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Particulate air pollution from different emission sources, cognitive performance, and cognitive declines in India

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ABSTRACT

Background: Low- and middle-income countries experience some of the highest fine particulate matter ($PM_{2.5}$) exposures globally, with emissions from sources like residential combustion, industry, and transportation continuing to increase in many locations. While total $PM_{2.5}$ has been linked to cognitive decline, little is known about the relative importance of $PM_{2.5}$ from different emission sources, especially in low and middle-income settings.

Methods: We used cognitive performance data from the 2017–2019 and 2022–2024 waves of the Harmonized Diagnostic Assessment of Dementia for the Longitudinal Aging Study in India (LASI-DAD) and 5-year average $PM_{2.5}$ concentrations of total mass and mass from 9 emission sources estimated at each participant's residential location using spatiotemporal models. We then quantified associations of these exposures with cognitive performance and decline using generalized estimating equation models accounting for survey weights and clustering, as well as adjusted for age, gender, individual and community-level socioeconomic status, urbanicity, place-related covariates, fuel type use, and co-pollutants.

Results: Among 5,699 participants (mean age: 70±8 years), we observed total $PM_{2.5}$ concentrations ranging from 16 to 206 μg/m^3. Higher concentrations of total $PM_{2.5}$ were not associated with cognitive performance at baseline but were associated with faster declines over time (−0.012/year per SD, 95 % CI: −0.021, −0.004). Among $PM_{2.5}$ from different sources, $PM_{2.5}$ from energy production, industry, and residential combustion were associated with steeper cognitive declines over time, whereas $PM_{2.5}$ from agriculture, transportation, wildfires, and windblown dust were associated with slower cognitive declines.

Conclusion: Higher long-term total ambient $PM_{2.5}$ concentrations and those from residential combustion sources were associated with accelerated cognitive declines. This suggests that intervention in residential sources might reduce or delay the onset of dementia and promote healthier aging in low and middle-income settings.

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1. Introduction

Dementia, defined as cognitive decline severe enough to cause limitations in independent daily function, brings heavy emotional and economic burdens to older adults, their families, and society (Hebert et al., 2013; Matthews et al., 2019). Currently, there are over 55 million people worldwide suffering from dementia (Organization, 2021), with approximately 60 % living in developing countries (Guerchet and Prince, 2015). By 2050, this burden is projected to increase to nearly 139 million, with the proportion of those affected in low and middle-income countries (LMICs) rising to 71 % (Guerchet and Prince, 2015). This suggests a pressing need to identify modifiable risk factors for poorer cognitive performance in these settings to eliminate or postpone cognitive impairment and reduce the future burden of dementia.

Fine particulate matter air pollution ($PM_{2.5}$) was identified as one of 12 key modifiable risk factors for dementia by the 2024 Lancet Commission on Dementia Prevention (Weuve et al., 2021; Livingston et al., 2024). $PM_{2.5}$ may be especially important in LMIC due to higher concentrations as a result of reliance on biomass fuel use and fewer emission controls as compared to higher- to middle-income countries (McDuffie et al., 2021; Chatterjee et al., 2023). Mechanistic research suggests that the smallest particles are often coated with neurotoxic chemicals and can directly enter the brain through the olfactory bulb or cross the blood–brain barrier, leading to damage to the brain (Jayaraj et al., 2017). Larger particles of $PM_{2.5}$ may impact cognitive function through neuroinflammation as a result of systematic inflammation and oxidative stress initially triggered in the respiratory system (Santos et al., 2021).

While the evidence for the impact of air pollution on cognitive impairment and dementia has expanded rapidly in recent years (Weuve et al., 2021), most existing research has focused on $PM_{2.5}$ as an overall category. However, $PM_{2.5}$ originates from many sources in the environment, such as residential combustion, industry, transportation, and energy production. Given that different sources can emit $PM_{2.5}$ with distinct physical and chemical characteristics, it is likely that not all sources have similar impacts on the brain. In fact, variations in emission sources by place are hypothesized to contribute to the difference in associations across studies of $PM_{2.5}$ and cognitive health (Kioumourtzoglou et al., 2015). LMICs offer a particularly unique opportunity to study the impacts of $PM_{2.5}$ from different sources on the brain since they share many common sources with high-income countries; like transportation, energy production, and windblown dust, while also experiencing large burdens from the emissions of biomass fuel burning for residential heating and cooking (Chowdhury et al., 2023).

To address these knowledge gaps, we estimated the associations between long-term exposures to ambient $PM_{2.5}$ and cognitive decline, considering both the total mass of $PM_{2.5}$ and mass from nine unique emission sources using two waves of a nationally representative cohort in India.

2. Methods

2.1. Study population

The Harmonized Diagnostic Assessment of Dementia for the Longitudinal Aging Study in India (LASI-DAD) is the first and only nationally representative study on late-life cognition and dementia in India (Lee and Dey, 2020). Between 2017 and 2019, LASI-DAD first recruited 4,096 older adults aged 60 years and older from the LASI study, a prospective, population-based survey of more than 73,000 adults aged 45 years and older in India. The second wave of LASI-DAD was conducted between 2022 and 2024 (Khobragade et al., 2024). In addition to follow-up surveys of participants in the first wave, this wave also included a refresher sample of 2,070 participants sampled from the main LASI survey. For this analysis, we restricted the population to participants with at least one cognitive performance score and complete data on exposures and key covariates (Supplemental Fig. S1).

