ADVANCING EARTH AND SPACE SCIENCES

GeoHealth

RESEARCH ARTICLE

10.1029/2024GH001023

Qingyang Zhu and Yuebin Lyu contributed equally to this paper.

Key Points:

- We enhanced the precision of air pollution ($PM_{2.5}$, NO_2, and O_3) metrics by employing three advanced satellite-based models
- Air pollution was significantly associated with reduced scores on the Chinese Mini-Mental-State Exam and an increased likelihood of cognitive impairment
- O_3 is more harmful to cognitive function in the warm season (April–September)

Correspondence to:

X. Shi and Y. Liu,
shixm@chinacdc.cn;
yang.liu@emory.edu

Citation:

Zhu, Q., Lyu, Y., Huang, K., Zhou, J., Wang, W., Steenland, K., et al. (2025). Air pollution and cognitive impairment among the Chinese elderly population: An analysis of the Chinese Longitudinal Healthy Longevity Survey (CLHLS). *GeoHealth*, *9*, e2024GH001023. https://doi.org/10.1029/2024GH001023

Received 25 JAN 2024
Accepted 24 SEP 2024

© 2025 The Author(s). GeoHealth published by Wiley Periodicals LLC on behalf of American Geophysical Union. This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

Air Pollution and Cognitive Impairment Among the Chinese Elderly Population: An Analysis of the Chinese Longitudinal Healthy Longevity Survey (CLHLS)

Qingyang Zhu[1], Yuebin Lyu[2], Keyong Huang[3], Jinhui Zhou[2], Wenhao Wang[1], Kyle Steenland[1], Howard H. Chang[4], Stefanie Ebelt[1], Xiaoming Shi[2], and Yang Liu[1]

[1]Gangarosa Department of Environmental Health, Rollins School of Public Health, Emory University, Atlanta, GA, USA, [2]China CDC Key Laboratory of Environment and Population Health, Chinese Center for Disease Control and Prevention, National Institute of Environmental Health, Beijing, China, [3]Key Laboratory of Cardiovascular Epidemiology & Department of Epidemiology, Fuwai Hospital, National Center for Cardiovascular Diseases, Chinese Academy of Medical Sciences and Peking Union Medical College, Beijing, China, [4]Department of Biostatistics and Bioinformatics, Rollins School of Public Health, Emory University, Atlanta, GA, USA

Abstract Cognitive impairment and dementia have long been recognized as growing public health threats. Studies have found that air pollution is a potential risk factor for dementia, but the literature remains inconclusive. This study aimed to evaluate the association between three major air pollutants (i.e., $PM_{2.5}$, O_3, and NO_2) and cognitive impairment among the Chinese elderly population. Study participants were selected from the Chinese Longitudinal Health Longevity Survey (CLHLS) after 2005. We define cognitive impairment as a Chinese Mini-Mental-State Exam (CMMSE) score <24. The associations of air pollution with cognitive impairment and CMMSE score were evaluated with a logistic regression model and a linear mixed-effect model with random intercepts, respectively. A total of 3,887 participants were enrolled in this study. Of the 2,882 participants who completed at least one follow-up visit, 931 eventually developed cognitive impairment. In single-pollutant models, we found that yearly average $PM_{2.5}$ and NO_2 as well as warm season O_3, were positively associated with cognitive impairment. NO_2 remained positively associated with cognitive impairment in the multi-pollutant model. The linear mixed-effect models revealed that warm season O_3 and yearly average NO_2 were significantly associated with decreased CMMSE scores. Our research has established a positive association between cognitive impairment and air pollution in China. These findings underscore the imperative for the next iteration of China's Air Pollution Prevention and Control Action Plan to broaden its focus to encompass gaseous air pollutants since mitigating single air pollutant is insufficient to protect the aging population.

Plain Language Summary Our research investigates the impact of air pollution on cognitive well-being in China's elderly. We studied three pollutants—fine particles ($PM_{2.5}$), ozone (O_3), and nitrogen dioxide (NO_2)—and their relationship to cognitive function. By analyzing data from a large survey, we found that higher exposure to these pollutants, especially NO_2, correlates with an increased risk of memory and thinking issues. This insight is crucial for China's air pollution policies, highlighting the need to address a range of pollutants to safeguard the cognitive health of its aging population.

1. Introduction

Cognitive impairment and dementia have long been recognized as growing public health threats, especially in an aging society. The all-age mortality rates attributable to dementia skyrocketed by 100.1% (95% CI: 89.1–117.5) from 1990 to 2019, placing it the seventh leading risk factor of excessive deaths globally among all age groups, and the fourth among individuals aged 70 and older (Collaborators, 2021). Meanwhile, the global prevalence of dementia was projected to increase from 57.4 (95% CI: 50.4–65.1) million in 2019 to 152.8 (95% CI: 130.8–175.9) million in 2050 (Nichols et al., 2022), posing a great challenge to the healthy aging of the world's elderly population. In 2020 alone, the prevalence of dementia among the Chinese population aged 60 and above reached 6.0% (Ren et al., 2022). More strikingly, it was estimated that cognitive impairment, an intermediate stage between normal cognitive function and dementia, affected 22.4% of the Chinese elderly population in 2018 (Qin et al., 2022).

Amidst this unfolding crisis, air pollution has emerged as a potential risk factor for cognitive impairment and dementia. For example, A handful of studies have linked $PM_{2.5}$ to poor cognitive performance (Lin et al., 2017), slower reaction time (Cullen et al., 2018), memory loss (Ailshire & Clarke, 2014; Ailshire & Crimmins, 2014), global cognitive decline (Weuve et al., 2012), and Alzheimer's disease (AD) (Jung et al., 2015; Li et al., 2019). Gaseous pollutants, such as ozone (O_3) and nitrogen dioxide (NO_2), were also found to be associated with cognitive decline (Cleary et al., 2018), semantic fluency (Zare Sakhvidi et al., 2022), lower executive function, and impaired logic memory (Gatto et al., 2014). However, as reviewed by Delgado-Saborit et al., current study findings are inconsistent, especially regarding which pollutants have the strongest association with dementia (Delgado-Saborit et al., 2021). This inconsistency is possibly attributable to exposure measurement error, particularly when multiple air pollutants are investigated simultaneously.

Recent advances in satellite remote sensing have offered an opportunity to establish high-performance air pollution models for environmental epidemiological studies. However, satellite retrievals, such as aerosol optical depth (AOD), are typically not direct measurements of ground-level air pollution per se. A set of machine-learning approaches have been utilized to project the spatiotemporal distribution of multiple air pollutants from satellite-driven data. For example, Liang et al. established a 1-km ensemble learning model for $PM_{2.5}$ in China from 2000 to 2018 (Liang et al., 2020). The model had an overall monthly R^2 of 0.93 (Liang et al., 2020). In addition, we also established 0.05° (approximately 5 km) O_3 (Zhu et al., 2022) and NO_2 prediction models (Huang et al., 2023) covering 2005–2019 from Ozone Measurement Instrument (OMI) retrievals. Certain models not only expanded the spatial coverage of the ground-level monitoring network but also reliably hindcasted historical pollution status for ∼10 years before the onset of large-scale environmental monitoring in China (Zhu et al., 2022).

