



Impacts of contemporaneous air pollution exposure on cognitive performance in Kenya

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ARTICLE INFO

Dataset link: <https://doi.org/10.7910/DVN/VRXIXB>

JEL classification:

I10
J24
Q53
Q56

Keywords:

Air pollution
Cognitive performance
Cognition
Human capital
Sub-Saharan Africa
Kenya

ABSTRACT

We estimate the short-term cognitive effects of fine particulate matter (PM_{2.5}) exposure using novel exposure data collected during cognitive testing in Kenya. Unlike most existing studies that rely on satellite-based or fixed monitoring station data, we measure highly localized ambient pollution using portable monitors deployed at cognitive testing sites and link these readings directly to Harmonized Cognitive Assessment Protocol (HCAP) scores. Higher PM_{2.5} exposure during testing is associated with lower cognitive performance, particularly in executive function, memory, and visuospatial tasks. Binned exposure models suggest a monotonic pattern, with more negative estimates at higher exposure levels. Notably, effects are significantly larger among more educated individuals, possibly due to greater task demands or lower chronic exposure that limits physiological adaptation. Given that cognitive impairment is evident even at PM_{2.5} levels below Kenya's mean annual regulatory threshold of 35 µg/m³, the findings suggest that short-term exposure may impose underappreciated human capital costs that current regulatory standards fail to mitigate. The results highlight the potential cognitive and economic returns to interventions that reduce air pollution exposures in low-resource settings.

1. Introduction

Air pollution exposure is a growing global public health challenge (Brauer et al., 2024), responsible for an estimated 7.9 million deaths yearly (Health Effects Institute, 2025). As rapid urbanization and industrial expansion continue, particularly in low- and middle-income countries (LMICs), the burden of air pollution exposure is increasing (Health Effects Institute, 2025). A large literature links exposure to fine particulate matter (PM_{2.5}) to higher mortality (Anderson, 2020; Arceo et al., 2016; Pozzer et al., 2023), respiratory illness (Wu et al., 2022; Guarnieri and Balme, 2014; Shin et al., 2021), cardiovascular disease (de Bont et al., 2022), and neurological disorders (Shi et al., 2020, 2021). More recently, researchers have begun to examine the immediate cognitive effects of short-term particulate matter exposure, highlighting potential effects on attention, memory, and executive functioning (Faherty et al., 2025; Ke et al., 2022; Power et al., 2016; Zhou et al., 2023; Kang et al., 2021).

A growing body of evidence documents short-term effects of air pollution on cognitive and task performance across a range of settings, including high-stakes examinations in Israel (Ebenstein et al., 2016), Chile (Bharadwaj et al., 2017), Brazil (Carneiro et al., 2021), China (Graff Zivin et al., 2020; Yao et al., 2023), and the United Kingdom (Roth, 2021), brain-training games (La Nauze

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and Severnini, 2025; Krebs and Luechinger, 2024) in the United States, and laboratory experiments in Brazil (Bedi et al., 2021). Yet these cognitive-outcome studies rely almost exclusively on pollution measures from satellite reanalysis products or fixed monitoring stations, which assign exposure at relatively coarse spatial and temporal scales, and may therefore smooth over the fine-grained variation that could be relevant for short-term cognitive effects. Evidence from Sub-Saharan Africa (SSA) remains limited. The small existing SSA literature has focused more on child neuro-development and early-life exposures than on adult cognition (Duncan et al., 2025; Benki-Nugent et al., 2025), reflecting ongoing constraints in routine monitoring infrastructure (Fuller and Amegah, 2022). A key open question is therefore how pollution exposure measurement affects the ability to detect cognitive effects, and whether spatially aggregated measures attenuate estimated impacts relative to person-proximate monitoring.

To address these questions, we use new data collected as part of the fifth round of the Kenya Life Panel Survey (KLPS-5). KLPS is a long-running longitudinal study that originally tracked participants in a randomized school-based deworming program in rural western Kenya (Miguel and Kremer, 2004). The most recent round includes a Cognitive Plus (C+) module designed to measure mid-life cognitive performance and environmental risk factors, including air pollution exposure. The C+ module covers more than 5000 individuals, many of whom have been surveyed for over two decades, and was designed to establish a cognitive baseline for future aging and dementia research in this population.

We analyze data from 5398 respondents with highly time-resolved, real-time PM_{2.5} measurements collected during cognitive assessments using portable Atmotube Pro sensors (Pujante Pérez et al., 2024). Unlike most existing studies that assign exposure using satellite products or fixed monitoring stations, these devices record ambient pollution at the exact time and location of cognitive testing, providing person-proximate measures of short-run exposure. This design captures fine spatial and temporal variation that is typically smoothed over in aggregated pollution datasets. To assess the importance of exposure measurement, we construct parallel pollution proxies from three widely used sources – namely, CAMS EAC4 atmospheric reanalysis, MERRA-2 reanalysis, and PurpleAir fixed-site monitors – which differ in their spatial and temporal resolution relative to the portable-monitor data. Average PM_{2.5} concentrations in our sample are about 15 µg/m³, lower than levels documented in heavily polluted settings such as New Delhi or Beijing, but exceeding the U.S. EPA's annual standard of 9 µg/m³ (U.S. Environmental Protection Agency, 2025). This setting therefore allows us to test whether short-term cognitive effects arise even at pollution levels that may appear moderate from a regulatory perspective.

The study also benefits from a comprehensive and contextually adapted cognitive battery designed to ensure comparability with studies implementing the Harmonized Cognitive Assessment Protocol (HCAP) (Gross et al., 2023). The battery spans multiple domains – orientation, memory, executive function, language, and visuospatial skills – and was developed with careful attention to cultural and linguistic appropriateness for the Kenyan context (Gross et al., 2025). Such multidimensional assessment is uncommon in LMIC pollution studies, which typically rely on more limited measures such as high-stakes exam scores, single-domain instruments, or online task performance (Ebenstein et al., 2016; Carneiro et al., 2021; Graff Zivin et al., 2020; Heyes et al., 2023; Krebs and Luechinger, 2024; La Nauze and Severnini, 2025; Holub and Theis, 2023). By covering five cognitive domains within a validated framework, the battery improves the study's ability to detect domain-specific changes in cognition due to environmental stressors and facilitates comparison with the broader literature on cognition.

To estimate the relationship between contemporaneous air pollution exposure and cognitive outcomes, we employ a fixed-effects regression model with detailed time fixed effects (time-of-day, day-of-week, and month), geographic fixed effects, and controls for individual characteristics (gender, age, education) and environmental factors (temperature, humidity, and survey location). This strategy exploits short-term, within-location variation in PM_{2.5} to isolate plausibly exogenous exposure shocks, and the results are robust across alternative specifications. The key identifying assumption is that, conditional on geographic and temporal fixed effects, short-run deviations in PM_{2.5} during the testing window are uncorrelated with unobserved determinants of cognitive performance. We provide several pieces of evidence supporting this assumption: balance tests following the approach of Pei et al. (2019) show that residualized PM_{2.5} is uncorrelated with various observable respondent characteristics, and Oster bounds (Oster, 2019) indicate that selection on unobservables would need to be more than three times as large as selection on observables to explain away the estimated effect.

We find that a 10 µg/m³ increase in PM_{2.5} is associated with a statistically significant decline of 0.030 standard deviations in general cognitive ability ($p < 0.05$). Estimates based on portable-monitor data are consistently larger than those obtained using satellite or reanalysis measures, consistent with attenuation from spatial aggregation and the inability of coarser exposure assignments to capture high-frequency, individual-level variation (Dominici et al., 2000; Gryparis et al., 2009; Szpiro and Paciorek, 2013; Steinle et al., 2015). Several biological mechanisms may explain this cognitive effect: particulate exposure can trigger neuroinflammation and oxidative stress, impair synaptic function (Kang et al., 2021), and in severe cases compromise the blood-brain barrier (Li et al., 2022).

We also find suggestive evidence of a steeper cognition gradient at higher exposure levels, with larger estimated declines above 10 µg/m³, although not all differences across exposure ranges are statistically significant. This pattern is again visible only when exposure is measured using portable monitors; grid-based reanalysis measures substantially attenuate the estimated effects and do not reveal the same gradient. Effects on domain-specific scores vary: we detect robust negative associations for memory, executive functioning, and visuospatial skills, while effects on orientation and language are small and not statistically significant, likely reflecting ceiling effects in these domains for a mid-life adult sample (Gross et al., 2025).

We document heterogeneity by educational attainment: individuals with at least some secondary schooling exhibit an even larger 0.059 SD decline in general cognition per 10 µg/m³ increase. This pattern suggests that more educated individuals may be more vulnerable to short-term cognitive disruption, possibly because they perform at higher baseline levels, though the mechanisms require further study.

This study makes three key contributions. First, it provides new evidence on the pollution–cognition relationship in a low-resource Sub-Saharan African setting, a region that remains underrepresented in the literature (Fuller and Amegah, 2022). Prior studies in LMICs, including Carneiro et al. (2021) in Brazil, Graff Zivin et al. (2020) in China, and Bharadwaj et al. (2017) in Chile, focus on different institutional environments and typically examine children or educational outcomes. By contrast, we study mid-life cognitive performance in Kenya, a setting characterized by moderate but highly variable pollution levels and limited environmental monitoring infrastructure.

Second, the paper advances exposure measurement by aligning pollution measurement with the exact time and location of cognitive testing. Person-proximate measurement using wearable instruments is well-established in the household air pollution and cookstove-trial literature in low- and middle-income settings: the HAPIN multi-country trial used 24-hour personal PM_{2.5} monitoring to link LPG stove interventions to birth and respiratory outcomes (Ye et al., 2024; Johnson et al., 2022), the GRAPHS study in Ghana deployed wearable monitors to characterize pregnancy exposures and child health (Chillrud et al., 2021), and the PURE-AIR (Shupler et al., 2020) and CLEAN-Air(Africa) (Shupler et al., 2024) studies measured personal PM_{2.5} exposures across households using different cooking fuels. These studies have focused on physical health rather than cognition. We build on their measurement approach by deploying portable PM_{2.5} monitors during the cognitive assessment itself, capturing exposure in the immediate testing environment at high temporal resolution and reducing reliance on spatially aggregated proxies that may introduce assignment error when exposure varies at fine temporal or micro-spatial scales. We also directly compare estimates based on portable monitors with those derived from CAMS EAC4, MERRA-2, and PurpleAir in the same sample and specification. The fact that reanalysis-based estimates are attenuated toward zero, and that the dose–response pattern is detectable only with person-proximate monitoring, provides direct evidence that exposure measurement precision matters for estimating cognitive effects.

Third, the paper contributes to a growing literature on the dose–response relationship between pollution and cognition. These patterns echo prior evidence of steeper cognitive declines at higher pollution concentrations (Weuve et al., 2012; Zhang et al., 2018) and stronger short-term impairments under high cognitive load or in high-stakes settings (Ebenstein et al., 2016; Graff Zivin et al., 2020; Krebs and Luechinger, 2024; La Nauze and Severnini, 2025).

Taken together, these findings highlight the potential cognitive costs of short-term air pollution exposure, even at levels below many global air quality thresholds (World Health Organization, 2021; Health Effects Institute, 2025), including Kenya's mean annual regulatory threshold of 35 µg/m³ (Kenya G. and National Environment Management Authority, 2024).² While we view the observed impacts as moderate in magnitude, they are considerably larger among more educated individuals, suggesting that pollution may undermine cognitive inputs critical for productivity and decision-making. The findings are especially relevant in SSA, where air pollution is rising with urbanization and industrial development, yet enforcement of air quality standards and monitoring infrastructure remains limited. In such contexts, the cognitive impacts documented here may carry broader economic consequences, strengthening the case for investments in basic regulatory capacity, improved pollution monitoring, and targeted mitigation measures.

The remainder of the paper is structured as follows: Section 2 describes the data, Section 3 outlines the empirical methodology, Section 4 presents the main results, and Section 5 concludes.

2. Data

This study draws on the fifth round of the Kenya Life Panel Survey (KLPS-5), a long-running longitudinal dataset that follows a cohort of individuals originally enrolled in a randomized school-based deworming intervention between 1998 and 2001 in western Kenya (Miguel and Kremer, 2004).³ The KLPS sample has since been tracked across multiple survey rounds, providing rich information on respondents' socioeconomic conditions, health, and cognitive outcomes over more than two decades (Hamory et al., 2021).

The analytical sample consists of 5398 adults who participated in the 2023 KLPS-5 Cognitive Plus (C+) module. Data collection took place from January 2023 through February 2024. This module includes highly time-resolved air pollution measurements and a comprehensive battery of cognitive assessments. Respondents range in age from 28 to 47 (mean = 37.2, SD = 2.5), where an average of 52% have received at least one year of secondary schooling, and 56% are female (Appendix Table S1). The rate of secondary schooling in the sample is broadly comparable to national averages for this age cohort, though the sample is not designed to be nationally representative as it is drawn from participants in the original deworming program in western Kenya, many of whom have since migrated across the country (Hsu et al., 2026). Cognitive assessments were conducted during in-person interviews, most commonly at respondents' homes or workplaces, though some took place in public locations. The sample spans diverse geographic areas: roughly half of respondents remain in largely rural Busia County – the original study site – while the remainder have migrated across Kenya, many to urban and peri-urban centers including the capital Nairobi (Appendix Table S2). This spatial dispersion introduces meaningful variation in pollution exposure and enhances the external relevance of the findings.

² The 35 µg/m³ annual-average PM_{2.5} limit in Kenya's 2024 Air Quality Regulations applies to industrial areas (First Schedule, Table 1).

³ Replication data and code are available at: Xuqian Ma, Michelle Layvant, Edward Miguel, Eric Ochieng, Ajay Pillarisetti, and Michael Walker. 2026. "Replication Data for: Impacts of Contemporaneous Air Pollution Exposure on Cognitive Performance in Kenya." Harvard Dataverse. <https://doi.org/10.7910/DVN/VRXIXB>.

2.1. Air pollution data

The KLPS-5 C+ module measures contemporaneous personal exposure to fine particulate matter (PM_{2.5}) using Atmotube Pro devices, portable air quality monitors carried by survey enumerators (hereafter field officers or FOs) during all in-person cognitive assessments. These devices continuously record minute-level concentrations of PM_{2.5}, ambient temperature (°C), relative humidity (%), and volatile organic compounds (VOCs). PM_{2.5} observations were linked to each respondent's assessment via minute-level timestamps and FO identifiers. The C+ module lasted an average of 156 min (roughly two and a half hours), and mean PM_{2.5} exposure over this full testing window serves as the primary exposure measure. Approximately 5.3% of observations (305 out of 5730) were removed due to unmatched, missing, or incorrect timestamps.

Because FOs were physically present with respondents throughout testing, the device-recorded exposure closely matches respondents' real-time pollution environments across both indoor and outdoor assessments. FOs were instructed to place devices in an open location during the survey, typically on the table where the assessment took place, or clipped to their waist or bag, ensuring that the monitor remained co-located with the respondent throughout. This co-location means the measure does not rely on GPS-based assignment of pollution from a remote grid or monitoring station, avoiding spatial mismatch between assigned and actual exposure that can arise in satellite-based or fixed-monitor studies (Bista et al., 2025; Keller et al., 2017). The Atmotube Pro has demonstrated strong correlations with reference-grade monitors in field tests, with especially strong performance for PM₁ and PM_{2.5} ($R^2 = 0.70\text{--}0.93$) (Pujante Pérez et al., 2024). Following approaches used in related studies, the top 2.5% of PM_{2.5} values were trimmed to minimize the influence of extreme outliers and sensor noise (Li et al., 2023; Venuta et al., 2024). We also assess robustness to alternative treatments of the right tail, including the median exposure during the testing window, winsorization, log specifications, and models using the full untrimmed distribution (Section 4.5.6).

PM_{2.5} exposure varied substantially across the sample, ranging from 1 to 440 $\mu\text{g}/\text{m}^3$ (mean = 15.5 $\mu\text{g}/\text{m}^3$, SD = 21.2 $\mu\text{g}/\text{m}^3$), with higher values observed during Kenya's dry seasons (February–March and August) and in major urban areas such as Nairobi (Fig. 1). Appendix Figures S2 and S3 further characterize temporal and regional variation in PM_{2.5} exposure by presenting monthly exposure distributions and the share of respondents exposed to unsafe pollution levels across regions, respectively. Major sources of PM_{2.5} in Kenya include traffic emissions, windblown and mineral dust, industrial activity, and biomass combustion from households and open burning. Source-apportionment studies in Nairobi estimate that traffic and mineral dust together account for about 74% of PM_{2.5} (Gaita et al., 2014), while regional assessments point to additional contributions from residential biomass use, waste burning, and agricultural fires (Gaita et al., 2014; Oguge et al., 2024; Kirago et al., 2022; Singh et al., 2022; Gordon et al., 2023; Bauer et al., 2019). Average concentrations in this Kenyan sample are relatively modest compared with many other African settings: in Uganda, for example, Bassi et al. (2024) report annual averages of 29–41 $\mu\text{g}/\text{m}^3$, with urban levels roughly 40% higher than rural areas and pollution levels comparable to those in Nigeria and Ghana.

