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Article

The Impacts of Atmospheric $PM_{2.5}$ Components on Depression in Middle-Aged and Elderly People

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Abstract

Previous research has found association between $PM_{2.5}$ exposure and the worsening of depression. Nevertheless, studies specifically examining the harmful effect of components of $PM_{2.5}$ were relatively limited.A national survey enrolled individuals aged 45 and older, gathering personal data and assessing depression in mainland China. Monthly exposure to $PM_{2.5}$ and its seven components, black carbon (BC), organic matter (OM), nitrate (NO_3^-), sulfate (SO_4^{2-}), ammonium (NH_4^+), soil particles (SOIL) and sea salt (SS) were matched via each participant's residence. Linear mixed effect models (LME) to assess the association between single pollutants with depression score, and weighted quantile sum (WQS) regression was used to investigate the effect of mixed exposure and identify contribution of each component. The modified effects of social activity and green space were evaluated. 9,725 participants for depression were included in this analysis, respectively. In single exposure model, per interquartile range (IQR) rise in $PM_{2.5}$ (29.18μg/m³), BC (2.25μg/m³), OM (7.18μg/m³), SOIL (6.04μg/m³) and SS (0.14μg/m3) were significantly associated with increase of 0.90 (95%CI: 0.59, 1.20), 0.71[0.42, 1.09], 0.94[0.61, 1.26]), 0.51[0.38, 0.63]), 0.53[0.33, 0.73] point in depression score. In mixed exposure models, for each IQR increase in the mixture of all components, depression score increased by 1.104 (95%CI: 0.901, 1.307), and BC held the largest index weight (33.6%), followed by SOIL (28.59%) and SS (25.05%). The harmful effect of $PM_{2.5}$ and specific components on depression were lower in those participating in social activity or in higher level green space ($p<0.05$).The harmful effects of $PM_{2.5}$ on depression may be influenced by its components. Social activity and green space could reduce the risk of depression related to $PM_{2.5}$ and its components.

Keywords: $PM_{2.5}$ and its components; depression; middle-aged and older adults; social activity; green space

1. Introduction

Population ageing has become a major global challenge. According to WHO, the proportion of individuals aged 65 and over will rise from 12% in 2015 to 22% in 2050, reaching nearly 2 billion [1]. It is estimated that more than 20% of the population aged 60 and over suffered from mental or neurological disorders, which accounted for 6.6% of the total Disability-Adjusted Life Years (DALYs) of this population. Depression was the most prevalent of these disorders in older population, accounting for approximately 7%.

Air pollution is indeed a significant global public health issue. Epidemiological studies about the association of fine particulate matter with depression were mainly focused on the ambient $PM_{2.5}$

mass. However, $PM_{2.5}$ is complex heterogeneous mixture of miscellaneous chemical composition, whose major components include organic matter (OM), black carbon (BC), nitrate (NO_3^-), sulfate (SO_4^{2-}), ammonium (NH_4^+), soil particles (SOIL) and sea salt (SS). Previous studies were based on the assumption that the toxicity of $PM_{2.5}$ components was consistent, which overlooked the difference in potential toxicity of chemical components of $PM_{2.5}$, especially those derived from combustion processes [2,3]. Considering the facts of China's substantial elderly population and the continuous high levels of particulate matter, it is essential to assess the effect of exposure to various components of $PM_{2.5}$ on depression in middle-aged and elderly populations.

To fill these knowledge gaps, a national study was carried out, and the impact of long-term exposure to $PM_{2.5}$ and its components (including BC, OM, NO_3^-, SO_4^{2-}, NH_4^+, SOIL, and SS) on depression among middle-aged and elderly people in China was investigated. And then, the modifying effects of social activity and green space on the association were evaluated.

2. Materials and Methods

2.1. Study Population

All of participants were drawn from the China Health and Retirement Longitudinal Study (CHARLS) launched by National School for Development (China Center for Economic Research). The CHARLS constructed a nationally representative subsets of Chinese older adults (participants aged 45 years or above) based on a four-stage and well-established sample design [4], in which it covered 125 cities from 28 provinces across China's mainland. In each wave of survey, participants' information including socioeconomic and demographic characteristics, lifestyle, behavior patterns, and health status was comprehensively collected through standard questionnaires by well-trained investigators, in the form of face-to-face interviews. More details are available elsewhere (http://charls.pku.edu.cn/en/data/User2018.pdf).To avoid the influence of COVID-19 on depression [5,6], this analysis was conducted using the CHARLS data of four waves (2011-2018). In addition, CHARLS only provides the city in which each participant resides, and detailed home addresses are not disclosed to the public.

In this study, 17,596 participants were involved at baseline. Then, adults under the age of 45 at baseline were excluded. Additionally, considering the focus on mental and neurological diseases, participants diagnosed with memory-related diseases (such as Alzheimer's Disease, Brain Atrophy, and Parkinson's Disease), with emotional or psychiatric issues, with cancer or malignant tumors (excluding minor skin cancers) or who had previously taken medication for mental illness were excluded. Individuals with missing outcome information and key personal information were excluded. Ultimately, a total of 9,725 participants were included in the analysis. Detailed inclusion and exclusion criteria were shown in Supplementary Figure S1.