The availability of such long-term air pollution data facilitates epidemiological investigations with large existing cohorts that were established decades ago. The Chinese Longitudinal Health Longevity Survey (CLHLS) is the world's largest survey on centenarians with a compatible group of people aged 65 and above (Zeng et al., 2017). Participants of CLHLS were enrolled in 22 different provinces in China over eight waves of survey data collection that occurred during 1998–2018. Its database includes detailed information on the participants' sociodemographic status as well as medical records. The CLHLS used a Chinese Mini-Mental State Exam (CMMSE, localized from the original MMSE) to evaluate the subjects' cognitive function. To ensure the quality and consistency of the results throughout the whole nation, all the CMMSE tests were conducted face-to-face between trained interviewers and the participants. The CMMSE has proven to be effective for the Chinese elderly population (Ren et al., 2021).

The present study investigated the association between air pollution and cognitive impairment with the CLHLS data. In contrast to traditional analyses that used environmental monitoring data, pioneers the integration of three advanced satellite-driven models to evaluate population exposure to $PM_{2.5}$, O_3, and NO_2 at a fine resolution in China. The improvement in exposure matrices could make better use of CLHLS's long temporal coverage and thus benefit our mutual understanding of air pollution as a potential risk factor for dementia.

2. Methods

2.1. Study Population

The CLHLS is a nationwide survey on the healthy aging of the Chinese elderly population covering 22 out of the 31 provinces (Figure 1). It comprises eight rounds of data collection that took place in 1998, 2000, 2002, 2005, 2008–2009, 2011–2012, 2014, and 2018, respectively (Zeng et al., 2017). All participants were selected with a targeted random sampling approach to ensure representativeness. The details of CLHLS may also be found at https://agingcenter.duke.edu/CLHLS.

The present study selected CLHLS participants that were enrolled after 2005 to align with the temporal coverage of the available air pollution exposure data set. The inclusion criteria covered: (a) free of cognitive impairment (CMMSE $\geq$ 24) at enrollment; (b) fully completed at least one CMMSE measurement or unable to complete the test only due to significant cognitive impairment; and (c) had clear residential address records. We tracked participants until the end of the study, or the first time they developed a cognitive impairment, if any, assessed via the survey in this study. The detailed distribution of our study participants can be found in Figure 1.

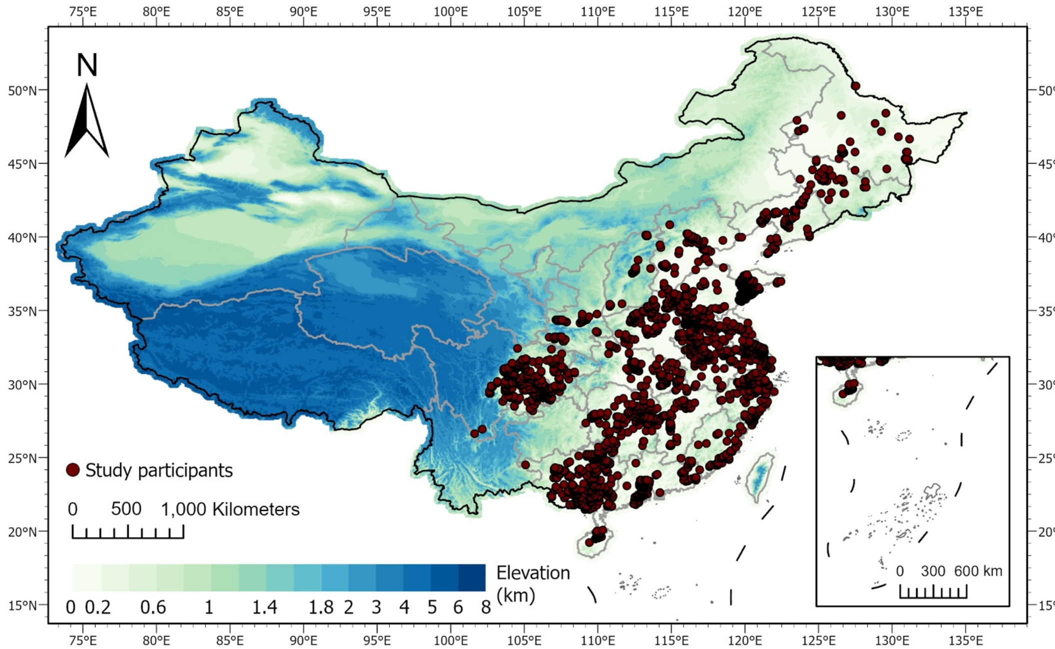

Figure 1. The distribution of study participants. The CLHLS participants came from 22 Chinese provinces, namely Beijing, Tianjin, Chongqing, Shanghai, Anhui, Fujian, Guangdong, Guangxi, Hubei, Hunan, Henan, Hebei, Heilongjiang, Liaoning, Jiangxi, Jiangsu, Jilin, Shandong, Shaanxi, Shanxi, Sichuan, and Zhejiang.

The study was approved by the Biomedical Ethics Committee of Peking University (IRB00001052-13074) and the Institutional Review Board of Emory University (STUDY00000950). Signed written consents were obtained from either the participants or their legal representatives for both the baseline and follow-up surveys.

2.2. Exposure Assessment

We used three satellite-driven machine learning models to estimate the level of exposure to ambient $PM_{2.5}$, O_3, and NO_2. Specifically, the 1-km $PM_{2.5}$ data were developed by Liang et al. using the Multi-Angle Implementation of Atmospheric Correction (MAIAC) aerosol optical depth (AOD) product as the main predictor. This model first used a multiple imputation approach to gap-fill the missing AOD values and then a generalized additive model to synthesize prediction results from two tree-based learning algorithms (i.e., RF and XGBoost). Its final predictions agreed well with the ground-level observations, with a monthly cross-validation (CV) R^2 of 0.93 after 2013 and a test R^2 of 0.67 for 2000–2012 (Liang et al., 2020). Surface-level O_3 concentrations were generated with the Smithsonian Astrophysical Observatory (SAO) OMI Ozone Profile (OMPROFOZ) at a 0.05° resolution as the main predictor (Zhu et al., 2022). The O_3 model considered surface ozone pollution generated either from the photochemical reactions involving NO_2 and volatile organic species (VOCs) or that came down from the stratosphere through the stratospheric intrusion process. Its monthly CV R^2 reached 0.86 for 2014–2019 and the test R^2 was 0.73 for 2005–2013. The NO_2 model was based on the OMI level-3 tropospheric NO_2 vertical column densities (VCD). It also used an ensemble learning approach to account for the non-linear relationship between model predictors and ground-level NO_2 concentrations. The final NO_2 predictions yielded a random CV R^2 of 0.88 at monthly level (Huang et al., 2023). Annual average exposure to $PM_{2.5}$, NO_2 as well as annual and warm season (April–September) average MDA8 (daily maximum 8-hr average) O_3 prior to the cognitive test were assigned to the participants based on their geocoded address (street level). To specify, we first matched all the participants' addresses to the model grid cells it completely fell into and then identified their exposure levels according to the date when the CMMSE was carried out. For participants whose addresses changed during two consecutive visits, we considered the midpoint of two visits as the date of moving.

2.3. Measurement of Cognitive Impairment

Participants' cognitive function was measured with the CMMSE. This measure was modified from the original MMSE developed by Folstein et al., in 1975 (Folstein et al., 1975) to fit the socioeconomic status of the Chinese elderly population. Given that most participants of the CLHLS are illiterate, the CMMSE simplified questions regarding calculation and verbal skills (Zeng & Vaupel, 2002). The details of the CMMSE and a sample questionnaire can be found at (https://doi.org/10.18170/DVN/WBO7LK). We define cognitive impairment as an MMSE score <24 or unable to complete the test only due to poor cognitive function. Based on previous studies, we treated questions that were marked "unable to answer" as wrong. Participants who were not able to complete the questionnaire for reasons other than cognitive impairment (e.g., physical disabilities) were removed from the current study.