Importantly, day-to-day variation in pollution concentration is plausibly unrelated to individual characteristics and behaviors once geographic and temporal fixed effects are included. Consistent with this interpretation, PM_{2.5} exposure shows no significant association with key respondent attributes after conditioning on these fixed effects, a pattern that holds across all alternative geographic fixed-effects groupings (Appendix Table S16).

In addition to the Atmotube-based measure, we construct parallel PM_{2.5} proxies from three widely used external sources to benchmark the importance of exposure measurement precision. These measures capture broader ambient conditions but are more spatially smoothed or spatially centralized than the person-proximate Atmotube readings, and may therefore introduce attenuation bias when the relevant exposure variation occurs at fine temporal or micro-spatial scales.

This comparison across measures is motivated by a growing literature documenting that environmental exposure measures can differ substantially across data sources and that these differences can materially affect empirical estimates. Validation studies comparing satellite and reanalysis products to ground-based observations show systematic bias and spatial heterogeneity in measurement error (Ahmed et al., 2024; Wodebo et al., 2025). Complementary work demonstrates that estimates of environmental impacts are often not robust to the choice of remote sensing dataset, reflecting differences in construction, spatial aggregation, and underlying inputs (Michler et al., 2022; Josephson et al., 2026). More broadly, recent evidence highlights that environmental measurement error is frequently non-classical and can vary systematically with geography and data construction, with important implications for inference (Carson and Yu, 2026).

The first alternative measure is the CAMS EAC4 atmospheric reanalysis (Inness et al., 2019), which provides global model-based PM_{2.5} estimates at approximately $0.75^\circ \times 0.75^\circ$ spatial resolution and 3-hour temporal frequency, combining satellite retrievals, emissions inventories, and atmospheric transport modeling (Copernicus Atmosphere Monitoring Service, 2024). For each assessment, we identify the midpoint of the testing window, match it to the nearest 3-hour CAMS timestamp, and assign the PM_{2.5} value from the grid cell containing the respondent's GPS coordinates. The second is MERRA-2 (Gelaro et al., 2017), which offers somewhat finer temporal resolution at hourly frequency and approximately $0.5^\circ \times 0.625^\circ$ spatial resolution (Global Modeling and Assimilation Office, 2024). For each assessment, we partition the testing window into hourly intervals, extract grid-cell PM_{2.5} values at the respondent's GPS coordinates, and compute a duration-weighted mean. Despite the improved temporal alignment relative to CAMS, the spatial resolution of both reanalysis products remains coarse relative to the neighborhood-level variation likely relevant for short-run, person-specific exposure. The third source is PurpleAir fixed-site monitors located at the field offices responsible for data collection in Nairobi and Busia (PurpleAir Inc., 2023). Using 10-minute readings, we compute mean PM_{2.5} over each respondent's testing window and restrict the sample to respondents within 50 km of a monitor (and examine robustness to alternative radii). Unlike the reanalysis products, PurpleAir captures high-frequency temporal variation at ground level, but because the monitors are centrally located, this proxy reflects broader temporal fluctuations rather than micro-spatial variation at the interview site.

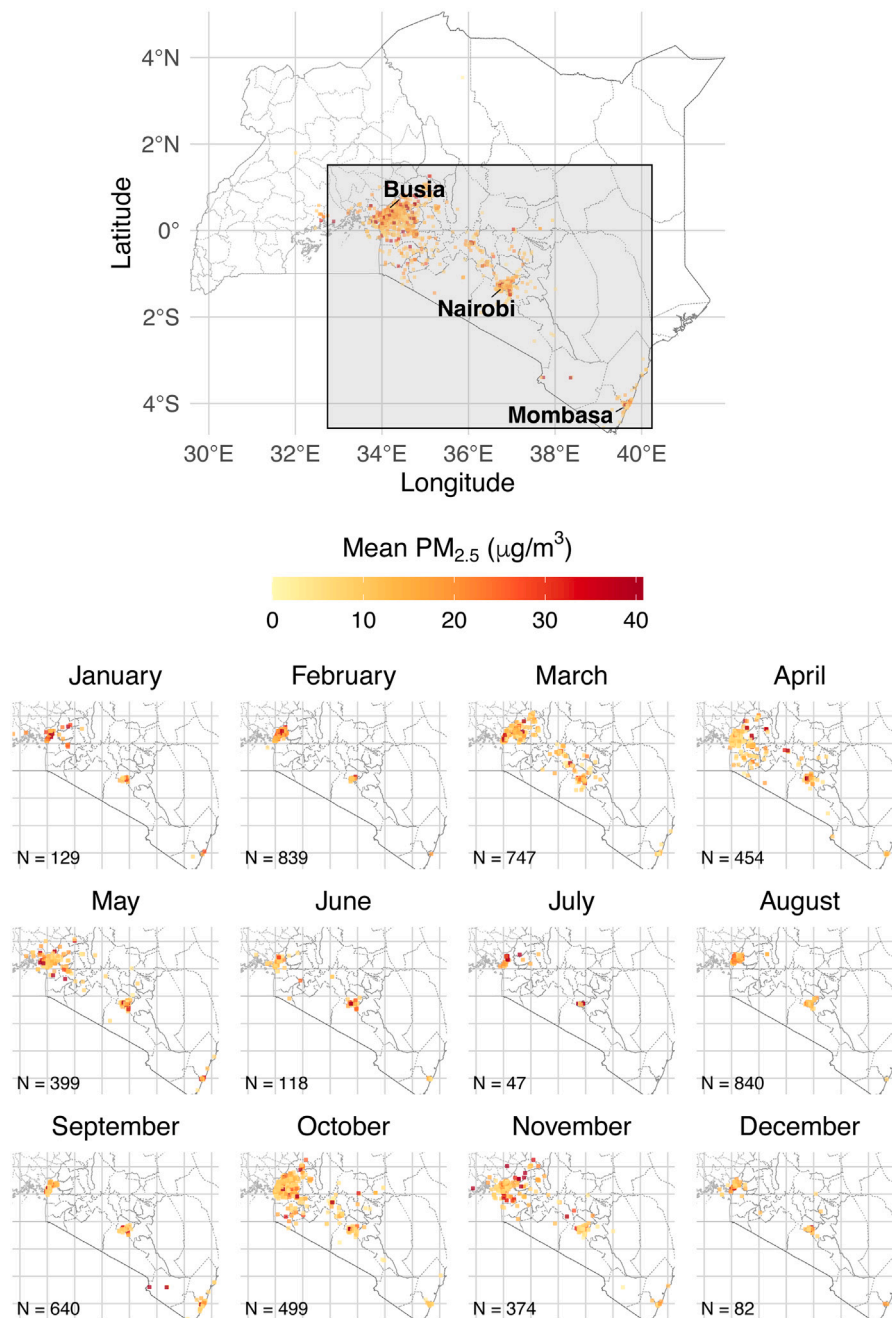


Fig. 1. Spatial and temporal variation of $PM_{2.5}$ exposure.

Notes: This figure displays the spatial distribution of individual mean $PM_{2.5}$ exposures recorded by Atmotube devices in Kenya and Uganda from January through December. The upper panel shows all observations on a combined map of Kenya and Uganda, with the gray rectangle indicating the zoomed extent used in the monthly panels below. Each point represents an individual's mean $PM_{2.5}$ concentration during the cognitive assessment interview window, plotted in the calendar month in which the interview was conducted. Observations with GPS coordinates outside Kenyan and Ugandan national boundaries are excluded. Colors indicate $PM_{2.5}$ concentrations (in $\mu g/m^3$), with darker shades corresponding to higher exposure levels. See Appendix Table S2 for observation counts by region and month.

Taken together, the four exposure measures span a range of spatial and temporal resolutions, from the person-proximate, minute-level Atmotube readings to the spatially aggregated reanalysis grids. Comparing estimates across these measures in the same sample and specification provides evidence on how exposure measurement precision affects the ability to detect the cognitive effects of $PM_{2.5}$.

2.2. Cognitive performance data

Cognitive functioning was measured as part of the KLPS-5 C+ module using an extensive battery of assessments aligned with the Harmonized Cognitive Assessment Protocol (HCAP), adapted for the Kenyan context (Gross et al., 2025). This protocol ensures comparability with major international cognition and aging studies (e.g., HRS-HCAP, LASI-DAD, HAALSI⁴) and supports future harmonization of cognitive research across countries (Gross et al., 2023).

The battery spans five core domains, each targeting a distinct cognitive process. Orientation captures general awareness of time and place. Memory reflects both learning and recall. Executive functioning and attention cover higher-order processes including problem solving, cognitive flexibility, and inhibitory control. Language taps verbal ability and semantic retrieval. Visuospatial skills capture spatial reasoning and visual construction.

Within each domain, multiple validated instruments were administered. Orientation was assessed through questions on time (day, month, year) and place (country, county, location). Memory was evaluated using the CERAD 10-Word List Learning task, the East Boston Memory Test (EBMT), and a Logical Memory test. Executive functioning and attention were measured through Raven's Progressive Matrices, Similarities and Differences, the Token Test, Go-No-Go, Trail Making, and Symbol Cancellation. Language and verbal fluency were captured via animal fluency and object-naming tasks. Visuospatial skills were assessed using CERAD Constructional Praxis, interlocking pentagons, and clock drawing. All assessments were administered in the respondent's preferred language (over 90% were conducted in Swahili, and the remainder were conducted in English) using standardized scripts and intensive enumerator training. Further details on the adaptation and validation of this battery in the Kenyan context are provided in Gross et al. (2025).

Domain-specific scores and an overall cognitive ability score were constructed using confirmatory factor analysis. We directly utilize the measures described in Gross et al. (2025), who report model fit statistics and test measurement invariance by respondent characteristics using the same sample.

This approach improves on much of the existing pollution and cognition literature, which often relies on narrower proxies such as high-stakes exam performance (Ebenstein et al., 2016; Carneiro et al., 2021; Graff Zivin et al., 2020; Heyes et al., 2023), structured brain-training games (Krebs and Luechinger, 2024; La Nauze and Severini, 2025), or behavioral outputs such as activity on digital platforms (Holub and Theis, 2023). These measures can conflate underlying cognitive capacity with task-specific incentives, effort, or context-dependent skills. By contrast, the multi-domain, low-stakes framework used in this study – aligned with HCAP and similar in spirit to Andersen et al. (2025), but applied to an adult population in a real-world field setting – combines multiple validated instruments within each domain, helping to reduce measurement error relative to single-task proxies. Crucially, it also makes it possible to identify which cognitive processes are most sensitive to short-run pollution exposure, rather than relying on aggregate or task-specific outcomes.

3. Methodology

We estimate the relationship between contemporaneous air pollution exposure ($PM_{2.5}$) and cognitive performance using a regression specification with rich sets of fixed effects, including geographic location and detailed temporal fixed effects (time-of-day, day-of-week, and month), to flexibly control for unobserved spatial and temporal confounders.⁵ Following the pre-analysis plan (PAP) (Miguel et al., 2023), we regress cognitive performance scores (focusing on overall cognitive ability but also domain specific scores in some cases) on contemporaneous $PM_{2.5}$ exposure measured during the cognitive assessments (as described above):

$$Y_{igt} = \beta_0 + \beta_1 PM_{igt} + X_{igt}\theta + \alpha_g + \delta_t + \epsilon_{igt} \quad (1)$$

where Y_{igt} denotes the cognitive score for individual i residing in geographic location g assessed at time t ; PM_{igt} represents the average $PM_{2.5}$ exposure for individual i measured contemporaneously during the C+ module; and X_{igt} is a vector of individual-level controls including gender, age, whether the individual has had at least one year of secondary schooling, whether the survey was conducted indoors or outdoors, and environmental controls during the time of the interview (temperature and humidity). Geographic fixed effects, α_g , control for spatial heterogeneity across respondents' locations, and time fixed effects, δ_t , account for variation related to the specific time-of-day, day-of-week, and month when cognitive assessments occurred. The error term, ϵ_{igt} , captures residual unexplained variation. Standard errors are clustered at the level of the geographic fixed effects to account for correlated exposure and cognitive outcomes among respondents within the same area. To minimize the influence of outliers, we trim the top 2.5% of $PM_{2.5}$ concentrations, as extreme values may reflect sensor noise or unrepresentative short-term spikes and can disproportionately affect point estimates.⁶

⁴ HRS-HCAP is the U.S. Health and Retirement Study's Harmonized Cognitive Assessment Protocol; LASI-DAD is the Longitudinal Aging Study in India-Diagnostic Assessment of Dementia; HAALSI is the Health and Aging in Africa: A Longitudinal Study of an INDEPTH Community in South Africa (Langa et al., 2020; Lee and Dey, 2020; Bassil et al., 2022). All three implement the HCAP framework to facilitate cross-country comparability in cognitive aging research.

⁵ This empirical setting does not involve a staggered or phased rollout of the exposure, nor repeated observations of the same units over time. Each cognitive assessment is matched to a contemporaneous measure of ambient $PM_{2.5}$, yielding a cross-sectional sample with highly time-resolved temporal and spatial variation but no unit-level panel structure. Consequently, the econometric identification concerns raised in the recent two-way fixed-effects difference-in-differences literature (e.g., Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021) are not directly relevant here. Instead, the regression specification leverages fine-grained temporal and geographic fixed effects to flexibly absorb unobserved spatial and temporal confounders without invoking the parallel-trends assumptions required in panel difference-in-differences settings.

The coefficient β_1 captures the causal effect of contemporaneous PM_{2.5} on cognitive performance under the assumption that, conditional on the geographic and temporal fixed effects, the individual-level controls, and weather conditions, the remaining variation in PM_{2.5} during the testing window is uncorrelated with unobserved determinants of cognitive performance. Intuitively, the identifying variation comes from short-run deviations in PM_{2.5} from the typical level for a given place and time, rather than from permanent differences across locations or seasons.

Several threats to this assumption merit discussion. First, if individuals with systematically different cognitive ability or socioeconomic characteristics are tested in locations or at times that happen to have higher pollution, β_1 could reflect selection rather than a causal effect. We address this concern through balance tests following [Pei et al. \(2019\)](#), which show that residualized PM_{2.5} (after partialing out geographic and temporal fixed effects and weather) is uncorrelated with education, gender, and age. We further report Oster bounds ([Oster, 2019](#)) showing that unobserved confounders would need to be more than three times as strongly related to both exposure and cognition as the observed controls to eliminate the estimated effect (Section 4.5.3). Second, individuals may time or locate their activities in response to perceived pollution levels. Yet in this setting, interview timing and location were determined by the field survey schedule rather than by respondent choice, limiting the scope for endogenous avoidance. Third, there may be co-occurring environmental stressors that influence cognition. In all analyses, temperature and humidity are controlled for directly, and the hour-of-day fixed effects absorb diurnal patterns in noise, light, and other time-varying environmental conditions. We report estimated temperature coefficients to facilitate comparison with the growing literature on heat and cognition ([Zhang et al., 2024](#); [Kong et al., 2025](#); [Yin et al., 2024](#)).

Additionally, we examine the shape of the dose–response relationship by estimating models with categorical PM_{2.5} exposure levels, using mutually exclusive bins of 0–10 $\mu\text{g}/\text{m}^3$, >10–20 $\mu\text{g}/\text{m}^3$, >20–30 $\mu\text{g}/\text{m}^3$, >30–40 $\mu\text{g}/\text{m}^3$, and > 40 $\mu\text{g}/\text{m}^3$. This binning approach allows us to flexibly capture changes in cognitive performance across increasing pollution intensity. This approach is motivated by emerging evidence suggesting that the neurological effects of PM_{2.5} may exhibit threshold and saturation dynamics, where minimal effects are observed at lower concentrations, but adverse impacts escalate disproportionately at higher exposures ([Power et al., 2015](#); [Weuve et al., 2012](#); [Bedi et al., 2021](#)). These patterns may reflect physiological responses that become more pronounced at higher exposure levels, such as oxidative stress and neuroinflammation, which may accelerate beyond certain exposure thresholds ([Block and Calderón-Garcidueñas, 2009](#); [Costa et al., 2020](#)). Importantly, recent toxicological and epidemiological research suggests that no level of PM_{2.5} exposure is entirely safe and that exposure–response relationships may be supralinear—meaning that marginal reductions at lower levels of pollution can yield disproportionately large health benefits ([Burnett et al., 2022](#); [Weichenthal et al., 2022](#)). From a policy perspective, allowing the exposure–response relationship to vary across pollution levels is crucial for identifying whether the largest cognitive benefits from pollution abatement occur above or below meaningful regulatory benchmark, such as the WHO Interim Targets or other context-relevant thresholds, rather than assuming a constant linear effect that may obscure important changes in slope.

We examine heterogeneity in the pollution–cognition relationship along several individual dimensions – including gender, age (above/below the median age of 37), education (indicator for any secondary schooling), and urban or rural residence – by interacting PM_{2.5} concentrations with each characteristic in the regression model. These interactions allow us to assess whether the cognitive impact of pollution differs across subgroups or by the environmental context.

