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# The Association Between Air Pollutant Exposure and Anxiety Symptoms in Older Chinese Adults and the Modifying Effect of Dietary Patterns: a Nationwide Study from CLHLS

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## Abstract

# Background

Evidence linking air pollutant exposure to anxiety symptoms is limited for Chinese older adults. Moreover, whether dietary patterns can modify the association, rather than single nutrients, remains scarce. This study aimed to investigate the aforementioned associations in older Chinese adults and to further analyze the potential modifying effects of dietary patterns.

# Methods

We obtained the relevant data from the Chinese Longitudinal Healthy Longevity Survey (CLHLS). The Generalized Anxiety Disorder 7-item (GAD-7) scale was adopted to assess anxiety symptoms. Through satellite remote sensing data combined with machine learning models, the level of air pollutant exposure was estimated. We used food frequency questionnaires to measure four common dietary patterns, including cMIND, DDS, PDI and HEI. Logistic regression models were employed to examine the association between air pollutants and anxiety symptoms; restricted cubic splines (RCS) were used to test for nonlinear relationships, and interaction analyses were conducted to examine the modifying effects of dietary patterns.

# Results

With the concentration of CO, $NO_2$, $O_3$, $PM_{2.5}$, $PM_{10}$ and $SO_2$ rising per unit, the risk of anxiety symptoms among participants increased accordingly, after adjusting for all confounders. Specifically, the risk increased by 81.4% for CO (OR = 1.814, 95% CI: 1.418–3.385), 2.0% for $NO_2$(OR = 1.020, 95% CI:1.004–1.035), 1.3% for $O_3$(OR = 1.013, 95% CI:1.002–1.024), 1.2% for $PM_{2.5}$(OR = 1.012, 95% CI: 1.001–1.022), 0.7% for $PM_{10}$(OR = 1.007, 95% CI: 1.002–1.012) and 4.0% for $SO_2$(OR = 1.040, 95% CI: 1.014–1.067). RCS analysis suggested significant linear relationships of $PM_{2.5}$, $PM_{10}$ and $NO_2$ with anxiety symptoms (*p* for nonlinear > 0.05). Interaction analyses showed that cMIND significantly modified the associations between long-term exposure to CO, $NO_2$, $PM_{10}$ and $SO_2$ and anxiety symptoms, while PDI significantly modified the $O_3$–anxiety symptom association.

# Conclusion

These findings suggest that air pollutant exposure is associated with a rising risk of anxiety symptoms, and dietary patterns may act as effect modifiers of this relationship in older adults. Initiatives to enhance air quality and optimize dietary patterns could play a pivotal role in advancing mental well-being.

## 1.Introduction

Anxiety disorders, clinically characterized by excessive fear and anxiety, represent a major global public health challenge [1, 2]. As of 2025, the World Health Organization (WHO) reported that approximately

970 million people worldwide suffer from mental disorders, among which anxiety and depressive disorders are the most prevalent disorders not only lead to cognitive decline and impaired social functioning, but also frequently co-occur with various chronic physical diseases. thereby seriously undermining individual health[3]. Multinational studies further indicated that anxiety disorders consistently rank among the top contributors to health loss within the mental disorder category [2, 5, 14].In China, anxiety disorders pose an equally urgent public health challenge [6]. There was research which indicated that the lifetime prevalence of anxiety disorders in the general Chinese population reaches 7.6% [8]. Partly driven by age-related physiological decline and shifts in social roles[7, 12], the lifetime prevalence in this group reached 9.2%, which far exceeded that of the general population[8]. Moreover, the identification of anxiety in older adults remains suboptimal, and targeted assessment and early intervention strategies have not yet received adequate attention [7, 9]. Many individuals experience persistent anxiety symptoms, such as tension and worry in the early stages. These symptoms often fall below the diagnostic threshold for anxiety disorders. Therefore, relevant cases fail to receive timely treatment. This progression from subclinical to clinical anxiety is particularly likely to be overlooked in older adults. Against the backdrop of accelerating global population aging, the burden of anxiety symptoms in older adults warrants particular attention. Thus, it's of great significance to identify modifiable risk factors and develop targeted interventions to prevent or delay anxiety symptoms for public health.

In recent years, the association between ambient air pollution and the onset as well as progression of anxiety symptoms has become increasingly clear[10]. Numerous epidemiological evidence indicates that long-term exposure to air pollutants like $PM_{2.5}$, $O_3$, and CO is significantly associated with the onset and progression of anxiety symptoms[14–15]. However, existing studies have almost focused on single-pollutant analyses, and the dose-response relationships remain inadequately characterized. Moreover, current evidence is largely derived from studies of adults or adolescents, with only limited data available for older populations[14, 24, 13]. Given age-related increases in blood-brain barrier permeability and neuroinflammation[12], older adults may be particularly susceptible to the adverse mental health effects of air pollution. Additionally, geographical coverage is largely limited to Europe, North America, and other high-income regions, with little data from China. Although there are some domestic studies, most are based on regional samples[3, 5, 42], which cannot fully capture the national situation. Therefore, there is a clear need for research centered on Chinese older adults to examine the association between air pollutant exposure and anxiety symptoms. More targeted efforts are warranted to explore this association, specifically among older adults in China

It is extremely challenging to avoid air pollutant exposure in daily practice. Accordingly, exploring whether modifiable lifestyle factors can buffer its adverse effects is of great scientific value. Dietary patterns as an integrated combination of food types, intake frequency, and consumption quantity can shape nutrient intake patterns and thereby regulate systemic metabolism and overall health[16]. Mounting evidence has tied dietary factors to the prevention of mental health conditions. Among the well-established dietary frameworks, the Chinese version of the Mediterranean-DASH Intervention for Neurodegenerative Delay (cMIND), the Dietary Diversity Score (DDS), the Plant-based Diet Index (PDI), and the Healthy Eating Index (HEI) are widely recognized for balanced nutritional profiles and health-enhancing effects[17, 18, 19]. While previous studies have demonstrated that certain dietary molecules can regulate neural plasticity and

emotional responses by enhancing antioxidant capacity, inhibiting pro-inflammatory cytokine release, improving gut-brain axis function, and modulating gut microbiota diversity[20, 21], such findings only focus on individual nutritional components. Whether healthy dietary patterns can modify the adverse effects of air pollution on anxiety symptoms in older adults remains largely unexplored, with empirical evidence being extremely scarce.

To bridge the aforementioned research gaps, this study utilized data from the Chinese Longitudinal Healthy Longevity Survey (CLHLS). We selected six common air pollutants, including carbon monoxide (CO), nitrogen dioxide ($NO_2$), ozone ($O_3$), $PM_{2.5}$, $PM_{10}$, and sulfur dioxide ($SO_2$), to explore their relationships with anxiety symptoms among older adults. We further analyzed the potential modifying roles of four dietary patterns in these associations. This study may provide new insights for the development of targeted dietary intervention strategies.