2.4. Covariates

We considered a set of variables as potential confounders. For sociodemographic status, we included age (in years), sex, body mass index (BMI) (kg/m^2), educational level (in years), ethnic group (Han, Zhuang, and others), and living in an urban/rural area.

We also considered the subjects' behavior patterns and chronic disease status as potential sources of confounding, including past or present smoking, drinking, and physical exercise as well as currently suffering from high blood pressure, diabetes, or heart disease. All covariates were updated at each round of survey.

2.5. Statistical Analysis

Since all the surveys of CLHLS were conducted on a cross-sectional basis, we were not able to identify the specific date that a participant developed cognitive impairment. Thus, a typical survival analysis using Cox proportional hazards modeling may be inappropriate (Steenland et al., 2018). As such, we used a logistic regression model that included the follow-up time to analyze the association between air pollution and cognitive impairment. The detailed model is illustrated in Equation 1.

$$\mathrm{Logit}(P(Y_{iz})) = \beta_0 + \beta_1 \mathrm{time}_{iz} + \sum \beta_j \text{air pollutant}_{ijz} + \sum \beta_k \mathrm{confounder}_{ikz} \tag{1}$$

where Y_{iz} denotes the cognitive impairment status for individual i at z^{th} measurement; time_{iz} denotes the time stayed in this cohort (in years) since enrollment for individual i; air $\mathrm{pollutant}_{ijz}$ denotes the average concentration of air pollutant j for individual i in the previous year of the z^{th} measurement; $\mathrm{confounder}_{ikz}$ represents all the confounders that are listed in the previous section.

We first ran single-pollutant models assessing associations of yearly average $PM_{2.5}$, NO_2, warm season MDA8 O_3, and yearly average MDA8 O_3, with cognitive impairment status. We then conducted two multipollutant models for yearly average $PM_{2.5}$, NO_2, and warm season O_3, respectively. Multiple air pollutants were included based on the temporal range, that is, the effect of warm season O_3 was adjusted for warm season $PM_{2.5}$ and NO_2, while yearly average $PM_{2.5}$ and NO_2 were evaluated simultaneously in a separate model adjusted for annual average MDA8 O_3 concentration. Furthermore, a generalized additive model (GAM) with a penalized spline function for each specific air pollutant was also utilized to study the concentration-response relationship between air pollution and cognitive impairment. The GAM models also adjusted for other air pollutants as well as the covariates previously listed. The reference point (where OR = 1) for all the concentration-response relationships were selected at each air pollutant's average value, that is, 61.4 $\mu g/m^3$, 30.5 $\mu g/m^3$ for annual average $PM_{2.5}$ and NO_2 as well as 107.1 $\mu g/m^3$ for warm season O_3, respectively.

Furthermore, we also evaluated the association between air pollution and the CMMSE score using a linear mixed-effect regression model with random intercept. The detailed model is illustrated in Equation 2.

$$Y_{iz} = \beta_0 + \theta_i + \sum \beta_j \text{air pollutant}_{ijz} + \sum \beta_k \mathrm{confounder}_{ikz} \tag{2}$$

where Y_{iz} denotes the CMMSE score for individual i at z^{th} measurement; θ_i is the random intercept. air pollutant$_{ijz}$ denotes the average concentration of air pollutant j for individual i in the previous year of the z^{th} measurement; confounder$_{ikz}$ represents all the confounders that are listed in the previous section.

All the statistical analyses were conducted with R (v 4.0.5, R core team). Two-sided p-value < 0.05 was considered statistically significant.

3. Results

As can be seen in Table 1, 3,887 participants at baseline were selected for the present study. Among them, 2,882 (74.1%), 1,362 (35.0%), and 521 (13.4%) completed one, two, and three rounds of the follow-up survey, respectively. At baseline, the average age and BMI were 80.0 ± 11.3 years and 22.0 ± 29.4 kg/m^2. Slightly more than half of the participants (2,088, 53.7%) were male, while 3,480 (89.5%) of them belonged to the Han ethnic group. A total of 2,642 (68.0%) individuals lived in a rural area. The majority of the participants self-identified as never drinkers (2,563, 65.9%) and never smokers (2,401, 61.8%), while 490 (12.6%) and 605 (15.6%) participants identified themselves as former drinkers and former smokers. Thirty-six-point-five percent (1,419) of them exercised regularly. Around 10.3% (401), 24.5% (951), and 4.0% (154) of the participants had heart diseases, high blood pressure (HBP), and diabetes at baseline, respectively. At the first follow-up visit, 752 (26.1%) of the remaining participants developed cognitive impairment, while 129 (9.5%) and 50 (9.6%) people developed CI at the second and third follow-up visits.

As illustrated in Table 2, per year increase in age was associated with a 0.7% increase in the risk of cognitive impairment (95% CI = [1.004, 1.010], $p < 0.001$). Females (OR and 95% CI = 1.040 [1.004, 1.075], $p < 0.001$), current smokers (OR and 95% CI = 1.026 [1.006, 1.045], $p = 0.008$) and former drinkers (OR and 95% CI = 1.024 [1.005, 1.042], $p = 0.012$) were at a higher risk of cognitive impairment. On the contrary, per year increase in education (OR and 95% CI = 0.997 [0.995, 0.999], $p = 0.003$), living in an urban area (OR and 95% CI = 0.980 [0.963, 0.996], $p = 0.018$), and regular exercise (OR and 95% CI = 0.966 [0.952, 0.980], $p < 0.001$) were protective factors for cognitive impairment. We did not observe significant association between cognitive impairment and ethnic groups, BMI, high blood pressure, diabetes, heart diseases, past smoking as well as current drinking status.

The baseline annual average exposure levels to $PM_{2.5}$, NO_2, and MDA8 O_3 were 62.5 ± 14.3, 29.1 ± 11.7, and 89.2 ± 5.82 μg/m^3, respectively (Table 3). Warm season average MDA8 O_3 was significantly higher than the annual average and reached 106 ± 12.2 μg/m^3. The exposure levels for three follow-up visits were generally comparable to the baseline. Yearly average $PM_{2.5}$ and NO_2 were moderately correlated with each other ($r = 0.57$) while warm season O_3 also showed moderate correlation with NO_2 and $PM_{2.5}$ in the warm season ($r = 0.69$ and 0.57, respectively).

3.1. The Association Between Air Pollution and Congnitive Impairment

In the single-pollutant models (Table 4), we found that exposures to O_3, $PM_{2.5}$, and NO_2 were all positively associated with cognitive impairment. Specifically, per IQR (18.34 μg/m^3) increase in annual average $PM_{2.5}$ was associated with a 1% increased odds of cognitive impairment (OR and 95% CI = 1.009 [1.001, 1.016], $p = 0.034$). The OR and 95% CI values per IQR increase in annual average NO_2 (18.20 μg/m^3) and warm season average O_3 (20.98 μg/m^3) were 1.019 ([1.007, 1.031], $p = 0.001$) and 1.011 ([1.000, 1.022], $p = 0.033$), respectively. Annual average O_3 exposure was not significantly associated with cognitive impairment (OR and 95% CI per 8.54 μg/m^3 = 1.001 [0.997, 1.014], $p = 0.192$).