Robustness checks are conducted to assess whether findings are driven by random fluctuations, omitted variables, or sample selection biases. First, we include a lagged PM_{2.5} measure from the two hours prior to testing, alongside the contemporaneous exposure measure. Following prior work on short-term exposure windows ([Wu et al., 2022](#); [Ke et al., 2022](#)), this allows us to examine whether the contemporaneous measure captures immediate spikes during the assessment or instead reflects broader background pollution levels preceding the interview. Second, we assess potential selection bias by examining correlations between PM_{2.5} exposure and observable socioeconomic characteristics – including gender, age, and education – conditional on the geographic and temporal fixed effects. This step evaluates whether individuals with certain traits systematically experienced different pollution levels during testing, which could generate confounding if those traits are also related to cognition ([Archsmith et al., 2018](#); [Zhang et al., 2018](#); [La Nauze and Severini, 2025](#)). Third, we conduct robustness checks using alternative constructions of geographic fixed effects, including both more granular and broader spatial groupings. For each specification, we also compute correlations between exposure and socioeconomic characteristics to assess whether the identifying assumption holds consistently across spatial controls.

Fourth, we test for heterogeneity by interview setting (indoor versus outdoor) to assess whether the pollution–cognition relationship varies across micro-environments, thereby probing whether real-time, person-proximate exposure measurement captures meaningful local concentration dynamics beyond broader ambient pollution levels. Fifth, we assess sensitivity to the treatment of high-exposure observations by re-estimating the model under alternative approaches to summarizing PM_{2.5}, including the median (rather than mean) exposure during the testing window, winsorization, log specifications, and models using the full untrimmed distribution. Finally, we assess robustness to extreme temperature and humidity conditions by excluding interviews conducted under

⁶ This analysis closely follows the pre-specified regression framework outlined in the PAP ([Miguel et al., 2023](#)). There are three main deviations. First, we exclude a planned instrumental variable analysis using wind direction, as most of the identifying variation in the data arises from seasonal and time-of-day fluctuations rather than from short-run directional shifts in wind, which we also found challenging to operationalize in practice. Second, we extend the pre-specified model to incorporate interaction analyses and additional flexible specifications, as discussed below, to more fully characterize the relationship between pollution and cognition. Third, the PAP specifies geographic fixed effects at the county or city level but in practice this generates many sparsely populated groups, raising concerns about small numbers of observations per bin. To preserve statistical precision and avoid over-fragmentation, the main specification uses a somewhat coarser set of 15 regional fixed effects. Appendix Table S15 demonstrates, however, that the results are broadly robust across several alternative geographic fixed-effects constructions, including more granular specifications aligned with the PAP.

Table 1
Association between contemporaneous PM_{2.5} exposure and cognition.

	(1) General cognitive	(2) General cognitive	(3) General cognitive	(4) General cognitive
Mean PM _{2.5}	−0.0034*** (0.0008)	−0.0026** (0.0011)	−0.0030** (0.0011)	
PM _{2.5} 10–20 µg/m ³				−0.0514* (0.0261)
PM _{2.5} 20–30 µg/m ³				−0.0491 (0.0376)
PM _{2.5} 30–40 µg/m ³				−0.0857* (0.0426)
PM _{2.5} above 40 µg/m ³				−0.1389* (0.0683)
Interviewed Outdoor	0.2028*** (0.0537)	0.1711*** (0.0497)	0.0871* (0.0455)	0.0878* (0.0464)
Female			−0.1529*** (0.0478)	−0.1523*** (0.0482)
Age			−0.0333*** (0.0036)	−0.0334*** (0.0036)
Any Secondary Schooling			0.7618*** (0.0227)	0.7620*** (0.0227)
Geographic and Time FE		YES	YES	YES
Number Observations	5264	5264	5131	5131
Adjusted R-squared	0.010	0.038	0.210	0.210

Notes: This table presents the estimated association between contemporaneous PM_{2.5} exposure and a general cognitive index. The general cognitive index is standardized to have mean zero and unit standard deviation and is constructed via confirmatory factor analysis over orientation, memory, executive function, language, and visuospatial subdomains (see Gross et al., 2025). PM_{2.5} is measured as the mean Atmotube reading (µg/m³) during the cognitive assessment interview window. The top 2.5% of PM_{2.5} values are trimmed to reduce the influence of extreme outliers. All regressions control for mean temperature, mean humidity, and the interview setting (indoor vs. outdoor) to account for potential environmental confounders. Column (1) includes no fixed effects. Columns (2)–(4) include hour-of-day, day-of-week, month, and geographic fixed effects. Column (3) additionally controls for gender, age, and an indicator for any secondary schooling (9 or more years). Columns (1)–(3) model PM_{2.5} as a continuous linear term. Column (4) replaces the linear term with categorical bins (10–20 µg/m³, 20–30 µg/m³, 30–40 µg/m³, and above 40 µg/m³), with PM_{2.5} ≤ 10 µg/m³ as the omitted reference category, to explore potential dose-response relationships. Standard errors are clustered at the geographic level and reported in parentheses. Statistical significance is denoted as follows:

*** p < 0.01

** p < 0.05

* p < 0.1.

high-humidity and extreme-temperature environments, where sensor-based PM_{2.5} measurement may be more prone to error. These exercises allow us to evaluate whether the estimated effects are driven by a small number of extreme values or instead reflect broader exposure variation, while avoiding reliance on aggressive truncating of potentially genuine high-exposure levels.

As noted above, a key feature of the empirical design is that we estimate this specification using multiple alternative measures of PM_{2.5} exposure constructed from different data sources – namely, the reanalysis products CAMS EAC4 and MERRA-2, and fixed-site monitoring data from PurpleAir – to assess the sensitivity of estimated pollution effects to the choice of exposure measure within the same sample and empirical specification.

4. Results

4.1. Linear impacts of contemporaneous air pollution on cognitive test scores

Table 1 presents the primary regression estimates linking contemporaneous PM_{2.5} exposure to general cognitive performance, measured as a standardized factor score (with a mean of zero and SD of one). Higher PM_{2.5} concentrations at the time of assessment are associated with significantly worse cognitive performance in the specification without time or location fixed effects (Table 1, col. 1), and the relationship remains negative when geographic and temporal fixed effects are added (col. 2). In the preferred specification, which adds individual characteristics and survey controls to the geographic and temporal fixed effects (col. 3), a 10 µg/m³ increase in PM_{2.5} is associated with a 0.03 SD decline in cognitive ability ($p < 0.05$).

To make sense of the magnitude, this effect is comparable to the effect of aging by 0.90 years, as inferred from the age coefficient in the same specification (−0.0333 per year), suggesting that even short-term pollution exposure can produce deficits similar to the gradual cognitive declines associated with aging. Extrapolating this effect to larger increases in PM_{2.5} concentration – say, 30 or 40 µg/m³ – the implied 0.09 to 0.12 SD decline in cognitive ability suggests that transient pollution spikes could meaningfully impair productivity, decision-making quality, and learning outcomes. Given that survey participants were prime-aged adults, with many

currently employed in cognitively demanding tasks (see Byambaa et al., 2025), these impairments could plausibly affect real labor market and other economic outcomes.

To contextualize the findings, we compare them to prior estimates across diverse populations, exposure settings, and task environments. A growing literature documents small to moderate effects of short-term particulate exposure on cognitive and task performance in high-stakes settings. In Israel, a one SD increase in $PM_{2.5}$ (Air Quality Index) reduces exam scores by roughly 0.039 SD (Ebenstein et al., 2016). In the United Kingdom, a $10 \mu\text{g}/\text{m}^3$ increase in indoor PM_{10} is associated with a 0.003 SD reduction in university exam scores, and exposures exceeding $75 \mu\text{g}/\text{m}^3$ correspond to declines of about 0.21 SD (Roth, 2021). In applied performance settings, comparable magnitudes arise: a $10 \mu\text{g}/\text{m}^3$ rise in 12-hour $PM_{2.5}$ increases Major League Baseball umpire error rates by 2.6% (Archsmith et al., 2018) and raises the likelihood of chess errors, particularly under time pressure (Künn et al., 2019). Evidence from China's national college entrance exams shows that a one SD increase in upwind relative to downwind fire exposure lowers test scores by 0.014 SD, with larger effects among higher-ability students (Graff Zivin et al., 2020). Laboratory evidence from Brazil likewise finds significant declines in fluid and grammatical reasoning associated with elevated $PM_{2.5}$ (Bedi et al., 2021). Longer-term studies using China's Air Pollution Index also reveal adverse cognitive effects, though their estimates are not directly comparable to short-run elasticities and are best interpreted in their own exposure units (Zhang et al., 2018).

The preferred estimate of a 0.03 SD decline in general cognitive performance per $10 \mu\text{g}/\text{m}^3$ increase in contemporaneous $PM_{2.5}$ exposure is thus broadly consistent with the magnitudes documented in earlier studies. However, several aspects of the empirical approach here differ from prior studies. First, we are able to utilize person-specific $PM_{2.5}$ exposure measurements precisely time-aligned with the cognitive assessments, minimizing measurement error that could attenuate effect estimates in studies using ambient monitors or daily averages. Second, we measure $PM_{2.5}$ specifically, avoiding the aggregation bias inherent in some composite pollution indices. Third, by focusing on acute exposure windows during testing rather than multi-day or long-term averages, we capture transient disruptions in cognitive functioning that are likely to be most relevant for immediate productivity, decision-making, and economic behavior.

To further characterize the cognitive impacts of short-term pollution exposure, we examine effects across the five specific cognitive domains underlying the overall cognitive score, namely, orientation, memory, executive functioning, language, and visuospatial skills (Appendix Tables S3–S7). These analyses reveal a somewhat mixed pattern. We detect robust negative associations between $PM_{2.5}$ exposure and performance in two of the five domains, executive functioning and visuospatial skills, and marginally statistically significant effects in a third domain, memory. For example, in the preferred specification (col. 3 in Appendix Tables S3–S7), a $10 \mu\text{g}/\text{m}^3$ increase is associated with a 0.026 SD decline in executive function ($p < 0.05$), a 0.024 SD decline in visuospatial skills ($p < 0.01$), and a 0.027 SD decline in memory performance ($p < 0.10$). In contrast, there is no significant association with orientation or language. The null effects on orientation likely reflect ceiling effects: many participants achieved near-perfect scores on tasks assessing awareness of time and place, which is expected for cognitively healthy mid-life adults and consistent with prior findings in this sample (Gross et al., 2025). The concentration of effects in executive function, visuospatial, and memory domains may reflect the attentional demands of these tasks, which require sustained focus and working memory resources that are plausibly more vulnerable to acute neurological disruption.

The emerging pattern suggests that short-term air pollution exposure impairs specific cognitive domains, particularly those involving working attentional control and visuospatial processing. This aligns with neurobiological evidence on how $PM_{2.5}$ affects the brain. Experimental studies show that fine particulates activate microglia and disrupt the blood–brain barrier, triggering rapid inflammatory responses (Ke et al., 2022). Related neuroimaging work links $PM_{2.5}$ -induced inflammation to reduced gray- and white-matter integrity in prefrontal and parietal regions responsible for executive and visuospatial functions (Marsland et al., 2015). These pathways provide a plausible mechanism for the domain-specific cognitive effects observed in the data.

4.2. Dose-response pattern of contemporaneous air pollution on cognitive test scores

To examine the shape of the relationship between contemporaneous $PM_{2.5}$ exposure and cognitive performance, we first plot the raw association between general cognitive scores and measured $PM_{2.5}$ concentrations. Fig. 2 presents a binned scatterplot of unadjusted cognitive performance against measured $PM_{2.5}$ concentrations, where the number of bins is selected using a data-driven mean-squared-error optimal procedure following Cattaneo et al. (2024). The fitted non-parametric LOESS curve reveals a negative gradient: cognitive scores remain relatively stable at lower exposure levels but decline as concentrations increase, with a visibly steeper slope beyond $10 \mu\text{g}/\text{m}^3$. We next isolate within-location, within-time variation by residualizing both cognition and $PM_{2.5}$ with respect to hour-of-day, day-of-week, month, and geographic fixed effects. Fig. 3 plots these residualized variables, where the x-axis captures deviations in pollution from expected local-temporal levels rather than absolute concentrations. The downward-sloping portion of the curve indicates that when pollution is higher than usual for a given place and time, cognitive performance is correspondingly lower. This pattern suggests that the negative pollution–cognition relationship is not driven solely by differences across sites or seasons but persists within locations over time. Both figures trim the top 2.5% of the $PM_{2.5}$ distribution to reduce the influence of outliers, and Appendix Figures S4 and S5 confirm similar results using the full untrimmed sample.

Regression results using categorical exposure bins suggest a broadly monotonic decline in cognitive performance as $PM_{2.5}$ exposure increases (Table 1, col. 4). Relative to the reference category ($<10 \mu\text{g}/\text{m}^3$), cognitive scores decline by 0.051 SD at $10\text{--}20 \mu\text{g}/\text{m}^3$ ($p < 0.10$), 0.049 at $20\text{--}30 \mu\text{g}/\text{m}^3$ (not significant), 0.086 SD at $30\text{--}40 \mu\text{g}/\text{m}^3$ ($p < 0.10$), and 0.14 SD above $40 \mu\text{g}/\text{m}^3$ ($p < 0.10$). The point estimates become more negative at higher exposure levels, which is suggestive of steeper effects in more polluted ranges. A similar pattern appears across several cognitive subdomains (col. 4 of Appendix Tables S3–S7): $PM_{2.5}$ levels at $10\text{--}20 \mu\text{g}/\text{m}^3$ are associated with declines of 0.052 SD in memory ($p < 0.10$), 0.039 SD in visuospatial skills ($p < 0.10$); $PM_{2.5}$ levels

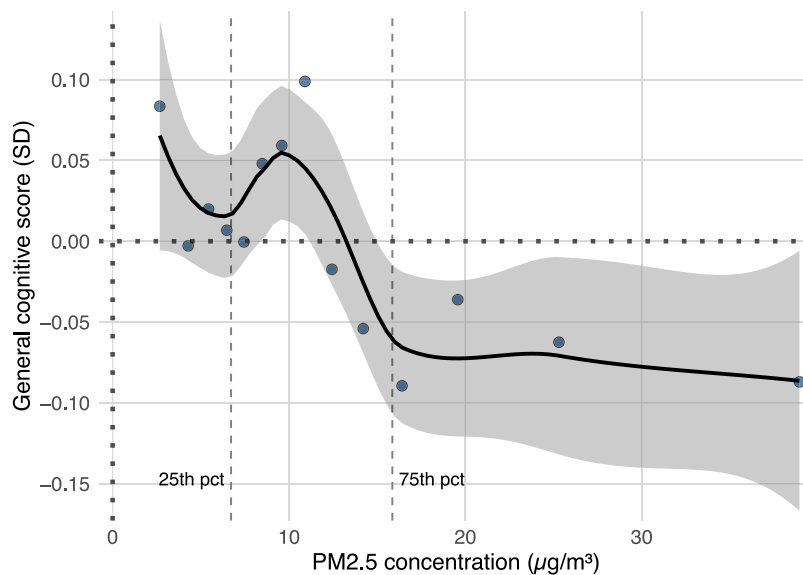


Fig. 2. Cognition vs. PM_{2.5} exposure (trimmed top 2.5%).

Notes: This figure presents a binned scatterplot of raw general cognitive performance (y-axis, in SD units) against raw PM_{2.5} concentrations (x-axis, in µg/m³). General cognitive performance is a standardized index (mean zero, unit standard deviation) constructed via confirmatory factor analysis over orientation, memory, executive function, language, and visuospatial subdomains (see Gross et al., 2025). PM_{2.5} is measured as the mean Atmotube reading during the cognitive assessment interview window. Observations with PM_{2.5} in the top 2.5% of the full-sample distribution are excluded to remove extreme outliers. The remaining observations are grouped into quantile-spaced bins, with the number of bins (19) selected using a data-driven procedure that minimizes the integrated mean squared error of the binscatter estimator, following Cattaneo et al. (2024). Each point plots the within-bin mean of PM_{2.5} and the within-bin mean of general cognitive performance. Dashed vertical lines mark the 25th and 75th percentiles of the binned PM_{2.5} distribution, and a LOESS curve (with a 95% confidence band) captures the flexible association between pollution and cognition.

at 30–40 µg/m³ are associated with declines of 0.092 SD in visuospatial skills ($p < 0.01$); PM_{2.5} levels above 40 µg/m³ are associated with declines of 0.125 SD in memory ($p < 0.10$), 0.158 SD in executive functioning ($p < 0.05$), and 0.121 SD in visuospatial skills ($p < 0.05$). Estimates for orientation and language remain small and not statistically significant across exposure bins, consistent with the earlier findings. The larger confidence intervals at the highest PM_{2.5} exposure levels appear to stem mainly from the smaller number of observations in that range.