## 2.Methods

# 2.1 Materials and Methods

The data for this study were drawn from CLHLS[23]. Through face-to-face interviews, the CLHLS collected information on the socioeconomic characteristics, lifestyles, health status, and cognitive function of Chinese adults aged 65 and above to identify potential risk factors affecting the lifespan of older adults in China. The CLHLS employed a multistage stratified random sampling method, with the sample covering 866 counties and cities across 23 provinces in China. The CLHLS was approved by the Biomedical Ethics Committee of Peking University (IRB00001052-13074), and all participants signed written informed consent forms prior to participation.

This study utilized cross-sectional data from the 2018 wave of the CLHLS. A total of 15,874 participants were initially included. After sequentially excluding 1,461 with missing data on anxiety symptoms, 1,600 with missing air pollutant data, and 8,709 with missing covariate data, the final analytical sample consisted of 4,104 participants. The detailed data cleaning process is presented in Fig. 1.

Figure 1. Flowchart of participant selection

# 2.2 Anxiety Symptoms Assessment

Anxiety symptoms were assessed with the Generalized Anxiety Disorder 7-item (GAD-7) scale, a validated instrument with well-established validity and reliability[26]. The GAD-7 contains seven items, and each item was scored according to symptom frequency. In detail, 0 represents not at all, 1 for several days, 2 for more than half the days, and 3 for nearly every day. The total score ranges from 0 to 21. Higher scores reflect more severe anxiety symptoms. Following established criteria, participants with a total score above 5 were classified as having anxiety symptoms[25]. In this study, the Cronbach's alpha of the GAD-7 was 0.914.

# 2.3. Exposure Assessment

We used satellite remote sensing data and machine learning models to estimate the exposure levels of CO, $NO_2$, $O_3$, $PM_{2.5}$, $PM_{10}$, and $SO_2$. Specifically, aerosol optical depth (AOD) served as the primary input variable

for particulate matter ($PM_{2.5}$ and $PM_{10}$). Multiple imputation techniques were applied to supplement missing AOD data, and high-resolution meteorological fields, land use types, and other auxiliary geographic information were integrated. By training ensemble machine learning algorithms such as random forests, we constructed complex nonlinear models relating AOD to ground-level monitoring concentrations, enabling the estimation of near-surface concentrations at high spatial and temporal resolution. These models demonstrated excellent predictive performance. The cross-validation in specific regions yielded coefficients of determination ($R^2$) exceeding 0.80 [27]. For gaseous pollutants ($NO_2$, $O_3$, $SO_2$, and CO), tropospheric vertical column densities retrieved by the next-generation satellite sensor TROPOMI were used as key predictor variables[28] .Taking $NO_2$ as an example, TROPOMI is capable of retrieving its vertical column density with high precision, offering a reliable basis for ground-level concentration estimation. Ensemble learning or deep learning frameworks were further adopted to integrate satellite column density data with multi-dimensional gridded data on meteorological parameters, road networks, and population distributions, for the purpose of effectively capturing urban-scale pollution gradients and spatiotemporal variation patterns. Previous studies have confirmed that hybrid models based on such frameworks (e.g., LSTM-CNN) can achieve correlation coefficients as high as 0.91 for multiple pollutants.

# 2.4. Dietary Assessment

To fully and reliably characterize the dietary status of the study population, we adopted multiple validated dietary assessment tools, including the cMIND, DDS, PDI, and HEI. The cMIND scoring system was developed by Huang et al. and has been validated in Chinese populations[29]. Food intake frequencies of twelve categories of food were obtained through a food frequency questionnaire (FFQ), then scores were determined according to specific criteria set out for each food group. Thus, the total cMIND score was obtained by the summation of corresponding scores[30], and scores were identified according to established criteria in each food group. The total cMIND score was then calculated as the sum of all component scores[30].Dietary diversity was assessed by the DDS, which was derived from the intake frequencies of 13 food items available in the CLHLS questionnaire[17]. Each food group was scored based on reported consumption, and the total DDS was computed as the sum of individual food scores, with higher scores indicating greater dietary diversity. To examine the extent to which elderly people eat plant-based diets, we adopted the PDI index to calculate this degree among elderly people[33]. This index comprises 16 food groups covering the most common plant-based and animal-based foods in the daily Chinese diet. PDI scores range from 16 to 80, with higher scores reflecting more frequent intake of plant-based foods[34]. Diet quality was evaluated using the HEI, which includes 13 dietary components[32]. Each component is scored according to intake level and then summed to yield a total score ranging from 0 to 50, with higher scores representing better diet quality and healthier dietary patterns[20].

Like other relevant studies before this study, the continuous score of each dietary index was transformed into categories by tertiles or quartiles for subsequent analyses. Specifically, cMIND scores were categorized into three groups according to tertile distribution[30]: T1 (0–4.5), T2 (5.0–5.5), and T3 (6.0–10.5). The DDS, PDI, and HEI were each divided into quartiles: DDS (Q1: 0–3, Q2: 4–5, Q3: 6–7, Q4: 8–13); PDI (Q1: 29–44, Q2: 45–48, Q3: 49–51, Q4: 52–67) and HEI (Q1: 4–21, Q2: 22–25, Q3: 26–30, Q4: 31–49)[33, 61, 62]. Detailed measurement and scoring criteria are provided in Tables S2–S5.

## 2.5 Covariates

Based on previous relevant studies [35, 36], this study selected potential confounding factors as covariates from the three aspects of sociodemographic characteristics, lifestyle, and health status. Specifically, sociodemographic characteristics included age, gender, residential location, marital status, and educational level. Lifestyle factors covered household ventilation frequency [37], sleep duration[38], smoking, alcohol drinking, physical exercise, physical activity, social participation, and living arrangement. Health-related indicators consisted of body mass index (BMI), visual and hearing impairment, as well as the number of chronic diseases, including hypertension, diabetes, heart disease, stroke and cerebrovascular diseases, respiratory diseases, and cancer. Detailed measurement methods and assignment criteria for all variables are presented in Supplementary Appendix 1.

