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Long-term exposure to major constituents of $PM_{2.5}$ and executive function among children and adolescents in China☆

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ABSTRACT

Epidemiological evidence regarding the effects of long-term exposure to fine particulate matter ($PM_{2.5}$) constituents on executive function (EF) in children and adolescents is limited. This cross-sectional study analyzed 67,622 children and adolescents aged 5–18 from China (2020–2021) and calculated the five-year average concentrations of $PM_{2.5}$ and its six constituents using the ChinaHighAirPollutants (CHAP) dataset. EF was assessed using the parent-completed Behavioral Rating Inventory of Executive Function (BRIEF). Generalized linear mixed models and weighted quantile sum regression were applied to evaluate the potential effects of individual $PM_{2.5}$ components and their mixtures. Long-term exposure to $PM_{2.5}$ and its components was linked to poorer EF (e.g., global executive composite (GEC) and metacognition index). For example, compared with the lowest quartile, the highest quartiles of $PM_{2.5}$ components were linked to higher risks for GEC dysfunction (e.g., odd ratio (OR) was 1.23 (1.05, 1.44) for ammonium (NH_4^+), 1.14 (1.01, 1.29) for organic matter (OM) and 1.18 (1.05, 1.32) for black carbon (BC)). Similarly, joint exposure to $PM_{2.5}$ constituents was related to GEC dysfunction (OR = 1.08 (1.03, 1.13)), with BC and NH_4^+ contributing more significantly to the association. Additionally, children under 12 years and those with parental education levels below high school appear to be more susceptible to the effects of $PM_{2.5}$ constituents. In conclusion, the reduction of combustion-related BC and NH_4^+ may reduce the burden of $PM_{2.5}$-related executive dysfunction in children and adolescents.

1. Introduction

Executive function (EF) commonly refers to “higher-order” cognitive function, which comprises a set of interrelated core skills, including but not limited to behavioral regulation and metacognition (Diamond, 2013). EF deficiency is inextricably linked to a variety of neurological, psychological, and behavioral abnormalities. For example, the prevalence of executive dysfunction in children with attention deficit

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hyperactivity disorder (ADHD) ranges from 50 % to 83 % (Lambek et al., 2011). These high-level cognitive skills originate in the early years of life and increase substantially during primary school (Luna et al., 2010). Additionally, several environmental, socioeconomic, and behavioral risk factors have been identified as contributors to executive dysfunction (Yang et al., 2024). Therefore, identifying and addressing modifiable risk factors during childhood, particularly environmental ones, is crucial, as they may play a significant role in the primary prevention of executive dysfunction.

Increasing evidence has demonstrated the negative association between air pollution and EF in children and adolescents, specifically atmospheric fine particulate matter ($PM_{2.5}$) (Cserbik et al., 2020; Forns et al., 2017; Gui et al., 2020; Ni et al., 2024; Wang et al., 2023). For example, exposure to $PM_{2.5}$ during childhood was associated with decreased learning and memory functions (Medrano et al., 2022), attention reduction (Shin et al., 2019), and impaired intelligence (Russ et al., 2021). Nevertheless, $PM_{2.5}$ is a complicated mixture of chemical components, and its toxicity depends largely on its specific composition. To facilitate the targeting of pollution control efforts, the World Health Organization (WHO) has attached great importance to determining which components of $PM_{2.5}$ may be the most hazardous (Shi et al., 2023). Previous studies on exposure to $PM_{2.5}$-specific components and EF in children and adolescents are limited, with most research focusing primarily on a few constituents, such as black carbon (Alvarez-Pedrerol et al., 2017; Cowell et al., 2015) and elemental carbon (Alemany et al., 2018; Forns et al., 2017; Sunyer et al., 2015; Sunyer et al., 2017). Moreover, elucidating the potential associations between $PM_{2.5}$ constituents and executive dysfunction in children and adolescents has been challenging due to the scarcity of accurate chemical constituent measurements and the insidious characteristics of executive dysfunction.

To address the aforementioned gaps, we established a large cross-sectional study in southern China to investigate the link between long-term exposure to key components of $PM_{2.5}$ and executive dysfunction in children and adolescents. Our findings aim to provide evidence for developing preventive measures against executive dysfunction from an environmental perspective and suggest future research directions to uncover the mechanisms linking $PM_{2.5}$ constituents and executive function.

2. Method

2.1. Study populations

All subjects (n = 69,610) were selected from the Four City Study in the Pearl River Delta region of China, a large cross-study designed to examine the impacts of environmental chemicals on health outcomes, which has been previously described in detail elsewhere (Wu et al., 2024; Zhang et al., 2021). The Behavior Rating Inventory of Executive Function (BRIEF), completed by parents, was used for children and adolescents aged 5–18 years. Participants over the age of 18 years (N = 70), individuals with unavailable BRIEF scores (N = 1650), and subjects with incomplete data (N = 268) were excluded. The final sample comprised a total of 67,622 children and adolescents (Fig. S1). The data collection spanned from 2020 to 2021. The research was approved by the Human Studies Committee of Sun Yat-sen University (No.2019-138), with written consent obtained from all guardians. This cross-sectional study adhered to the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines.

2.2. $PM_{2.5}$ constituent data

High-quality and high-resolution data on $PM_{2.5}$ mass and its constituents (ammonium (NH_4^+), nitrate (NO_3^-), black carbon (BC), sulfate (SO_4^{2-}), organic matter (OM), and chloride (Cl^-)) were fetched from ChinaHighAirPollutants (CHAP) (https://weijing-rs.github.io/product.html) at a 1 km × 1 km grid resolution across China. Detailed methodology and validation of the models were previously documented (Wei et al., 2023a; Wei et al., 2023b). Briefly, this data employed a four-dimensional spatiotemporal deep forest (4D-STDF) to derive daily $PM_{2.5}$ chemical composition at a spatial resolution of 1 km in China since 2000. This integrative modeling system assimilated multi-source observational data, including speciated $PM_{2.5}$ measurements from national monitoring networks, spaceborne aerosol optical depth products, meteorological reanalysis fields, and chemical transport model outputs. In conclusion, this dataset effectively captures spatiotemporal variations in $PM_{2.5}$ concentrations, demonstrating high accuracy (cross-validation coefficient of determination, CV-R^2 = 0.86–0.90) and strong predictive power (R^2 = 0.80–0.82), outperforming previous reports (Wei et al., 2023a). As the two key periods of EF development are early life and primary school years (Vohr et al., 2021), five-year average concentrations (2016–2020) prior to the survey were used as long-term exposure levels. Individual exposure concentrations to $PM_{2.5}$ and its constituents were estimated based on participants' residential addresses.