These findings are consistent with prior research suggesting that the cognitive effects of air pollution may become more pronounced at higher exposure levels. For instance, Weuve et al. (2012) find faster cognitive decline among older adults at higher levels of chronic PM exposure, while Zhang et al. (2018) report stronger memory and executive function impairments above 35 µg/m³. The results here extend this literature by identifying similar patterns in short-term, contemporaneous exposure measured at the individual level.

Importantly, the lack of statistical significance in some exposure bins should not be interpreted as evidence of no effect. Rather, these patterns highlight the need for flexible functional forms and sufficient coverage across the pollution distribution in future work. If replicated, these results suggest that the cognitive risks of air pollution may be underestimated when analyses rely solely on average exposure metrics. This has direct implications for the design of air quality regulations, which often focus on compliance with fixed thresholds and may fail to account for the outsized cognitive costs concentrated in high-exposure settings.

4.3. Comparison to alternative exposure measurements

To isolate the role of exposure measurement, we re-estimate the baseline specification using alternative PM_{2.5} data sources that differ in spatial and temporal resolution. Specifically, we compare (i) Atmotube-based personal exposure, (ii) satellite-based reanalysis products (CAMs EAC4 and MERRA-2), and (iii) ground-based fixed-site monitoring from PurpleAir.

For the reanalysis products, we assign exposure by linking each respondent's interview location and date to the corresponding grid cell and day in the CAMs EAC4 and MERRA-2 datasets, as described above. These products provide near-global coverage but at relatively coarse spatial resolution (on the order of tens of kilometers), and represent modeled ambient concentrations that smooth over local variation. For PurpleAir, we match respondents to the nearest monitor within a 50 km radius and assign exposure based on contemporaneous readings from that monitor. This approach may increase spatial resolution relative to reanalysis data but still relies on fixed-site measurements that may not fully capture individual-level exposure conditions.

Fig. 4 and Appendix Figure S6 show that the alternative measures differ systematically from Atmotube-based personal exposure. In Fig. 4, PurpleAir exhibits the strongest correspondence with Atmotube PM_{2.5} (corr = 0.396, Panel C), while CAMs EAC4 is only

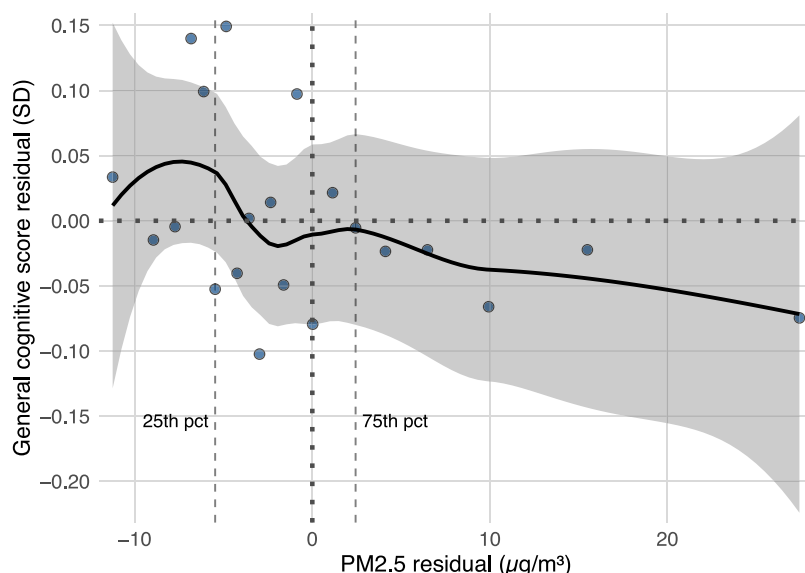


Fig. 3. Residualized cognition vs. residualized PM_{2.5} exposure (trimmed top 2.5%).

Notes: This figure presents a binned scatterplot of residualized general cognitive performance (y-axis) against residualized PM_{2.5} concentrations (x-axis). General cognitive performance is a standardized index (mean zero, unit standard deviation) constructed via confirmatory factor analysis over orientation, memory, executive function, language, and visuospatial subdomains (see Gross et al., 2025). PM_{2.5} is measured as the mean Atmotube reading during the cognitive assessment interview window. Observations with raw PM_{2.5} values in the top 2.5% of the full-sample distribution are first dropped to remove extreme outliers. Both PM_{2.5} and cognitive scores are then residualized by regressing each on hour-of-day, day-of-week, month, and geographic fixed effects (defined at the region level; see Appendix Table S2 for region definitions); the x-axis therefore shows each bin's average deviation from its predicted mean. The remaining observations are grouped into quantile-spaced bins, with the number of bins (16) selected using a data-driven procedure that minimizes the integrated mean squared error of the binscatter estimator, following Cattaneo et al. (2024). Each point plots the within-bin mean PM_{2.5} residual (µg/m³) and the within-bin mean general cognitive residual (SD units). Dashed vertical lines mark the 25th and 75th percentiles of the PM_{2.5} residual distribution, and a LOESS curve (with a 95% confidence band) captures the flexible association.

modestly correlated (corr = 0.284, Panel A) and MERRA-2 shows the weakest alignment (corr = 0.113, Panel B). Appendix Figure S6 reveals distinct distributional patterns across sources. CAMS EAC4 is shifted moderately to the right relative to Atmotube (mean 17.6 vs. 13.1 µg/m³, Panel A) with a somewhat compressed distribution, suggesting that grid-cell averaging smooths local variation. MERRA-2 diverges more substantially, with a much higher mean (29.5 vs. 12.9 µg/m³, Panel B) and a considerably wider distribution (SD = 21.0 vs. 9.2), indicating systematic differences in the pollution field it captures rather than simple smoothing. PurpleAir is also shifted right relative to Atmotube (mean 24.4 vs. 13.2 µg/m³, Panel C) and has a heavier right tail, though the overall shape of the distribution bears more resemblance to the Atmotube data than either reanalysis product does.

Table 2 reports the regression results. The Atmotube-based estimate is stable across the full sample and matched subsamples (cols. 1, 2, and 5), ranging from −0.0030 to −0.0033 per 1 µg/m³. The CAMS EAC4 exposure measure attenuates the estimate to −0.0003 (col. 3), while MERRA-2 yields a positive and marginally significant coefficient of 0.0010 (col. 4), suggesting that its systematic divergence from ground-level conditions introduces non-classical measurement error rather than simple attenuation toward zero. PurpleAir produces a negative estimate of −0.0024 (col. 6), somewhat smaller than the Atmotube estimate but in the same direction and statistically significant, consistent with its closer correspondence to ground-level exposure conditions. Appendix Table S8 further examines sensitivity to the PurpleAir monitor-matching radius by re-estimating the specification using distance thresholds of 50, 100, and 200 km. The estimated association remains negative across all thresholds, but its magnitude declines as the radius increases: the coefficient falls from −0.0024 at 50 km to −0.0019 at 100 km and to −0.0018 at 200 km (unlike the corresponding Atmotube matched samples, across which estimates are largely stable). The pattern of attenuation toward zero as the PurpleAir radius expands is consistent with greater spatial misalignment between respondents and the assigned fixed-site monitors.

Because the regression specification and estimation sample are held constant (across Atmotube results versus those from alternative measures), these differences arise from how exposure is measured and assigned. The attenuation observed for CAMS EAC4 and MERRA-2 is consistent with spatial and temporal aggregation in reanalysis products, which smooth high-frequency, local variation in pollution that is central to identifying short-run cognitive effects. In contrast, both Atmotube and PurpleAir capture ground-level concentrations with finer temporal resolution, preserving more of the variation relevant for within-day exposure.

At the same time, these comparisons highlight an important distinction between personal and ambient monitoring. While PurpleAir approximates local ambient conditions, Atmotube measures exposure in the respondent's immediate microenvironment during the cognitive assessment. This difference is particularly relevant in settings with heterogeneous exposure sources (e.g., indoor

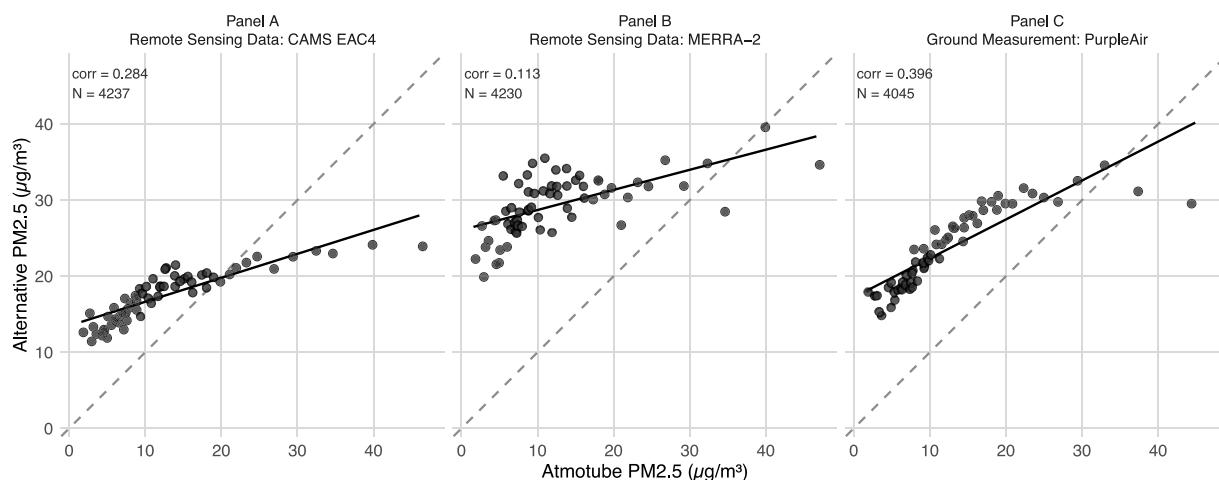


Fig. 4. Comparison of Atmotube $PM_{2.5}$ with alternative $PM_{2.5}$ measures.

Notes: This figure compares individual-level Atmotube $PM_{2.5}$ measurements with three alternative $PM_{2.5}$ measures: CAMS EAC4 reanalysis, MERRA-2 reanalysis, and PurpleAir ground monitors. Atmotube $PM_{2.5}$ is the mean concentration recorded by the Atmotube monitor during the cognitive assessment interview window. CAMS EAC4 and MERRA-2 values are extracted at each respondent's GPS coordinates and matched to the nearest temporal grid point (3-hourly for CAMS; hourly for MERRA-2, then collapsed to a time-overlap-weighted mean over the interview window). PurpleAir values are drawn from fixed ground monitors located within a 50 km radius of the respondent's interview location, averaged over the interview window. Each panel uses the subset of observations with non-missing values for both the Atmotube and the corresponding alternative measure. To reduce the influence of extreme values, observations above the 97.5th percentile of either measure within each panel are excluded separately. Within each panel, observations are then sorted by Atmotube $PM_{2.5}$ and divided into approximately equal-sized bins, where the number of bins is set to $\lfloor \sqrt{N} \rfloor$, bounded between 15 and 80. Each point plots the within-bin mean Atmotube $PM_{2.5}$ and the within-bin mean alternative $PM_{2.5}$; bins with fewer than 20 observations are excluded. The solid line shows the ordinary least squares fit across binned observations, and the dashed 45-degree line indicates equality between the Atmotube and alternative measures. Each panel reports the Pearson correlation coefficient and the number of underlying individual-level observations used in that comparison.

cooking, traffic proximity), where individual-level exposure may diverge from nearby ambient monitors. The relative similarity of the PurpleAir and Atmotube estimates suggests that fixed-site monitors can recover comparable effects when sufficiently proximate, while the larger attenuation observed in reanalysis data underscores the importance of high-resolution measurement for capturing acute exposure–response relationships. The attenuation pattern across data sources is consistent with the measurement error concerns discussed in Section 3 (Dominici et al., 2000; Szpiro and Paciorek, 2013; Gryparis et al., 2009; Steinle et al., 2015; Carson and Yu, 2026).

Table 3 shows that the Atmotube estimates display a clear dose–response gradient, with progressively larger cognitive declines at higher exposure bins relative to concentrations below $10 \mu\text{g}/\text{m}^3$. No comparable pattern emerges using CAMS EAC4, and MERRA-2 coefficients are in fact positive and statistically significant across several bins, suggesting systematic and non-classical mismeasurement at the individual level. PurpleAir estimates, by contrast, are consistently negative and broadly align with the Atmotube results, though their magnitudes differ. These differences reflect a gradient in measurement fidelity across data sources. Atmotube provides individual-level, time-resolved exposure and is best suited to capture short-run variation relevant for cognitive performance. PurpleAir, while offering high spatial resolution, measures fixed-location ambient concentrations and cannot account for individual mobility or indoor exposure, leading to systematic scaling differences and possibly greater sensitivity to local pollution peaks. In contrast, CAMS EAC4 and MERRA-2 rely on coarse spatial averaging, which compresses variation – especially in the upper tail – and introduces non-classical measurement error that can attenuate or even reverse estimated effects.

These comparisons also clarify that different measures identify related but distinct parameters. Reanalysis products capture broad ambient pollution conditions and may be well suited for studying medium- to long-run exposure, while missing the high-frequency variation relevant for acute cognitive effects. Fixed-site monitors such as PurpleAir approximate local ambient exposure, though they may not fully reflect individual-level conditions in environments with substantial local heterogeneity. In contrast, Atmotube-based measures capture real-time exposure in the respondent's immediate microenvironment during the cognitive task, aligning most closely with the short-run exposure channel of interest in this study.

Taken together, the results highlight that the measurement choice is a central methodological issue in studies of short-run pollution effects.

4.4. Heterogeneous impacts of contemporaneous air pollution on cognitive test scores

To assess whether the cognitive effects of $PM_{2.5}$ exposure vary across population subgroups, we examine heterogeneity by gender, age (above/below the median age of 37), education (indicator of any secondary schooling), and urban or rural residence. Fig. 5 plots

Table 2Comparison with other PM_{2.5} measurement sources: Linear specifications.

	Reanalysis (CAMS/MERRA-2)				PurpleAir	
	(1) Atmotube	(2) Atmotube subsample	(3) CAMS EAC4	(4) MERRA-2	(5) Atmotube 50 km	(6) PurpleAir 50 km
Mean PM _{2.5}	−0.0030** (0.0011)	−0.0033** (0.0012)	−0.0003 (0.0009)	0.0010* (0.0005)	−0.0030* (0.0014)	−0.0024*** (0.0007)
Temperature (°C)	0.0002 (0.0014)	0.0004 (0.0016)	−0.0005 (0.0013)	−0.0006 (0.0013)	0.0006 (0.0018)	0.0000 (0.0014)
Interviewed Outdoor	0.0871* (0.0455)	0.1273 (0.0789)	0.1286 (0.0771)	0.1273 (0.0776)	0.1599* (0.0815)	0.1604* (0.0781)
Female	−0.1529*** (0.0478)	−0.1504*** (0.0492)	−0.1506*** (0.0499)	−0.1504*** (0.0497)	−0.1293** (0.0420)	−0.1298** (0.0424)
Age	−0.0333*** (0.0036)	−0.0327*** (0.0047)	−0.0327*** (0.0046)	−0.0327*** (0.0046)	−0.0292*** (0.0028)	−0.0291*** (0.0028)
Any Secondary Schooling	0.7618*** (0.0227)	0.7368*** (0.0222)	0.7370*** (0.0222)	0.7369*** (0.0219)	0.7352*** (0.0184)	0.7346*** (0.0193)
Geographic and Time FE	YES	YES	YES	YES	YES	YES
Number Observations	5131	4188	4188	4188	3359	3359
Adjusted R-squared	0.210	0.200	0.199	0.199	0.181	0.181

Notes: This table compares the estimated association between contemporaneous PM_{2.5} exposure and general cognitive performance across alternative pollution measurement sources. The dependent variable is a standardized general cognitive index (mean zero, unit standard deviation) constructed via confirmatory factor analysis over orientation, memory, executive function, language, and visuospatial subdomains (see Gross et al., 2025). PM_{2.5} exposure is measured using personal monitors (Atmotube), satellite-based reanalysis products (CAMS EAC4 and MERRA-2), and ground-based monitors (PurpleAir). Atmotube PM_{2.5} is the mean concentration recorded during the interview window. CAMS EAC4 values are extracted at each respondent's GPS coordinates at the nearest 3-hourly time step. MERRA-2 values are extracted hourly and collapsed to a time-overlap-weighted mean over the interview window. PurpleAir values are averaged from fixed ground monitors within 50 km of the interview location over the interview window. Column (1) reproduces the baseline specification from Table 1, Column (3), for comparison. Columns (3), (4), and (6) use the full available sample for each alternative PM_{2.5} measure among observations within the Atmotube-trimmed sample. Columns (2) and (5) are estimated on subsamples defined by the overlap between Atmotube measurements and the corresponding alternative data source, allowing for direct comparisons across measurement methods within the same set of individuals. The top 2.5% of the Atmotube PM_{2.5} distribution is trimmed to reduce the influence of extreme outliers. All regressions control for mean temperature, mean humidity, interview setting (indoor vs. outdoor), gender, age, and an indicator for any secondary schooling, as well as fixed effects for hour-of-day, day-of-week, month, and geographic location. Standard errors are clustered at the geographic level and reported in parentheses. Statistical significance is denoted as follows:

*** p < 0.01

** p < 0.05

* p < 0.1.

residualized general cognitive performance against residualized PM_{2.5} exposure, stratified by subgroup. Observations are grouped into quantile-spaced bins again following Cattaneo et al. (2024). The top 2.5% of PM_{2.5} observations are trimmed in this figure to limit sensitivity to extreme values (and Appendix Figure S7 presents a similar analysis with the full untrimmed data). Across subgroups, cognition tends to be lower when PM_{2.5} is unexpectedly elevated relative to the local mean, suggesting that transient increases in pollution are associated with short-term declines in performance.