2.2. Exposure Assessment

Monthly spatially-resolved estimates of surface-level total PM2.5 and its seven specific components, including organic matter (OM), black carbon (BC), sulfate (SO_4^{2-}), nitrate (NO_3^-), ammonium (NH_4^+), soil particles (SOIL), and sea salt (SS) for the period 2000-2017, were obtained from the V4.CH.02 product, a dataset formulated by the Atmospheric Composition Analysis Group at Washington University [7,8]. Datasets for China was developed using the methodology described previously [9,10]. By well incorporating satellite-based aerosol optical depth observations, gridded estimates at 0.01° × 0.01° spatial resolution were predicted by utilizing the nested GEOS-Chem chemical transport model (http://geos-chem.org, accessed on November 15th, 2023) and geographically weighted regression. The predicted $PM_{2.5}$ estimates demonstrated substantial alignment with measurements from globally dispersed ground sites, evidenced by a high coefficient of determination ($R^2 = 0.81$) and a slope of 0.90. While further calibration for the compositional values was not undertaken due to the absence of available ground-based observations across mainland China, this methodology proved effective without calibration, as evidenced by its application in

North America [8] and global estimates [10]. Currently, the V4.CH.02 product from China is extensively utilized for exposure assessment in the field of environmental epidemiology [3,11,12].

In this study, we extracted data on the monthly total mass of $PM_{2.5}$ and the concentrations of its seven chemical components across mainland China for the period from 2000 to 2017. Consistent with prior studies [13,14], we employed a 1-year average of $PM_{2.5}$ mass and its seven components at the city level prior to the survey year as a measure of $PM_{2.5}$ influence in our primary analyses. For instance, for participants enrolled in 2018, we aligned the annual average concentrations for 2017 as their final exposure in the wave 4 survey.

2.3. Outcome Assessment

The depression status of the participants was measured using the 10-item Center for Epidemiologic Studies Depression scale (CES-D-10). The validity of CES-D-10 has been examined among Chinese adults [15]. Each question measured the frequency of a specific type of negative mood using a score of 0 (rarely or none), 1 (some days), 2 (occasionally), 3 (most of the time). The sum of score for each question was calculated as the depressive score to indicate the general depressive status for each participant. The depressive score ranged from 0 to 30, with a higher score indicating a higher severity of depressive symptoms.

2.4. Statistical Analysis

Baseline characteristics were summarized as proportions (%) for categorical variables and mean (SD) for continuous variables. The Spearman rank correlation analysis was applied to assess the relationship among $PM_{2.5}$ mass and each component in 125 cities in 2011.

Linear mixed effect models (LME) with time-varying exposures were established to investigate associations of $PM_{2.5}$ or its components with depression score. Our analysis was first performed without adjustments (M1) and then expanded by introducing additional covariates. M2 was adjusted for age and sex. M3 (main model) was further adjusted for sociodemographic background (education attainment, marital status, building type, cooking fossil type, location of residence), health status (cardiovascular related diseases, disabled), and behavior characteristics (smoking, alcohol drinking, social activity).

$$Y_{i,j} = \beta_0 + \beta_1 PM_{i,j} + \gamma \mathbf{z}_{i,j} + city_i + \lambda(i)$$

Where i denoted the subject index; j denoted the visit index; β_0 denoted the intercept; β_1 denoted the regression coefficients for $PM_{2.5}$ and its components, respectively. $\mathbf{z}_{i,j}$ denoted a set of adjusted covariates and γ denoted the corresponding coefficients; $city_i$ denoted a fixed effect to control the unmeasured city-specific risk 7 factors, such as traditional culture [14,16]; λ denoted random intercept to model the correlation between records from the same subject, respectively.

To check the exposure-response (ER) curve for the associations of exposure to $PM_{2.5}$ and its 7 components with depression score, we separately included a cubic spline with 4 knots for each exposure of interest based on generalized additive mixed models (GAMM). The significance of linear and nonlinear terms was obtained using the Wald test, while the likelihood ratio test was used to compare the merits of linear and nonlinear models. Subgroup analyses were performed stratified by whether participated in social activity (yes / no) and level of green space coverage (high / low), which based on the median Normalized Difference Vegetation Index (NDVI) of study cities. Furthermore, we merged these two factors, to compare the effect in population participated in social activity and in high greenness (Yes + High) with no social activity and in low greenness(No + Low). In line with prior studies, the 2-sample z-test were used to examine potential effect differences between subgroups [17]. The subgroup analyses were conducted only for $PM_{2.5}$ and components which were significantly associated with outcomes. To determine the effect of mixed exposure of $PM_{2.5}$, and identify the relative contribution of each component, weighted quantile sum (WQS) regression was conducted adjusting confounders which were included in the main model [18].

Several sensitivity analyses were performed to evaluate the robustness of our effect estimates. First, we further adjusted $PM_{2.5}$ or residuals of $PM_{2.5}$ to control for confounding among the components of $PM_{2.5}$ due to high correlation. Second, we further adjusted the random effect of community using a random intercept. Third, we switched the model from an individual random effects model to an individual fixed effects model (less efficient in estimation, but with smaller bias) [19], controlling for the same covariates as in the main model, although some covariates that do not vary across individuals were absorbed by the individual fixed effects. Fourthly, to explore how the measurement error influenced the estimated association between $PM_{2.5}$ and its constituents with depression, we used a bootstrap method to incorporate the data-generation procedure during model inference [20]. The detailed information for bootstrap method could be found in Supplementary Text S1.