2.3. Executive function assessment

The parent-completed BRIEF, validated for use with Chinese children and adolescents, was employed to evaluate participants' EF over the past six months. Cronbach's alpha coefficients of the parent-completed BRIEF range from 0.70 to 0.96, indicating strong internal consistency (Gui et al., 2020). The scale comprises 72 items linked to EF and contains three composite indices and eight subscales: behavioral regulation index (BRI), encompassing inhibit, shift, and emotional control; metacognition index (MI), including initiate, working memory (WM), organize/plan, organization of material (OMM), and monitoring; and global executive composite (GEC), comprising all eight subscales. The raw scores were converted into standardized T-scores based on the child's age and sex, with a mean of 50 and standard deviation (SD) of 10, enabling comparisons across different composite indices and subscales. Higher T-scores indicate poorer EF, and participants with T-scores ≥65 (equivalent to 1.5 SD above the mean) were defined as having "executive dysfunction" (Gioia et al., 2002).

2.4. Covariates

We utilized a structured questionnaire to gather individuals information on socio-demographic, behavioral, and living environment factors, mainly including sex (boys or girls), age (years), height (in centimeters), weight (in kilograms), annual family income (≤30,000 Yuan, 30,001–100,000 Yuan, or >100,000 Yuan), parent education (<high school or ≥high school), sibling (yes or no), main road distance (<100 m or ≥100 m) (Guxens et al., 2016; Héroux et al., 2015), breastfeeding (yes or no), premature birth ("yes" defined as those <37 weeks gestation), exercise (<1 h/day or ≥1 h/day), secondhand smoke exposure ("yes" defined as those whose family members smoke in front of the participant), kitchen ventilation (yes vs. no), and recent interior decoration (defined as using renovation materials in housing in the last two years, yes vs. no). Additionally, childhood obesity and overweight status were assessed using body mass index (BMI) z-scores, which were age- and gender-standardized according to the WHO growth reference. BMI was calculated as weight (kg) divided by height in meters squared (m^2). Residential greenness was estimated using the normalized difference vegetation index (NDVI) derived from the National Ecosystem Science Data Center, with a 1km × 1 km resolution.

Subsequently, a directed acyclic graph (DAG) was used to select potential confounders (Fig. S2), utilizing DAGitty 3.1 software. Based on the DAG and previous literature, we considered the following variables as adjusting covariates: sex, age, BMI, annual family income, parent education, main road distance, breastfeeding, premature birth, and secondhand smoke exposure.

2.5. Statistical analysis

Continuous variables were reported as mean ± standard deviation (SD), while categorical variables were expressed as n (%). Spearman's correlation analysis was utilized to determine correlations among $PM_{2.5}$ constituents.

Next, restricted cubic spline (RCS) functions with three knots were employed to elucidate the association between air pollution and EF, capturing nonlinear exposure-outcome relationships through smooth segmented functions. The optimal degrees of freedom were determined by minimizing the Akaike Information Criterion (AIC), and model fit was assessed via likelihood ratio tests, with their p-values used to determine potential nonlinearity. Given the non-linear nature of most exposure-outcome relationships in the RCS functions (Fig. S3), we evaluated the odds ratios (ORs) and corresponding confidence intervals (CIs) for executive dysfunction at higher $PM_{2.5}$ concentrations and its major constituents against the lowest quartile using generalized linear mixed models (GLMMs), with cities as random effects and air pollutant/confounders as fixed effects. Furthermore, given the differences in the distribution of $PM_{2.5}$ component concentrations and their direct impact on observed associations, as well as the linear relationship of certain constituents with executive dysfunction, the ORs were calculated for the increase in $PM_{2.5}$ and its constituents per interquartile range (IQR) increment and per 1 $\mu g/m^3$ increment. Additionally, trend tests were conducted by entering the median of each interquartile interval as a continuous variable in the adjusted model, enabling the evaluation of linear trends across different exposure levels.

Weighted Quantile Sum regression (WQS) and Quantile g-computation (QGC) were used to help understand how various $PM_{2.5}$ components were linked with executive dysfunction and identify the key contributors to the combined effect. The estimated OR for executive dysfunction per quartile increment of the WQS index and the weight of each constituent in the associations were calculated. QGC was developed to analyze the combined effect of high-dimensional mixtures on a single outcome, presenting changes in the outcome by simultaneously increasing all chemicals by one quartile (Eatman et al., 2024). Unlike WQS, which assumes directional homogeneity among components, QGC flexibly assigns positive or negative weights to individual chemicals based on the direction of the independent effects. Random forest, a machine-learning technique, was also utilized to determine the contribution weights of $PM_{2.5}$ components to the combined effect. The optimal number of trees was determined by the minimization of the Out-of-Bag (OOB) error rate, ranging from 50 to 1000. Model validation followed a 2:1 split ratio, with two-thirds of the dataset allocated for bootstrap sampling during forest construction, while the remaining third served as an independent test set for performance evaluation. Variable importance was averaged over all runs and measured via Mean Decrease Accuracy.

To assess potential effect modification, we performed several stratified analyses based on age (5–12 years vs. 13–18 years), sex (boys vs. girls), parental educational level (<high school vs. ≥high school), family income level (≤100,000 Yuan vs. >100,000 Yuan), exercise (non-regular exercise vs. regular exercise), and weight status (normal weight vs. overweight or obesity). Several sensitivity analyses were also conducted to assess the robustness of our findings: (1) calculating estimated regression coefficients (β) with 95 % CIs of $PM_{2.5}$ and its components to EF scores; (2) replacing raw BMI measures in children with BMI z-scores during confounding adjustment; (3) additionally adjusting the main models for other potential risk factors of EF (e.g., Gross Domestic Product (GDP) per capita at the county level, and sibling); (4) additionally adjusting NDVI, a potential factor influencing exposure concentrations of $PM_{2.5}$ and its components; (5) exclusion of participants with a family history of mental illness (n = 5,707, 8.44 %) to determine whether genetic or familial factors influenced the observed associations; (6) exclusion of participants born prematurely (n = 6,817, 10.08 %); and (7) development of a component-residual model to assess the unique contribution of each $PM_{2.5}$ component to the observed outcomes by controlling for the influence of the remaining components.