## 2.6 Statistical Analysis

Normality of continuous variables was assessed using the Kolmogorov–Smirnov test. Categorical variables were presented as frequencies and percentages [n (%)], and non-normally distributed continuous variables as the median and first and third quartiles [M (Q1, Q3)]. Between-group comparisons were performed with the chi-squared test for categorical variables and the Mann–Whitney U test for two-group comparisons of non-normally distributed continuous variables. We used logistic regression models to estimate odds ratios (OR) and their 95% confidence intervals (95% CI) for the associations between air pollutant exposures and anxiety symptoms. Three models were sequentially built. Model 1 was unadjusted. Model 2 adjusted for gender, age, residence, marital status, education level, and living arrangement. Model 3 further adjusted for social participation, physical labor, sleep duration, ventilation frequency, smoking, drinking, exercise, body mass index, visual impairment, hearing impairment, and the number of chronic diseases. The Hosmer–Lemeshow test was used to assess model goodness-of-fit. A variance inflation factor (VIF) below 5 was considered indicative of no substantial multicollinearity among covariates. The E-value was calculated to assess the potential influence of unmeasured confounding on the observed associations. To explore possible dose–response relationships, continuous air pollutant concentrations were modeled using restricted cubic splines (RCS) while adjusting for the same covariates as in Model 3. Subgroup analyses were performed stratified by categories of cMIND, DDS, PDI, and HEI, and interaction terms between each pollutant and dietary pattern were included to test for effect modification. As a sensitivity analysis, multiple linear regression models were additionally fitted to examine the associations between air pollutants and anxiety symptom levels.

All statistical analyses were conducted using R version 4.3.0. A two-sided $p < 0.05$ was considered statistically significant.

# 3.Result

## 3.1 Baseline characteristics

As shown in Table 1, a total of 4,104 Chinese older adults were included in this study, of whom 348 (8.5%) had anxiety symptoms. Compared with the group without anxiety symptoms, the group with anxiety

symptoms had significantly higher proportions of women, rural residents, individuals with no formal education, insufficient sleep duration (≤ 7 h/day), visual impairment, and hearing impairment, as well as a greater chronic disease burden (all $p < 0.05$). The anxiety symptoms group was also exposed to higher concentrations of $NO_2$, $O_3$, $SO_2$, and CO (all $p < 0.05$) and had significantly poorer diet quality, as reflected by unfavorable shifts in the distributions of cMIND, DDS, PDI, and HEI (all $p < 0.05$).

Table 1
Baseline characteristics of the study participants by anxiety symptoms status

| Variables | Total (n = 4104) | Normal(n = 3756) | Anxiety symptom (n = 348) | Statistic | *P* |
|---|---|---|---|---|---|
| Age, M ($Q_1$, $Q_3$) | 82.00(73.00,91.00) | 82.00(73.00,91.00) | 80.00(72.00,90.00) | Z=-2.34 | **0.019** |
| Gender, n(%) | | | | $\chi^2$=15.50 | **< .001** |
| Male | 1935 (47.15) | 1806 (48.08) | 129 (37.07) | | |
| Female | 2169 (52.85) | 1950 (51.92) | 219 (62.93) | | |
| Residence, n(%) | | | | $\chi^2$=8.68 | **0.003** |
| Urban | 853 (20.78) | 802 (21.35) | 51 (14.66) | | |
| Rural | 3251 (79.22) | 2954 (78.65) | 297 (85.34) | | |
| Marital status, n(%) | | | | $\chi^2$=0.06 | 0.813 |
| 0thers | 2145 (52.27) | 1961 (52.21) | 184 (52.87) | | |
| Married | 1959 (47.73) | 1795 (47.79) | 164 (47.13) | | |
| Education level(year), n(%) | | | | $\chi^2$=12.95 | **0.002** |
| 0 | 1828 (44.54) | 1643 (43.74) | 185 (53.16) | | |
| 1–6 | 1454 (35.43) | 1342 (35.73) | 112 (32.18) | | |
| ≥ 6 | 822 (20.03) | 771 (20.53) | 51 (14.66) | | |
| BMI, n(%) | | | | $\chi^2$=6.06 | 0.109 |
| 18.5–24 | 545 (13.28) | 485 (12.91) | 60 (17.24) | | |
| < 18.5 | 2158 (52.58) | 1976 (52.61) | 182 (52.30) | | |
| 24–28 | 1044 (25.44) | 964 (25.67) | 80 (22.99) | | |
| ≥ 28 | 357 (8.70) | 331 (8.81) | 26 (7.47) | | |
| Visual impairment, n(%) | | | | $\chi^2$=13.64 | **< .001** |
| No | 2912 (70.96) | 2695 (71.75) | 217 (62.36) | | |
| Yes | 1192 (29.04) | 1061 (28.25) | 131 (37.64) | | |
| Hearing impairment, | | | | $\chi^2$=8.56 | **0.003** |

Note:Z: Mann-Whitney test, $\chi^2$: Chi-square test, M: Median, $Q_1$: 1st Quartile, $Q_3$: 3rd Quartile

| Variables | Total (n = 4104) | Normal(n = 3756) | Anxiety symptom (n = 348) | Statistic | *P* |
|---|---|---|---|---|---|
| n(%) | | | | | |
| No | 2754 (67.11) | 2545 (67.76) | 209 (60.06) | | |
| Yes | 1350 (32.89) | 1211 (32.24) | 139 (39.94) | | |
| Number of chronic diseases, n(%) | | | | $\chi^2$=8.92 | **0.012** |
| 0 | 1785 (43.49) | 1654 (44.04) | 131 (37.64) | | |
| 1 | 1405 (34.23) | 1286 (34.24) | 119 (34.20) | | |
| ≥ 2 | 914 (22.27) | 816 (21.73) | 98 (28.16) | | |
| cMIND tertiles, n(%) | | | | $\chi^2$=39.75 | **< .001** |
| 0–4 | 2077 (50.61) | 1848 (49.20) | 229 (65.80) | | |
| 4.5–5.5 | 963 (23.46) | 893 (23.78) | 70 (20.11) | | |
| 6–12 | 1064 (25.93) | 1015 (27.02) | 49 (14.08) | | |
| DDS quartiles, n(%) | | | | $\chi^2$=44.81 | **< .001** |
| 0–3 | 771 (18.79) | 673 (17.92) | 98 (28.16) | | |
| 4–5 | 1046 (25.49) | 933 (24.84) | 113 (32.47) | | |
| 6–7 | 1150 (28.02) | 1073 (28.57) | 77 (22.13) | | |
| 8–13 | 1137 (27.70) | 1077 (28.67) | 60 (17.24) | | |
| PDI quartiles, n(%) | | | | $\chi^2$=10.96 | **0.012** |
| 29–44 | 957 (23.32) | 854 (22.74) | 103 (29.60) | | |
| 45–48 | 1154 (28.12) | 1054 (28.06) | 100 (28.74) | | |
| 49–51 | 929 (22.64) | 856 (22.79) | 73 (20.98) | | |
| 52–67 | 1064 (25.93) | 992 (26.41) | 72 (20.69) | | |
| HEI quartiles, n(%) | | | | $\chi^2$=48.27 | **< .001** |
| 4–21 | 1112 (27.10) | 967 (25.75) | 145 (41.67) | | |
| 22–25 | 874 (21.30) | 796 (21.19) | 78 (22.41) | | |
| 25–30 | 1030 (25.10) | 967 (25.75) | 63 (18.10) | | |
| Note:Z: Mann-Whitney test, $\chi^2$: Chi-square test, M: Median, $Q_1$: 1st Quartile, $Q_3$: 3rd Quartile | | | | | |