Statistical analyses were conducted using R (version 4.2.1). This included the application of the "lme4", "lmerTest", and "gamm4" packages for the execution of linear mixed effect model and generalized additive mixed model analyses. Additionally, the "plm" package was employed for the analysis of the fixed effects model. The "gWQS" package was employed for identifying contributions of all components. Two-sided p-value< 0.05 was considered statistically significant.

3. Results

3.1. Descriptive Results

The distribution of annual average of $PM_{2.5}$ and its components at baseline were shown in Table S1 in the supplement. The concentration of $PM_{2.5}$ ranged from 4.32 to 82.41μg/m³, with an average [SD] concentration of 44.11[18.63]μg/m³. The average [SD] concentrations of BC, OM, NO_3^-, SO_4^{2-}, NH_4^+, SOIL, and SS were 2.76 [1.59]μg/m³, 8.62 [4.05]μg/m³, 10.17 [5.45]μg/m³, 10.15 [3.53]μg/m³, 6.71 [2.78]μg/m³, 4.52 [5.42]μg/m³, and 0.15 [0.15]μg/m³, respectively. Notably, NH_4^+, NO_3^-, BC, OM, and SO_4^{2-} demonstrated higher correlations with $PM_{2.5}$, with correlation coefficients of 0.944, 0.932, 0.917, 0.886, and 0.868, respectively. SOIL exhibited a moderately correlation with $PM_{2.5}$, with a coefficient of 0.428. SS presented negative correlation with $PM_{2.5}$ and most of other components, although these correlations were relatively weaker. The correlation coefficients among BC, OM, NO_3^-, SO_4^{2-}, and NH_4^+ were varied among 0.735-0.967 (Table S2 in the supplement).

Table 1 showed the characteristics for population in this analysis (N=36,847). The age (mean [SD]) of participants at baseline was 57.63 [8.34] years, and 4,736 (48.7%) were male. At baseline (2011), a higher proportion of participants completed primary education (41.6%), got married (90.5%), never drank (65.6%), lived in single story (62.6%) and used fossil fuels (55.0%). A lower proportion of participants were smokers (39.9%), lived in urban area (38.1%), and had cardiovascular disease (35.2%) or diabetes (13.9%). By 2018, the proportion married, living in a single story and using fossil fuels had declined to 84.8%, 49.3% and 33.4%, respectively. The proportion smoking had increased to 43.1%, and the proportion with CVD and diabetes had increased to 59.2% and 38.4%, respectively.

Table 1. Longitudinal characteristics for the population.

Sample	Total	2011	2013	2015	2018
Sample	36847	9725	9134	9203	8785
Age (mean±SD)	60.75±8.64	57.63±8.34	59.74±8.35	61.64±8.34	64.30±8.08
Sex = Male (%)	17872 (48.5)	4736 (48.7)	4457 (48.8)	4483 (48.7)	4196 (47.8)
Education (%)					
Middle school or above	13066 (35.5)	3495 (35.9)	3311 (36.2)	3259 (35.4)	3001 (34.2)
Primary school	15429 (41.9)	4042 (41.6)	3738 (40.9)	3828 (41.6)	3821 (43.5)
Illiteracy	8352 (22.7)	2188 (22.5)	2085 (22.8)	2116 (23.0)	1963 (22.3)
Marriage = Yes (%)	32412 (88.0)	8797 (90.5)	8145 (89.2)	8017 (87.1)	7453 (84.8)
Smoking = Yes (%)	15801 (42.9)	3880 (39.9)	3960 (43.4)	4173 (45.3)	3788 (43.1)
Drinking (%)					

<1/month	2866 (7.8)	778 (8.0)	706 (7.7)	755 (8.2)	627 (7.1)
≥1/month	9828 (26.7)	2572 (26.4)	2518 (27.6)	2452 (26.6)	2286 (26.0)
Never	24153 (65.5)	6375 (65.6)	5910 (64.7)	5996 (65.2)	5872 (66.8)
Social Activity = Yes (%)	18175 (49.3)	4688 (48.2)	5032 (55.1)	4535 (49.3)	3920 (44.6)
Building type = one story (%)	20925 (56.8)	6089 (62.6)	5689 (62.3)	4814 (52.3)	4333 (49.3)
Place of residence = Urban (%)	13877 (37.7)	3709 (38.1)	3439 (37.7)	3471 (37.7)	3258 (37.1)
Cooking energy type = fossil (%)	16408 (44.5)	5352 (55.0)	4231 (46.3)	3889 (42.3)	2936 (33.4)
Cardiovascular disease = Yes (%)	16972 (46.1)	3424 (35.2)	3929 (43.0)	4416 (48.0)	5203 (59.2)
Disabled = Yes (%)	9709 (26.3)	1349 (13.9)	2056 (22.5)	2927 (31.8)	3377 (38.4)

3.2. Association of $PM_{2.5}$ and Its Components with Depression Score

The results from the primary linear mixed effect model analysis (M3) revealed significant associations between exposure to $PM_{2.5}$, BC, OM, SOIL, and SS and increased depression scores in the population. For each interquartile range (IQR) increase in exposure to these pollutants, depression score significantly rose by 0.90 (95% CI: 0.59, 1.21), 0.71 (95% CI: 0.34, 1.09), 0.94 (95% CI: 0.61, 1.26), 0.51 (95% CI: 0.38, 0.63) and 0.53 (95% CI: 0.33, 0.73), respectively. For each IQR increase in SO_4^{2-}, depression score rose by 0.18 (95% CI: -0.03, 0.38, p=0.088), although not significantly. No significant associations were observed of exposure to NO_3^- and NH_4^+ with depression scores (Table 2).