All statistical analyses were conducted using R software (version 4.4.1). The WQS, QGC, and random forest analyses were performed using the R packages "gWQS", "qgcomp", and "randomForest", respectively. The Benjamini-Hochberg multiple correction was used to control for false discovery rate (FDR), and FDR <0.05 was defined as statistical significance.

3. Results

3.1. Descriptive statistics

A total of 67,622 children and adolescents were included in this study, and 4651 (6.88 %) participants were identified as having executive dysfunction (Table 1). The mean age and BMI z-scores of the study participants were 9.90 years (SD = 2.90) and 0.23 (SD = 1.53), respectively, with an almost equal gender distribution. Most participants exercised for over 1 h per day (71.06 %), had an annual family income exceeding 100,000 Yuan (52.58 %), and lived within 100 m of a main road (64.15 %). Similar results were found in the participants with executive dysfunction. Participants with executive dysfunction exhibited higher scores on all subscales of BRIEF compared to the rest of the participants.

The five-year average concentrations and correlation of $PM_{2.5}$ and its six constituents are detailed in Table 2. OM (9.63 $\mu g/m^3$) and SO_4^{2-} (7.00 $\mu g/m^3$) exhibited the highest mean concentrations. Most of the correlations between $PM_{2.5}$ and its six constituents were statistically significant, with moderate to high correlation coefficients.

3.2. Associations between EF and $PM_{2.5}$ constituents

The dose-response relationship between the six components and executive dysfunction in the three composite indices (GEC, BRI, and MI) exhibited both linear and nonlinear patterns, whereas the association between $PM_{2.5}$ mass and executive dysfunction was found to be strictly linear (Fig. S3). Positive associations between executive dysfunction and exposure to OM, NH_4^+, and BC were observed in single-component models. For instance, compared to the first quartile of NH_4^+ concentration, higher quartiles of exposures were linked to increased odds of dysfunction in GEC (i.e., the adjusted ORs respectively were 1.27 (95 % CI: 1.17, 1.39); 1.11 (95 % CI: 1.02, 1.22); and 1.23 (95 % CI: 1.05, 1.44) for the second, third, and fourth quartiles, respectively), with P-trend = 0.200 (Table 3). However, a negative association was found between exposure to the second quartile of NO_3^- levels and executive dysfunction (Table 3).

Similar results were observed in the BRIEF subscales (Table S1). A 1 $\mu g/m^3$ and an IQR increase in $PM_{2.5}$ mass were associated with higher odds of GEC dysfunction, with adjusted ORs of 1.03 (95% CI: 1.01, 1.05) and 1.05 (95 % CI: 1.02, 1.09), respectively (Fig. S4). Exposure to $PM_{2.5}$ major constituents was positively associated with dysfunction in emotional control, WM, planning, organization of material, and monitoring, especially in the WM dimension. Similar patterns were observed in the crude models (Tables S2 and S3).

In the WQS models, joint exposure to six $PM_{2.5}$ constituents was positively linked to GEC dysfunction (OR = 1.08; 95 % CI: 1.03, 1.13) and MI dysfunction (OR = 1.07; 95 % CI: 1.02, 1.11), but no significant association was found with BRI (Table S4). In the QGC models, NH_4^+, OM, and BC were positively associated with executive dysfunction in three comprehensive dimensions (Fig. 1b), and BC showed the highest contribution weight among the three composite dimensions in the WQS analyses and random forest model (Fig. 1a; Fig. 1c). The WQS results of $PM_{2.5}$ components and the BRIEF subscales further supported these findings (Table S5 and Fig. S5). Moreover, the QGC analysis revealed statistically significant results for the WM, monitoring, and shift subscales (Fig. S6).

Table 1
Characteristics of the study participants (n = 67,622).

Variables	Overall (N = 67,622)	Normal executive function (N = 62,971)	Executive dysfunction (N = 4,651)	*P*
Age, years (mean (SD))	9.91 (2.90)	9.91 (2.90)	9.98 (2.89)	0.071
Sex, n (%)				
Boys	36,654 (54.20)	34,162 (54.25)	2492 (53.58)	0.384
Girls	30,968 (45.80)	28,809 (45.75)	2159 (46.42)	
BMI z-scores (mean (SD))	0.23 (1.53)	0.23 (1.53)	0.28 (1.59)	0.016[a]
Exercise, n (%)				
<1 h/day	19,570 (28.94)	17,868 (28.37)	1702 (36.59)	<0.001[a]
≥1 h/day	48,052 (71.06)	45,103 (71.63)	2949 (63.41)	
Family income, n (%)				
≤30,000 ¥ per year	15,767 (23.32)	14,558 (23.12)	1209 (25.99)	<0.001[a]
30,001–100,000 ¥ per year	16,298 (24.10)	15,165 (24.08)	1133 (24.36)	
>100,000 ¥ per year	35,557 (52.58)	33,248 (52.80)	2309 (49.65)	
Parent education level, n (%)				
Less than high school	26,087 (38.58)	24,152 (38.35)	1935 (41.60)	<0.001[a]
High school or greater	41,535 (61.42)	38,819 (61.65)	2716 (58.40)	
Residential proximity to major roadways, n (%)				
<100 m	43,382 (64.15)	40,483 (64.29)	2899 (62.33)	0.008[a]
≥100 m	24,240 (35.85)	22,488 (35.71)	1752 (37.67)	
Breastfeeding, n (%)	57,130 (84.48)	53,305 (84.65)	3825 (82.24)	<0.001[a]
Premature birth, n (%)	6817 (10.08)	6302 (10.01)	515 (11.07)	0.021[a]
Secondhand smoke exposure, n (%)	30,585 (45.23)	28,208 (44.80)	2377 (51.11)	<0.001[a]
8 subscales scores of BRIEF, (mean (SD))				
Inhibit	13.61 (3.49)	13.18 (3.07)	19.39 (3.72)	<0.001[a]
Shift	11.45 (2.80)	11.16 (2.57)	15.41 (2.76)	<0.001[a]
Emotional Control	14.13 (3.91)	13.68 (3.48)	20.29 (4.18)	<0.001[a]
Initiate	12.91 (3.18)	12.56 (2.91)	17.75 (2.68)	<0.001[a]
Working Memory	16.18 (4.28)	15.63 (3.81)	23.68 (3.03)	<0.001[a]
Plan	19.89 (5.17)	19.27 (4.70)	28.39 (3.56)	<0.001[a]
Organization of Materials	10.39 (3.91)	10.06 (2.95)	14.98 (2.69)	<0.001[a]
Monitor	14.78 (3.77)	14.35 (3.47)	20.55 (2.82)	<0.001[a]
2 composite indexes scores of BRIEF, (mean (SD))				
Behavioral Regulation Index	39.19 (8.76)	38.02 (7.62)	55.09 (7.64)	<0.001[a]
Metacognition Index	74.16 (17.01)	71.86 (15.07)	105.34 (9.27)	<0.001[a]