| Variables | Total (n = 4104) | Normal(n = 3756) | Anxiety symptom (n = 348) | Statistic | *P* |
|---|---|---|---|---|---|
| 31–49 | 1088 (26.51) | 1026 (27.32) | 62 (17.82) | | |
| Sleep duration, n(%) | | | | $\chi^2$=101.62 | **< .001** |
| 7–9 | 1841 (44.86) | 1752 (46.65) | 89 (25.57) | | |
| ≤7 | 1576 (38.40) | 1355 (36.08) | 221 (63.51) | | |
| ≥9 | 687 (16.74) | 649 (17.28) | 38 (10.92) | | |
| Window ventilation frequency, n(%) | | | | $\chi^2$=12.69 | **0.002** |
| Low | 230 (5.60) | 199 (5.30) | 31 (8.91) | | |
| Medium | 2376 (57.89) | 2163 (57.59) | 213 (61.21) | | |
| High | 1498 (36.50) | 1394 (37.11) | 104 (29.89) | | |
| Smoking, n(%) | | | | $\chi^2$=1.80 | 0.18 |
| No | 3421 (83.36) | 3122 (83.12) | 299 (85.92) | | |
| Yes | 683 (16.64) | 634 (16.88) | 49 (14.08) | | |
| Drinking, n(%) | | | | $\chi^2$=0.52 | 0.472 |
| No | 3447 (83.99) | 3150 (83.87) | 297 (85.34) | | |
| Yes | 657 (16.01) | 606 (16.13) | 51 (14.66) | | |
| Exercise, n(%) | | | | $\chi^2$=8.08 | **0.004** |
| No | 2787 (67.91) | 2527 (67.28) | 260 (74.71) | | |
| Yes | 1317 (32.09) | 1229 (32.72) | 88 (25.29) | | |
| Physical labor n(%) | | | | $\chi^2$=0.09 | 0.77 |
| No | 910 (22.17) | 835 (22.23) | 75 (21.55) | | |
| Yes | 3194 (77.83) | 2921 (77.77) | 273 (78.45) | | |
| Social participation, n(%) | | | | $\chi^2$=4.07 | **0.044** |
| No | 3493 (85.11) | 3184 (84.77) | 309 (88.79) | | |
| Yes | 611 (14.89) | 572 (15.23) | 39 (11.21) | | |
| Note:Z: Mann-Whitney test, $\chi^2$: Chi-square test, M: Median, $Q_1$: 1st Quartile, $Q_3$: 3rd Quartile | | | | | |

| Variables | Total (n = 4104) | Normal(n = 3756) | Anxiety symptom (n = 348) | Statistic | *P* |
|---|---|---|---|---|---|
| Living arrangements, n(%) | | | | $\chi^2$=5.76 | 0.056 |
| Live with family | 3334 (81.24) | 3068 (81.68) | 266 (76.44) | | |
| Live alone | 712 (17.35) | 636 (16.93) | 76 (21.84) | | |
| Live in an institution | 58 (1.41) | 52 (1.38) | 6 (1.72) | | |
| CO, M ($Q_1$, $Q_3$) | 1.12 (0.91, 1.15) | 1.12 (0.91, 1.15) | 1.12 (0.91, 1.17) | Z=-2.19 | **0.028** |
| $NO_2$, M ($Q_1$, $Q_3$) | 24.86 (24.32, 36.34) | 24.86 (24.32, 35.01) | 28.35 (24.32, 39.79) | Z=-2.76 | **0.006** |
| $O_3$, M ($Q_1$, $Q_3$) | 81.25 (80.68, 96.30) | 81.25 (80.68, 96.30) | 85.74 (80.68, 96.74) | Z=-2.72 | **0.007** |
| $PM_{2.5}$, M ($Q_1$, $Q_3$) | 34.13 (26.98, 48.66) | 34.13 (26.98, 48.66) | 34.13 (26.98, 50.65) | Z=-1.03 | 0.304 |
| $PM_{10}$, M ($Q_1$, $Q_3$) | 58.65 (39.70, 88.67) | 58.65 (39.70, 88.67) | 62.81 (39.70, 89.35) | Z=-1.93 | 0.053 |
| $SO_2$, M ($Q_1$, $Q_3$) | 30.85 (26.32, 33.71) | 30.85 (26.32, 33.71) | 30.85 (26.32, 34.12) | Z=-2.25 | **0.024** |
| Note:Z: Mann-Whitney test, $\chi^2$: Chi-square test, M: Median, $Q_1$: 1st Quartile, $Q_3$: 3rd Quartile | | | | | |

Table 1. Baseline characteristics of the participants by anxiety symptoms status

# 3.2 Association of Air Pollutants with Anxiety Symptoms

Table 2 presents the associations of air pollutant exposure levels with anxiety symptoms. Logistic regression analyses showed that in the fully adjusted model, exposures to CO, $SO_2$, $NO_2$, $O_3$, $PM_{2.5}$, and $PM_{10}$ were all significantly associated with anxiety symptoms (all $p < 0.05$). Specifically, in Model 3, each unit increase in the concentration of CO, $NO_2$, $O_3$, $PM_{2.5}$, $PM_{10}$, and $SO_2$ was associated with an 81.4% (OR = 1.814, 95% CI: 1.418–3.385), 2.0% (OR = 1.020, 95% CI: 1.004–1.035), 1.3% (OR = 1.013, 95% CI: 1.002–1.024), 1.2% (OR = 1.012, 95% CI: 1.001–1.022), 0.7% (OR = 1.007, 95% CI: 1.002–1.012), and 4.0% (OR = 1.040, 95% CI: 1.014–1.067) increase in the risk of anxiety symptoms, respectively. The E-values for these associations ranged from 1 to 2, suggesting that unmeasured confounding had a negligible impact on the observed associations.