Table 2. The effect (β [95%CI]) for each IQR increase of $PM_{2.5}$ and each component on depression score.

Exposure	IQR	M1	M2	M3	M4	M5	M6	M7
$PM_{2.5}$	29.18	0.89 (0.58, 1.20)	0.94 (0.63, 1.24)	0.90 (0.59, 1.20)	0.90 (0.59, 1.20)	0.90 (0.59, 1.20)	0.95 (0.64, 1.25)	0.93 (0.65, 1.23)
BC	2.25	0.51 (0.13, 0.89)	0.70 (0.32, 1.08)	0.71 (0.34, 1.09)	0.24 (-0.18, 0.65)	0.72 (0.34, 1.09)	0.82 (0.44, 1.20)	0.70 (0.34, 1.06)
OM	7.18	1.61 (1.30, 1.92)	1.17 (0.85, 1.49)	0.94 (0.61, 1.26)	1.06 (0.72, 1.40)	0.93 (0.61, 1.26)	0.89 (0.54, 1.23)	0.92 (0.58, 1.26)
NO_3^-	8.48	-1.16 (-1.51, -0.81)	-0.50 (-0.86, -0.14)	-0.20 (-0.57, 0.18)	0.13 (-0.26, 0.51)	-0.19 (-0.56, 0.19)	0.11 (-0.30, 0.53)	-0.18 (-0.56, 0.20)
SO_4^{2-}	5.32	0.16 (-0.04, 0.36)	0.20 (0.00, 0.41)	0.18 (-0.03, 0.38)	0.75 (0.50, 1.00)	0.18 (-0.02, 0.38)	0.22 (0.02, 0.42)	0.20 (-0.01, 0.41)
NH_4^+	4.58	-0.30 (-0.60, -0.00)	0.01 (-0.29, 0.31)	0.10 (-0.20, 0.40)	0.54 (0.23, 0.86)	0.10 (-0.20, 0.40)	0.25 (-0.06, 0.56)	0.10 (-0.25, 0.45)
SOIL	6.04	0.64 (0.52, 0.76)	0.55 (0.43, 0.68)	0.51 (0.38, 0.63)	0.55 (0.42, 0.67)	0.51 (0.38, 0.63)	0.49 (0.36, 0.62)	0.48 (0.42, 0.54)
SS	0.14	0.66 (0.47, 0.85)	0.55 (0.36, 0.75)	0.53 (0.33, 0.73)	0.39 (0.18, 0.59)	0.53 (0.33, 0.73)	0.49 (0.29, 0.69)	0.54 (0.35, 0.73)

Note: M1: unadjusted linear effect mixed model; M2: M1 additionally adjusted for individual information (age, sex); M3: main model, M2 additionally adjusted for sociodemographic background (education attainment, marital status, building type, cooking fossil type, location of residence), health status (cardiovascular related diseases, disabled), and behavior characteristics (smoking, alcohol drinking, social activity) ; M4: M3 additionally adjusted for residual of $PM_{2.5}$; M5: M3 additionally adjusted for random intercept of community; M6: Similar to control variables in M3, but replacing individual random intercepts with individual fixed effects. M7: Similar to control variables in M3, but the estimated effects are obtained through 1000 bootstrap iterations. Bold values were statistical significant (P<0.05).

Figure 1 showed the nonlinear associations of $PM_{2.5}$ and its components with depression scores. The exposure-response relationship for depression scores indicated that the nonlinear models for $PM_{2.5}$, BC, OM, and SS did not significantly improve over the linear models (pcompare > 0.05). The associations of NO_3^-, SO_4^{2-}, NH_4^+ were not significant in either linear or nonlinear models (plinear > 0.05, pnonlinear >0.05). The nonlinear model for SOIL showed a significant improvement over the linear model, but the association between SOIL and depression scores was almost linear within 95% of the concentration distribution.