Abbreviations: SD, standard deviation;
[a] false discovery rate (FDR) < 0.05.

3.3. Stratified analyses

As $PM_{2.5}$ and its constituents were significantly associated with MI in single-pollutant and mixed-pollutant models, the subscales of MI were selected for further analysis to investigate the association between constituents of $PM_{2.5}$ and EF, stratified by potential modifying factors (Fig. 2 and Tables S6–S9). Compared to participants aged 13–18 years, those aged 5–12 years showed stronger associations between $PM_{2.5}$ mass and its constituents with executive dysfunction. This was particularly evident in the associations between GEC dysfunction and $PM_{2.5}$ (OR: 1.06; 95 % CI: 1.03, 1.10 vs OR: 0.94; 95 % CI: 0.87, 1.02), OM (OR: 1.17; 95 % CI: 1.10, 1.24 vs OR: 0.93; 95 % CI: 0.83, 1.04) and SO_4^{2-} (OR: 1.12; 95 % CI: 1.03, 1.22 vs OR: 0.89; 95 % CI: 0.76, 1.04) (Fig. 2). For WM, significant modification effects by parental education level were observed for NO_3^-, NH_4^+, BC, and Cl^- (Fig. 2), with stronger associations among children and adolescents with parental education levels lower than high school. However, no significant modification effects were observed in the associations between executive dysfunction and $PM_{2.5}$ components when stratified by sex, family income, regular exercise, and BMI z-scores (Tables S6–S9).

3.4. Sensitivity analysis

The results of the multiple sensitivity analyses are shown in Tables S10–S17. Firstly, when assessing the associations between $PM_{2.5}$ and its components and EF using the continuity score, the results were slightly different, but it still showed that elevated pollutant concentrations impaired EF in children and adolescents (Tables S10 and S11). Secondly, the associations between long-term exposure to $PM_{2.5}$ and its components and executive dysfunction were similar to the main models, after additionally adjusting for BMI z-scores, GDP and sibling, and NDVI (Tables S12–S14). Thirdly, the exclusion of participants with a family history of mental illness and born prematurely from the analysis did not significantly alter our findings (Tables S15 and S16). Finally, in the component residuals model, OM exhibited a positive association with executive dysfunction, whereas SO_4^{2-} displayed a negative association. No statistically significant differences were observed for the other $PM_{2.5}$ components (Table S17).

4. Discussion

4.1. Key findings

This study identified positive associations between long-term exposure to $PM_{2.5}$ and its constituents (NH_4^+, OM, and BC) and GEC dysfunction as well as MI dysfunction. However, constituent-specific associations varied across different EF domains. In addition, joint exposure to $PM_{2.5}$ constituents was linked to an increased risk of executive dysfunction, with NH_4^+, OM, and BC mainly driving the observed associations. Furthermore, the observed associations were significantly modified by the child's age and parental education level, with stronger effects observed in children under 12 years old and in those whose parents had education levels below high school.

4.2. Comparisons with other studies and interpretation

Most studies consistently found a positive association between exposure to $PM_{2.5}$ and executive dysfunction in children and adolescents (Gui et al., 2020; Harris et al., 2016; Medrano et al., 2022). For example, a cross-sectional study conducted in 39 schools in Spain (N = 2,897)

Table 2
Five-year (2016–2020) average concentration of air pollutants and pairwise spearman correlation.

Pollutants ($\mu g/m^3$)	Summary statistics					Spearman correlation coefficients						
	Mean (SD)	Median	Minimum	Maximum	IQR	$PM_{2.5}$ mass	SO_4^{2-}	NO_3^-	NH_4^+	OM	BC	Cl^-
$PM_{2.5}$ mass	28.49 (2.69)	28.18	21.29	37.67	1.70	1.00	0.78[a]	0.61[a]	0.82[a]	0.49[a]	0.66[a]	0.57[a]
SO_4^{2-}	7.00 (0.54)	7.07	5.78	8.56	0.80		1.00	0.90[a]	0.42	0.04	0.86[a]	0.86[a]
NO_3^-	4.67 (1.00)	4.30	3.38	7.90	0.99			1.00	0.15[a]	−0.20	0.86[a]	0.96[a]
NH_4^+	3.51 (0.42)	3.37	2.86	5.01	0.39				1.00	0.80[a]	0.29	0.10
OM	9.63 (1.08)	9.52	4.18	11.92	1.53					1.00	0.04	−0.30
BC	2.70 (0.31)	2.63	1.64	3.59	0.45						1.00	0.79[a]
Cl^-	0.98 (0.25)	0.91	0.57	2.24	0.37							1.00

Abbreviations: $PM_{2.5}$, particle with aerodynamic diameter ≤2.5 μm; SO_4^{2-}, sulfate; NO_3^-, nitrate; NH_4^+, ammonium; OM, organic matter; BC, black carbon; Cl^-, chloride; SD, standard deviation; IQR, interquartile range;
[a] false discovery rate (FDR) < 0.05.

revealed that both prenatal and lifetime exposure to $PM_{2.5}$ were associated with executive dysfunction in school children (Rivas et al., 2018). Similar findings were observed in our study (N = 67,622). However, other studies have reported non-significant associations between exposure to $PM_{2.5}$ and EF (Cserbik et al., 2020; Wang et al., 2023). These inconsistencies across studies may be due to variations in population characteristics (e.g., genetic background and lifestyle factors), study regions (e.g., differences in the physicochemical properties of pollutants and levels of economic development), and the tools used to assess EF (Gui et al., 2020).