In the multi-pollutant model, only annual average exposure to NO_2 remained positively associated with cognitive impairment (OR and 95% CI = 1.018 [1.002, 1.033] per 18.20 μg/m^3 increase, $p = 0.023$). On the contrary, $PM_{2.5}$ and warm season O_3 did not demonstrate a statistically significant relationship with cognitive impairment (Table 4).

Figure 2 shows the concentration-response relationship between air pollutants and cognitive impairment. Specifically, the OR of NO_2 increased almost monotonously with higher concentrations (Figure 2a). The concentration-response relationship between warm season O_3 and cognitive impairment showed a stage-wise increase (Figure 2b). That is to say, the effect of warm season O_3 was generally stable for the concentration

Table 1
Sociodemographic Characteristics of the CLHLS Participants

	Baseline (N = 3,887)	First follow-up (N = 2,882)	Second follow-up (N = 1,362)	Third follow-up (N = 521)
Age (years)				
Mean (SD)	80.0 ± 11.3	81.6 ± 10.9	79.7 ± 8.54	80.7 ± 6.63
Gender				
Male	2,088 (53.7%)	1,464 (50.8%)	724 (53.2%)	276 (53.0%)
Female	1,799 (46.3%)	1,418 (49.2%)	638 (46.8%)	245 (47.0%)
BMI				
Mean (SD)	22.0 ± 29.4	22.3 ± 7.14	23.0 ± 12.4	23.1 ± 7.59
Ethnic group				
Han	3,480 (89.5%)	2,539 (88.1%)	1,200 (88.1%)	324 (62.2%)
Zhuang	112 (2.9%)	94 (3.3%)	48 (3.5%)	12 (2.3%)
Others	295 (7.6%)	249 (8.6%)	114 (8.4%)	185 (35.5%)
Education (years)				
Mean (SD)	3.09 ± 3.88	3.13 ± 3.88	3.62 ± 4.02	2.90 ± 4.04
Living area				
Rural	2,642 (68.0%)	1,802 (62.5%)	830 (60.9%)	336 (64.5%)
Urban	1,245 (32.0%)	1,080 (37.5%)	532 (39.1%)	185 (35.5%)
Cognitive impairment				
Normal cognitive function	3,887 (100%)	2,130 (73.9%)	1,233 (90.5%)	471 (90.4%)
Yes	0 (0%)	752 (26.1%)	129 (9.5%)	50 (9.6%)
Alcohol drinking				
Current drinker	834 (21.5%)	556 (19.3%)	251 (18.4%)	103 (19.8%)
Former drinker	490 (12.6%)	451 (15.6%)	176 (12.9%)	63 (12.1%)
Never drinker	2,563 (65.9%)	1,875 (65.1%)	935 (68.6%)	355 (68.1%)
Tobacco smoking				
Current smoker	881 (22.7%)	603 (20.9%)	298 (21.9%)	94 (18.0%)
Former smoker	605 (15.6%)	521 (18.1%)	243 (17.8%)	94 (18.0%)
Never smoker	2,401 (61.8%)	1,758 (61.0%)	821 (60.3%)	333 (63.9%)
Exercise				
Yes	1,419 (36.5%)	1,254 (43.5%)	587 (43.1%)	232 (44.5%)
No	2,468 (63.5%)	1,628 (56.5%)	775 (56.9%)	289 (55.5%)
Heart diseases				
Yes	401 (10.3%)	392 (13.6%)	221 (16.2%)	105 (20.2%)
No	3,486 (89.7%)	2,490 (86.4%)	1,141 (83.8%)	416 (79.8%)
High blood pressure				
Yes	951 (24.5%)	880 (30.5%)	532 (39.1%)	236 (45.3%)
No	2,936 (75.5%)	2,002 (69.5%)	830 (60.9%)	285 (54.7%)
Diabetes				
Yes	154 (4.0%)	185 (6.4%)	117 (8.6%)	55 (10.6%)
No	3,733 (96.0%)	2,697 (93.6%)	1,245 (91.4%)	466 (89.4%)

range between 80 and 110 μg/m^3. The OR of O_3 increased sharply for 110–130 μg/m^3 and then stabilized for concentrations higher than 130 μg/m^3. The OR of $PM_{2.5}$ were greater at both low (<40 μg/m^3) and high concentrations (>100 μg/m^3) (Figure 2c).

Table 2
The Association Between Model Covariates and Cognitive Impairment

Covariates	OR (95% CI)	*p*-value
Age (yr)	1.007 (1.004, 1.010)	<0.001*
BMI (kg/m^2)	1.000 (0.999, 1.000)	0.948
Time since enrollment (yr)	1.010 (1.008, 1.012)	<0.001*
Sex		
Male	–	–
Female	1.040 (1.004, 1.075)	<0.001*
Ethnic group		
Han	–	–
Zhuang	1.020 (0.982, 1.059)	0.339
Others	0.983 (0.954, 1.012)	0.145
Living area		
Rural	–	–
Urban	0.980 (0.963, 0.996)	0.018*
Education (yr)	0.997 (0.995, 0.999)	0.003*
Tobacco smoking		
Never smoker	–	–
Former smoker	1.017 (0.997, 1.036)	0.104
Current smoker	1.026 (1.006, 1.045)	0.008*
Alcohol drinking		
Never drinker	–	–
Former drinker	1.024 (1.005, 1.042)	0.012*
Current drinker	1.006 (0.986, 1.026)	0.571
Exercise		
No	–	–
Yes	0.966 (0.952, 0.980)	<0.001*
Heart disease		
No	–	–
Yes	1.010 (0.991, 1.030)	0.304
High blood pressure		
No	–	–
Yes	1.008 (0.993, 1.023)	0.252
Diabetes		
No	–	–
Yes	1.002 (0.975, 1.028)	0.924

Note. OR (95% CI) and *p*-value were from the multi-pollutant model includes yearly average NO_2, O_3, and $PM_{2.5}$ concentrations. $^*p < 0.05$.

3.2. The Association Between Air Pollution and CMMSE Score

In the single pollutant models (Table 5), per IQR increase in the warm season and yearly exposure to O_3 were both significantly associated with a decrease in the CMMSE score (β and 95% CI per 20.98 μg/m^3 = −0.271 [−0.441, −0.102], p = 0.001 for warm season and β and 95% CI per 8.54 μg/m^3 = −0.200 [−0.341, −0.058], p = 0.006 for yearly exposure, respectively). Similarly, yearly exposure to NO_2 was also associated with a decrease in the CMMSE score (β and 95% CI per 18.20 μg/m^3 = −0.254 [−0.446, −0.062], p = 0.009). However, $PM_{2.5}$ was not significantly associated with CMMSE score in the single-pollutant model (β and 95% CI per 18.34 μg/m^3 = 0.062 [−0.064, 0.189], p = 0.332).

Warm season and yearly exposure to O_3 remained negatively associated with CMMSE score in the multi-pollutant model (β and 95% CI per 20.98 μg/m^3 = −0.753 [−1.024, −0.483], p < 0.001 for warm season and β and 95% CI per 8.54 μg/m^3 = −0.186 [−0.335, −0.036], p = 0.015 for yearly exposure, respectively). Per IQR (18.20 μg/m^3) increase in yearly exposure to NO_2 was associated with a 0.240 (95% CI = [0.030, 0.451], p = 0.025) decrease in the CMMSE score. $PM_{2.5}$ was associated with an increase in the CMMSE score in the multi-pollutant model (β and 95% CI per 18.34 μg/m^3 = 0.197 [0.045, 0.348], p = 0.011).