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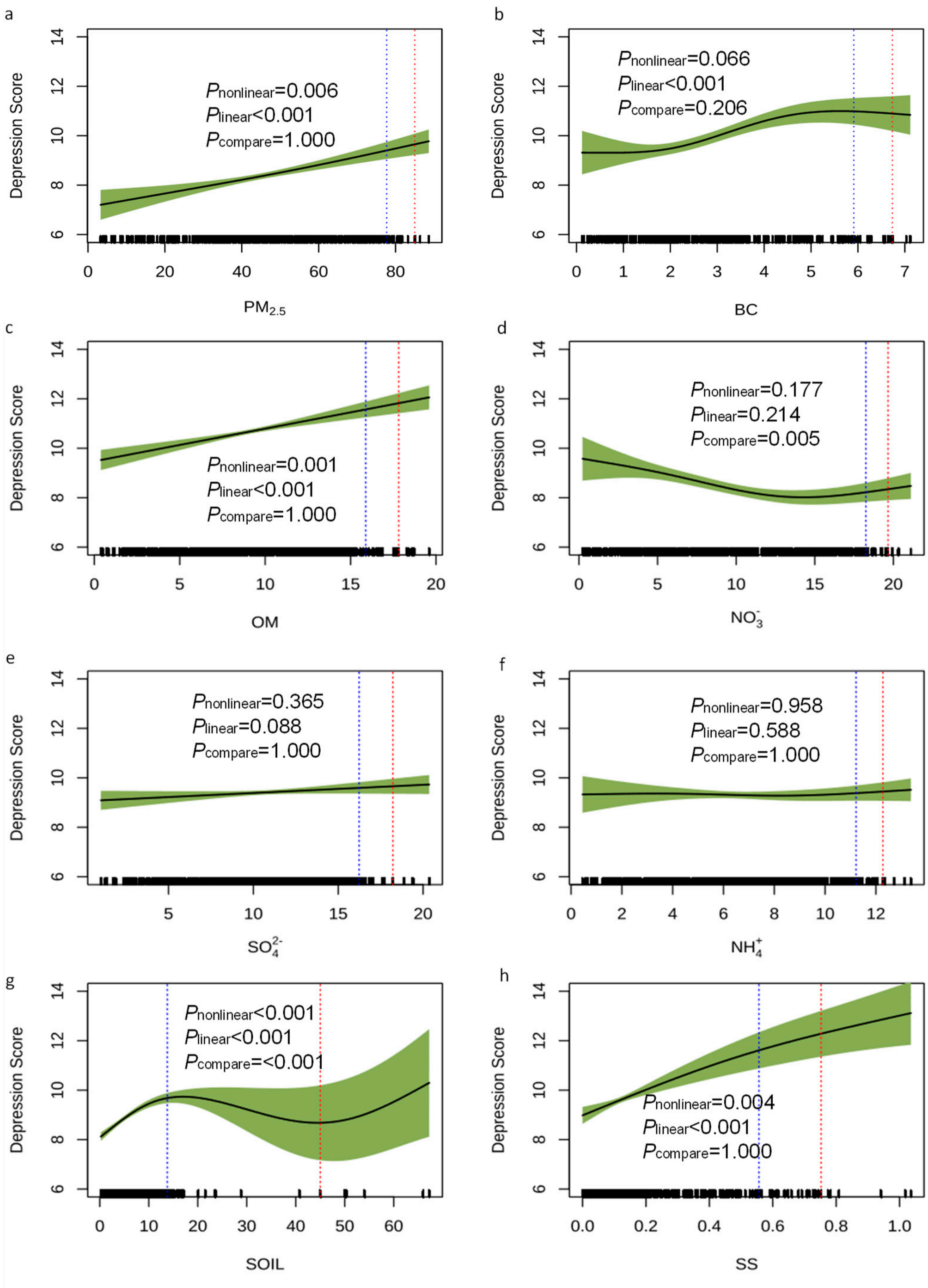

Figure 1. Exposure-Response Curves of $PM_{2.5}$ and Its Components with Depression Score. Notes: Adjusted for individual information (age, sex), sociodemographic background (education attainment, marital status, building type, cooking fossil type, location of residence), health status (cardiovascular related diseases, disabled), and behavior characteristics (smoking, alcohol drinking, social activity); the blue dashed line represents the 95% concentration distribution of the pollutant, and the red dashed line represents the 99% concentration distribution of the pollutant. Plinear represents the p-value for linear mixed model; Pnonlinear represents the p-value for smooth item in generalized additive mixed model; Pcompare represents the p-value from the likelihood ratio test between the linear model and the nonlinear model, if $p < 0.05$, it indicates that the nonlinear model did not significantly improve the performance of the linear model. Abbreviation: $PM_{2.5}$ = fine particulate matter; BC= black carbon; OM= organic matter; NO_3^-= nitrate; SO_4^{2-} = sulfate; NH_4^+ = ammonium; SOIL = soil particles; SS = sea salt.

3.3. Contribution of $PM_{2.5}$ Components to Depression

The combined effects and contribution of the seven components were shown in Figure 2. For each IQR increase in the mixture of all components, depression score increased by 1.104 (95%CI: 0.901, 1.307), and BC held the largest index weight (33.6%), followed by SOIL (28.59%) and SS (25.05%). Compared with single exposure model, the contribution of OM was weaker in the mixture, with index weight of 7.38%.