All participants provided consent (written or thumb impression) to participate. If participants were cognitively impaired, consent was obtained from a legal representative, authorized to sign on their behalf. Informed consent and interviews were collected and conducted in the participant's language, and all interview materials, as well as consent documents, were translated into 12 Indian languages. Ethics approval to conduct this study was obtained from Institutional Review Boards at the Indian Council of Medical Research and all collaborating institutions including the University of Southern California and All India Institute of Medical Sciences, New Delhi.

2.2. Study surveys

All participants completed detailed surveys of the individual and their household. The individual survey characterized participant characteristics, including demographics, health and health behaviors, social interactions, and occupation. When participants were incapable of responding to the full interview, the surveys were completed by a close family member or friend as a proxy (Perianayagam et al., 2022). The household survey included information on income, consumption, fuel use, home location, and housing features and was completed by the most knowledgeable household member. All residential addresses of LASI-DAD participants were collected and updated during follow-up.

2.3. Cognitive performance

To characterize cognitive function, we used a general cognitive performance score summarizing cognitive performance, assessing orientation, memory, executive function, language/fluency, and visuospatial performance. Specifically, well-trained interviewers visited with the participants in a clinic or at their home to administer a cognitive test battery developed specifically for the Indian setting that included object naming, the Consortium to Establish a Registry for Alzheimer's Disease word recall, backward digit span, logical memory, constructional praxis, retrieval fluency, serial 7 s, Community Screening Instrument for Dementia (CSI-D), and Raven's test (Perianayagam et al., 2022; Lee et al., 2019). For Wave 1, we also leveraged information from proxies to ensure data capture from individuals with severe cognitive impairment to impute missing information when necessary, using demographic, health, and other cognitive performance variables (Chien et al., 2019). We estimated the latent cognitive functioning, which captures the common covariance between cognitive test items, as a way of quantifying the underlying latent trait (Toland, 2014). We then scaled the general factor score to have a mean of zero and a variance of one among the LASI-DAD participants at Wave 1.

2.4. Exposure assessment

We estimated total $PM_{2.5}$ concentrations in ambient air at the participants' residential addresses using the Data Integration Model for Air Quality (DIMAQ), which was initially developed for the World Health Organization for the global assessment of disease and used by the Institute of Health Metric Evaluation's Global Burden of Disease study. DIMAQ was refined for LASI, to produce higher-resolution estimates and applied to an extended time period (from 2010 to 2019) (Shaddick et al., 2018). DIMAQ integrates information from multiple sources, including (i) ground-level measurements; (ii) estimates (based upon aerosol optical depth) from remote sensing satellites, (iii) simulations from a chemical transport model; and (iv) land use, population, and topographic data. Estimates were generated at 1 km^2 resolution with high values observed for cross-validation ($R^2 = 0.81$).

We derived source-specific concentrations of $PM_{2.5}$ from 15 sources, including agriculture, road transportation, non-road transportation, energy production from coal combustion, other energy, industry coal combustion, other industry, wildfires, windblown dust, anthropogenic dust, residential biofuel combustion, residential coal combustion, other residential combustion, agriculture waste burning, and waste (Supplementary Appendix 1), by multiplying the total $PM_{2.5}$ concentrations at each address by local fractions of $PM_{2.5}$ attributable to each source. These fractions were generated at a resolution of $0.5^{\circ} \times 0.625^{\circ}$ (about 55.5 km × 64.4 km) by McDuffie and colleagues who serially ran an atmospheric chemistry-transport model (GEOS-Chem) with all sources but one to isolate the unique contribution of that source to the total $PM_{2.5}$ (McDuffie et al., 2021). Though this model used emission data in 2017, we assumed that the resulting predictions apply to the time period of the LASI-DAD survey. In our main analyses, we aggregated similar sources within each sector to define nine primary source-specific exposures. These included: combined agriculture (agriculture and agricultural waste burning), transportation (road and non-road transportation), energy production (coal combustion and other energy sources), industry (industrial coal combustion and other industrial sources), wildfires, windblown dust, anthropogenic dust, residential combustion (biofuel, coal, and other residential combustion), and waste. We assigned concentrations of all air pollutants during the 5-year period before the baseline interview using participants' residential addresses to reflect their long-term exposures. To adjust for potential confounding by co-pollutants, we also estimated average concentrations of nitrogen dioxide (NO_2) and ozone (O_3) at participant homes by applying existing spatiotemporal prediction models derived from ground measurements, chemical transport models, land use information, and satellite data (Anenberg et al., 2022; Becker, 2021).

2.5. Statistical analyses

We examined the association of residential concentrations of total and source-specific $PM_{2.5}$ with the general cognitive performance score and its rate of decline over time using generalized estimating equation (GEE) models to accommodate correlations between repeated measures. To assess associations with cognitive performance, we included a term for $PM_{2.5}$, whereas for associations with the rate of cognitive decline, we included a term for the cross-product of time (years) since the baseline interview and $PM_{2.5}$.