4. Discussion

In the present study, we found that yearly exposure to $PM_{2.5}$ and warm season exposure O_3 were associated with an increased risk of cognitive impairment in the single-pollutant models, annual average exposure to NO_2 was associated with cognitive impairment in both the single- and multi-pollutant models. The linear mixed-effect model further substantiated these findings, showing that exposure to O_3 during the warm season, in addition to annual exposure to O_3 and NO_2, was correlated with reduced CMMSE scores across both model types. Notably, our findings align well with existing literature and previous studies utilizing the same data set in the positive association between air pollution and cognitive impairment, although the effect size may differ. For example, Wang et al. reported that a 10 μg/m^3 increase in ambient $PM_{2.5}$ concentrations was associated with a 5.1% increased risk of poor cognitive function (defined as CMMSE <18, HR and 95% CI = 1.05 [1.02, 1.08]) using the CLHLS data after 2002 (Wang et al., 2020). Yao et al. found that China's clean air policy significantly decelerated the decline in MMSE score using a quasi-experimental design (Yao et al., 2022). Furthermore, utilizing CLHLS data from after 2008, Ma et al. examined the impact of a 2-year average exposure to $PM_{2.5}$, O_3, and NO_2 on cognitive function. Their findings suggest that $PM_{2.5}$ increased the risk of cognitive impairment (threshold of CMMSE varied from 18 to 24, HR and 95% CI = 1.10 [1.02, 1.18] per 20 μg/m^3), while O_3 and NO_2 yielded elevated but statistically insignificant risks (Ma et al., 2022). Compared to the studies above, our study enhanced the assessment of air pollution exposure by using three high-performance satellite-driven air pollution models at fine resolutions. With this advanced approach, we identified significant positive associations between all three air pollutants and cognitive impairment, even when using a more sensitive definition of cognitive impairment (CMMSE <24). The subtler definition of cognitive impairment in our study also possibly explains why our observed magnitudes of association are relatively smaller than those reported in the aforementioned studies. The findings based on CLHLS collectively suggest that air pollution poses a substantial threat to the cognitive health of the aging population in China. This concern is heightened by the fact that air pollution levels in China remain well above the thresholds recommended by the WHO—5 μg/m³ for annual average $PM_{2.5}$, 10 μg/m³ for NO_2, and 60 μg/m³ for peak season MDA8 O_3.

Table 3
Exposure Levels to O_3, $PM_{2.5}$, and NO_2 (μg/m^3)

	Baseline (N = 3,887)	First follow-up (N = 2,882)	Second follow-up (N = 1,362)	Third follow-up (N = 521)	Overall (N = 8,652)
Warm season O_3					
Mean (SD)	106 ± 12.2	107 ± 13.1	108 ± 14.7	113 ± 18.9	107 ± 13.5
Annual average O_3					
Mean (SD)	89.2 ± 5.82	89.0 ± 6.45	89.4 ± 7.53	93.2 ± 8.86	89.4 ± 6.61
Annual average $PM_{2.5}$					
Mean (SD)	62.5 ± 14.3	62.6 ± 16.0	61.1 ± 18.7	47.5 ± 11.1	61.4 ± 15.9
Annual average NO_2					
Mean (SD)	29.1 ± 11.7	32.2 ± 12.4	31.7 ± 12.8	28.5 ± 11.5	30.5 ± 12.2

Studies in other countries also examined the association between air pollution and cognitive impairment, but the consistency of results varied across different air pollutants. Specifically, studies in Sweden (Grande et al., 2021), South Korea (Lee et al., 2022), and the US (Grande et al., 2021) reported that $PM_{2.5}$ would escalate the risk of cognitive decline measured by the MMSE. NO_2 has also been positively linked to cognitive decline or dementia in the US (Shi et al., 2021), England (Carey et al., 2018), and Canada (Chen et al., 2017; Smargiassi et al., 2020). In combination with our results, the importance of NO_2 needs to be highlighted since it is the only air pollutant that remained positively associated with cognitive impairment in our multi-pollutant model and it is also significantly positively associated with the CMMSE score in the mixed-effect models. However, the findings were more controversial for ozone. For example, Cleary et al. reported that ozone is correlated with faster cognitive decline (Cleary et al., 2018) in the US. On the contrary, Chen et al. found no significant association between O_3 and dementia in a Canadian cohort study. Park et al. even reported that O_3 yielded protective effects for cognitive decline in Korea (Park et al., 2022).

A possible reason for this controversy is the time window of ozone exposure. As a secondary pollutant, ground-level ozone is predominantly formed by the photochemical reactions between NOx and VOCs in the presence of heat and solar radiation (Li et al., 2020; Zhu et al., 2022). Consequently, ozone exhibits distinct seasonality in most Chinese regions, where elevated ozone pollution usually occurs from late spring to early autumn (Zhu et al., 2022). In this study, O_3 posted null or even protective effects at low-medium concentrations (70–110 μg/m^3), but its risk surged at concentrations higher than 110 μg/m^3 (Figure 2). Additionally, we found that warm season exposure to ozone is positively associated with cognitive impairment, but annual averages yielded insignificant effects. This phenomenon has also been spotted for other health outcomes. As reviewed by Atkinson et al., studies that used warm season exposure to ozone generally reported a positive association with mortality, while no evidence was shown for annual concentrations (Atkinson et al., 2016). These findings suggest that the health impacts of ozone may be more pronounced during the warmer seasons when pollution levels are at their peak.

Table 4
The Association Between Air Pollution and Cognitive Impairment

Air pollutants	IQR (μg/m^3)	OR (95% CI)[a]	p-value[a]	OR (95% CI)[b]	p-value[b]
$PM_{2.5}$ (yearly)	18.34	1.009 (1.001, 1.016)	0.034*	1.001 (0.992, 1.010)	0.721
O_3 (yearly)	8.54	1.006 (0.997, 1.014)	0.192	1.000 (0.991, 1.009)	0.889
O_3 (warm season)	20.98	1.011 (1.000, 1.022)	0.033*	1.007 (0.989, 1.024)	0.452
NO_2 (yearly)	18.20	1.019 (1.007, 1.031)	0.001*	1.018 (1.002, 1.033)	0.033*

Note. Multiple air pollutants were included based on the temporal range, that is, the effect of warm season O_3 was adjusted for warm season $PM_{2.5}$ and NO_2, while yearly average air pollutants were evaluated simultaneously in a separate model. The OR values are per IQR increase of the air pollutants. *p < 0.05. [a]OR (95% CI) and p-value from the single pollutant model. [b]OR (95% CI) and p-value from the multi-pollutant models.