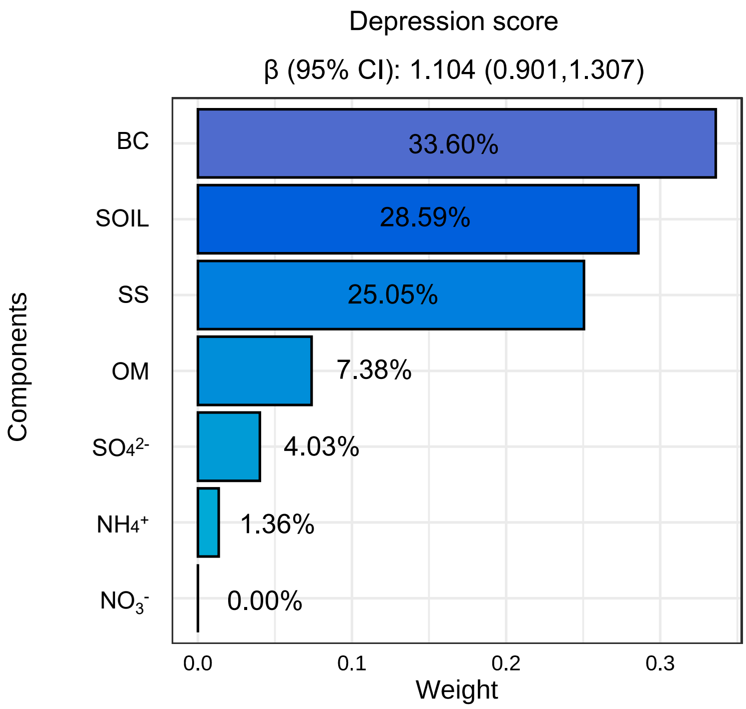

Figure 2. Index weights of $PM_{2.5}$ constituents from weighted quartile sum (WQS) regression for depression score associated with per quartile increases in the co-exposures of $PM_{2.5}$ constituents. Notes: Adjusted for individual information (age, sex), sociodemographic background (education attainment, marital status, building type, cooking fossil type, location of residence), health status (cardiovascular diseases, disabled), and behavior characteristics (smoking, alcohol drinking, social activity). Abbreviation: $PM_{2.5}$ = fine particulate matter; BC= black carbon; OM= organic matter; NO_3^-= nitrate; SO_4^{2-} = sulfate; NH_4^+ = ammonium; SOIL = soil particles; SS = sea salt.

3.4. Subgroup Analyses

For this analysis, stratified analyses were conducted for $PM_{2.5}$, BC, OM, SOIL, SS, which were significantly associated with depression, as well as for SO_4^{2-}, which was marginally significant. Social activity may be a potential modifier of $PM_{2.5}$, OM, and SO_4^{2-}. In those did not participated in social activities, depression scores increased by 0.99 (95% CI: 0.68, 1.31), 1.04 (95% CI: 0.71, 1.37), and 0.26 (95% CI: 0.04, 0.48) for each IQR increase of these three pollutants, respectively. The harmful effects of these three pollutants were lower among those who participated in social activities, with depression scores increasing by 0.81 (95% CI: 0.50, 1.13), 0.85 (95% CI: 0.51, 1.18), and 0.11 (95% CI: -0.11, 0.32), respectively. Green space may be a potential modifier of OM, SO_4^{2-}, SOIL and SS. In those exposed to low level green space, depression scores increased by1.18 (95% CI: 0.83, 1.53) and 0.22 (95% CI: 0.00, 0.44) for each IQR increase of OM and SO_4^{2-}, respectively. The harmful effects of these pollutants were even lower among those exposed to higher level green space, with depression scores changing by 0.82 (95% CI: 0.49, 1.16) and -0.01 (95% CI:-0.27, 0.25), respectively. Furthermore, compared with population with “social activity + high greenness”, those with “no social activity +

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low greenness" showed higher depression score cause by these pollutants. We also found that individuals living in high levels green space were more susceptible to SOIL and SS. For each IQR increase in SOIL or SS, the increase in depression scores was 0.81 (95% CI: 0.61, 1.01) and 0.65 (95% CI: 0.44, 0.86) in high level green space, higher than 0.45 (95% CI: 0.31, 0.58) and 0.48 (95% CI: 0.28, 0.68) for low level green space (Figure 3 and Table S3 in the supplement).