We identified potential confounders *a priori* using theory informed by prior literature and our previous analyses in LASI that illustrated the distribution of exposures and health in this population. We included all factors as main effects and with terms for the cross-products between each covariate and time to account for confounding of the baseline cognitive level and declines over time. Specifically, we adjusted our models for individual-level age, sex (male, female), marital status (married/partnered or not), education (less than upper secondary, upper secondary & vocational training, tertiary), literacy (can read or write, cannot read or write), caste (scheduled caste, scheduled tribe, other backwards caste, none or other castes), per capita consumption, per capita wealth, and use of highly polluting fuel (i.e., kerosene, charcoal/coal/lignite, crop residue, wood/shrub, or dung cake) vs. clean fuels (i.e., liquefied petroleum gas, biogas, and electric fuel). We also adjusted for interview calendar year to account for possible temporal confounding and area-level urbanicity (urban, rural), climate zones (Arid, Humid Subtropical, Montane, Semi-Arid, Tropical Wet, Tropical Wet+Dry), and region (Northern, Central, Eastern, Western, Southern, Northeastern) to account for the spatial differences that may introduce confounding by place. Although this study occurred during the COVID-19 pandemic, our exposure estimates were calculated at baseline so cannot be influenced (i.e., not confounded) by the pandemic. Similarly, we adjusted for broad trends over time but not individual-level infection since air pollution is hypothesized to increase COVID infections, which may in turn influence cognition, thus making it an intermediate rather than a confounder. Similarly, we did not adjust for chronic diseases or lifestyle factors like exercise or smoking, as these are more likely to be potential consequences of exposure than confounders after adjustment for demographics and region. Finally, we incorporated person-level sampling weights and clustering to account for the complex survey design in LASI-DAD, as well as inverse probability weights to adjust for attrition in all models, including death from COVID or other causes (Khobragade et al., 2024; Lee et al., 2019).

Our analyses first focused on the single-pollutant model (Model 1) to estimate the difference in general cognitive performance and the difference in the rates of cognitive decline over time per standard deviation (SD) higher concentration of each pollutant. Then, we further adjusted for the sum of $PM_{2.5}$ from all other sources for source-specific $PM_{2.5}$ (Model 2) and other co-pollutants in the multi-pollutant model (Model 3) to account for correlations across pollutants. We next examined whether our observed association varied by age group (60–69, 70–79, ≥80 years), sex, urbanicity, and region by conducting stratified analyses in the multi-pollutant models. Specifically, we analyzed the association of $PM_{2.5}$ with cognitive performance and decline separately within each category of these potential effect modifiers as independent strata.

In sensitivity analyses, we further adjusted multi-pollutant models for predicted indoor $PM_{2.5}$ concentrations based on a published algorithm partly determined by ambient $PM_{2.5}$ levels (Balakrishnan et al., 2013), and different combinations of place-related covariates, including regions, climate zones, and a flexible set of unpenalized thin-plate regression splines with 10 df (Keller and Szpiro, 2020). We also examined the associations of 15 source-specific $PM_{2.5}$ before aggregation with both cognitive performance and cognitive decline. Finally, to assess the potential impact of "healthy survivor" bias, we compared the characteristics of participants included in Wave 1 with those who remained in the study for follow-up in Wave 2. We also used a joint model that simultaneously estimated the model for the cognitive data and survival models for mortality data. By simultaneously estimating the associations of $PM_{2.5}$ with rates of cognitive decline and the hazard of mortality, this approach attempted to account for potential survival bias from informative attrition during the follow-up, particularly during the pandemic period (Rustand et al., 2024).

3. Results

Of the 6,166 LASI-DAD participants, 5,699 (94 %) had at least one general cognitive performance score and complete information on our exposures and key covariates (Supplementary Fig. S1). With a mean age of 70 (±8) years at baseline, participants were 55 % female, 62 % illiterate, 19 % from a scheduled caste, 6 % from a scheduled tribe, and 67 % resided in rural areas. Approximately 2,177 (38 %) completed follow-up interviews with a mean follow-up time of 4.7 (±0.7) years. Compared to participants with higher general cognitive performance scores at baseline, those with lower scores were older, more likely to be female, unmarried/without a partner, less educated, of lower socioeconomic position, and lived in rural areas, in the humid subtropical climate zones, and in the Northern part of India (Table 1).

The average $PM_{2.5}$ concentration before baseline was 55 (±27) μg/m^3 with a range of 16 to 206 μg/m^3. Total $PM_{2.5}$ concentrations had a clear regional distribution with the highest levels in northern India, with similar patterns for $PM_{2.5}$ from agriculture, road transportation, industry, and residential combustion (Fig. 1). $PM_{2.5}$ from non-road transportation, energy production, anthropogenic dust, and waste had a wider distribution across the nation, while $PM_{2.5}$ from wildfires and windblown dust was mainly concentrated in the north/northeast and northwest areas, respectively. Relatively high correlations were observed among $PM_{2.5}$ from agriculture, road transportation, non-road transportation, and waste. Similarly, strong correlations were observed between sources within the same category, such as industry-related coal combustion and other industrial sources, as well as between residential biofuel and coal combustion. These sources, which have been aggregated in the main analyses, show Pearson correlation coefficients greater than 0.8 (Supplementary Fig. S2). Exposure to $PM_{2.5}$ was also distributed differentially across the population. Compared to participants with lower $PM_{2.5}$ concentrations, those with higher $PM_{2.5}$ were more likely to be of higher socioeconomic status, live in urban

Table 1
Characteristics of study participants, overall and by general cognitive performance and $PM_{2.5}$ concentrations at baseline in LASI-DAD (mean (SD) or %(N)).