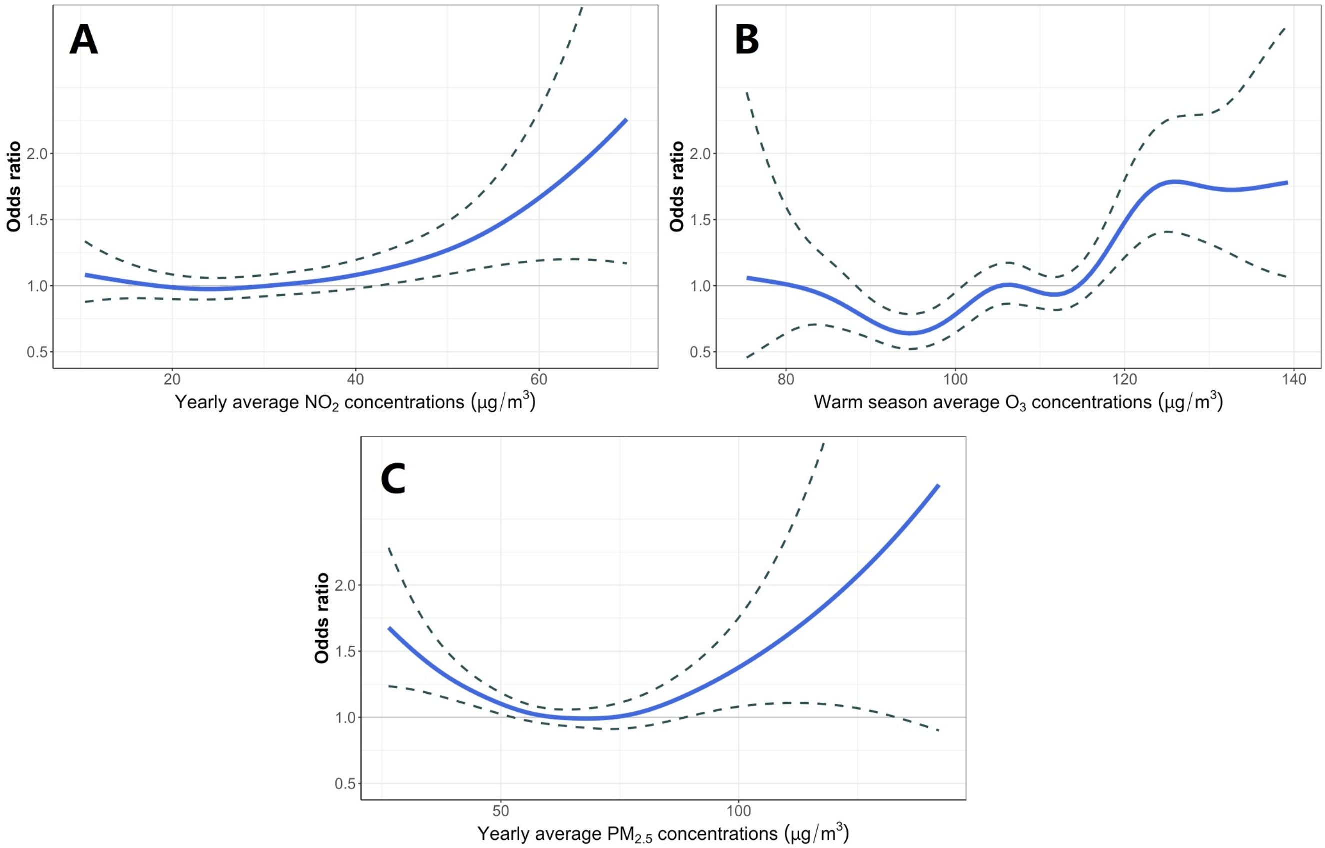

Figure 2. Concentration-response relationship between air pollutants and cognitive impairment. The plots were generated with the multi-pollutant model. (a) Yearly average NO_2; (b) Warm season (April–September) average O_3; (c) yearly average $PM_{2.5}$. Y axis are the ORs compared with the mean values of each air pollutant, that is, 61.4 μg/m³, 30.5 μg/m³ for annual average $PM_{2.5}$ and NO_2 as well as 107.1 μg/m³ for warm season O_3, respectively.

The association between air pollution and dementia may be attributed to biological mechanisms such as oxidative stress and neuroinflammation. For example, Li and Xin found that NO_2 inhalation could induce dose-dependent excitotoxicity and increase the risk of vascular dementia in healthy rats (Li & Xin, 2013). This finding also agreed with the monotonic increasing concentration-response relationship between NO_2 and cognitive impairment in this study (Figure 2). Furthermore, Li et al. also reported that exposure to NO_2 may accelerate neural apoptosis and express neurotoxicity (Li et al., 2012). Similarly, as oxidative stressors, studies have also reported the impact of O_3 and $PM_{2.5}$ on neuroinflammatory response (Kang et al., 2021; Tyler et al., 2018; Velázquez-Pérez et al., 2021). Moreover, the aging process itself also has the potential to exacerbate the neuroinflammation caused by air pollution (Tyler et al., 2018), highlighting the need to mitigate air pollution in an aging society like China.

Table 5
The Association Between Air Pollution and CMMSE Scores

Air pollutants	IQR (μg/m³)	β (95% CI)[a]	p-value[a]	β (95% CI)[b]	p-value[b]
$PM_{2.5}$ (yearly)	18.34	0.062 (−0.064, 0.189)	0.332	0.197 (0.045, 0.348)	0.011*
O_3 (yearly)	8.54	−0.200 (−0.341, −0.058)	0.006*	−0.186 (−0.335, −0.036)	0.015*
O_3 (warm season)	20.98	−0.271 (−0.441, −0.102)	0.001*	−0.753 (−1.024, −0.483)	<0.001*
NO_2 (yearly)	18.20	−0.254 (−0.446, −0.062)	0.009*	−0.240 (−0.451, −0.030)	0.025*

Note. Multiple air pollutants were included based on the temporal range, that is, the effect of warm season O_3 was adjusted for warm season $PM_{2.5}$ and NO_2, while yearly average air pollutants were evaluated simultaneously in a separate model. The OR values are per IQR increase of the air pollutants. *$p < 0.05$. [a]β (95% CI) and p-value from the single pollutant model. [b]β (95% CI) and p-value from the multi-pollutant models.

A major strength of this study is the inclusion of three high-performance satellite-driven air pollution models. To date, China's air quality monitoring network has covered most cities, but rural areas remain largely unmonitored. Given that most participants of the CLHLS lived in rural areas, using satellite-driven exposure estimates could significantly improve the accuracy of exposure measurement. The extended temporal coverage of our exposure data sets also facilitates the investigations with historical cohort data, especially on chronic health outcomes like cognitive impairment and dementia. Another advantage is that the CLHLS used face-to-face interviews to measure cognitive function and collect other covariates. This process guaranteed the data quality and consistency across the whole nation.

This study also has some limitations. First, we were unable to identify the specific time when a participant developed cognitive impairment, which may lead to exposure misalignment. Accounting for this, we adjusted for the follow-up in the logistic regression model since it could still be an informative predictor of cognitive impairment (Steenland et al., 2018). Second, we could not generate exposure data before 2005 due to the availability of OMI products. Consequently, only four out of the eight waves of the CLHLS were included in the study. Future studies may use a bigger sample size to study the impact of air pollution on healthy aging if the exposure data set can be further generated to the late 1990s. Additionally, it is important to note that the CLHLS has a propensity to oversample older adults (aged > 80), potentially leading to survivorship bias. This is because individuals who have not developed cognitive impairment at a very advanced age may exhibit reduced sensitivity to neurodegenerative diseases. To mitigate this bias, future studies are advised to recruit participants at a younger age. Moreover, the great majority of our study participants belonged to the Han ethnic group, but there are more than 50 minority groups in China that are not well studied to date. Further investigations are encouraged to focus on different subgroups divided by region, sex, and ethnic groups to further promote environmental justice in China.