Table 2
Associations between air pollutants and anxiety symptoms based on logistic regression models

| | CO | $NO_2$ | $O_3$ | $PM_{2.5}$ | $PM_{10}$ | $SO_2$ |
|---|---|---|---|---|---|---|
| | **OR(95% CI)** | | | | | |
| Model 1 | 1.662 (0.884, 3.125) | 1.017(1.003, 1.032)* | 1.009(1.000, 1.019)* | 1.008 (1.002, 1.018)* | 1.006 (1.001, 1.011)* | 1.035 (1.011, 1.060)** |
| Model 2 | 2.042 (1.060, 3.933)* | 1.017 (1.002, 1.032)* | 1.010 (1.000, 1.021)* | 1.012(1.001, 1.022)* | 1.007(1.002, 1.012)** | 1.034(1.015, 1.065)** |
| Model 3 | 1.814(1.418, 3.385)** | 1.020 (1.004, 1.035)* | 1.013 (1.002, 1.024)** | 1.012 (1.001, 1.022)* | 1.007(1.002, 1.012)** | 1.040 (1.014, 1.067)** |
| *Note: OR, odds ratio; CI, confidence interval; *: p < 0.05; **: p < 0.01; ***: p < 0.001* | | | | | | |
| *Model 1: Crude model* | | | | | | |
| *Model 2: Adjusted for gender,age, residence, marital status, education level, living arrangement* | | | | | | |
| *Model 3: Adjusted for gender, age, residence, marital status, education level, living arrangement, social participation, physical labor, sleep duration, window frequency, smoking, drinking, exercise, BMI, visual impairment, hearing impairment, number of chronic diseases* | | | | | | |

Table 2. Associations between air pollutants and anxiety symptoms based on logistic regression models

# 3.3 Restricted Cubic Spline Analysis

The RCS analysis is presented in Fig. 2. Significant nonlinear relationships were observed between CO, $O_3$, and $SO_2$ and anxiety symptoms (*p* for nonlinear = 0.044, 0.004, and 0.040, respectively). By contrast, $PM_{2.5}$, $PM_{10}$, and $NO_2$ showed significant dose–response relationships with anxiety symptoms (*p* for nonlinear = 0.103, 0.290, and 0.749, respectively).

Figure 2: Dose-response relationships between air pollutants and anxiety symptoms

# 3.4 Modifying Effects of Dietary Patterns

As shown in Fig. 3, the significant modifying effect by cMIND was observed for the associations of CO, $NO_2$, $PM_{10,}$ and $SO_2$ with anxiety symptoms (*p* for interaction = 0.015, 0.045, 0.038, and 0.011, respectively). And the association between $O_3$ and anxiety symptoms can be modified by PDI (*p* for interaction = 0.038). No significant effect modification by DDS or HEI was observed for any of the six air pollutants in relation to anxiety symptoms.

Figure 3 Modifying effect of dietary patterns on the association between air pollutants and anxiety symptoms.

## 3.5 Sensitivity Analysis

A sensitivity analysis was performed using multiple linear regression models to assess the robustness of the logistic regression findings. The adjustment strategy was identical to that used in the logistic regression models. As shown in Table S5, in the fully adjusted Model 3, significant associations with anxiety symptoms were observed for CO(β = 0.176, 95% CI: 0.085–0.537, $p < 0.05$), $NO_2$ (β = 0.011, 95% CI: 0.000–0.021, $p < 0.05$), $O_3$(β = 0.007, 95% CI: 0.001–0.015, $p < 0.05$), $PM_{2.5}$(β = 0.004, 95% CI: 0.003–0.011, $p < 0.01$), $PM_{10}$ (β = 0.003, 95% CI: 0.000–0.007, $p < 0.05$) and $SO_2$ (β = 0.015, 95% CI: 0.001–0.031, $p < 0.05$). The direction of these associations was fully consistent with the logistic regression results.

## 4.Discussion

This study systematically explored the significant associations of multiple air pollutants with anxiety symptoms among Chinese older adults. The main findings were generally consistent with previous research that focused on single pollutants. In a study by Yang et al., greater exposure to $PM_{2.5}$, $PM_{10}$, and NO was associated with an elevated risk of developing depression and anxiety[14].

Similarly, a study involving 4,008 older adults in the United States found that $PM_{2.5}$ exposure was related to anxiety symptoms, especially among those with low socioeconomic status or specific health-related characteristics[39].

Zundel et al. also pointed out that gaseous pollutants such as $O_3$, $SO_2$, and $NO_2$ may increase the risk of anxiety through neurotoxicity in the central nervous system[15].

While the majority of existing evidence aligns with our observations, certain discrepancies exist. Specifically, a meta-analysis of seven studies on CO reported no statistically significant association between CO and anxiety symptoms (RR = 1.012, 95% CI: 0.996–1.028) [44]. Furthermore, a nationally representative cross-sectional study from Portugal detected no statistically significant link between long-term $PM_{10}$ exposure and the likelihood of a diagnosis of common mental disorders[53]. These inconsistencies may stem from regional differences in air pollution control stringency, varying exposure levels, and inter-population differences in environmental susceptibility, all of which warrant further investigation in future studies.

CO exposure was significantly associated with an elevated risk of anxiety symptoms, which could be partially explained by cellular damage and cerebral damage. CO can bind to cytochrome c oxidase and impair cellular respiration[60], leading to apoptosis, dysregulated cell proliferation, and autophagy. In addition, CO readily binds to hemoglobin to form carboxyhemoglobin, which is unable to carry oxygen and thus causes tissue hypoxia[46, 47]The brain has a high demand for oxygen; prolonged exposure may damage brain regions involved in emotion regulation and thereby contribute to anxiety and other mood disorders. It is worth noting, however, that CO can also modulate neurotransmitter release and metabolism, moderately inhibit oxidative stress and neuroinflammation, and exert neuroprotective and anxiolytic effects[45]. Further investigation through cohort studies is needed to clarify these mechanisms.

Compared with CO, $SO_2$ is a strong irritant. Long-term exposure can trigger physical symptoms such as chest tightness, shortness of breath, and cough[40], which can easily generate anxiety and cognitive bias. Such cognitive bias may, in turn, heighten an individual's sensitivity to physical signals, amplify the perception of discomfort, and create a self-reinforcing cycle of anxiety. Moreover, after entering the circulation, $SO_2$ and its metabolites can cross the blood–brain barrier, induce central oxidative stress and neuroinflammation, and disrupt the regulation of mood-related neurotransmitters involved in mood, thereby enhancing anxiety-inducing effects[41]. Notably, 75.22% of the participants in this study came from rural areas, where coal is the main domestic fuel, indoor $SO_2$ concentrations often exceed outdoor levels[49], and residents spend relatively more time indoors[57]. Therefore, actual indoor and outdoor exposure concentrations and cumulative exposure may have been higher in this population, which could partly explain the prominent effect of $SO_2$ on anxiety symptoms observed in our study.