		General Cognitive Performance		Total $PM_{2.5}$	
	Total Sample (n = 5,699)	Low (<0, n = 3,117)	High (≥0, n = 2,582)	Low (<49.6 μg/m³, n = 2,846)	High (≥49.6 μg/m³, n = 2,853)
Age, years	70.0 (7.7)	71.6 (8.3)	68.0 (6.2)	70.1 (7.8)	69.9 (7.6)
Female, %(n)	55 (3,162)	68 (2,109)	41 (1,053)	56 (1,600)	55 (1,562)
Education					
Less than upper secondary	78 (4,458)	97 (3,029)	55 (1,429)	79 (2,257)	77 (2,201)
Upper secondary & vocational training	18 (1,009)	3 (80)	36 (929)	17 (498)	18 (511)
Tertiary	4 (232)	0 (8)	9 (224)	3 (91)	5 (141)
Marital/Partnered, %(n)	62 (3,546)	53 (1,662)	73 (1,884)	60 (1,705)	65 (1,841)
Illiterate %(n)	62 (3,507)	88 (2,758)	29 (749)	59 (1,690)	64 (1,817)
Caste					
Scheduled	19 (1,111)	23 (731)	15 (380)	17 (477)	22 (634)
Scheduled Tribe	6 (332)	8 (250)	3 (82)	7 (199)	5 (133)
Other Backward Caste	43 (2,463)	44 (1,362)	43 (1,101)	52 (1,472)	35 (991)
No Caste	31 (1,793)	25 (774)	39 (1,019)	25 (698)	38 (1,095)
Per Capita Household Consumption (Rupee)	51,510 (202,637)	41,774 (70,686)	63,264 (290,458)	50,358 (81,525)	52,660 (274,598)
Household Income (Rupee)	3,176,154 (14,802,822)	2,198,883 (6,985,954)	4,355,920 (20,549,629)	2,293,289 (6,135,516)	4,056,854 (19,966,978)
Rural, %(n)	67 (3,795)	78 (2,438)	53 (1,357)	72 (2,041)	61 (1,754)
Climate Zones					
Arid	6 (331)	8 (243)	3 (88)	0	12 (331)
Humid Subtropical	28 (1,573)	32 (987)	23 (586)	14 (396)	41 (1,177)
Montane	3 (171)	4 (119)	2 (52)	0 (11)	6 (160)
Semi-arid	14 (802)	14 (443)	14 (359)	12 (341)	16 (461)
Tropical Wet	8 (433)	4 (138)	11 (295)	15 (433)	0
Tropical Wet + Dry	42 (2,389)	38 (1,187)	47 (1,202)	59 (1,665)	25 (724)
Region					
Northern	24 (1,349)	25 (785)	22 (564)	1 (15)	41 (1,179)
Central	10 (596)	13 (390)	8 (206)	5 (147)	22 (633)
Eastern	19 (1,069)	19 (591)	19 (478)	15 (419)	23 (657)
Western	14 (801)	14 (427)	14 (374)	18 (527)	10 (296)
Southern	29 (1,651)	25 (776)	34 (875)	47 (1,366)	4 (127)
Northeastern	4 (233)	5 (148)	3 (85)	14 (410)	0 (14)
General Cognition	−0.06 (0.91)	−0.74 (0.51)	0.76 (0.56)	−0.07 (0.92)	−0.05 (0.91)
Air Pollution					
$PM_{2.5}$ (μg/m³)	54.9 (26.7)	54.6 (24.8)	55.2 (28.8)	34.9 (8.8)	74.8 (23.5)
Source-specific $PM_{2.5}$ (μg/m³)					
Agriculture	4.8 (2.8)	4.9 (2.7)	4.7 (2.9)	2.8 (1.6)	6.8 (2.2)
Road Transportation	3.2 (2.1)	3.2 (2.0)	3.1 (2.2)	1.7 (0.6)	4.6 (2.0)
Non-Road Transportation	0.6 (0.3)	0.6 (0.3)	0.5 (0.3)	0.4 (0.2)	0.7 (0.3)
Energy Coal	3.2 (1.7)	3.1 (1.6)	3.2 (1.8)	2.1 (1.0)	4.2 (1.6)
Energy Other	3.7 (1.7)	3.7 (1.7)	3.7 (1.8)	2.7 (1.1)	4.6 (1.7)
Industry Coal	4.6 (2.4)	4.5 (2.3)	4.7 (2.6)	2.9 (0.9)	6.3 (2.2)
Industry Other	3.8 (2.4)	3.6 (2.2)	4.0 (2.5)	2.4 (1.0)	5.1 (2.6)
Wildfires	0.5 (0.3)	0.5 (0.4)	0.5 (0.3)	0.4 (0.3)	0.6 (0.4)
Windblown Dust	2.1 (1.9)	2.2 (2.0)	2.0 (1.7)	1.3 (1.1)	2.9 (2.1)
Anthropogenic Dust	6.8 (3.4)	6.6 (3.2)	6.9 (3.7)	4.7 (1.7)	8.8 (3.5)
Residential Biofuel	11.8 (6.8)	11.7 (6.4)	11.8 (7.2)	6.9 (1.9)	16.6 (6.4)
Residential Coal	0.7 (0.4)	0.7 (0.4)	0.7 (0.4)	0.5 (0.1)	1.0 (0.4)
Residential Other	0.9 (0.6)	1.0 (0.6)	0.9 (0.6)	0.5 (0.2)	1.4 (0.6)
Agriculture Waste Burning	0.6 (0.6)	0.6 (0.5)	0.6 (0.6)	0.3 (0.2)	0.9 (0.7)
Waste	2.3 (0.9)	2.3 (0.9)	2.3 (1.0)	1.6 (0.4)	3.0 (0.8)
NO_2 (ppb)	7.0 (4.7)	6.2 (4.1)	8.0 (5.2)	5.6 (3.4)	8.5 (5.2)
O_3 (ppb)	58.8 (6.5)	59.3 (6.3)	58.3 (6.6)	55.8 (6.3)	61.9 (5.1)