5. Conclusion

This study used satellite-driven data sets to study the association between air pollution and cognitive impairment among the Chinese elderly population. We found that warm season mean MDA8 O_3, annual mean $PM_{2.5,}$ and NO_2 were positively associated with cognitive impairment (CMMSE < 24). The association between O_3 and NO_2 with cognitive decline was also supported by the linear mixed effect models. Our findings underscore the imperative for the next iteration of China's Air Pollution Prevention and Control Action Plan to broaden its focus to encompass gaseous air pollutants rather than $PM_{2.5}$ alone, since mitigating single air pollutant is insufficient in the context of population aging. Besides, the biological mechanisms underlying the association between air pollution and cognitive impairment are yet to be fully understood. Future studies are encouraged to explore these mechanisms so that intervention approaches might be applied to mitigate the cognitive impairment caused by air pollution.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The authors are prohibited from sharing the individual-level CLHLS data to protect sensitive personal data. The de-identified CLHLS sample data and questionnaires are publicly available at Center for Healthy Aging and Development Studies (2020). The de-identified monthly level air pollution data covering all CLHLS participants' geocoded addresses can be found at 10.5281/zenodo.14424283. The sample code for major analysis and plots can be also found at the GitHub repository (Zhu, 2024). The concentration-response relationship curves are made with the R package *ggplot2* (version 3.5.1) (Wickham, 2016).

Acknowledgments
This work was supported by the National Institute of Environmental Health Sciences (NIEHS) of the National Institutes of Health (Award 1R01ES032140). The content is solely the responsibility of the authors and does not necessarily represent the official views of NIEHS.

References

Ailshire, J. A., & Clarke, P. (2014). Fine particulate matter air pollution and cognitive function among U.S. older adults. *The Journals of Gerontology: Serie Bibliographique*, *70*(2), 322–328. https://doi.org/10.1093/geronb/gbu064

Ailshire, J. A., & Crimmins, E. M. (2014). Fine particulate matter air pollution and cognitive function among older US adults. *American Journal of Epidemiology*, *180*(4), 359–366. https://doi.org/10.1093/aje/kwu155

Atkinson, R. W., Butland, B. K., Dimitroulopoulou, C., Heal, M. R., Stedman, J. R., Carslaw, N., et al. (2016). Long-term exposure to ambient ozone and mortality: A quantitative systematic review and meta-analysis of evidence from cohort studies. *BMJ Open*, *6*(2), e009493. https://doi.org/10.1136/bmjopen-2015-009493

Carey, I. M., Anderson, H. R., Atkinson, R. W., Beevers, S. D., Cook, D. G., Strachan, D. P., et al. (2018). Are noise and air pollution related to the incidence of dementia? A cohort study in London, England. *BMJ Open*, *8*(9), e022404. https://doi.org/10.1136/bmjopen-2018-022404

Center for Healthy Aging and Development Studies. (2020). The Chinese longitudinal healthy longevity survey (CLHLS)-longitudinal data (1998-2018) [dataset]. *Peking University Open Research Data Platform, V2*. https://doi.org/10.18170/DVN/WBO7LK

Chen, H., Kwong, J. C., Copes, R., Hystad, P., van Donkelaar, A., Tu, K., et al. (2017). Exposure to ambient air pollution and the incidence of dementia: A population-based cohort study. *Environment International*, *108*, 271–277. https://doi.org/10.1016/j.envint.2017.08.020

Cleary, E. G., Cifuentes, M., Grinstein, G., Brugge, D., & Shea, T. B. (2018). Association of low-level ozone with cognitive decline in older adults. *Journal of Alzheimer's Disease*, *61*(1), 67–78. https://doi.org/10.3233/JAD-170658

Collaborators, G. (2021). Global mortality from dementia: Application of a new method and results from the Global Burden of Disease Study 2019. *Alzheimer's and Dementia: Translational Research & Clinical Interventions*, *7*(1), e12200. https://doi.org/10.1002/trc2.12200

Cullen, B., Newby, D., Lee, D., Lyall, D. M., Nevado-Holgado, A. J., Evans, J. J., et al. (2018). Cross-sectional and longitudinal analyses of outdoor air pollution exposure and cognitive function in UK Biobank. *Scientific Reports*, *8*(1), 12089. https://doi.org/10.1038/s41598-018-30568-6

Delgado-Saborit, J. M., Guercio, V., Gowers, A. M., Shaddick, G., Fox, N. C., & Love, S. (2021). A critical review of the epidemiological evidence of effects of air pollution on dementia, cognitive function and cognitive decline in adult population. *Science of the Total Environment*, *757*, 143734. https://doi.org/10.1016/j.scitotenv.2020.143734

Folstein, M. F., Folstein, S. E., & McHugh, P. R. (1975). Mini-mental state". A practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatric Research*, *12*(3), 189–198. https://doi.org/10.1016/0022-3956(75)90026-6

Gatto, N. M., Henderson, V. W., Hodis, H. N., St. John, J. A., Lurmann, F., Chen, J.-C., & Mack, W. J. (2014). Components of air pollution and cognitive function in middle-aged and older adults in Los Angeles. *NeuroToxicology*, *40*, 1–7. https://doi.org/10.1016/j.neuro.2013.09.004

Grande, G., Wu, J., Ljungman, P. L. S., Stafoggia, M., Bellander, T., & Rizzuto, D. (2021). Long-term exposure to PM 2.5 and cognitive decline: A longitudinal population-based study. *Journal of Alzheimer's Disease*, *80*(2), 591–599. https://doi.org/10.3233/JAD-200852

Huang, K., Zhu, Q., Lu, X., Gu, D., & Liu, Y. (2023). Satellite-based long-term spatiotemporal trends in ambient NO_2 concentrations and attributable health burdens in China from 2005 to 2020. *GeoHealth*, *7*(5), e2023GH000798. https://doi.org/10.1029/2023GH000798

Jung, C. R., Lin, Y. T., & Hwang, B. F. (2015). Ozone, particulate matter, and newly diagnosed Alzheimer's disease: A population-based cohort study in Taiwan. *Journal of Alzheimer's Disease*, *44*(2), 573–584. https://doi.org/10.3233/jad-140855

Kang, Y. J., Tan, H.-Y., Lee, C. Y., & Cho, H. (2021). An air particulate pollutant induces neuroinflammation and neurodegeneration in human brain models. *Advanced Science*, *8*(21), 2101251. https://doi.org/10.1002/advs.202101251

Lee, J. J., Kim, J. H., Song, D. S., & Lee, K. (2022). Effect of short- to long-term exposure to ambient particulate matter on cognitive function in a cohort of middle-aged and older adults: KoGES. *International Journal of Environmental Research and Public Health*, *19*(16), 9913. https://doi.org/10.3390/ijerph19169913

Li, C. Y., Li, C. H., Martini, S., & Hou, W. H. (2019). Association between air pollution and risk of vascular dementia: A multipollutant analysis in Taiwan. *Environment International*, *133*(Pt B), 105233. https://doi.org/10.1016/j.envint.2019.105233

Li, H., Chen, L., Guo, Z., Sang, N., & Li, G. (2012). In vivo screening to determine neurological hazards of nitrogen dioxide (NO_2) using Wistar rats. *Journal of Hazardous Materials*, *225–226*, 46–53. https://doi.org/10.1016/j.jhazmat.2012.04.063

Li, H., & Xin, X. (2013). Nitrogen dioxide (NO_2) pollution as a potential risk factor for developing vascular dementia and its synaptic mechanisms. *Chemosphere*, *92*(1), 52–58. https://doi.org/10.1016/j.chemosphere.2013.02.061