Prolonged exposure to $O_3$ could affect multiple physiological pathways, inducing structural and functional changes in the central nervous system and contributing to the development of mental disorders. Key mechanisms underlying such effects involve the hypothalamic–pituitary–adrenal (HPA) axis stress response, oxidative stress, as well as the lung–brain axis[51, 52, 56]. More recent evidence also suggests that $PM_{2.5}$ may interfere with normal HPA axis function and disrupt neuroendocrine balance, thereby giving rise to anxiety symptoms. This is supported by animal experiments in which decreased corticotropin-releasing hormone and elevated glucocorticoid levels were observed, indicating HPA axis activation[59]. $PM_{2.5}$ has also been found to exert impacts on the CNS[59]. Similarly, for $PM_{10}$, its relation to anxiety symptoms appears to operate via enhanced inflammatory response, neuronal degeneration, and oxidative stress[43].

However, unmeasured factors that differ across exposure levels (e.g.,, green space exposure[50] and noise[54]) may introduce systematic differences, and residual confounding could still influence the shape of the exposure–response curve.

This study further indicated that dietary patterns could modify the associations of certain air pollutants with anxiety symptoms. PDI exerted a significant modifying effect only for the $O_3$–anxiety association, with no significant interactions observed for the other pollutants. This may be because $O_3$ acts as a strong oxidant, and its health damage is closely linked to oxidative stress, which can further affect mood through pulmonary inflammation and lung–brain axis signaling[52]. PDI emphasizes plant-based foods, which provide high levels of antioxidant factors such as polyphenols, carotenoids, and vitamins. These components may be more directly involved in scavenging $O_3$-induced oxidative damage, reducing stress responses, and neuroinflammation[22]. Meanwhile, cMIND exhibited a relatively stable effect modification on the anxiety risk associated with multiple pollutants, consistent with previous findings. Prior research has shown that cMIND can significantly attenuate the associations of $PM_{2.5}$, $NO_2$, and $SO_2$ with depression in older adults[18], and international studies have reported that MIND-type diets can reduce $PM_{10}$- and $SO_2$-induced neuroinflammation and anxiety[53]. cMIND captures complex and diverse interactions among food components[29]. Its constituent food groups benefit mental health through different components and mechanisms—reducing inflammation and oxidative stress and providing neuroprotection via antioxidants and signal transduction regulation[58].These properties may jointly produce a relatively consistent buffering

effect against the anxiety-inducing effects of several pollutants[16, 22]. No significant interactions were observed for DDS or HEI, which may be because these indices are more oriented toward overall dietary diversity or composite diet quality. Such scores can reflect dietary balance well, but may not sensitively capture key dietary components closely related to neuroinflammation, oxidative stress, and blood–brain barrier homeostasis.

Our work has several strengths. Firstly, this study focused on the susceptible group of environmental exposure of the elderly in China and systematically analyzed the comprehensive impact of six common air pollutants, making up for the shortcomings of previous studies focusing on single pollutants or adults, children, pregnant women, and other groups, and filling the shortcomings of past studies focusing more on foreign people. Secondly, compared to previous studies that paid attention mostly to one kind of air pollution or focused solely on the type of population, such as adults, children, and pregnant women, our study analyzed jointly the influences exerted collectively by six kinds of common pollutants. Hence, our research would fill in the gap existing in prior investigations. Thirdly, we paid attention mainly to the Chinese population, while most papers studied other countries' people before. Fourthly, four kinds of major dietary patterns were taken into consideration instead of only single nutrients in the past research. Finally, it provides direct evidence for developing mental health protection strategies for older adults from the perspective of overall dietary patterns and delivers greater feasibility for practical implementation.

This study also has limitations. First, the cross-sectional design only permitted identification of associations and could not establish causal relationships between air pollutants and anxiety symptoms. Future longitudinal cohort studies are necessary to validate these findings. Second, most data were collected through questionnaire-based retrospective surveys. Older participants may experience recall problems and subjective differences in self-reported health status, leading to recall bias and social desirability bias. Incorporating objective biological indicators to calibrate errors in self-reported dietary intake and disease symptoms may be utilized to improve assessment validity. Third, due to constraints of the questionnaire, potential confounders may not have been fully considered. Fourth, air pollutant concentrations were estimated based on satellite remote sensing data and machine learning models, which only reflect outdoor exposure levels for populations in a given area and period. This approach cannot precisely capture the true exposure levels or their dynamic changes among older adults. In future work, integrating personal exposure monitoring devices will be necessary.

# 5.Conclusion

This study confirms that exposure to CO, $NO_2$, $PM_{2.5}$, $PM_{10}$, $O_3$, and $SO_2$ is associated with an increased risk of anxiety symptoms among the elderly population in China. Certain dietary patterns are able to weaken such pollution-related risks to a noticeable extent. Thus, this study expands the evidence on the association between air pollution and mental health and offers useful strategic guidance to environmental public health and the prevention and control work regarding mental health problems of the elderly. Besides, the findings also help protect elderly mental health and facilitate coordinated regulation of environmental conditions and nutritional health in regions with severe air pollution. In future work, more efforts may need to be put into big data collection in order to conduct large sample longitudinal studies. Meanwhile, in order to validate the

long-term protective effects, further exploration needs to focus on causal paths and varied biological mechanisms behind these relationships, with inflammatory factors and oxidative metabolites as core indicators.

## Abbreviations

95% CI
95% Confidence Intervals
AOD
Aerosol Optical Depth
BMI
Body Mass Index
CLHLS
Chinese Longitudinal Healthy Longevity Survey
cMIND
Chinese version of the Mediterranean-DASH Intervention for Neurodegenerative Delay
DDS
Dietary Diversity Score
FFQ
Food Frequency Questionnaire
GAD-7
Generalized Anxiety Disorder 7-item
HEI
Healthy Eating Index
HPA
Hypothalamic–Pituitary–Adrenal
OR
Odds Ratios
PDI
Plant-based Diet Index
RCS
Restricted Cubic Splines
VIF
Variance Inflation Factor
WHO
World Health Organization

## Declarations

**Ethics approval and consent to participate**

The CLHLS study was approved by the research ethics committees of Duke University and Peking University (IRB00001052–13074). The procedures used in this study adhere to the tenets of the Declaration of Helsinki. All participants provided written informed consent.

**Consent for publication**

Not applicable.

**Availability of data and materials**

The dataset used in this study is available upon registration and application on the official website of the CLHLS at https://opendata.pku.edu.cn/dataverse/CHADS.

**Competing interests**

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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**Author Contributions**

M Y: Resources, Data curation, Supervision, Project Administration, Writing-Review & editing

R R : Data curation, Formal analysis, Writing-Original Draft, Writing-Review & editing.