areas, live in the humid subtropical climate zones, and in the Northern part of India (Table 1).

In all models (Fig. 2 and Supplementary Table S1), we observed no association of general cognitive performance with the average concentrations of total and source-specific $PM_{2.5}$ during the 5 years before baseline, with the exception of an association between higher concentrations of $PM_{2.5}$ from windblown dust and better general cognitive performance.

For cognitive decline (Fig. 2 and Supplementary Table S1), we observed that an SD higher in total $PM_{2.5}$ concentration was associated with a −0.012 (95 %CI: −0.021, −0.004) standard unit faster decline in the general cognitive performance per year. These differences were similar to the difference in rates of change we observed between participants who received upper secondary or vocational training and those who had less than an upper secondary education. Among $PM_{2.5}$ from different emission sources, we observed generally imprecise results for the multi-pollutant as compared to the single-pollutant models. Higher exposure to $PM_{2.5}$ from residential combustion was associated with a faster decline in general cognitive performance, with a −0.035 (95 %CI: −0.061, −0.008) standard unit accelerated annual rates per SD increase in the source-specific $PM_{2.5}$. We also observed associations with faster decline for $PM_{2.5}$ emitted from energy production (−0.011, 95 % CI: −0.025, 0.003), industry (−0.015, 95 % CI: −0.033, 0.003), and anthropogenic dust (−0.008, 95 % CI: −0.018, 0.002), though these were imprecise and could not be distinguished from no association. In contrast, we observed that higher $PM_{2.5}$ concentrations from transportation, wildfires, and windblown dust were associated with slower annual rates of cognitive decline that ranged from 0.015 (95 % CI:

