the regions of interest; (b): Forest plot showing mean difference in the FCs between ADHD decision-making subtypes. Frontal_Sup: superior frontal gyrus; Postcentral: postcentral gyrus; Frontal_Mid: middle frontal gyrus; Occipital_Mid:middle occipital gyrus; Frontal_Sup_Medial: medial superior frontal gyrus; Parietal_Inf: inferior parietal gyrus; Parietal_Sup: superior parietal gyrus; Frontal_Sup_Medial: medial superior frontal gyrus.

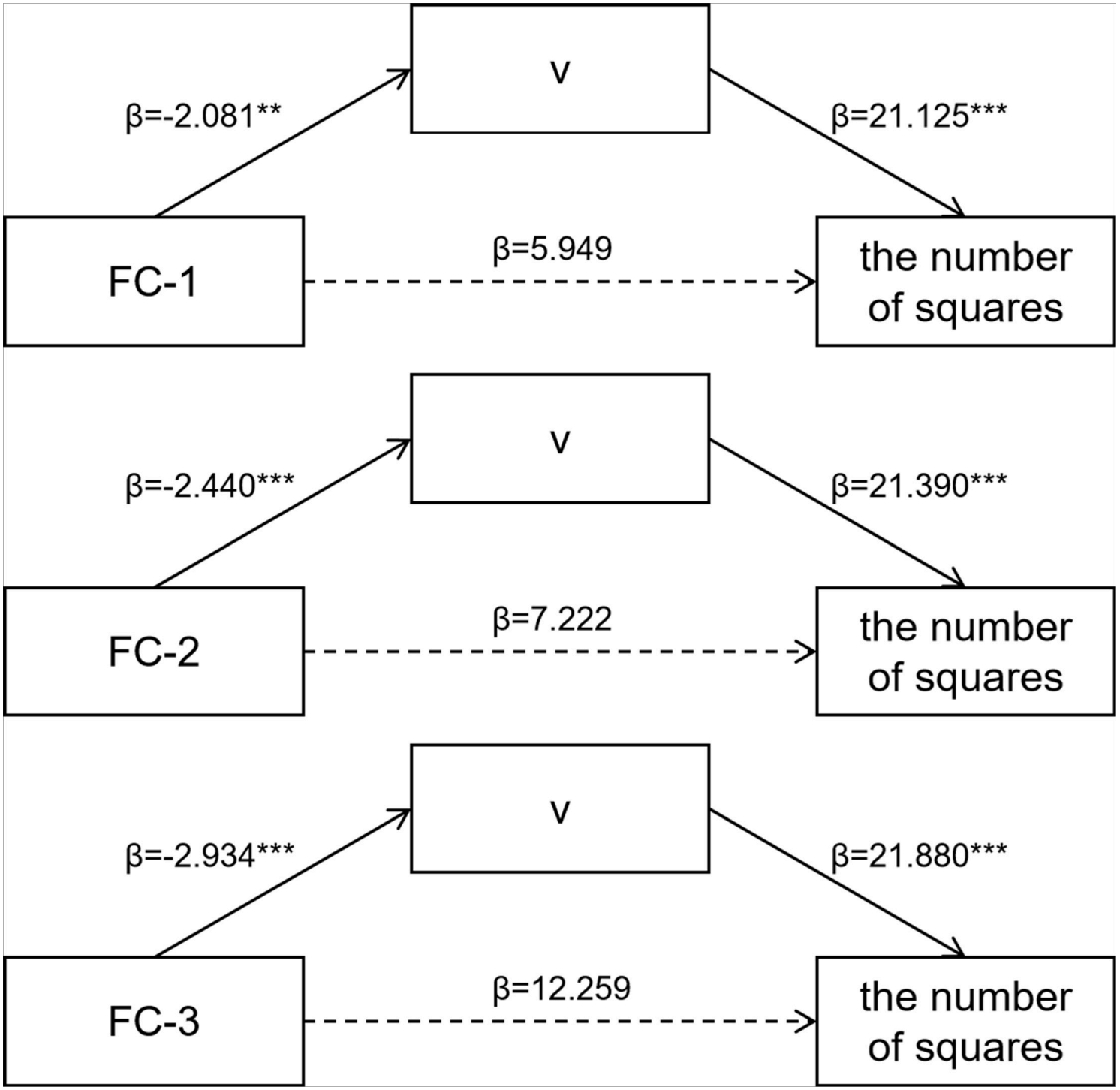


Figure 5

Mediation models of FC, drift rate (v), and the number of squares. FC-1: the FC between the left medial superior frontal gyrus and the right middle frontal gyrus; FC-2: the FC between the left medial superior frontal gyrus and the right postcentral gyrus; FC-3: the FC between the right medial superior frontal gyrus and the right postcentral gyrus. v: the drift rate.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.