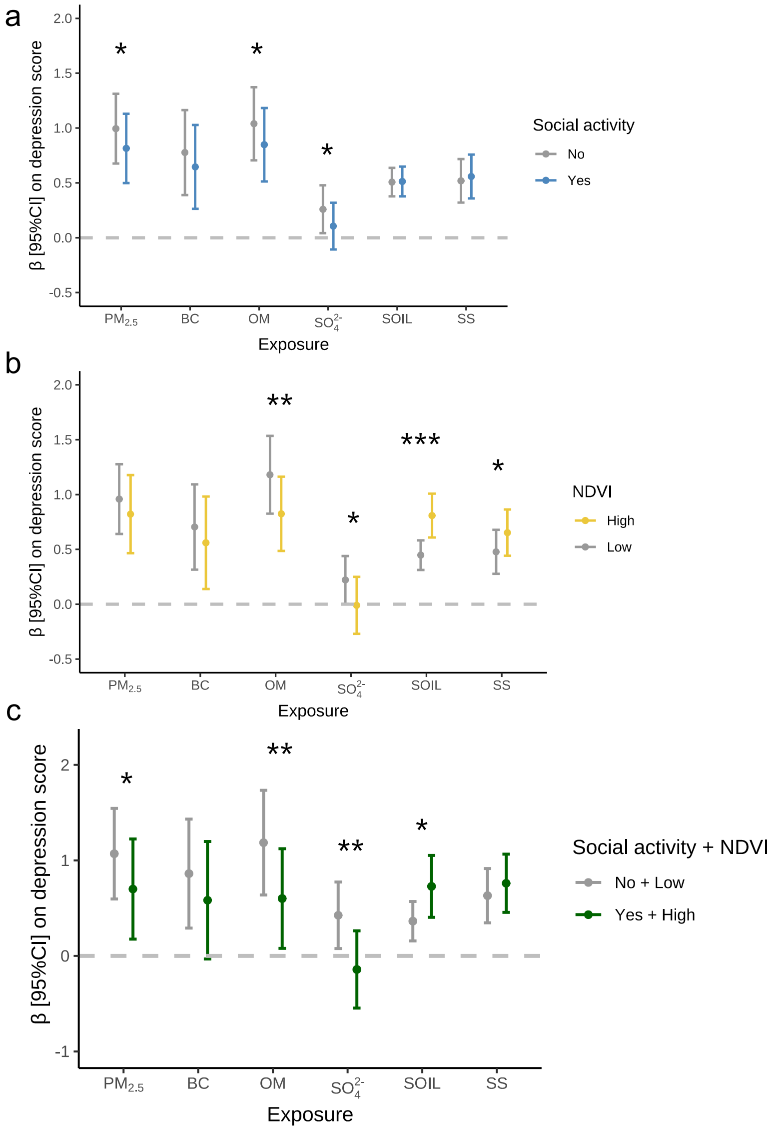

Figure 3. The Association of $PM_{2.5}$ and Its Components with Depression Score, stratified by social activity or NDVI. Notes: *p-interaction<0.05; **p-interaction<0.01; ***p-interaction<0.001. Abbreviation: $PM_{2.5}$ = fine particulate matter; BC= black carbon; OM= organic matter; NO_3^-= nitrate; SO_4^{2-} = sulfate; NH_4^+ = ammonium; SOIL = soil particles; SS = sea salt.

3.5. Sensitivity Analyses

The sensitivity analysis results were shown in Table 2. After adjustment for within-community correlations, the results for each pollutant remained robust. After further adjustment for residual of $PM_{2.5}$, or replacing individual random intercepts with individual fixed effects, the point estimate for the association between NO_3^- and depression scores changed from negative to positive, although not significantly. The results after bootstrap error correction were all comparable to the estimates obtained directly from regression in the two analysis.

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4. Discussion

In this research, we found that exposure to $PM_{2.5}$ mass and its components (BC, OM, SOIL, SS) were associated with higher depression levels in middle aged and older population in China. We further identified the relative contribution of each components, and found the protective effect of social activity and green space. The results would potentially contribute to a more nuanced understanding of the health impact of harmful components in ambient particulate pollution.

4.1. Main Findings

Consistent with our findings, a meta-analysis encompassing 16 studies [21] identified significant positive correlations between $PM_{2.5}$ exposure and depression within the middle-aged and older populations in China. A quasi-experimental study utilizing the CHARLS database found that long-term exposure to $PM_{2.5}$ led to a linear increase in depression score [14]. A cohort study based on China Family Panel Studies (CFPS) found that long-term exposure to $PM_{2.5}$ components were associated with the existence of depressive symptoms in adults, and for each standard unit increase in BC, OM, NH_4^+, NO_3^- and SO_4^{2-}, the odds ratio (OR) was 1.118 (95%CI: 1.020, 1.225), 1.134 (95%CI: 1.028, 1.252), 1.127 (95%CI: 1.011, 1.255), 1.107(95%CI: 9.981, 1.248) and 1.117 (95%CI: 1.020, 1.224), respectively [12]. Our research based on the CHARLS cohort offered results for older population and about additional components. We further found the potential harmful effect of natural sources of $PM_{2.5}$, such as SOIL and SS. Although we did not find significant association between water-soluble ions (NO_3^-, SO_4^{2-}, NH_4^+) and depression, we found that after further adjusting for residual of $PM_{2.5}$, or applying fixed-effect model, the harmful effects tended to be significant, which suggested that the associations we did not initially find may be influenced by confounder. The evaluation of non-linear relationships indicated that linear models in our main analysis were able to simulate the actual associations of pollutants with outcomes, as the application of non-linear models did not significantly improve model performance in comparison to linear models. Despite of the high variability in SOIL, the exposure-response relationship within the 95% concentration range essentially maintained a linear association with the outcomes.

4.2. Contributions of $PM_{2.5}$ Components and Underlying Biological Mechanism

The toxicity of $PM_{2.5}$ mixtures may be depended on its components. However, there is currently insufficient evidence on the toxicity of the various components of $PM_{2.5}$ on depression. We observed that BC had the largest hazardous contribution to depression. BC is smaller and more likely to enter the circulation and brain parenchyma through olfactory or sensory nerve pathways, inducing neurotoxic effects. Animal experiments showed that BC may cause inflammation and oxidative stress and its molecular precursors, polycyclic aromatic hydrocarbons (PAHs), could also cause neurotoxicity [22,23]. We observed that the effect of OM on depression in the single exposure model was higher than other pollutants, while in the mixed exposure model the contribution of OM was relative weaker. It may be attribute to the similar sources of OM and BC, and the high correlation possibly affect the result of single exposure model for OM. BC and OM predominantly originates from the incomplete combustion of fossils, biofuels, and biomass, including motor vehicle emissions and coal combustion [24,25].

We found the relative high contribution of SS and SOIL to depression. SOIL particles often contain heavy metals and silica dioxide [26,27], substances that can pose toxicity risks to human health, and are mainly suspended in the air due to mechanical processes, including wind erosion and transportation, as well as industrial activities such as mining and cement production. A Boston study found the association of Nickel (Ni) in $PM_{2.5}$ with reduced verbal memory, recognition, and executive function [28]. A cross-sectional study found that potassium (K) and iron (Fe) were associated with poorer cognitive function [29]. SS is primarily composed of elements such as sodium (Na+), chloride (Cl-), and potassium (K+), along with other typical ions in seawater. The concentration of these naturally occurring particulate matters is influenced by wind speed, temperature, and humidity levels [30]. It was reported that SS was associated with hypertension [3] and dementia [31]. There were almost no epidemiological studies or mechanistic studies about the effects of sea salt on depression, but both our study and that of Li et al. have found that SS may have a detrimental effect on brain function, which deserved to be brought to the attention of future researchers.