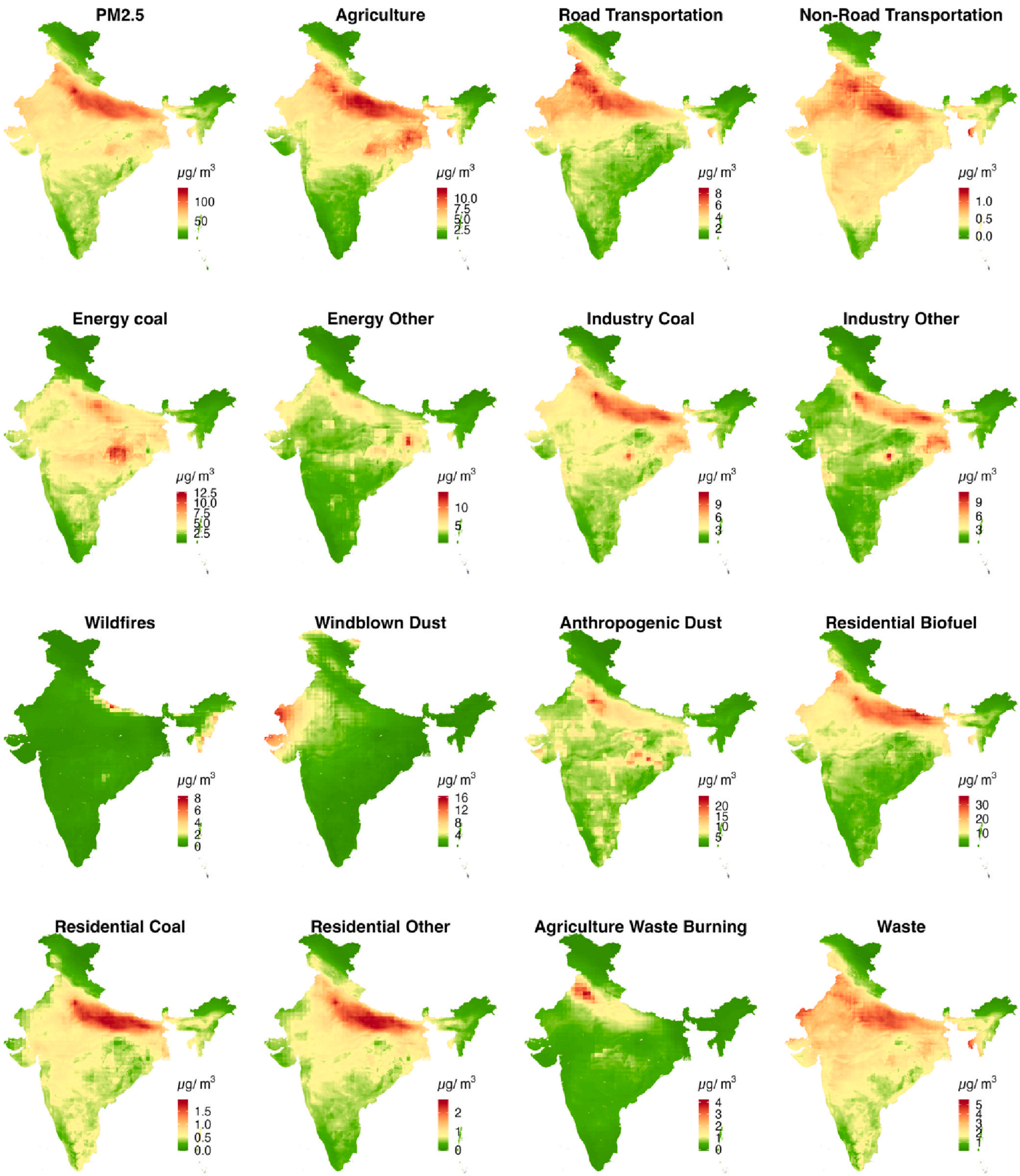

Fig. 1. Spatial distribution of long-term concentrations of total and source-specific $PM_{2.5}$ across India.

0.005, 0.025) standard unit slower in cognitive decline per year for windblown dust to 0.051 (95 %CI: 0.025, 0.077) for transportation.

When examining potential effect modification, we found no evidence of effect modification by age and only very weak evidence suggesting steeper cognitive declines with greater $PM_{2.5}$ concentrations among those residing in rural areas. When stratified by gender, the associations of $PM_{2.5}$ varied across different emission sources. Specifically, steeper declines in cognitive function with $PM_{2.5}$ from energy production were observed only among males, whereas stronger deficits and steeper declines associated with $PM_{2.5}$ from residential combustion were only detect among females. When stratified by regions, we generally found poorer cognitive function with higher $PM_{2.5}$ among those living in the Western and Southern regions, while faster declines with greater $PM_{2.5}$ were observed among those in the Northern and Eastern regions (Supplementary Tables S2-S5).

In sensitivity analyses, our findings remained relatively robust to

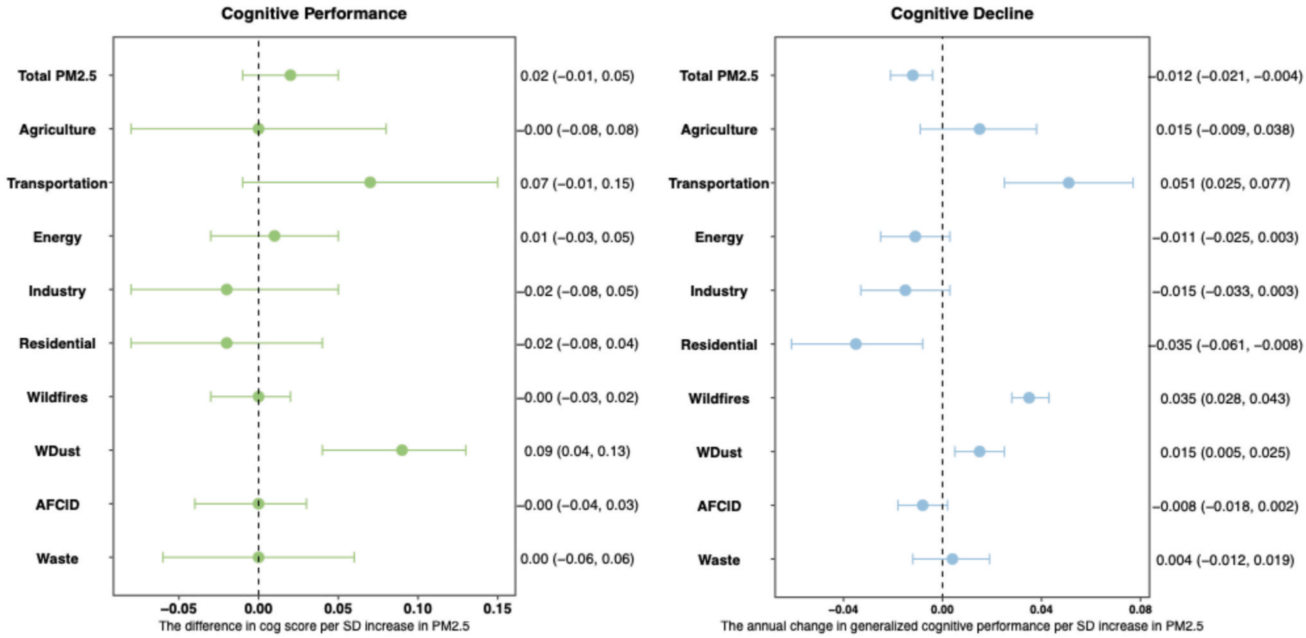

Fig. 2. Differences in cognitive performance and the annual rate of cognitive decline associated with per SD increase in the level of total and source-specific $PM_{2.5}$ in multi-pollutant models in LASI-DAD. Notes: Models adjusted for age, sex, marital status, education, literacy, caste, per capita consumption, per capita wealth, interview calendar year, urbanicity, climate zones, region, fuel type use, the sum of $PM_{2.5}$ from all other sources for source-specific $PM_{2.5,}$ NO_2, and O_3. Sources are defined as: Agriculture: agriculture and agriculture waste burning; Transportation: road transportation and non-road transportation; Energy: energy coal and other energy; Industry: industry coal and other industry; Residential: residential biofuel, residential coal, and other residential; Wildfires: wildfires; WDust: windblown dust; AFCID: anthropogenic dust; Waste: waste.