The most striking pattern of heterogeneity is by education. Panel C of Fig. 5 shows a clear separation between respondents with and without secondary schooling: those with secondary education exhibit consistently higher residualized cognition across the exposure distribution and a steeper negative slope at higher PM_{2.5} levels. The higher average residual cognitive scores for this group are consistent with prior evidence from Gross et al. (2025), who show that general cognitive performance is strongly correlated with education in midlife. This pattern is confirmed formally in Table 4: for every 10 µg/m³ increase in pollution, individuals with at least some secondary schooling exhibit a decline in general cognitive scores approximately 0.059–0.062 SD larger than their less-educated peers (cols. 3 and 6), while the effect for those with less than secondary schooling is close to zero and not statistically significant. In other words, the cognitive impact of PM_{2.5} exposure in this Kenyan sample appears concentrated almost entirely among the more educated.

What could explain this pattern? One plausible mechanism is task engagement. More educated respondents may process information more deeply and exert greater cognitive effort during testing (recall that they score considerably higher on these assessments on average), increasing their susceptibility to pollution-induced disruption. The mental effort required for tasks involving executive control, reasoning, or working memory may expose these individuals to greater marginal impairment from transient exposure. This is consistent with evidence showing that air pollution has larger cognitive impacts under high cognitive load and among higher-ability individuals in high-stakes settings. Krebs and Luechinger (2024) find that acute NO_x exposure reduced performance among trained players but not novices in an online arithmetic training game, and Ebenstein et al. (2016) show that temporary increases in PM_{2.5} on exam days in Israel reduced student performance, with downstream effects on educational attainment and earnings.

A second, more speculative mechanism is differential adaptation. More educated individuals may have been less chronically exposed to high pollution levels – due to differences in residential location, occupation, or lifestyle – and may therefore lack the physiological or behavioral adaptations that attenuate acute exposure effects. A substantial literature links socioeconomic status

Table 3Comparison with other PM_{2.5} measurement sources: Binned exposure specifications.

	Full sample	Reanalysis comparison			PurpleAir comparison	
	(1) Atmotube	(2) Atmotube subsample	(3) CAMS EAC4	(4) MERRA-2	(5) Atmotube 50 km	(6) PurpleAir 50 km
PM2.5 10-20 µg/m ³	−0.0514* (0.0261)	−0.0658** (0.0256)	−0.0389 (0.0255)	0.0834 (0.0589)	−0.0562* (0.0256)	−0.1051** (0.0409)
PM2.5 20-30 µg/m ³	−0.0491 (0.0376)	−0.0480 (0.0374)	−0.0805* (0.0456)	0.0987** (0.0383)	−0.0275 (0.0376)	−0.1063* (0.0551)
PM2.5 30-40 µg/m ³	−0.0857* (0.0426)	−0.1385** (0.0641)	−0.0312 (0.0279)	0.2073*** (0.0418)	−0.1555 (0.0920)	−0.1766*** (0.0532)
PM2.5 above 40 µg/m ³	−0.1389* (0.0683)	−0.1436** (0.0575)	−0.0671 (0.0507)	0.1027** (0.0400)	−0.1339** (0.0452)	−0.1424** (0.0504)
Temperature (°C)	0.0002 (0.0015)	0.0005 (0.0018)	−0.0004 (0.0013)	−0.0005 (0.0013)	0.0008 (0.0020)	0.0002 (0.0014)
Interviewed Outdoor	0.0878* (0.0464)	0.1283 (0.0803)	0.1271 (0.0769)	0.1270 (0.0777)	0.1608* (0.0829)	0.1632* (0.0772)
Female	−0.1523*** (0.0482)	−0.1500*** (0.0498)	−0.1499*** (0.0503)	−0.1513*** (0.0490)	−0.1282** (0.0424)	−0.1293** (0.0412)
Age	−0.0334*** (0.0036)	−0.0327*** (0.0048)	−0.0326*** (0.0047)	−0.0323*** (0.0047)	−0.0291*** (0.0028)	−0.0293*** (0.0028)
Any Secondary Schooling	0.7620*** (0.0227)	0.7374*** (0.0220)	0.7380*** (0.0222)	0.7392*** (0.0224)	0.7365*** (0.0180)	0.7336*** (0.0186)
Geographic and Time FE	YES	YES	YES	YES	YES	YES
Number Observations	5131	4188	4188	4188	3359	3359
Adjusted R-squared	0.210	0.200	0.199	0.200	0.181	0.181

Notes: This table presents estimates of the association between contemporaneous PM_{2.5} exposure and general cognitive performance using categorical (binned) measures of PM_{2.5} across alternative data sources. The dependent variable is a standardized general cognitive index (mean zero, unit standard deviation) constructed via confirmatory factor analysis over orientation, memory, executive function, language, and visuospatial subdomains (see Gross et al., 2025). PM_{2.5} exposure is measured using personal monitors (Atmotube), satellite-based reanalysis products (CAMS EAC4 and MERRA-2), and ground-based monitors (PurpleAir). PM_{2.5} is grouped into bins (10–20, 20–30, 30–40, and above 40 µg/m³), with PM_{2.5} ≤ 10 µg/m³ as the omitted reference category. Column (1) reproduces the baseline specification from Table 1, Column (4), for comparison. Columns (3), (4), and (6) use the full available sample for each alternative PM_{2.5} measure among observations within the Atmotube-trimmed sample. Columns (2) and (5) are estimated on subsamples defined by the overlap between Atmotube measurements and the corresponding alternative data source, allowing for direct comparisons across measurement methods within the same set of individuals. The top 2.5% of the Atmotube PM_{2.5} distribution is trimmed to reduce the influence of extreme outliers. All regressions control for mean temperature, mean humidity, interview setting (indoor vs. outdoor), gender, age, and an indicator for any secondary schooling, and include hour-of-day, day-of-week, month, and geographic fixed effects. Standard errors are clustered at the geographic level and reported in parentheses. This specification allows for flexible characterization of exposure–response relationships across measurement sources. Statistical significance is denoted as follows:

*** p < 0.01

** p < 0.05

* p < 0.1.

to both long-run exposure patterns and the health impact of acute pollution episodes: more educated individuals tend to live in cleaner neighborhoods, occupy lower-exposure indoor jobs, and have behavioral patterns that reduce effective pollutant contact (Quispe-Haro et al., 2024; Mustansar et al., 2025; Ferguson et al., 2023; de Souza et al., 2023; Domínguez et al., 2025; Gao et al., 2025; Dasgupta et al., 2006). Combined with evidence from ecological and toxicological studies suggesting that persistent exposure can induce physiological or behavioral adaptation (Hamilton et al., 2017; Loria et al., 2019; Jacquin et al., 2020), this points to a mechanism in which relatively shielded individuals are more vulnerable to short-run pollution spikes, while those with greater cumulative exposure develop partial adaptive responses that attenuate the marginal cognitive impact.

These two mechanisms – acute susceptibility among high-effort individuals, and lower adaptation among the less chronically exposed – are not mutually exclusive and may reinforce one another. They also help reconcile an apparent contradiction in the literature. Zhang et al. (2018) report greater vulnerability among less-educated elderly adults in China, which seems to run counter to our findings. But the contrast may reflect a meaningful distinction between chronic and acute exposure regimes: in settings where exposure is cumulative and sustained, less-educated individuals may face compounding disadvantages from both higher lifetime burdens and fewer mitigation resources. When exposure is acute and measured in real time during cognitively demanding tasks – as in the present study – higher-functioning individuals may simply have more performance to lose.

In contrast, the other dimensions we examine yield little evidence of heterogeneity. Panels A, B, and D of Fig. 5 show broadly overlapping exposure–response profiles across gender, age, and rural–urban residence, and Table 4 finds no statistically significant interaction effects along these dimensions. The absence of a gender difference is consistent with the broader literature: many cohorts and meta-analyses do not find consistent sex differences in the cognitive impacts of air pollution (Thompson et al., 2023; Delgado-Saborit et al., 2021; Peters et al., 2019; Clifford et al., 2016; Castagna et al., 2022; Chauhan et al., 2025; Schikowski and Altuğ, 2020). Evidence on age is similarly inconclusive: while some large studies report stronger effects among older adults (Zhang et al., 2018; Yao et al., 2022; Liu and Hu, 2023; Saha et al., 2024), systematic reviews generally conclude that age does not emerge as a robust or generalizable effect modifier (Delgado-Saborit et al., 2021; Clifford et al., 2016; Wood et al., 2024). The absence of an

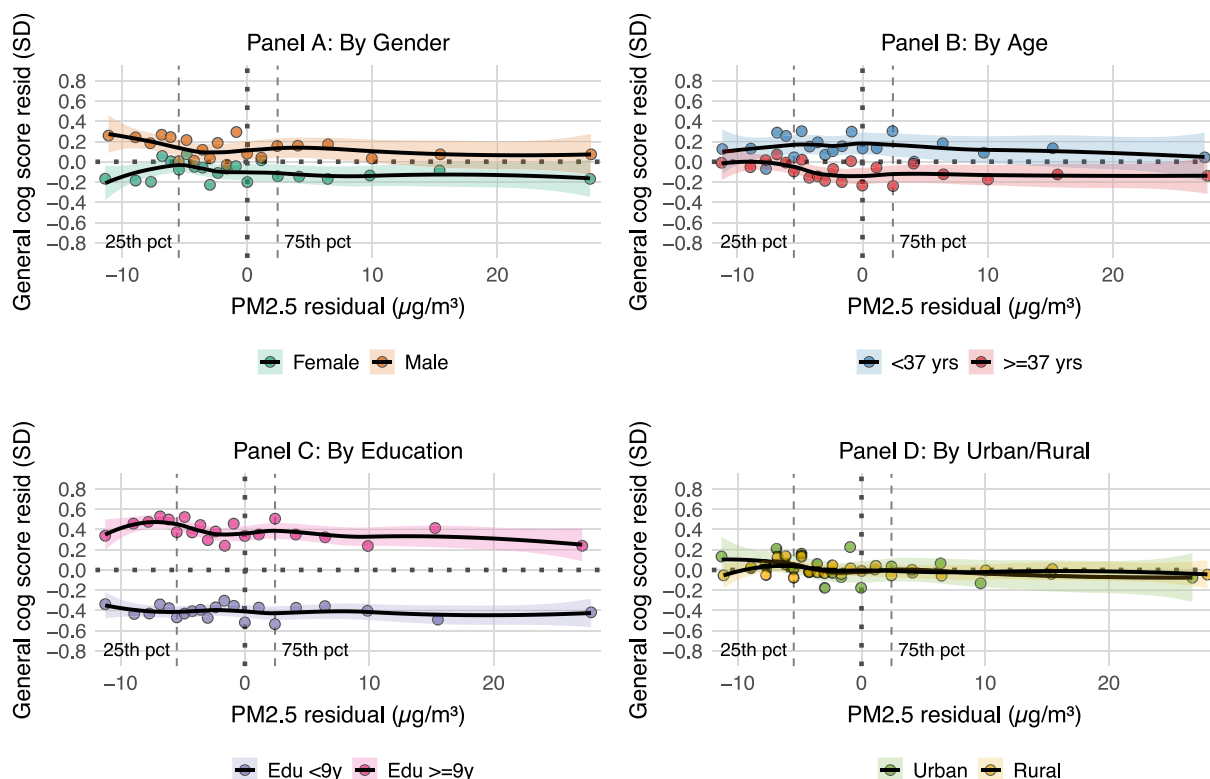


Fig. 5. Residualized cognition vs. $PM_{2.5}$ exposure, by subgroup (trimmed top 2.5%).

Notes: Panels A–D show binned scatterplots of residualized general cognitive performance (y-axis) against residualized $PM_{2.5}$ (x-axis) within each subgroup. General cognitive performance is a standardized index (mean zero, unit standard deviation) constructed via confirmatory factor analysis over orientation, memory, executive function, language, and visuospatial subdomains (see Gross et al., 2025). $PM_{2.5}$ is measured as the mean Atmotube reading during the cognitive assessment interview window. Subgroups are defined as follows: gender (female vs. male), age (below 37 years vs. 37 years or older, the approximate sample median), education (fewer than 9 years of schooling vs. 9 or more years, i.e., any secondary schooling), and urban vs. rural residence. Observations with raw $PM_{2.5}$ in the top 2.5% of the full-sample distribution are first excluded to remove extreme outliers. Both $PM_{2.5}$ and cognitive scores are then residualized by regressing each on hour-of-day, day-of-week, month, and geographic fixed effects; the x-axis therefore reflects each bin's average deviation from its predicted mean. Within each subgroup, observations are grouped into quantile-spaced bins, with the number of bins (18 in each subgroup) selected using a data-driven procedure that minimizes the integrated mean squared error of the binscatter estimator, following Cattaneo et al. (2024). Each point plots the within-bin mean $PM_{2.5}$ residual ($\mu g/m^3$) and within-bin mean general cognitive residual (SD units). Dashed vertical lines mark the 25th and 75th percentiles of the residual distribution, and a LOESS curve (with 95% confidence band) in each panel captures the flexible association.

urban–rural difference is also unsurprising. Prior work suggests that apparent urban–rural differences largely reflect differences in exposure profiles rather than differences in susceptibility per se: urban populations may face stronger effects of ambient $PM_{2.5}$ from traffic and industrial sources (Odo et al., 2023; Chandra et al., 2022), whereas rural populations – especially women, who are largely responsible for cooking – often face greater harm from indoor pollution due to solid-fuel use (Saha et al., 2024; Krishnamoorthy et al., 2022; Dakua et al., 2022; Luo et al., 2021; Rani et al., 2023; Jana et al., 2022; Mani et al., 2025). When ambient $PM_{2.5}$ is the exposure of interest, as here, these compositional differences wash out and urban and rural respondents exhibit nearly overlapping exposure–response profiles.

There are several other domain-specific interaction effects – underscoring that pollution susceptibility may vary across cognitive tasks and that subgroup differences must be interpreted in light of the specific mental processes involved – although heterogeneity by education remains the most robust pattern across domains (Appendix Tables S9–S13).

Overall, these findings identify educational attainment as a consistent moderator of the cognitive effects of $PM_{2.5}$ exposure. Rather than falling most heavily on the socioeconomically disadvantaged, short-term pollution appears to impair performance particularly among higher-functioning individuals engaged in cognitively intensive activities. These heterogeneous effects highlight the need for regulatory frameworks that account not only for health risks, but also for productivity and human capital losses across the socioeconomic spectrum.

Table 4
Interaction effects on general cognitive scores.

	(1) General cognitive	(2) General cognitive	(3) General cognitive	(4) General cognitive	(5) General cognitive	(6) General cognitive
Mean PM _{2.5}	−0.0039** (0.0016)	−0.0019 (0.0011)	0.0002 (0.0017)	−0.0048*** (0.0014)	−0.0030** (0.0012)	−0.0004 (0.0021)
Female	−0.1756*** (0.0589)	−0.1367** (0.0486)	−0.1523*** (0.0482)	−0.1526*** (0.0478)	−0.1529*** (0.0475)	−0.1445** (0.0587)
Female × PM _{2.5}	0.0018 (0.0016)					0.0007 (0.0015)
Age ≥ 37		−0.0688* (0.0385)				−0.0536 (0.0387)
Age ≥ 37 × PM _{2.5}		−0.0018 (0.0022)				−0.0030 (0.0021)
Any Secondary Schooling	0.7619*** (0.0226)	0.7883*** (0.0216)	0.8386*** (0.0470)	0.7619*** (0.0227)	0.7618*** (0.0227)	0.8687*** (0.0451)
Any Secondary Schooling × PM _{2.5}			−0.0059*** (0.0018)			−0.0062*** (0.0017)
Rural				−0.0935 (0.0869)		−0.0947 (0.0845)
Rural × PM _{2.5}				0.0029 (0.0021)		0.0025 (0.0016)
Interviewed Outdoor	0.0875* (0.0453)	0.0885* (0.0447)	0.0877* (0.0466)	0.0860* (0.0454)	0.0844 (0.0562)	0.0663 (0.0524)
Interviewed Outdoor × PM _{2.5}					0.0002 (0.0021)	0.0018 (0.0018)
Temperature (°C)	0.0003 (0.0014)	0.0002 (0.0016)	0.0005 (0.0013)	0.0006 (0.0012)	0.0002 (0.0014)	0.0008 (0.0014)
Geographic and Time FE	YES	YES	YES	YES	YES	YES
Number Observations	5131	5131	5131	5131	5131	5131
Adjusted R-squared	0.210	0.205	0.210	0.210	0.210	0.206

Notes: This table presents the estimated association between PM_{2.5} exposure and a general cognitive index, with interactions by gender, age, education, rural residence, and interview setting. The general cognitive index is standardized to have mean zero and unit standard deviation and is constructed via confirmatory factor analysis over orientation, memory, executive function, language, and visuospatial subdomains (see Gross et al., 2025). PM_{2.5} is measured as the mean Atmotube reading (μg/m³) during the cognitive assessment interview window. Interaction variables are defined as follows: Female is a binary indicator equal to one for female respondents; Age ≥ 37 is a binary indicator equal to one for respondents aged 37 or older in 2023, where 37 is the median age in the sample; Any Secondary Schooling equals one if the respondent completed 9 or more years of schooling; Rural equals one for respondents in rural survey locations; and Interviewed Outdoor equals one if the cognitive assessment was conducted outdoors. The top 2.5% of PM_{2.5} values are trimmed to reduce the influence of extreme outliers. All regressions control for mean temperature and mean humidity. All regressions include hour-of-day, day-of-week, month, and geographic fixed effects. Columns (1), (3), (4), and (5) control for continuous age in years. Column (6) includes all interaction terms simultaneously. Standard errors, clustered at the geographic level, are reported in parentheses. Statistical significance is denoted as follows:

*** p < 0.01

** p < 0.05

* p < 0.1.