The toxicity and health impacts of $PM_{2.5}$ are largely determined by its specific composition. An important finding from this study identified a positive association between NH_4^+, OM, and BC with executive dysfunction across multiple domains, suggesting that these components may be major contributors to $PM_{2.5}$-associated executive dysfunction. For example, exposure to OM, such as polycyclic aromatic hydrocarbons (PAHs), has been linked to neural tube defects, intellectual decline, and learning disabilities (Xu et al., 2024). A cohort study conducted in the United States (N = 1,212) reported that higher BC exposure from birth until the age of six years was associated with increased difficulties in emotional regulation in children (Harris et al., 2016). In addition, higher NH_4^+ exposure has been associated with lower scores in multiple domains of the Ages and Stages Questionnaire (ASQ) (Lei et al., 2019). Moreover, joint exposure to $PM_{2.5}$ components was associated with an elevated risk of executive dysfunction, with NH_4^+, OM, and BC contributing more to the observed associations. Based on these findings, we hypothesize that NH_4^+, OM, and BC could be critical contributors to $PM_{2.5}$-related executive dysfunction. Hence, implementing region-specific exposure reduction measures for these components may reduce the burden of $PM_{2.5}$-related executive dysfunction in children and adolescents.

The effects of $PM_{2.5}$ components on various dimensions of EF were not entirely consistent in this study, showing a stronger impact on MI compared to BRI. Notably, one study (N = 8,293) in China reported that a doubling of the monthly cumulative hours of incense burning was related to an increase in BRI scores by 0.21 points (95 % CI: −0.02, 0.44 points) and MI scores by points 0.31 (95 % CI: 0.09, 0.53 points) (Gui et al., 2022), which partly supports our findings. However, a study showed an association between exposure to BC in childhood and BRI, but not with MI (Harris et al., 2016). Conversely, Gui et al. (N = 5,028) demonstrated that air pollution had detrimental effects on both MI and BRI (Gui et al., 2020). These inconsistencies may stem from differences in sample size, methodologies, and air pollutant measurements across studies. For example, Harris et al. had a small sample size (N = 1,212) and low exposure levels (the annual mean for BC = 0.55 $\mu g/m^3$) (Harris et al., 2016), which may lead to a lack of sensitivity in identifying significant associations. Furthermore, while Harris et al. utilized pollutant data derived from validated spatiotemporal models at a 10 × 10 km spatial resolution, our study employed higher-resolution 1 × 1 km estimates. This discrepancy in spatial resolution may introduce exposure assessment errors; for instance, coarse-resolution data fail to capture localized pollution gradients (e.g., near traffic or industrial point sources), potentially leading to non-differential exposure misclassification and attenuation of true effect estimates (Zeger et al., 2000). Besides, Gui et al. employed standardized neuropsychological batteries (e.g., BRIEF questionnaire combined with computerized WM tasks) (Gui et al., 2020), whereas others (Harris et al., 2016) relied solely on parent-reported BRIEF scores, introducing potential rater bias. In this present study, both WQS and QGC analyses revealed that combined exposure to the six $PM_{2.5}$ components was associated with MI dysfunction but not BRI dysfunction. Furthermore, we also found that $PM_{2.5}$ components exhibited varying effects on four dimensions (WM, organization of materials, plan, and monitoring) of MI, with the impact on WM being the most significant. Several studies on air pollution have supported this finding (Gui et al., 2020; Gui et al., 2022; Quist et al., 2019; Yang et al., 2024).

Our study highlights that the observed associations were significantly modified by age and parental education level. Children under 12 years appear to be more susceptible to the effects of $PM_{2.5}$ constituents on EF. This finding is supported by several studies (Ni et al., 2024; Wang et al., 2023). Core components of EF, including information processing, cognitive flexibility, and goal-setting, attain relative neurocognitive maturity by age 12, potentially diminishing susceptibility to environmental perturbations (Gioia et al., 2002). Besides, children under 12 years (typically in primary education stages) exhibit increased outdoor activity durations, heightening their inhalation frequency and cumulative exposure to airborne pollutants compared to older adolescents (Vrijheid et al., 2016). Therefore, it is crucial to reduce $PM_{2.5}$ exposure during early childhood years for optimal EF development (Vohr et al., 2021). Additionally, a more pronounced inverse effect of $PM_{2.5}$ exposure on EF was observed among children and adolescents whose parents had education levels below high school, particularly in the WM domain. This may be due to parents with higher educational levels being able to intervene early and provide better support and guidance for their children's learning and memory development.

4.3. Potential biological mechanisms

According to recent reviews, $PM_{2.5}$ may adversely affect brain development through multiple mechanisms, including inflammation, oxidative stress, DNA methylation, ferroptosis, and neuronal dysfunction (Cory-Slechta et al., 2023; Liu et al., 2023). Children and adolescents exhibit increased susceptibility to neurotoxic effects of air pollution due to an immature immune system and blood-brain barriers (Costa et al., 2020), and elevated outdoor activity patterns substantially augment inhalation exposure doses, particularly during peak pollution hours (Brockmeyer and D'Angiulli, 2016).

Moreover, the neurotoxicity of $PM_{2.5}$ is influenced not only by its source and concentration but also by its specific chemical components (Luo et al., 2019). For example, BC and OM primarily originate from combustion-related sources, including vehicle exhaust, industrial emissions, and agricultural burning (Li et al., 2022). Notably, traffic-related

Table 3
Associations between $PM_{2.5}$ and its major components and executive dysfunction in composite indices of BRIEF.