additional adjustments for indoor air pollution indicators (Supplementary Table S6). Although there was some variability in findings for cognitive performance with differing levels of adjustment for place, the qualitative findings were generally consistent (Supplementary Table S7). For associations with cognitive declines, associations of $PM_{2.5}$ from agriculture, industry, transportation, residential combustion, and wildfires remained most robust across models with different place-related covariates. When examining associations with 15 detailed source-specific $PM_{2.5}$ components, we observed that the association observed for residential combustion sources was primarily attributable to $PM_{2.5}$ from residential biofuel burning (Supplementary Table S8). We found little evidence of large differences in the population who were retained in Wave 2 (Supplementary Table S9). Findings were largely unchanged in the joint models that accounted for mortality over the follow-up period, though some of the observed associations were strengthened (Supplementary Table S10).

4. Discussion

In this nationally representative cohort study of older adults in India, we found that higher long-term exposure to total $PM_{2.5}$ was associated with faster rates of cognitive decline even after accounting for individual-level risk factors and gaseous co-pollutants. When investigating associations with $PM_{2.5}$ by emission source, however, the results were less clear. Steeper cognitive declines over time were associated with $PM_{2.5}$ from energy production, industry, and residential combustion sources. In contrast, $PM_{2.5}$ from transportation, wildfires, and windblown dust were associated with improved cognitive performance over time. This research suggests that more attention on specific sources of air pollution may be helpful to improve cognitive performance and prevent cognitive decline in LMICs, though more research is needed to confirm these findings.

When considering total $PM_{2.5}$, our findings are in general alignment with the accumulating evidence that higher levels of exposure are associated with greater cognitive decline among middle-aged and older adults (Weuve et al., 2021; Weuve et al., 2012; Duchesne et al., 2022; Grande et al., 2021; Kulick et al., 2020). However, we did not find the same cross-sectional association of poorer cognitive function with total $PM_{2.5}$ that has been observed in many previous studies (Ailshire and Crimmins, 2014; Ailshire and Clarke, 2015; Cullen et al., 2018; Salinas-Rodríguez et al., 2018/08/01/ 2018,; Schikowski et al., 2015/10/01/ 2015,; Zhang et al., 2018). Differences in study design might be one of the reasons for this inconsistency. While most previous studies were restricted to cross-sectional information, our study employed a longitudinal study design that evaluated the effect of long-term exposures on cognitive performance simultaneously with the rate of change in cognitive performance over time. Since cognitive level and declines are connected constructs, it may be that it is difficult to disentangle the two with cross-sectional studies fully attributing any declines over time to the current level and longitudinal models attributing some of the current level to declines. Another potential explanation relates to the fact that India has one of the highest annual average $PM_{2.5}$ concentrations in the world (Hammer et al., 2020) and lower life expectancies than many of the high-income countries that have been studied previously (Grande et al., 2021; Ailshire and Crimmins, 2014; Ailshire and Clarke, 2015; Power et al., 2011). Therefore, it could also be that there is a “healthy survivor” effect among older adults living with such high pollution levels, such that air pollution is not as strongly predictive of cognition in this population. We suspect that this may be a possible explanation for the limited associations with cognitive performance at baseline, although air pollution remains more related to cognitive declines.

In fact, one unique contribution of this work is its extension of the literature on air pollution and cognition by newly examining associations of cognitive performance and rate of cognitive decline with $PM_{2.5}$ from key emission sources. In India, we found that $PM_{2.5}$ from residential combustion was most strongly and robustly associated with poorer cognitive performance and faster rates of cognitive decline. This may represent an important finding given that residential combustion was the leading contributor to $PM_{2.5}$ in India and the surrounding region in 2019, accounting for 28 % of the annual population-weighted mean concentrations (Chatterjee et al., 2023). Globally, approximately 3 billion people still rely on highly polluting fuels like biofuel and coal for residential heating and cooking, especially in the rural areas of LMICs (Who, 2018), which results in higher exposure levels both within households and in the ambient air. Given existing interventions, our findings suggest that a transition to cleaner fuel may help improve cognitive performance and prevent cognitive decline in LMICs.

When comparing to the limited literature on air pollution and cognition in LMICs, there is support for our findings in papers of cognition and household air pollution (Jana et al., 2022; Dakua et al., 2022; Saenz et al., 2021). For example, indicators for the use of polluting cooking fuels have been linked to poorer cognitive function in the main LASI and its sister studies in Mexico and China (Jana et al., 2022; Dakua et al., 2022; Saenz et al., 2021). Interestingly, existing studies identified organic matter (OM) and black carbon (BC) as the largest contributors to $PM_{2.5}$ from residential combustion (McDuffie et al., 2021; Chatterjee et al., 2023) and as the primary $PM_{2.5}$ components contributing to cognitive impairment (Qi et al., 2024; Liu et al., 2023). This provides additional support for our findings since the neurotoxicity of $PM_{2.5}$ emitted from residential combustion has been partly attributed to OM and BC. Due to the high surface-area-to-volume ratio of small particles from household combustion; these particles can also mix with other chemicals in the air and serve as a transporter for highly toxic compounds into the brain; where they can activate oxygen species in microglia and inhibit the brain antioxidant scavenging system (Saunders et al., 2006).