S C : Conceptualization, Methodology, Writing-Review & editing.

S W : Validation, Writing-Review & editing.

W D : Visualization, **Corresponding Author**.

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# Figures

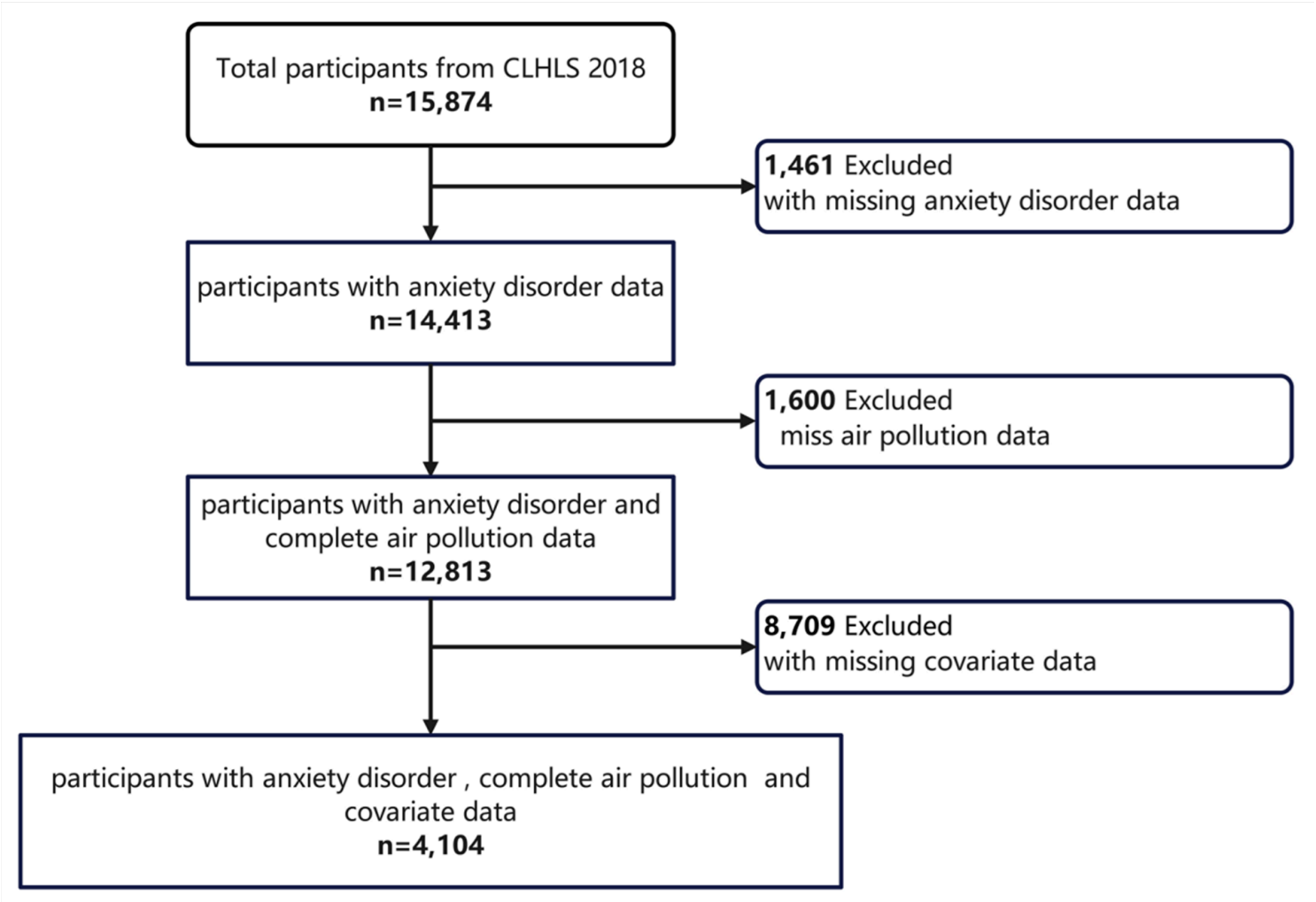
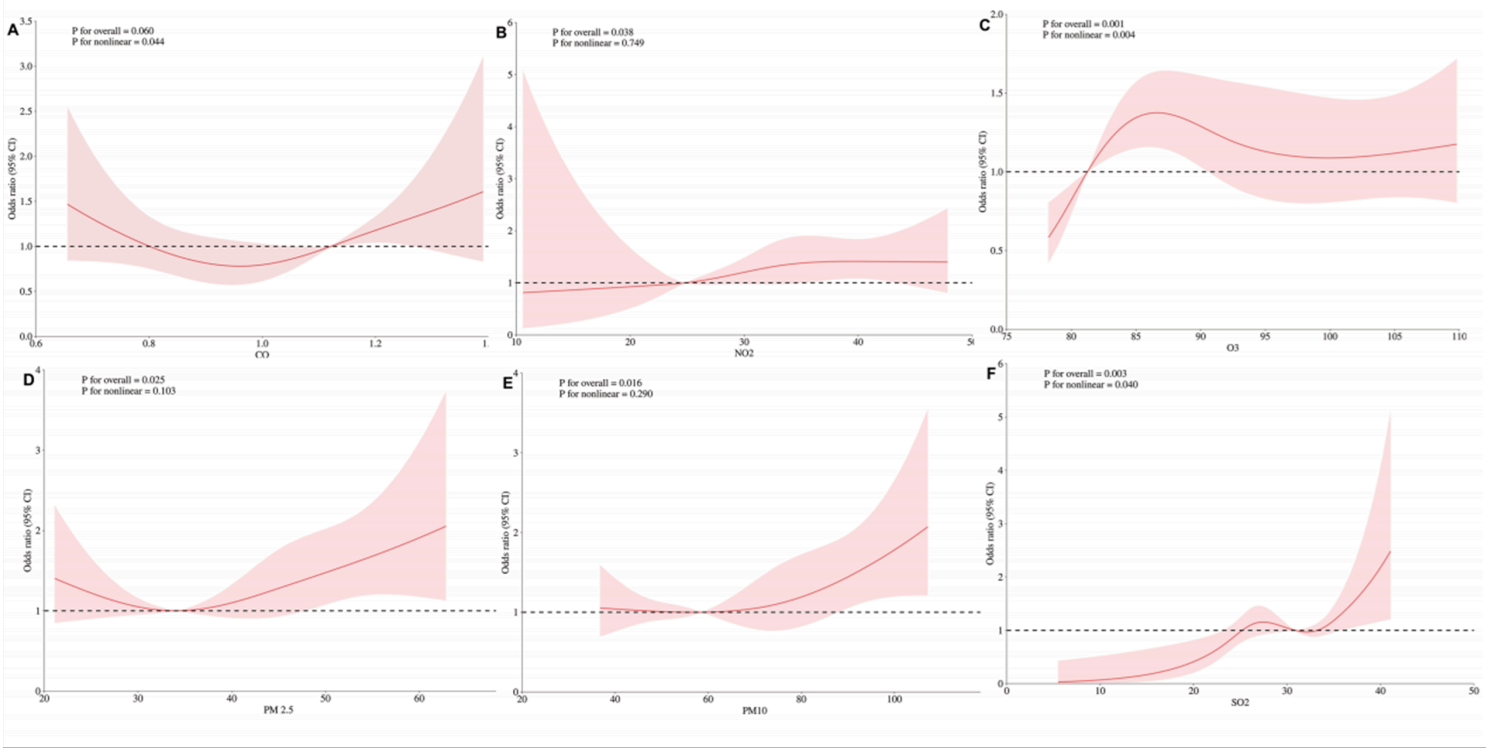