4.5. Robustness and sensitivity checks

We next conduct a series of robustness checks to evaluate the stability of the empirical strategy and probe the underlying identification assumptions. In particular, we examine (1) whether the contemporaneous exposure measure is a proxy for earlier ambient pollution, (2) measurement error considerations, (3) whether exposure varies systematically with socioeconomic characteristics, (4) whether the results are sensitive to alternative constructions of geographic fixed effects, (5) heterogeneity by interview setting, (6) sensitivity to extreme exposure values, and (7) sensitivity to humidity and temperature.

4.5.1. Immediate vs. lagged exposure

To distinguish between contemporaneous and recent exposure, we estimate models that include both current PM_{2.5} and PM_{2.5} averaged over the preceding two hours (Appendix Table S14). The lagged measure reflects ambient conditions recorded shortly before the interview, but note that the spatial correspondence between this lagged exposure and the respondent's exact location may vary. In many cases, FOs were already at or near the interview site during this two-hour window; in other cases, they were still walking or in transit. As a result, the lagged measure should be interpreted as a noisy proxy for recent background pollution in the respondent's general vicinity rather than a precise measure of prior exposure at the exact assessment site.

Including this lagged measure offers a suggestive diagnostic: if the contemporaneous coefficient were instead capturing broader ambient pollution patterns or short-lived sensor noise, its magnitude should change meaningfully once the lagged measure is introduced. In practice, adding the lagged PM_{2.5} term has only minimal impact on the contemporaneous coefficient, while the effect of the lagged term itself is generally small and not statistically significant across domains. (An exception is the visuospatial

domain, where the lagged $PM_{2.5}$ coefficient is statistically significant at the 5 percent level.) Although this exercise is imperfect given the potential spatial misalignment noted above, the regression patterns are consistent with the view that contemporaneous pollution during the cognitive test, and not earlier ambient conditions, is the primary driver of performance.

Appendix Figure S8 further illustrates the relationship between the two measures. Panel A shows that contemporaneous and lagged $PM_{2.5}$ follow similar right-skewed distributions, while Panel B indicates a moderate correlation of $r = 0.50$. This suggests that the two measures capture related but distinct exposure windows, allowing the regression to differentiate between immediate and recent pollution spikes. Taken together, the regression and descriptive evidence provide a useful – though not entirely definitive – robustness check supporting the temporal specificity of the contemporaneous measure.

4.5.2. Measurement error considerations

While the use of portable $PM_{2.5}$ monitors allows for highly time-resolved, individual-level exposure measurement, some degree of measurement error remains likely. First, despite the precision of the Atmotube Pro devices, classical measurement error may arise from factors such as brief delays in exposure registration, sensor drift, or misalignment between ambient and inhaled air. Such error is likely to be close to random and would attenuate estimates toward zero, implying that the true cognitive effects of pollution may be somewhat larger than those reported. Because the Atmotube Pro relies on optical light scattering, its response can vary with aerosol composition: biomass smoke, traffic emissions, and dust scatter light differently even at the same true mass concentration, which may introduce setting-specific systematic error (Jayaratne et al., 2020). However, the comparison with alternative exposure sources provides a direct empirical assessment of how measurement differences affect estimated effects: the portable-monitor estimates are larger and more precise than those from reanalysis products, consistent with at least some classical attenuation in the latter rather than upward bias in the former (Table 3).

Second, we address potential non-classical measurement error concerns by controlling in the preferred specification (i.e., Table 1, col. 3) for whether the interview occurred outdoors, which may capture systematic differences in exposure measurement. While residual discrepancies between recorded exposure and exposure in the “breathing zone” (e.g., if the device is in a bag or pocket) may remain, such error is unlikely to generate upward bias and would instead likely dilute observed effects.

Third, we consider the possibility of temporal misalignment between exposure measurement and the physiological window during which pollution impairs cognition. If cognitive functioning is most sensitive to exposure 15–30 min prior to testing, the real-time and two-hour lagged measures may mischaracterize the true window of effect. However, the robustness checks presented above, including both contemporaneous and lagged $PM_{2.5}$ as explanatory variables (Appendix Table S14), show that only the immediate measure predicts cognitive performance, while the estimated effect of lagged exposure is generally small and not statistically significant across most outcomes, except for visuospatial skills. This pattern reinforces the interpretation that the focus on $PM_{2.5}$ during the testing period aligns closely with the relevant neurocognitive sensitivity windows and arguably further supports the validity of the empirical strategy.

Taken together, several potential forms of measurement error present in the data are likely to bias estimates conservatively toward zero, making the observed effects a lower bound on the true cognitive impact of acute air pollution exposure.

4.5.3. Exposure and socioeconomic selection

To assess whether short-run pollution exposure during testing is systematically related to observable respondent characteristics, we follow Pei et al. (2019) and regress residualized $PM_{2.5}$ exposure on education, gender, and age under each of the four alternative geographic fixed-effects definitions (Appendix Table S16). As Pei, Pischke, and Schwandt show, such balance tests can be more informative than checking how the treatment coefficient moves as controls are added, particularly when observed covariates are noisy proxies for underlying confounders. Across all specifications, the estimated associations are small in magnitude and statistically indistinguishable from zero, suggesting that short-run deviations in pollution during testing are not systematically related to observable demographic characteristics once the main control set is applied. It also supports interpreting the heterogeneity by education (Table 4) as mainly stemming from differences in vulnerability rather than differences in exposure.

To further assess robustness to omitted variable bias, Appendix Table S17 implements the selection-on-unobservables approach of Oster (2019), which evaluates how sensitive the estimated coefficient is to potential selection on unobserved confounders. The key identifying assumption is that selection on unobservables is proportional to selection on observables: that is, unobserved factors affecting both pollution exposure and cognitive outcomes are assumed to be no stronger, relative to their variance, than the observed controls included in the regression. Under this framework, coefficient stability and changes in explanatory power across specifications can be used to bound the extent of omitted variable bias.

Consistent with this logic, moving from the baseline specification to the fully controlled model increases the R^2 substantially while leaving the estimated $PM_{2.5}$ coefficient largely unchanged. This pattern suggests that observed covariates capture meaningful variation in cognitive outcomes but do not explain away the pollution effect, implying limited scope for omitted variables to drive the results. Following Oster (2019), we set the maximum attainable R^2 to be 1.3 times that of the fully controlled specification and compute bias-adjusted bounds on the coefficient. The parameter δ summarizes the relative importance of selection on unobservables compared to observables: $\delta = 1$ corresponds to the case where unobserved confounders are as strongly related to both treatment and outcome as the included controls. We find that the value of δ required to attenuate the estimated $PM_{2.5}$ effect to zero exceeds three. This implies that unobserved factors would need to be more than three times as strongly correlated with both pollution exposure and cognitive performance as the observed socioeconomic controls in order to fully explain away the estimated effect, which seems unlikely in this setting.

In all, the absence of sorting on observables and the magnitude of the Oster bound provide complementary evidence that the main results are unlikely to be driven by omitted socioeconomic factors.

4.5.4. Alternative geographic fixed effects

We also test whether the estimated pollution–cognition relationship depends on how geographic variation is absorbed. Respondents are dispersed across rural Busia County, major cities such as Nairobi and Mombasa, and numerous smaller towns, raising the possibility that alternative spatial groupings could yield different estimates. Appendix Table S15 re-estimates the preferred specification using four fixed-effects constructions with varying degrees of granularity, ranging from county-level fixed effects (41 groups) to a simple urban–rural classification, with two intermediate schemes that distinguish major cities and broader regional clusters.

Across all four constructions, the contemporaneous $PM_{2.5}$ coefficient remains negative and similar in magnitude to the main estimate. Although precision varies slightly with the level of spatial aggregation, the point estimates fall within a narrow band, indicating that the results are not an artifact of any specific geographic partitioning and instead reflect within-location fluctuations in short-term pollution.

Appendix Table S16 further shows that the socioeconomic exposure balance documented above holds under all four geographic fixed-effects constructions: education, gender, and age remain uncorrelated with contemporaneous $PM_{2.5}$ once geographic and temporal fixed effects are applied. Taken together, the stability of the coefficient across geographic fixed-effects definitions, and the absence of socioeconomic gradients under any of them, reinforce the robustness of the estimated pollution–cognition relationship to alternative ways of capturing spatial heterogeneity.

4.5.5. Heterogeneity by interview setting

We examine heterogeneity by interview setting in Appendix Table S18. In the full sample, a $10 \mu\text{g}/\text{m}^3$ increase in $PM_{2.5}$ is associated with a 0.030 SD decline in general cognition (col. 1). Dropping the interview-setting control leaves the estimate virtually unchanged (col. 2), indicating that the baseline relationship is not driven by conditioning on indoor/outdoor status. Restricting the sample to indoor interviews yields a nearly identical and statistically significant estimate (col. 3, -0.0030 per $\mu\text{g}/\text{m}^3$), while the outdoor-only estimate is similar in magnitude but less precisely estimated (col. 4, -0.0031 per $\mu\text{g}/\text{m}^3$).

Appendix Figure S9 provides descriptive context. Panel A shows that indoor interviews exhibit slightly higher mean $PM_{2.5}$ (approximately $1.3 \mu\text{g}/\text{m}^3$ higher than outdoor interviews) and a modest rightward shift in the exposure distribution. Panel B shows that mean cognitive performance is approximately 0.2 SD higher among respondents interviewed outdoors. These unconditional differences in cognitive scores are far too large to be explained by the small gap in pollution levels: at the estimated coefficient, a $1.3 \mu\text{g}/\text{m}^3$ difference in $PM_{2.5}$ would predict only about a 0.003 SD difference in cognition, so this gap instead likely reflects selection into the interview setting. For instance, respondents interviewed outdoors may differ in ways correlated with cognitive performance, such as in terms of their residential environment, housing quality, or other unobserved characteristics. The important finding here is that the $PM_{2.5}$ coefficient itself is stable regardless of whether interview setting is controlled for or restricted, indicating that interview setting is not a confounder driving the main pollution–cognition relationship.

4.5.6. Robustness to alternative treatments of extreme $PM_{2.5}$ values

Because portable sensors can occasionally record extreme values which may reflect either genuine short-lived exposure spikes (e.g., nearby combustion or dust events) or measurement artifacts, we assess robustness to alternative treatments of the right tail and to alternative exposure summaries in Appendix Table S19.

The preferred specification trims the top 2.5% of $PM_{2.5}$ observations (col. 1) and yields a negative and statistically significant association between mean $PM_{2.5}$ and general cognition. Trimming a smaller share of the upper tail – retaining observations up to the 99th percentile rather than the 97.5th (col. 2) – reduces the magnitude of the coefficient somewhat but preserves statistical significance. Winsorizing at the 97.5th percentile (col. 3) yields a smaller but still significant estimate, while winsorizing at the 99th percentile (col. 4) further attenuates the coefficient and this effect is not statistically significant at traditional levels. Retaining the full, untrimmed distribution (col. 5) attenuates the estimate further toward zero, consistent with additional noise and measurement error in the extreme upper tail. The pattern across columns 1–5 therefore suggests that moderate trimming or winsorizing preserves the signal, while retaining the extreme right tail introduces sufficient variance to obscure it. To the extent that some extreme readings reflect true high-exposure episodes (rather than just noise), trimming would bias estimates toward zero, so the persistence of a negative association across moderate levels of exposure is arguably conservative.

Several alternative exposure statistics produce qualitatively similar results. Replacing the mean with the median (col. 6) yields a negative but not statistically significant estimate, while modeling $PM_{2.5}$ in logs (col. 7) produces a negative and statistically significant coefficient. Overall, the direction and approximate magnitude of the estimated effect are largely stable across reasonable treatments of high-exposure observations and functional forms, and the main findings are not driven by a small number of extreme values.

4.5.7. Robustness to extreme temperature and humidity

A key concern when using optical low-cost sensors such as the Atmotube is that measured $PM_{2.5}$ concentrations may be biased upward in high-humidity environments.⁷ Because these sensors infer particle mass from light scattering, elevated humidity causes hygroscopic particles to absorb water and swell (Hagan and Kroll, 2020; Di Antonio et al., 2018; Brattich et al., 2020), increasing

⁷ We thank Emilia Tjernström for insightful comments, informed by her familiarity with the performance of low-cost optical sensors, which motivated these robustness checks.

light scattering and leading to overestimation of true particulate mass (Di Antonio et al., 2018; Badura et al., 2018; Brattich et al., 2020). This bias is non-linear (Guo et al., 2020; Zheng et al., 2018) and potentially correlated both with ambient humidity and true pollution levels, raising concerns about measurement error in the main regressor. While our baseline specification controls for mean temperature and humidity during the interview window, such controls may not fully capture this non-linear distortion.

To directly address this concern, Appendix Table S20 implements a series of robustness checks that progressively exclude observations most susceptible to humidity- and temperature-induced measurement error. Column (2) drops interviews conducted under high-humidity conditions (mean humidity > 80%), a threshold identified in prior validation work as the point at which Atmotube readings may become substantially biased (Shittu et al., 2025). Column (3) excludes observations recorded under extreme temperature conditions (those with mean temperature below 10 degrees C or above 40 degrees C), and Column (4) applies both restrictions simultaneously. Across all specifications, the estimated association between PM_{2.5} exposure and general cognitive performance remains remarkably stable in magnitude and statistical significance. The consistency of estimates after excluding high-humidity observations provides reassuring evidence that the main results are not driven by humidity-related sensor artifacts.

For transparency, we also separately report the temperature coefficients from each regression. These coefficients are generally close to zero and not statistically significant across specifications, with the main exception being orientation outcomes (see, for example, Appendix Table S3, Appendix Table S9, and column 2 of Appendix Table S14). This pattern further suggests that the main cognitive results are not driven by direct temperature effects.

5. Conclusion

This study provides new evidence on the short-term cognitive effects of air pollution using highly time-resolved, individual-level exposure data collected during comprehensive cognitive assessments in Kenya. Unlike most prior research that relies on fixed monitoring stations and aggregated pollution metrics, we use portable PM_{2.5} monitors linked to person-specific cognitive performance to estimate the immediate effects of ambient pollution exposure. The data used here spanning rural, urban and peri-urban settings in a Sub-Saharan African country (Kenya) also expands the empirical scope of the literature, which has largely focused on middle-income and high-income countries.

The data indicate that even brief increases in ambient PM_{2.5} concentrations impair cognitive performance in real time, with stronger effects in tasks requiring executive function, memory, and visuospatial processing. These impairments are economically meaningful: in contexts where cognitive capacity is essential for educational engagement, informal entrepreneurship, or other economic decision-making, marginal declines in performance of the observed magnitude may reduce productivity or labor market effectiveness. Notably, performance losses occur at pollution levels below current regulatory thresholds, including those in Kenya (Kenya G. and National Environment Management Authority, 2024), suggesting that the cognitive costs of exposure may be underestimated in conventional cost-benefit analyses of air quality policies.

Another main finding is that exposure measurement matters. Estimates based on person-proximate portable monitors are consistently larger than those obtained from satellite reanalysis or grid-based measures, and the dose-response gradient across the exposure distribution is detectable only with the finer-resolution data. This pattern is consistent with classical attenuation from spatial aggregation in reanalysis products, and it suggests that prior studies relying on such measures may understate the true cognitive effects of short-term pollution exposure.