In contrast to the residential combustion source, we found counter-to-hypothesis evidence of changes in cognition over time with several other sources, including agriculture and wildfire emissions. This finding notably differs from what we observed in the United States, where $PM_{2.5}$ from agriculture and wildfires was robustly associated with an increased risk of dementia (Zhang et al., 2023). One possible explanation for the agriculture result is that after accounting for education, agricultural communities work longer and thus have less cognitive decline over time. Another possible explanation for the conflicting evidence is that the association may vary across different concentration ranges. Notably, the average concentration of $PM_{2.5}$ in India (54.9 $\mu g/m^3$) is much higher than that in the US (11.2 $\mu g/m^3$). However, due to the limited sample size, we were unable to obtain stable results when restricting our analyses to those with $PM_{2.5}$ levels typically found in high-income countries.

4.1. Strengths and limitations

To our knowledge, this is the first study to investigate the association between $PM_{2.5}$ in ambient air and cognitive function in India and one of the few papers on the relationships with cognitive decline in an LMIC. This work also fills a gap in the existing literature regarding the association of source-specific $PM_{2.5}$ with cognitive function and the rate of cognitive decline more generally. Instead of using chemical components as tracers for sources, we used estimates of source-specific $PM_{2.5}$ generated by sequentially removing each source individually from a chemical-transport dispersion model. As a result, we are able to account for both primary and secondary pollutants generated from specific sources, and investigate the counter-factual question of how would health change if the emissions from each source was removed from the atmosphere. Other strengths of this work include the high-quality information from LASI-DAD with detailed information on confounders based on personal and community-level information as well as precise estimates of general cognitive functioning from an hour-long cognitive test battery.

Despite the many strengths of this work, limitations exist. Given the sensitivity to the adjustment of place-related covariates, it remains possible that there is residential confounding by region in our analyses. Although this is a large study with intensive data collection, India is a complex nation and it may be that we are underpowered to tease apart differences by place. Relatedly, correlations among different sources may interfere with our ability to confidently disentangle the effects of single sources. Leveraging future waves of information and repeated measures may be helpful for a more stable trend of cognitive decline over a longer follow-up time. Other important limitations relate to the relatively crude resolution of the emissions data for the derivation of fractional source contributions over space and time. First, the emission source data reflects larger spatial scales, so it will fail to capture the impacts of highly localized sources like transportation. As a result, the findings of this work reflect the contributions of sources at a more regional than local level and should be interpreted with some caution. Relatedly, the emission data relies on estimates from 2017 alone, so we must assume that this year is reflective of longer durations. This may be an issue, especially for the residential combustion exposures since the Indian government invested in campaign to replace biofuel stoves with liquid petroleum gas stoves, especially those in poor households. If these errors resulted in the systematic patterning in the under- or over-estimation of exposures that is not captured by our adjustments for time and place, bias could potentially result. In addition, our results could be underestimated by "healthy survivor" bias because those with comorbidities associated with both $PM_{2.5}$ and impaired cognition may be more likely to be lost to follow-up. However, we found little evidence of large differences in the population who were followed in Wave 2 (Supplemental Table S9), and the use of sampling and attrition weights should minimize this bias. Also, our results remained largely robust to adjustment for deaths during follow-up in our longitudinal analyses (Supplementary Table S10). We also found little evidence of effect modification by age or differences in the population that was observed for two rounds of sampling from the baseline population. Finally, although we used a nationally representative sample from LASI-DAD, which provides valuable insights into the associations between $PM_{2.5}$ and cognitive performance, the limited sample size may not fully capture the vast geographic, socioeconomic, and cultural heterogeneity of the Indian population.

5. Conclusion

With rapid growth in the older population and the dramatically rising burden of dementia in LMICs, slowing cognitive decline has become increasingly important. Our study suggests that reducing $PM_{2.5}$ and perhaps selectively targeting residential combustion sources might be effective strategies for reducing or delaying the onset of dementia in India. Future studies would benefit from higher spatial resolution of emission data, larger sample sizes, and more repeated measures of cognitive performance to provide more robust and generalizable evidence.

Patents and intellectual property

There are no patents to disclose.

Other activities

There are no additional activities to disclose.

CRediT authorship contribution statement

Boya Zhang: Conceptualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Sara D. Adar:** Conceptualization, Funding acquisition, Supervision, Writing – review & editing, Data curation. **Emma Nichols:** Methodology, Writing – review & editing. **Alden L. Gross:** Methodology, Writing – review & editing. **Gavin Shaddick:** Methodology, Writing – review & editing. **Matthew L. Thomas:** Methodology, Writing – review & editing. **Jennifer D'Souza:** Writing – review & editing, Data curation. **Sarah Petrosyan:** Project administration. **Sandy Chien:** Project administration. **Albert Weerman:** Project administration. **Kenneth M. Langa:** Funding acquisition, Writing – review & editing. **Aparajit B. Dey:** Funding acquisition, Writing – review & editing. **Sharmistha Dey:** Funding acquisition, Writing – review & editing. **Jinkook Lee:** Conceptualization, Data curation, Funding acquisition, Supervision, Writing – review & editing.

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2025.109826.

Data availability

The data used for this article can be requested through the Gateway to Global Aging Data research enclave.

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