Pollutants	Q1	Q2	Q3	Q4	*P*-trend
$PM_{2.5}$					
GEC	Ref	0.98 (0.90, 1.07)	1.03 (0.93, 1.14)	1.01 (0.89, 1.15)	0.850
BRI	Ref	0.97 (0.90, 1.05)	1.09 (1.00, 1.20)	1.08 (0.95, 1.22)	0.722
MI	Ref	0.96 (0.88, 1.05)	0.99 (0.89, 1.09)	0.94 (0.82, 1.09)	0.596
SO_4^{2-}					
GEC	Ref	0.96 (0.85, 1.09)	0.94 (0.81, 1.09)	0.93 (0.78, 1.10)	0.589
BRI	Ref	1.03 (0.91, 1.15)	1.07 (0.93, 1.23)	1.03 (0.89, 1.20)	0.781
MI	Ref	1.07 (0.94, 1.22)	1.00 (0.86, 1.17)	0.92 (0.77, 1.10)	0.324
NO_3^-					
GEC	Ref	0.86 (0.79, 0.95) [a]	0.99 (0.87, 1.13)	1.03 (0.84, 1.27)	0.467
BRI	Ref	0.98 (0.91, 1.07)	1.01 (0.90, 1.13)	1.13 (0.86, 1.48)	0.722
MI	Ref	0.82 (0.75, 0.90) [a]	0.96 (0.84, 1.09)	1.00 (0.85, 1.18)	0.324
NH_4^+					
GEC	Ref	1.27 (1.17, 1.39) [a]	1.11 (1.02, 1.22)	1.23 (1.05, 1.44) [a]	0.200
BRI	Ref	1.10 (1.02, 1.19)	1.02 (0.95, 1.11)	1.13 (0.95, 1.33)	0.722
MI	Ref	1.19 (1.09, 1.30) [a]	1.03 (0.94, 1.13)	1.18 (1.03, 1.35) [a]	0.238
OM					
GEC	Ref	1.16 (1.06, 1.26) [a]	1.22 (1.08, 1.37) [a]	1.14 (1.01, 1.29)	0.589
BRI	Ref	1.07 (0.99, 1.16)	1.14 (1.03, 1.28)	1.06 (0.95, 1.19)	0.722
MI	Ref	1.11 (1.02, 1.21)	1.18 (1.05, 1.32) [a]	1.15 (1.02, 1.29)	0.858
BC					
GEC	Ref	1.10 (1.01, 1.20)	0.96 (0.88, 1.06)	1.18 (1.05, 1.32) [a]	0.367
BRI	Ref	1.03 (0.95, 1.11)	1.03 (0.95, 1.11)	1.04 (0.95, 1.15)	0.781
MI	Ref	1.12 (1.03, 1.21) [a]	0.95 (0.87, 1.03)	1.18 (1.09, 1.28) [a]	0.238
Cl^-					
GEC	Ref	0.99 (0.90, 1.08)	0.91 (0.80, 1.03)	0.98 (0.85, 1.14)	0.851
BRI	Ref	0.99 (0.91, 1.07)	0.96 (0.86, 1.07)	0.97 (0.85, 1.11)	0.781
MI	Ref	1.00 (0.91, 1.09)	0.89 (0.78, 1.01)	0.98 (0.84, 1.14)	0.858

Note: All models were adjusted for sex, age, BMI, parent education, family income, exercise, main road distance, breastfeeding, premature birth, and secondhand smoke exposure. Abbreviations: $PM_{2.5}$, particle with aerodynamic diameter $\leq$2.5 μm; SO_4^{2-}, sulfate; NO_3^-, nitrate; NH_4^+, ammonium; OM, organic matter; BC, black carbon; Cl^-, chloride; Q, quartile; GEC, global executive composite; BRI, behavioral regulation index; MI, metacognition index;
[a] false discovery rate (FDR) < 0.05.

BC particles can be extremely small, approximately 50 nm in size, enabling them to pass through the olfactory nerve and potentially cross the blood-brain barrier (Li et al., 2022; Niessner, 2014). Then, it induces oxidative damage in the prefrontal cortex and weakens organizational skills and memory (Cserbik et al., 2020). Emerging evidence has revealed that BC particles accumulate in hippocampal and cortical regions critical for memory consolidation, suggesting their potential involvement in the onset and progression of neurological disorders (Vanbrabant et al., 2024). BC particles may also act as carriers, transporting highly hazardous OM species, such as polychlorinated biphenyls and polycyclic aromatic hydrocarbons, into the brain, thereby contributing to neurotoxicity (Cornelissen et al., 2005). Subsequently, these particles infiltrate the nervous system, where they activate microglia, leading to oxidative stress and neuroinflammation (Kim et al., 2020; Wei et al., 2017). Additionally, it may disrupt mitochondrial energy metabolism, reducing synaptic plasticity and hindering complex information organization (Allen et al., 2014; Calderón-Garcidueñas et al., 2016). Synergizes with metals (e.g., Fe) to generate reactive oxygen species, damaging the default mode network (DMN) and impairing self-monitoring (Brockmeyer and D'Angiulli, 2016; Guo et al., 2023; Philippi et al., 2015). NH_4^+ is generated through the neutralization of atmospheric nitric and sulfuric acids by ammonia (Li et al., 2022). A plausible hypothesis for NH_4^+-induced neurotoxicity is that it may promote or exacerbate systemic inflammation and oxidative stress by directly stimulating inflammatory processes or by altering the solubility and bioavailability of other toxic compounds (Bates et al., 2019; Zhang et al., 2021), thereby disrupting glutamatergic signaling in working memory circuits (prefrontal-hippocampal networks) (Sigurdsson et al., 2010). NH_4^+ emitted with SO_4^{2-}, synergistically amplifying neuroinflammation and compromising information integration and monitoring (Fonken et al., 2011). An animal study found that exposure to an inorganic extract of $PM_{2.5}$ during pre- and postnatal periods led to the activation of neurogliocytes and neuroinflammation in the brain of Wistar rats (Rahmatinia et al., 2024).

Although these findings provide insights into potential biological mechanisms linking $PM_{2.5}$ components to executive dysfunction, further experimental studies are needed. These studies should utilize both single and mixtures of $PM_{2.5}$ components at doses comparable to human exposure to better elucidate their effects on executive dysfunction.