From a policy perspective, the findings support targeted interventions that reduce short-term exposure during cognitively demanding activities. Low-cost strategies – such as mobile air quality alerts, portable air filtration in schools and workplaces, or scheduling adjustments that shift cognitively intensive tasks away from high-pollution periods – could improve cognitive outcomes. The finding that effects are concentrated among more educated individuals performing demanding tasks suggests that workplace interventions may yield particularly high returns. More broadly, these results underscore the need to incorporate cognitive functioning into the welfare analysis of pollution regulation, particularly in LMIC settings where such costs have rarely been quantified. The low cost of the portable monitors used in this study (approximately \$200 per unit) also demonstrates the feasibility of deploying real-time exposure measurement at scale, which could support both research and policy-relevant monitoring infrastructure in resource-constrained settings.

Several limitations merit discussion. Although the Atmotube PM_{2.5} exposure data are both temporally and spatially precise, some degree of measurement error remains possible. Because the Atmotube relies on optical light scattering, as noted above its response can vary with aerosol composition (Jayaratne et al., 2020). Any residual classical measurement error is likely to attenuate estimates toward zero, so the main estimates should be interpreted as lower bounds on the true cognitive impacts of acute pollution exposure. We also address potential non-classical error by controlling for interview location (indoors vs. outdoors), and robustness checks suggest that results are not driven by sensor artifacts. In addition, although we examine both contemporaneous and lagged exposure, the precise neurocognitive timing window may vary across individuals, introducing further attenuation bias. Other limitations include restricted external validity to other age groups, and ceiling effects in some cognitive domains (especially orientation, where there is little variation in a mid-life sample).

Several directions for future research follow naturally from these findings. Most importantly, the longitudinal structure of KLPS offers a valuable opportunity to examine whether repeated pollution exposure accumulates into lasting cognitive deficits over time—a question that the current cross-sectional analysis cannot address but that may be possible with future air pollution measurement in KLPS. Understanding whether the education gradient documented here persists across other LMIC settings would also help sharpen the targeting of mitigation strategies.

CRediT authorship contribution statement

Xuqian Ma: Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Michelle Layvant:** Writing – review & editing, Visualization, Funding acquisition, Data curation, Conceptualization. **Edward Miguel:** Writing – review & editing, Project administration, Methodology, Funding acquisition, Conceptualization. **Eric Ochieng:** Writing – review & editing, Project administration, Data curation. **Ajay Pillarisetti:** Writing – review & editing, Methodology. **Michael Walker:** Writing – review & editing, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Edward Miguel reports financial support was provided by National Institutes of Health. Edward Miguel reports financial support was provided by National Science Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We thank Patrick Collard, Daniela Pinto Veizaga, and Zan Song for excellent research assistance. We gratefully acknowledge funding from the U.S. National Institutes of Health (NIH) (#R01-HD108281, #R01-AG077001), and the U.S. National Science Foundation (#SES-2149446). KLPS data collection received IRB approval from Maseno University and the University of California, Berkeley. We certify that no generative AI tools were used in the preparation of the manuscript.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.jhealeco.2026.103166>.

Data availability

A replication package for the paper has been made available on Harvard Dataverse. This includes the Kenya Life Panel Survey (KLPS) data (including the cognitive scores) and air pollution data (including the Atmotube and PurpleAir measures) used in the paper. To maintain respondent confidentiality, the specific GPS coordinates are not included in the public-use data, but can be obtained from the authors upon request and after securing the necessary human subjects approvals.

The air pollution re-analysis datasets used in the paper (CAMS EAC4 and MERRA2) are publicly available.

Ma, Xuqian, Michelle Layvant, Edward Miguel, Eric Ochieng, Ajay Pillarisetti, and Michael Walker. 2026. “Replication Data for: ‘Impacts of Contemporaneous Air Pollution Exposure on Cognitive Performance in Kenya.’” Harvard Dataverse. <https://doi.org/10.7910/DVN/VRXIXB>.

References

- Ahmed, J.S., Buizza, R., Dell’Acqua, M., Demissie, T., Pè, M.E., 2024. Evaluation of ERA5 and CHIRPS rainfall estimates against observations across Ethiopia. *Meteorol. Atmos. Phys.* 136 (3), 17.
- Andersen, C.M., Brandt, J., Christensen, J.H., Frohn, L.M., Geels, C., Hener, T., Simonsen, M., Skipper, L., 2025. Air pollution and cognition in children: Evidence from national tests in Denmark. *J. Hum. Resour.*
- Anderson, M.L., 2020. As the wind blows: The effects of long-term exposure to air pollution on mortality. *J. Eur. Econ. Assoc.* 18 (4), 1886–1927.
- Arceo, E., Hanna, R., Oliva, P., 2016. Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico city. *Econ. J.* 126 (591), 257–280.
- Archsmith, J., Heyes, A., Saberian, S., 2018. Air quality and error quantity: Pollution and performance in a high-skilled, quality-focused occupation. *J. Assoc. Environ. Resour. Econ.* 5 (4), 827–863.
- Badura, M., Batog, P., Drzeniecka-Osiadacz, A., Modzel, P., 2018. Evaluation of low-cost sensors for ambient PM2. 5 monitoring. *J. Sensors* 2018 (1), 5096540.
- Bassi, V., Kahn, M.E., Lozano Gracia, N., Porzio, T., Sorin, J., 2024. Jobs in the smog: Firm location and workers’ exposure to pollution in african cities. Manuscript, latest version (Accessed November 18 2025).
- Bassil, D.T., Farrell, M.T., Wagner, R.G., et al., 2022. Cohort profile update: Cognition and dementia in the health and aging in africa longitudinal study of an INDEPTH community in South Africa (HAALSI dementia). *Int. J. Epidemiol.* 51, e217–e226.
- Bauer, S.E., Im, U., Mezuman, K., Gao, C.Y., 2019. Desert dust, industrialization, and agricultural fires: Health impacts of outdoor air pollution in Africa. *J. Geophys. Res.: Atmospheres* 124 (7), 4104–4120.
- Bedi, A.S., Nakaguma, M.Y., Restrepo, B.J., Rieger, M., 2021. Particle pollution and cognition: Evidence from sensitive cognitive tests in Brazil. *J. Assoc. Environ. Resour. Econ.* 8 (3), 443–474.
- Benki-Nugent, S., Were, F.H., Riederer, A.M., Gatari, M., Karr, C.J., Seto, E.Y., Maleche-Obimbo, E., 2025. Air pollution exposures in early life and brain development in children (ABC): Protocol for a pregnancy cohort study. *BMJ Paediatr. Open* 9 (1), e002758.
- Bharadwaj, P., Gibson, M., Graff Zivin, J., Neilson, C., 2017. Gray matters: Fetal pollution exposure and human capital formation. *J. Assoc. Environ. Resour. Econ.* 4 (2), 505–542.
- Bista, S., Fancello, G., Zeitouni, K., Annesi-Maesano, I., Chaix, B., 2025. Relationships between fixed-site ambient measurements of nitrogen dioxide, ozone, and particulate matter and personal exposures in grand Paris, France: the MobiliSense study. *Int. J. Health Geogr.* 24 (1), 5.
- Block, M.L., Calderón-Garcidueñas, L., 2009. Air pollution: Mechanisms of neuroinflammation and CNS disease. *Trends Neurosci.* 32 (9), 506–516.
- Brattich, E., Bracci, A., Zappi, A., Morozzi, P., Di Sabatino, S., Porcù, F., Di Nicola, F., Tositti, L., 2020. How to get the best from low-cost particulate matter sensors: Guidelines and practical recommendations. *Sensors* 20 (11), 3073.

- Brauer, M., Roth, G.A., Aravkin, A.Y., Zheng, P., Abate, K.H., Abate, Y.H., Abbafati, C., Abbasgholizadeh, R., Abbasi, M.A., Abbasian, M., et al., 2024. Global burden and strength of evidence for 88 risk factors in 204 countries and 811 subnational locations, 1990–2021: a systematic analysis for the global burden of disease study 2021. *Lancet* 403 (10440), 2162–2203.
- Burnett, R.T., Spadaro, J.V., Garcia, G.R., Pope, C.A., 2022. Designing health impact functions to assess marginal changes in outdoor fine particulate matter. *Environ. Res.* 204, 112245.
- Byambaa, U., Miguel, E., Walker, M.W., Wang, S.Z., 2025. Beyond education and occupation: Unpacking the large gender wage gap in Kenya. Working Paper w34375, National Bureau of Economic Research.
- Callaway, B., Sant'Anna, P.H.C., 2021. Difference-in-differences with multiple time periods. *J. Econometrics* 225 (2), 200–230.
- Carneiro, J., Cole, M.A., Strobl, E., 2021. The effects of air pollution on students' cognitive performance: Evidence from Brazilian university entrance tests. *J. Assoc. Environ. Resour. Econ.* 8 (6), 1051–1077.
- Carson, R., Yu, C.A., 2026. Exploring the sources and nature of temperature measurement error in estimating climate-related impacts. Working paper.
- Castagna, A., Mascheroni, S., Montirosso, R., 2022. Air pollution and neurodevelopmental skills in preschool- and school-aged children: A systematic review. *Neurosci. Biobehav. Rev.* 136, 104623.
- Cattaneo, M.D., Crump, R.K., Farrell, M.H., Feng, Y., 2024. On binscatter. *Am. Econ. Rev.* 114 (5), 1488–1514.
- Chandra, M., Rai, C.B., Kumari, N., Sandhu, V.K., Chandra, K., Krishna, M., Kota, S.H., Anand, K.S., Oudin, A., 2022. Air pollution and cognitive impairment across the life course in humans: a systematic review with specific focus on income level of study area. *Int. J. Environ. Res. Public Health* 19 (3), 1405.
- Chauhan, R., Dande, S., Hood, D.B., Chirwa, S.S., Langston, M.A., Grady, S.K., Dojcsak, L., Tabatabai, M., Wilus, D., Valdez, R.B., et al., 2025. Particulate matter 2.5 (PM_{2.5})-associated cognitive impairment and morbidity in humans and animal models: a systematic review. *J. Toxicol. Environ. Health, Part B* 28 (4), 233–263.
- Chillrud, S.N., Ae-Ngibise, K.A., Gould, C.F., Owusu-Agyei, S., Mujtaba, M., Manu, G., Burkart, K., Kinney, P.L., Quinn, A., Jack, D.W., Asante, K.P., 2021. The effect of clean cooking interventions on mother and child personal exposure to air pollution: Results from the Ghana randomized air pollution and health study (GRAPHS). *J. Expo. Sci. Environ. Epidemiology* 31 (4), 683–698.
- Clifford, A., Lang, L., Chen, R., Anstey, K. J., Seaton, A., 2016. Exposure to air pollution and cognitive functioning across the life course—a systematic literature review. *Environ. Res.* 147, 383–398.
- Copernicus Atmosphere Monitoring Service, 2024. CAMS global reanalysis (EAC4). Dataset, (Accessed 31 March 2026), European Centre for Medium-Range Weather Forecasts (ECMWF).
- Costa, L.G., Cole, T.B., Dao, K., Chang, Y.-C., Coburn, J., Garrick, J.M., 2020. Effects of air pollution on the nervous system and its possible role in neurodevelopmental and neurodegenerative disorders. *Pharmacol. Ther.* 210, 107523.
- Dakua, M., Karmakar, R., Barman, P., 2022. Exposure to indoor air pollution and the cognitive functioning of elderly rural women: a cross-sectional study using LASI data, India. *BMC Public Health* 22 (1), 2272.
- Dasgupta, S., Huq, M., Khaliqzaman, M., Pandey, K., Wheeler, D., 2006. Who suffers from indoor air pollution? Evidence from Bangladesh. *Health Policy Plan.* 21 (6), 444–458.
- de Bont, J., Jaganathan, S., Dahlquist, M., Persson, Å., Stafoggia, M., Ljungman, P., 2022. Ambient air pollution and cardiovascular diseases: An umbrella review of systematic reviews and meta-analyses. *J. Intern. Med.* 291 (6), 779–800.
- De Chaisemartin, C., d'Haultfoeulle, X., 2020. Two-way fixed effects estimators with heterogeneous treatment effects. *Am. Econ. Rev.* 110 (9), 2964–2996.
- de Souza, P., Anenberg, S., Makarewicz, C., Shirgaokar, M., Duarte, F., Ratti, C., Durant, J.L., Kinney, P.L., Niemeier, D., 2023. Quantifying disparities in air pollution exposures across the united states using home and work addresses. *Environ. Sci. Technol.* 58 (1), 280–290.
- 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. *Sci. Total Environ.* 757, 143734.
- Di Antonio, A., Popoola, O.A.M., Ouyang, B., Saffell, J., Jones, R.L., 2018. Developing a relative humidity correction for low-cost sensors measuring ambient particulate matter. *Sensors* 18 (9), 2790.
- Domínguez, P., et al., 2025. Inequality in Air Pollution Monitoring and Exposure: Evidence from Four Latin American Cities. Technical Report, Inter-American Development Bank.
- Dominici, F., Zeger, S.L., Samet, J.M., 2000. A measurement error model for time-series studies of air pollution and mortality. *Biostatistics* 1 (2), 157–175.
- Duncan, S.D., Adeniyi, C.Y., Ayoola, F.I., Giurcanu, M., Ibigbami, T., Chartier, R.T., Olopade, C.O., 2025. Impact of fine particulate matter air pollution (PM_{2.5}) on Nigerian children's performance on tests of cognitive and neurobehavioral development at age seven years. *Environ. Int.* 109843.
- Ebenstein, A., Lavy, V., Roth, S., 2016. The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. *Am. Econ. J.: Appl. Econ.* 8 (4), 36–65.
- Faherty, T., Raymond, J.E., McFiggans, G., Pope, F.D., 2025. Acute particulate matter exposure diminishes executive cognitive functioning after four hours regardless of inhalation pathway. *Nat. Commun.* 16 (1), 1339.
- Ferguson, L., Taylor, J., Symonds, P., Davies, M., Dimitroulopoulou, S., 2023. Analysis of inequalities in personal exposure to PM_{2.5}: A modelling study for the greater London school-aged population. *Sci. Total Environ.* 905, 167056.
- Fuller, C.H., Amegah, A.K., 2022. Limited air pollution research on the african continent: Time to fill the gap. *Int. J. Environ. Res. Public Health* 19 (11), 6359.
- Gaita, S.M., Boman, J., Gatari, M.J., Petterson, J.B.C., Janhäll, S., 2014. Source apportionment and seasonal variation of PM 2.5 in a Sub-Saharan African city: Nairobi, Kenya. *Atmospheric Chem. Phys.* 14 (18), 9977–9991.
- Gao, R., Qi, L., Lu, C., 2025. Activity-related exposure to outdoor air pollution: a spatiotemporal inquiry of residents in Beijing, China. *Environ. Res.* 285, 122306.
- Gelaro, R., McCarty, W., Suárez, M.J., Todling, R., Molod, A., Takacs, L., et al., 2017. The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). *J. Clim.* 30 (14), 5419–5454.
- Global Modeling and Assimilation Office, 2024. Modern-era retrospective analysis for research and applications, version 2 (MERRA-2): Surface PM_{2.5}. Dataset, (Accessed 31 March 2026), NASA Goddard Space Flight Center.
- Gordon, J.N.D., Bilsback, K.R., Fiddler, M.N., Pokhrel, R.P., Fischer, E.V., Pierce, J.R., Bilal, S., 2023. The effects of trash, residential biofuel, and open biomass burning emissions on local and transported PM_{2.5} and its attributed mortality in africa. *GeoHealth* 7 (2), e2022GH000673.
- Graff Zivin, J., Liu, T., Song, Y., Tang, Q., Zhang, P., 2020. The unintended impacts of agricultural fires: Human capital in China. *J. Dev. Econ.* 147, 102560.
- Gross, A.L., Duhon, M., Ochieng, E., Ikanga, J.N., Dow, W.H., Lee, J., et al., 2025. Midlife cognitive testing in africa: Validity of the harmonised cognitive assessment protocol in the Kenya life panel survey. *BMJ Open* 15 (8), e096619.
- Gross, A.L., et al., 2023. Harmonisation of later-life cognitive function across six large population-based studies of cognitive ageing. *EclinicalMedicine* 63, 100801.
- Gryparis, A., Paciorek, C.J., Zeka, A., Schwartz, J., Coull, B.A., 2009. Measurement error caused by spatial misalignment in environmental epidemiology. *Biostatistics* 10 (2), 258–274.
- Guarnieri, M., Balmes, J.R., 2014. Outdoor air pollution and asthma. *Lancet* 383 (9928), 1581–1592.
- Guo, Q., Zhu, Z., Cheng, Z., Xu, S., Wang, X., Duan, Y., 2020. Correction of light scattering-based total suspended particulate measurements through machine learning. *Atmosphere* 11 (2), 139.
- Hagan, D.H., Kroll, J.H., 2020. Assessing the accuracy of low-cost optical particle sensors using a physics-based approach. *Atmospheric Meas. Tech. Discuss.* 2020, 1–36.