**Figure 1**

Flowchart of the participant selection process. After excluding missing data on anxiety symptoms n=1,461, air pollutants n=1,600, and covariates 8,709, 4,104 participants from the 2018 CLHLS wave were included. CLHLS, Chinese Longitudinal Healthy Longevity Survey.




## Figure 2

Restricted cubic spline analysis showing the dose–response relationships between (A) CO, (B) $NO_2$, (C) $O_3$, (D) $PM_{2.5}$, (E) $PM_{10}$, (F) $SO_2$ and anxiety symptoms. Dark solid lines represent OR; light pink shading represents 95% CI; dashed line indicates OR = 1. P for overall and P for nonlinear are shown in each panel. Adjusted for age, sex, residence, education, marital status, smoking, alcohol consumption, exercise, BMI, and dietary patterns. OR, odds ratio; CI, confidence interval.

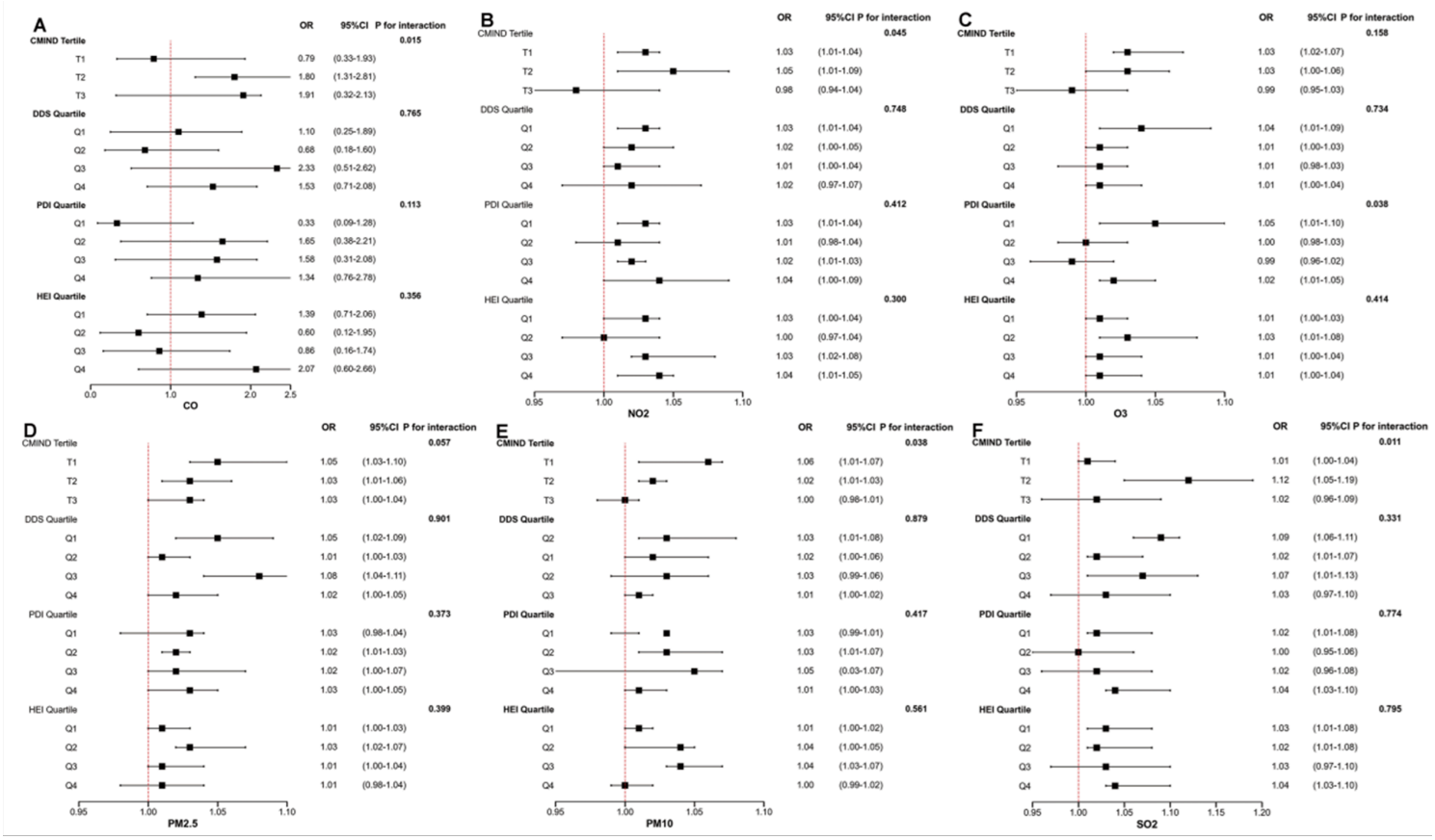



**Figure 3**

Modification of air pollutant–anxiety associations by dietary patterns. (A) CO, (B) $NO_2$, (C) $O_3$, (D) $PM_{2.5}$, (E) $PM_{10}$, (F) $SO_2$. cMIND significantly modified CO, $NO_2$, $PM_{10}$, and $SO_2$; PDI modified $O_3$; DDS and HEI showed no significant modification. cMIND was categorized as T1–T3; DDS, PDI, and HEI as Q1–Q4. Adjusted for the covariates listed in Figure 2 plus the other dietary patterns. cMIND, Chinese Mediterranean-DASH Intervention for Neurodegenerative Delay; DDS, dietary diversity score; PDI, plant-based diet index; HEI, healthy eating index.

# Supplementary Files

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- Supplementarymaterial.docx
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