4.4. Strengths and limitations

Our study has several strengths. First, this is the largest epidemiological study to date on exposure to $PM_{2.5}$ constituents and EF in children and adolescents (n = 67,622) in China, providing precise air pollution estimates at the individual level with a spatiotemporal resolution of 1 km × 1 km. Second, this study provides a comprehensive evaluation of both the individual and combined effects of six $PM_{2.5}$ constituents on EF, which may offer new insights into the health impacts of key-specific $PM_{2.5}$ components, aiding policymakers and researchers in developing targeted strategies. The chemical composition of $PM_{2.5}$ can be regulated through source control, process intervention, and end-of-pipe treatment strategies, though such targeted regulation requires context-specific evaluations of technical complexities and associated costs. For example, advanced diesel technologies should be used to reduce OM emissions, and switch to cleaner fuels to reduce BC emissions. Moreover, impaired neurological development during childhood poses a significant public health concern, due to its immediate and long-term impacts on overall well-being. Identifying vulnerable populations, such as children under 12 years of age or those with parents whose education levels are below high school, has important implications for prevention and intervention strategies.

Despite these strengths, this research had several limitations. First, the study employed a cross-sectional design, which constrained our ability to establish causality. However, the possibility of reverse causality, in which executive dysfunction influences the distribution of air

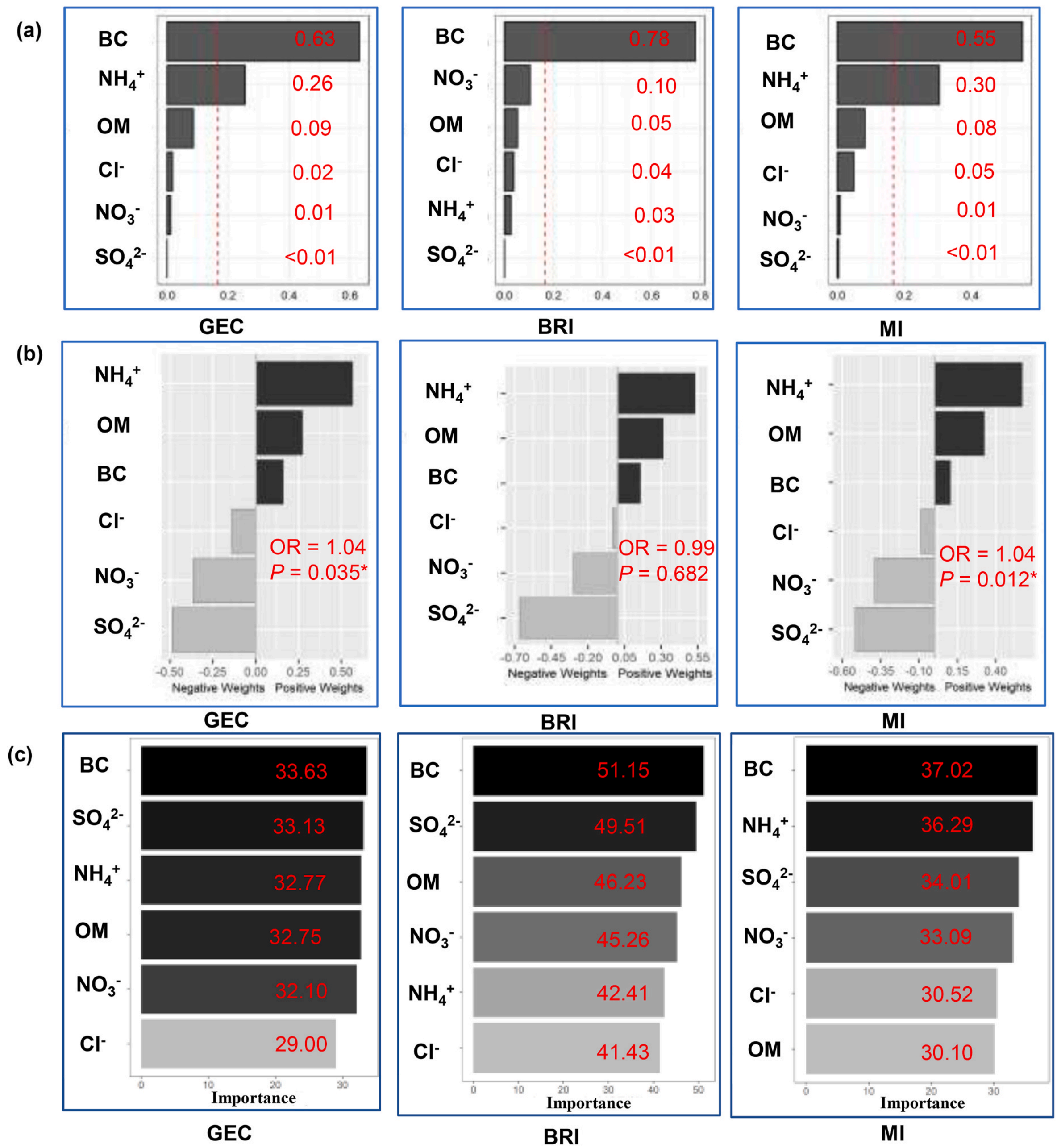

Fig. 1. The overall effect of major constituents of $PM_{2.5}$ on dysfunction in GEC, BRI, and MI, as assessed by WQS (a), QGC (b), and random forest model (c). Note: The red numbers in the figure (a) are the weights of each component. All models were adjusted for sex, age, BMI, parent education, family income, exercise, main road distance, breastfeeding, premature birth, and secondhand smoke exposure. Abbreviations: $PM_{2.5}$, particle with aerodynamic diameter ≤2.5 μm; SO_4^{2-}, sulfate; NO_3^-, nitrate; NH_4^+, ammonium; OM, organic matter; BC, black carbon; Cl^-, chloride; GEC, global executive composite; BRI, behavioral regulation index; MI, metacognition index; WQS, weighted quantile sum regression; QGC, quantile g-computation; *false discovery rate (FDR) < 0.05. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

pollution around participants' residences, is minimal. Second, the six chemical components typically constituted over 90 % of $PM_{2.5}$, with approximately 10 % being unidentified components. Consequently, the relative contributions of the six identified constituents may have been slightly skewed. Third, as with all observational studies, residual confounding from unmeasured factors—such as diet, outdoor light at night, and noise—cannot be entirely ruled out. In addition, $PM_{2.5}$ constituent concentrations were estimated based on participants' residential addresses without accounting for individual mobility data, which may have introduced exposure measurement error. Future studies should incorporate mobility data and exposure information from additional sources to enhance the precision of exposure assessment strategies. Lastly, the CHAP database may bias exposure-response estimations across urban-rural gradients due to differential monitoring capacities and heterogeneous emission profiles. However, it remains one of the most comprehensive and validated sources for air pollution exposure assessment in China. Methodological refinements incorporating localized sensor networks or individual-level exposure tracking could enhance spatial precision in future investigations.