NO_3^-, SO_4^{2-}, NH_4^+ are secondary inorganic aerosols present in the atmosphere, predominantly generated from photochemical reactions involving gases released from the combustion of fuels like coal and petroleum. These reactions transpire under the influence of ultraviolet light, ozone, and hydroxyl radicals. Although we did not observe significant associations between these ions and depression, previous studies indicated that they could be neurotoxic agents [32]. Sulphate was able to create an acidic environment in the microcirculation and promotes the absorption of metallic components of particulate matter, allowing toxic compounds to settle deep in the lungs [33]. NH_4^+ and NO_3^- could lead to inflammation, oxidative stress and mitochondrial impairment [34,35].

Our results showed the high contribution of BC, SOIL, and SS to depression in Chinese middle-aged and elder population, suggesting precise control of $PM_{2.5}$ emissions in the following ways. Firstly, we should continue to promote the use of clean energy, strictly control new production capacity in high-energy-consuming and high-polluting industries, and strengthen the control of industrial and traffic emissions. Secondly, the prevention and control of soil pollution and groundwater pollution should be promoted, including the monitoring of soil heavy metals and other harmful substances, pollution risk control and remediation, and the control of pollution sources in arable land and industrial and mining enterprises. Thirdly, establishing a cooperative management system for sea salt in coastal cities, improving the monitoring of the exposure level and composition of sea salt, and strengthening health education for local residents [35].

4.3. Modification Effect of Social Activity and Greenspace

Previous studies have shown that frequent social activity was associated with lower risk of depression in older adults [36–38]. In this study, we found the associations of $PM_{2.5}$ and some of its components with depression were lower in middle-aged and elderly people who regularly participated in social activities. We found that the associations of OM、SO_4^{2-} with depression were lower in those living at high green space levels. The findings also indicated that those who both engaged in social activities and resided in areas with high green space levels exhibited the least adverse effect of $PM_{2.5}$ components on depression. Previous research has indicated that green space was associated lower risk of depression and anxiety in the elderly population [39]. The potential mechanisms for the effect of green remains unclear, but may be explained by improving air quality, providing places for physical and social activity, and reducing stress. We also found that the harmful effect of SOIL on depression was higher in people in high level green space. It may be attributed to the different components of SOIL particles in different areas of China [40,41] and from different sources. Previous studies have found the effect of residential, transport and power generation on iron and lead concentrations in $PM_{2.5}$ [42]. A cross-sectional study found that the adverse effect of TC, NH_4^+, K, and Fe was higher in people living in areas with lower greenspace, while the effects of Ca^{2+}, Na^+ and V were lower in lower greenspace [29]. More researches about the effect of different SOIL components in various area are needed to achieve precise control of air quality. In conclusion, this study calls for multi-pronged social support to reduce the risk of depression more effectively in the elderly population. On the one hand, for the individual, older people should be encouraged to go out of their homes and participate in social activities. On the other hand, at the environmental level, more outdoor activity areas and social facilities should be provided, such as pocket park and forest park.

4.4. Strengths and Limitations

This study has several major strengths. Primarily, it was the first nationwide epidemiological investigation exploring the relationship between $PM_{2.5}$ and its components with depression in China's middle-aged and older populations utilizing a longitudinal design. We identified several components that play a major contribution, which would provide theoretical support for precise control of $PM_{2.5}$ pollution, particularly in low- and middle-income regions experiencing high levels of air pollution. Secondly, our study employed a range of sensitivity analyses to verify the robustness of our findings. These methods encompassed adjustments for all available confounding factors, additional adjustments for $PM_{2.5}$ residual to assess the independent effects of each component, the use of fixed-effect models that offer reduced bias albeit with lower power, bootstrap simulations to model the impact of exposure errors, and accounting for community correlation.

However, our study also acknowledges some limitations. First, due to lack of detailed residential addresses of participants, we assigned exposure at the city level. Previous study suggested that bias might result in the investigated associations towards null effects and generally underestimated the risk [43]. However, the results kept robust after the simulation of exposure errors using the bootstrap methods. What's more, because this was an observational study, it was not possible to determine causal associations. To more definitively ascertain the health impacts of $PM_{2.5}$ and its components on mental and neurodegenerative diseases, larger population samples, more accurate exposure measurements, and enhanced study methodologies are needed in future research.

5. Conclusions

In conclusion, exposure to $PM_{2.5}$ and its components were associated with depression, and BC, SOIL and SS may make major contributions. More social activity and higher greenspace may help to reduce the depression symptoms caused by $PM_{2.5}$ and its components. These findings hold substantial relevance for enhancing the understanding of the harmful effects of $PM_{2.5}$ components and offer epidemiological evidence particularly pertinent to low- and middle-income regions experiencing high levels of pollution.

Supplementary Materials: The following supporting information can be downloaded at: Preprints.org, Text S1. A bootstrap method to correct the exposure measurement errors.; Table S1. Descriptive statistics of $PM_{2.5}$ and its components in the baseline year (2011).; Table S2. Correlation between pollutants in 125 cities in the CHARLS dataset in 2011.; Table S3. The effect (β [95%CI]) of total $PM_{2.5}$ and each component on depression, stratified by social activity (Yes / No) and NDVI (high / low).; Figure S1. Flowchart of participants included in this study.

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Data Availability Statement: Health-related data is available at http://opendata.pku.edu.cn/, while $PM_{2.5}$ and its component can be found at https://sites.wustl.edu/acag/datasets/surface-pm2-5-archive/.

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