Li, K., Jacob, D. J., Shen, L., Lu, X., De Smedt, I., & Liao, H. (2020). Increases in surface ozone pollution in China from 2013 to 2019: Anthropogenic and meteorological influences. *Atmospheric Chemistry and Physics*, *20*(19), 11423–11433. https://doi.org/10.5194/acp-20-11423-2020

Liang, F., Xiao, Q., Huang, K., Yang, X., Liu, F., Li, J., et al. (2020). The 17-y spatiotemporal trend of PM(2.5) and its mortality burden in China. *Proceedings of the National Academy of Sciences of the United States of America*, *117*(41), 25601–25608. https://doi.org/10.1073/pnas.1919641117

Lin, H., Guo, Y., Zheng, Y., Zhao, X., Cao, Z., Rigdon, S. E., et al. (2017). Exposure to ambient PM(2.5) associated with overall and domain-specific disability among adults in six low- and middle-income countries. *Environment International*, *104*, 69–75. https://doi.org/10.1016/j.envint.2017.04.004

Ma, Y.-H., Chen, H.-S., Liu, C., Feng, Q.-S., Feng, L., Zhang, Y.-R., et al. (2022). Association of long-term exposure to ambient air pollution with cognitive decline and Alzheimer's disease–related amyloidosis. *Biological Psychiatry*, *93*(9), 780–789. https://doi.org/10.1016/j.biopsych.2022.05.017

Nichols, E., Steinmetz, J. D., Vollset, S. E., Fukutaki, K., Chalek, J., Abd-Allah, F., et al. (2022). Estimation of the global prevalence of dementia in 2019 and forecasted prevalence in 2050: An analysis for the Global Burden of Disease Study 2019. *The Lancet Public Health*, *7*(2), e105–e125. https://doi.org/10.1016/S2468-2667(21)00249-8

Park, S. Y., Han, J., Kim, S. H., Suk, H. W., Park, J. E., & Lee, D. Y. (2022). Impact of long-term exposure to air pollution on cognitive decline in older adults without dementia. *Journal of Alzheimer's Disease*, *86*(2), 553–563. https://doi.org/10.3233/JAD-215120

Qin, F., Luo, M., Xiong, Y., Zhang, N., Dai, Y., Kuang, W., & Cen, X. (2022). Prevalence and associated factors of cognitive impairment among the elderly population: A nationwide cross-sectional study in China. *Frontiers in Public Health*, *10*, 1032666. https://doi.org/10.3389/fpubh.2022.1032666

Ren, R., Qi, J., Lin, S., Liu, X., Yin, P., Wang, Z., et al. (2022). The China Alzheimer report 2022. *General Psychiatry*, *35*(1), e100751. https://doi.org/10.1136/gpsych-2022-100751

Ren, Z., Li, Y., Li, X., Shi, H., Zhao, H., He, M., et al. (2021). Associations of body mass index, waist circumference and waist-to-height ratio with cognitive impairment among Chinese older adults: Based on the CLHLS. *Journal of Affective Disorders*, *295*, 463–470. https://doi.org/10.1016/j.jad.2021.08.093

Shi, L., Steenland, K., Li, H., Liu, P., Zhang, Y., Lyles, R. H., et al. (2021). A national cohort study (2000–2018) of long-term air pollution exposure and incident dementia in older adults in the United States. *Nature Communications*, *12*(1), 6754. https://doi.org/10.1038/s41467-021-27049-2

Smargiassi, A., Sidi, E. A. L., Robert, L.-E., Plante, C., Haddad, M., Gamache, P., et al. (2020). Exposure to ambient air pollutants and the onset of dementia in Québec, Canada. *Environmental Research*, *190*, 109870. https://doi.org/10.1016/j.envres.2020.109870

Steenland, K., Zhao, L., John, S. E., Goldstein, F. C., Levey, A., & Alvaro, A. (2018). A "Framingham-like" algorithm for predicting 4-year risk of progression to amnestic mild cognitive impairment or Alzheimer's disease using multidomain information. *Journal of Alzheimer's Disease*, *63*(4), 1383–1393. https://doi.org/10.3233/jad-170769

Tyler, C. R., Noor, S., Young, T. L., Rivero, V., Sanchez, B., Lucas, S., et al. (2018). Aging exacerbates neuroinflammatory outcomes induced by acute ozone exposure. *Toxicological Sciences*, *163*(1), 123–139. https://doi.org/10.1093/toxsci/kfy014

Velázquez-Pérez, R., Rodríguez-Martínez, E., Valdés-Fuentes, M., Gelista-Herrera, N., Gómez-Crisóstomo, N., & Rivas-Arancibia, S. (2021). Oxidative stress caused by ozone exposure induces changes in P2X7 receptors, neuroinflammation, and neurodegeneration in the rat hippocampus. *Oxidative Medicine and Cellular Longevity*, *2021*(1), 3790477. https://doi.org/10.1155/2021/3790477

Wang, J., Li, T., Lv, Y., Kraus, V. B., Zhang, Y., Mao, C., et al. (2020). Fine Particulate matter and poor cognitive function among Chinese older adults: Evidence from a community-based, 12-year prospective cohort study. *Environmental Health Perspectives*, *128*(6), 067013. https://doi.org/10.1289/EHP5304

Weuve, J., Puett, R. C., Schwartz, J., Yanosky, J. D., Laden, F., & Grodstein, F. (2012). Exposure to particulate air pollution and cognitive decline in older women. *Archives of Internal Medicine*, *172*(3), 219–227. https://doi.org/10.1001/archinternmed.2011.683

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag. Retrieved from https://ggplot2.tidyverse.org

Yao, Y., Lv, X., Qiu, C., Li, J., Wu, X., Zhang, H., et al. (2022). The effect of China's clean air act on cognitive function in older adults: A population-based, quasi-experimental study. *The Lancet Healthy Longevity*, *3*(2), e98–e108. https://doi.org/10.1016/S2666-7568(22)00004-6

Zare Sakhvidi, M. J., Yang, J., Lequy, E., Chen, J., de Hoogh, K., Letellier, N., et al. (2022). Outdoor air pollution exposure and cognitive performance: Findings from the enrolment phase of the CONSTANCES cohort. *The Lancet Planetary Health*, *6*(3), e219–e229. https://doi.org/10.1016/S2542-5196(22)00001-8

Zeng, Y., Vaupel, J., Xiao, Z., Liu, Y., & Zhang, C. (2017). *Chinese longitudinal healthy longevity survey (CLHLS), 1998-2014*. Inter-university Consortium for Political and Social Research. [distributor]. https://doi.org/10.3886/ICPSR36692.v1

Zeng, Y., & Vaupel, J. W. (2002). Functional capacity and self–evaluation of health and life of oldest old in China. *Journal of Social Issues*, *58*(4), 733–748. https://doi.org/10.1111/1540-4560.00287

Zhu, Q. (2024). Dataset for air pollution and cognitive impairment [dataset]. *Zenodo*. https://doi.org/10.5281/zenodo.14424284

Zhu, Q., Bi, J., Liu, X., Li, S., Wang, W., Zhao, Y., & Liu, Y. (2022). Satellite-based long-term spatiotemporal patterns of surface ozone concentrations in China: 2005-2019. *Environmental Health Perspectives*, *130*(2), 027004. https://doi.org/10.1289/EHP9406