5. Conclusions

This study highlights a positive association between long-term exposure to $PM_{2.5}$ and its key chemical components (OM, BC, and

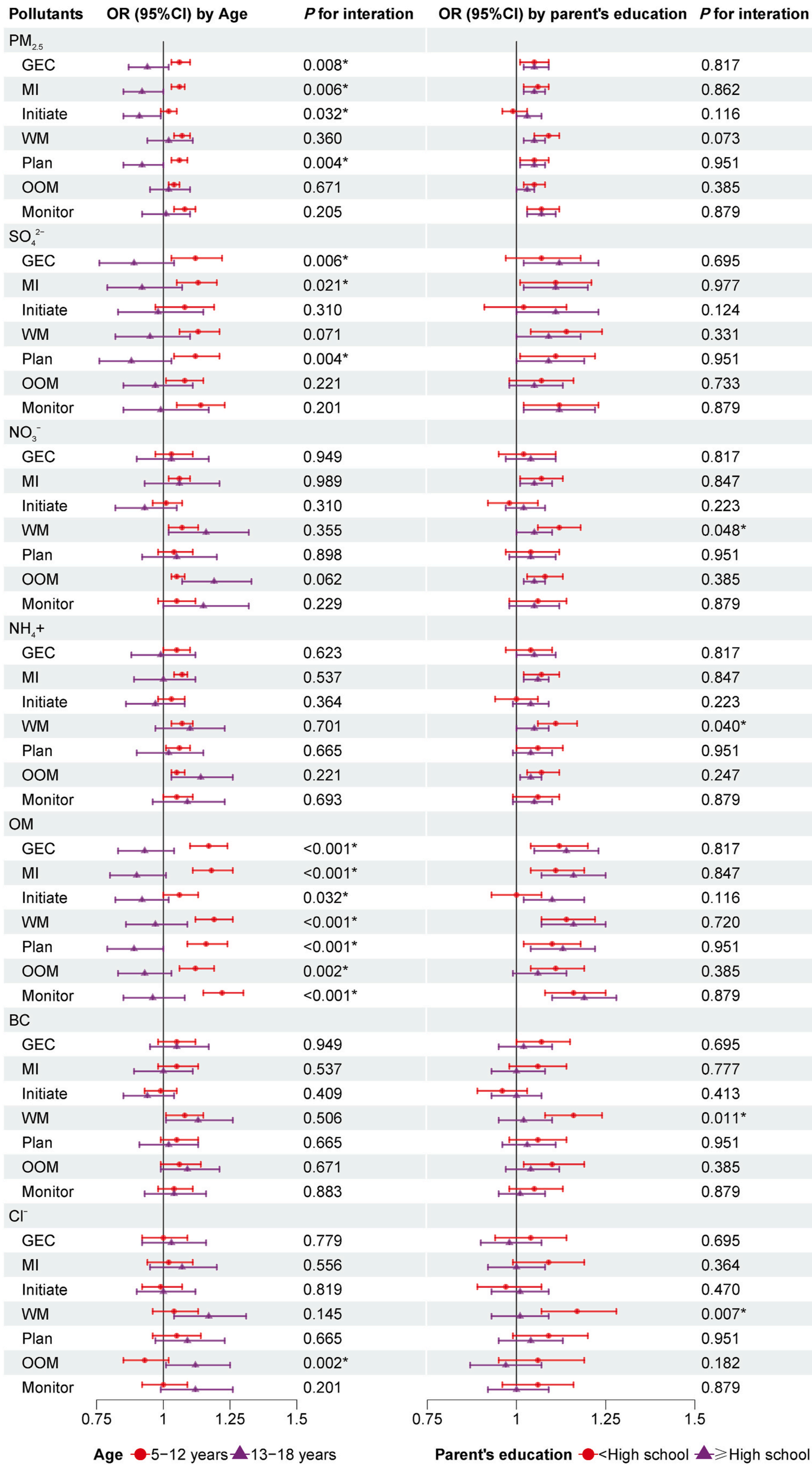

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Fig. 2. The estimated odd ratios (ORs) of executive dysfunction associated with IQR increase of $PM_{2.5}$ and its major components exposure, stratified by age and parent's education level. Note: All models were adjusted for sex, age, BMI, parent education, family income, exercise, main road distance, breastfeeding, premature birth, and secondhand smoke exposure. Abbreviations: $PM_{2.5}$, particle with aerodynamic diameter $\leq$2.5 μm; SO_4^{2-}, sulfate; NO_3^-, nitrate; NH_4^+, ammonium; OM, organic matter; BC, black carbon; Cl^-, chloride; GEC, global executive composite; MI, metacognition index; WM, working memory; OOM, organization of material; CI, confidence interval; *false discovery rate (FDR) < 0.05.

NH_4^+) with executive dysfunction in children and adolescents, particularly in WM dysfunction. Additionally, combustion-related BC and NH_4^+ were identified as significant contributors to these associations, indicating that targeted control and reduction of these components could be pivotal in mitigating the societal burden of executive dysfunction. Future well-designed, large-sample cohort studies are essential to validate these findings and to further investigate the underlying biological mechanisms.

CRediT authorship contribution statement

Hua-Lian Chen: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Qing-Guo Zeng:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Jing Wei:** Writing – review & editing, Supervision, Methodology. **Qiong Zhang:** Writing – review & editing, Methodology. **Hui-Xian Zeng:** Writing – review & editing. **Katja Kanninen:** Writing – review & editing, Conceptualization. **Bin Jalaludin:** Writing – review & editing. **Jian Dai:** Writing – review & editing. **Yuan Lv:** Writing – review & editing. **Bin Zhao:** Writing – review & editing. **Pasi Jalava:** Writing – review & editing. **Guang-Hui Dong:** Writing – review & editing, Supervision, Conceptualization. **Xiao-Wen Zeng:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2025.126740.

Data availability

Data will be made available on request.

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