- Hamilton, P.B., Rolshausen, G., Uren Webster, T.M., Tyler, C.R., 2017. Adaptive capabilities and fitness consequences associated with pollution exposure in fish. *Phil. Trans. R. Soc. B* 372 (1712).
- Hamory, J., Miguel, E., Walker, M., Kremer, M., Baird, S., 2021. Twenty-year economic impacts of deworming. *Proc. Natl. Acad. Sci.* 118 (14), e2023185118.
- Health Effects Institute, 2025. State of Global Air 2025: A Report on Air Pollution and Its Role in the World's Leading Causes of Death. Technical Report, Health Effects Institute, Boston.
- Heyes, A., Cook, N., Rivers, N., 2023. Clean air and cognitive productivity: Effect and adaptation. *J. Assoc. Environ. Resour. Econ.* 10 (5), 1265–1308.
- Holub, F., Theis, B., 2023. Air quality, high-skilled worker productivity and adaptation: Evidence from GitHub. <http://dx.doi.org/10.2139/ssrn.4398088>, SSRN Working Paper.
- Hsu, E., Miguel, E., Ochieng, E., Walker, M., 2026. Cohort Profile: Kenya Life Panel Survey. CEGA Working Paper Series No. WPS-258, Center for Effective Global Action, University of California, Berkeley, Text.
- Inness, A., Ades, M., Agustí-Panareda, A., Barré, J., Benedictow, A., Blechschmidt, A.-M., et al., 2019. The CAMS reanalysis of atmospheric composition. *Atmospheric Chem. Phys.* 19 (6), 3515–3556.
- Jacquin, L., Petitjean, Q., Côte, J., Laffaille, P., Jean, S., 2020. Effects of pollution on fish behavior, personality, and cognition: some research perspectives. *Front. Ecol. Evol.* 8, 86.
- Jana, A., Varghese, J.S., Naik, G., 2022. Household air pollution and cognitive health among Indian older adults: Evidence from LASI. *Environ. Res.* 214, 113880.
- Jayarathne, R., Liu, X., Ahn, K.-H., Asumadu-Sakyi, A., Fisher, G., Gao, J., Mabon, A., et al., 2020. Low-cost PM_{2.5} sensors: An assessment of their suitability for various applications. *Aerosol Air Qual. Res.* 20 (3), 520–532.
- Johnson, M., Pillarisetti, A., Piedrahita, R., Balakrishnan, K., Peel, J.L., Steenland, K., Underhill, L.J., Rosa, G., Kirby, M.A., Díaz-Artiga, A., McCracken, J., Clark, M.L., Waller, L., Chang, H.H., Wang, J., Dusabimana, E., Ndagijimana, F., Sambandam, S., Mukhopadhyay, K., 2022. Exposure contrasts of pregnant women during the household air pollution intervention network randomized controlled trial. *Environ. Health Perspect.* 130 (9).
- Josephson, A.L., Kilic, T., Michler, J.D., 2026. The mismeasure of weather: Using earth observation data for estimation of socioeconomic outcomes. *J. Dev. Econ.* 178.
- Kang, Y.J., Tan, H.-Y., Lee, C.Y., Cho, H., 2021. An air particulate pollutant induces neuroinflammation and neurodegeneration in human brain models. *Adv. Sci.* 8 (21), 2101251.
- Ke, L., Zhang, Y., Fu, Y., Shen, X., Zhang, Y., Ma, X., Di, Q., 2022. Short-term PM_{2.5} exposure and cognitive function: Association and neurophysiological mechanisms. *Environ. Int.* 170, 107593.
- Keller, J.P., Chang, H.H., Strickland, M.J., Szpiro, A.A., 2017. Measurement error correction for predicted spatiotemporal air pollution exposures. *Epidemiology* 28 (3), 338–345.
- Kenya G and National Environment Management Authority, 2024. The environmental management and co-ordination (air quality) regulations, 2024. Kenya Gazette Supplement No. 198, Legal Notice No. 180, accessed April 9, 2026, <https://nema.go.ke/wp-content/uploads/2025/07/AIR-QUALITY-AND-PLASTICS-2024.pdf>.
- Kirago, Leonard, Gatari, Michael J., Gustafsson, Örjan, Andersson, August, 2022. Black carbon emissions from traffic contribute substantially to air pollution in Nairobi, Kenya. *Commun. Earth & Environ.* 3 (1), 74.
- Kong, L.-s., Chen, D., Zhang, J.-d., Cheng, X.-f., Zhang, Y.-l., Li, B., 2025. The correlation between high temperature and cognitive function: a CHARLS 2018 cross-sectional study. *Arch. Public Health* 83 (1), 181.
- Krebs, B., Luechinger, S., 2024. Air pollution, cognitive performance, and the role of task proficiency. *J. Assoc. Environ. Resour. Econ.* 11 (4), 921–958.
- Krishnamoorthy, Y., Rajaa, S., Ramasubramani, P., Saya, G.K., 2022. Association between indoor air pollution and cognitive function among nationally representative sample of middle-aged and older adults in India—a multilevel modelling approach. *Indoor Air* 32 (1), e12929.
- Künn, S., Palacios, J., Pestel, N., 2019. Indoor air quality and cognitive performance. *J. Environ. Econ. Manag.* 98, 102254.
- La Nauze, A., Severnini, S., 2025. Air pollution and adult cognition: Evidence from brain training. *J. Assoc. Environ. Resour. Econ.* 12 (1), 221–255.
- Langa, K.M., Ryan, L.H., McCammon, R.J., et al., 2020. The health and retirement study harmonized cognitive assessment protocol project: Study design and methods. *Neuroepidemiology* 54, 64–74.
- Lee, J., Dey, A.B., 2020. Introduction to LASI-DAD: The longitudinal aging study in India-diagnostic assessment of dementia. *J. Am. Geriatr. Soc.* 68, S3–S4.
- Li, W., Lin, G., Xiao, Z., Zhang, Y., Li, B., Zhou, Y., Ma, Y., Chai, E., 2022. A review of respirable fine particulate matter (PM_{2.5})-induced brain damage. *Front. Mol. Neurosci.* 15, 967174.
- Li, Y., Zhu, L., Wang, Y., Tang, Z., Huang, Y., Wang, Y., Zhang, J., Zhang, Y., 2023. Emergency department visits in children associated with exposure to ambient PM₁ within several hours. *Int. J. Environ. Res. Public Health* 20 (6), 4910.
- Liu, H., Hu, T., 2023. Correlation between air pollution and cognitive impairment among older individuals: empirical evidence from China. *BMC Geriatr.* 23 (1), 366.
- Loria, A., Cristescu, M.E., Gonzalez, A., 2019. Mixed evidence for adaptation to environmental pollution. *Evol. Appl.* 12 (7), 1259–1273.
- Luo, Y., Zhong, Y., Pang, L., Zhao, Y., Liang, R., Zheng, X., 2021. The effects of indoor air pollution from solid fuel use on cognitive function among middle-aged and older population in China. *Sci. Total Environ.* 754, 142460.
- Mani, S.S., Gupta, A., Elo, I.T., 2025. Externalities of polluting cooking fuels, gender, and adult cognitive health in low-and middle-income countries. *Am. J. Epidemiol.* kwaf133.
- Marsland, A.L., Gianaros, P.J., Kuan, D.C., Sheu, L.K., Krajina, K., Manuck, S.B., 2015. Brain morphology links systemic inflammation to cognitive function in midlife adults. *Brain Behav. Immun.* 48, 195–204.
- Michler, J.D., Josephson, A.L., Kilic, T., 2022. Privacy protection, measurement error, and the integration of remote sensing and socioeconomic survey data. *J. Dev. Econ.* 155, 102783.
- Miguel, E., Kremer, M., 2004. Worms: Identifying impacts on education and health in the presence of treatment externalities. *Econometrica* 72 (1), 159–217.
- Miguel, E., Walker, M., Dow, W., Gross, A., Ikanga, J., Lee, J., 2023. Pre-analysis plan for ‘the long-term impacts of child deworming on mid-life cognition and exposure risk factors for alzheimer’s disease and related dementia in Kenya’. AEA RCT Registry, RCT ID AEARCTR-0001191.
- Mustansar, T., Timmermans, E.J., Silva, A., Bijnsens, E.M., Lefebvre, W., Saenen, N.D., Vanpoucke, C., Nawrot, T.S., Vaartjes, I., 2025. Socioeconomic inequalities and ambient air pollution exposure in school-aged children living in an affluent society: an analysis on individual and aggregated data in Belgium. *Health & Place* 93, 103473.
- Odo, D.B., Yang, I.A., Dey, S., Hammer, M.S., van Donkelaar, A., Martin, R.V., Dong, G.-H., Yang, B.-Y., Hystad, P., Knibbs, L.D., 2023. A cross-sectional analysis of long-term exposure to ambient air pollution and cognitive development in children aged 3–4 years living in 12 low-and middle-income countries. *Environ. Pollut.* 318, 120916.
- Oguge, O., Nyamondo, J., Adera, N., Okolla, L., Okoth, B., Anyango, S., Afulo, A., Kumie, A., Samet, J., Berhane, K., 2024. Fine particulate matter air pollution and health implications for Nairobi, Kenya. *Environ. Epidemiology* 8 (3), e307.
- Oster, E., 2019. Unobservable selection and coefficient stability: Theory and evidence. *J. Bus. Econom. Statist.* 37 (2), 187–204.
- Pei, Z., Pischke, J.-S., Schwandt, H., 2019. Poorly measured confounders are more useful on the left than on the right. *J. Bus. Econom. Statist.* 37 (2), 205–216.
- Peters, R., Ee, N., Peters, J., Booth, A., Mudway, I., Anstey, K.J., 2019. Air pollution and dementia: a systematic review. *J. Alzheimer’s Dis.* 70 (s1), S145–S163.
- Power, M.C., Adar, S.D., Yanosky, J.D., Weuve, J., 2016. Exposure to air pollution as a potential contributor to cognitive function, cognitive decline, brain imaging, and dementia: A systematic review of epidemiologic research. *Neurotoxicology* 56, 235–253.

- Power, M.C., Kioumourtzoglou, M.-A., Hart, J.E., Okereke, O.I., Laden, F., Weisskopf, M.G., 2015. The relation between past exposure to fine particulate air pollution and prevalent anxiety: Observational cohort study. *BMJ* 350, h1111.
- Pozzer, A., Anenberg, S.C., Dey, S., Haines, A., Lelieveld, J., Chowdhury, S., 2023. Mortality attributable to ambient air pollution: A review of global estimates. *GeoHealth* 7 (1), e2022GH000711.
- Pujante Pérez, A., Illueca Fernández, E., Shah, S.M.A., Casado-Mansilla, D., Jara Valera, A.J., López-De-Ipiña, D., 2024. Performance assessment of wearable atmotube pro sensor for air quality citizen science applications. In: 2024 9th International Conference on Smart and Sustainable Technologies (SpliTech). IEEE, pp. 1–6.
- PurpleAir Inc., 2023. PurpleAir real-time air quality monitoring network. Available at <https://www.purpleair.com>.
- Quispe-Haro, C., Szabó, D., Kordas, K., Capkova, N., Pikhart, H., Bobak, M., 2024. The mediating role of air pollutants in the association between education and lung function among the elderly, the HAPIEE study. *Sci. Total Environ.* 947, 174556.
- Rani, R., Arokiasamy, P., Meitei, W.B., Sikarwar, A., 2023. Association between indoor air pollution and cognitive function of older adults in India: a cross-sectional multilevel analysis. *J. Public Health* 31 (3), 369–379.
- Roth, S., 2021. The effect of indoor air pollution on cognitive performance. Working Paper, London School of Economics.
- Saha, S., Das, P., Das, T., Das, P., Roy, T.B., 2024. A study about the impact of indoor air pollution on cognitive function among middle-aged and older adult people in India. *Arch. Public Health* 82 (1), 57.
- Schikowski, T., Altuğ, H., 2020. The role of air pollution in cognitive impairment and decline. *Neurochem. Int.* 136, 104708.
- 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. *Nat. Commun.* 12 (1), 6754.
- Shi, L., Wu, X., Yazdi, M.D., Braun, D., Awad, Y.A., Wei, Y., et al., 2020. Long-term effects of PM_{2.5} on neurological disorders in the American medicare population: A longitudinal cohort study. *Lancet Planet. Health* 4 (12), e557–e565.
- Shin, S., Bai, L., Burnett, R.T., Kwong, J.C., Hystad, P., van Donkelaar, A., et al., 2021. Air pollution as a risk factor for incident chronic obstructive pulmonary disease and asthma: A 15-year population-based cohort study. *Am. J. Respir. Crit. Care Med.* 203 (9), 1138–1148.
- Shittu, A.I., Pringle, K.J., Arnold, S.R., Pope, R.J., Graham, A.M., Reddington, C., Rigby, R., McQuaid, J.B., 2025. Performance evaluation of atmotube PRO sensors for air quality measurements in an urban location. *Atmospheric Meas. Tech.* 18 (3), 817–828.
- Shupler, M., Hystad, P., Birch, A., Miller-Lionberg, D., Jeronimo, M., Arku, R.E., Chu, Y.L., Mushtaha, M., Heenan, L., Rangarajan, S., Lan, F., Cazor, F., Lopez-Jaramillo, P., Camacho, P.A., Perez, M., Yeates, K., West, N., Ncube, T., Ncube, B., Chifamba, J., Yusuf, R., Khan, A., Hu, B., Liu, X., Wei, L., Tse, L.Ah., Mohan, D., Kumar, P., Gupta, R., Mohan, I., Jayachitra, K.G., Mony, P.K., Rammohan, K., Nair, S., Lakshmi, P.V.M., Sagar, V., Khawaja, R., Iqbal, R., Kazmi, K., Yusuf, S., Brauer, M., 2020. Household and personal air pollution exposure measurements from 120 communities in eight countries: Results from the PURE-AIR study. *Lancet Planet. Health* 4 (10), e451–e462.
- Shupler, M., Tawiah, T., Nix, E., Baame, M., Lorenzetti, F., Betang, E., Chartier, R., Mangeni, J., Upadhy, A., Anderson de Cuevas, R., Sang, E., Piedrahita, R., Johnson, M., Wilson, D., Amenga-Etego, S., Twumasi, M., Ronzi, S., Menya, D., Puzzolo, E., Quansah, R., Asante, K.P., Pope, D., Mbatia, N., Ngahane, B.H., 2024. Household concentrations and female and child exposures to air pollution in peri-urban sub-Saharan Africa: Measurements from the CLEAN-Air(Africa) study. *Lancet Planet. Health* 8 (2), e95–e107.
- Singh, A., Bakare, H., Mazzeo, A., Avis, W.R., Ng'ang'a, D., Gatari, M., Bartington, S.E., Thomas, G.N., Bryson, J.R., Andres, L., et al., 2022. Urban diagnostics and a systems approach to air quality management: Pathways towards sustainable economic development and a healthy Nairobi, Kenya. *Front. Environ. Sci.* 10, 978002.
- Steinle, S., Reis, S., Sabel, C.E., 2015. Quantifying human exposure to air pollution—Moving from static monitoring to spatio-temporally resolved personal exposure assessment. *Sci. Total Environ.* 508, 317–332.
- Sun, L., Abraham, S., 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *J. Econometrics* 225 (2), 175–199.
- Szpiro, A.A., Paciorek, C.J., 2013. Measurement error in two-stage analyses, with application to air pollution epidemiology. *Environmetrics* 24 (8), 501–517.
- Thompson, R., Smith, R.B., Karim, Y.B., Shen, C., Drummond, K., Teng, C., Toledano, M.B., 2023. Air pollution and human cognition: A systematic review and meta-analysis. *Sci. Total Environ.* 859, 160234.
- U.S. Environmental Protection Agency, 2025. National ambient air quality standards (NAAQS) for particulate matter (PM). Last updated August 19, 2025; (Accessed 24 November 2025), <https://www.epa.gov/pm-pollution/national-ambient-air-quality-standards-naaqs-pm>.
- Venuta, A., Lloyd, M., Ganji, A., Xu, J., Simon, L., Zhang, M., Saeedi, M., et al., 2024. Predicting within-city spatiotemporal variations in daily median outdoor ultrafine particle number concentrations and size in montreal and toronto, Canada. *Environ. Epidemiology* 8 (4), e323.
- Weichenthal, S., Pinaut, L., Christidis, T., Burnett, R.T., Brook, J.R., Chu, Y., Brauer, M., et al., 2022. How low can you go? Air pollution affects mortality at very low levels. *Sci. Adv.* 8 (39), eabo3381.
- Wewe, 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. *Arch. Intern. Med.* 172 (3), 219–227.
- Wodebo, D.Y., Melesse, A.M., Woldeesenbet, T.A., Mekonnen, K., Amdihun, A., Korecha, D., Tedla, H.Z., Corzo, G., Teshome, A., 2025. Comprehensive performance evaluation of satellite-based and reanalysis rainfall estimate products in Ethiopia: For drought, flood, and water resources applications. *J. Hydrol.: Reg. Stud.* 57, 102150.
- Wood, D., Evangelopoulos, D., Beevers, S., Kitwiroon, N., Demakakos, P., Katsouyanni, K., 2024. Exposure to ambient air pollution and cognitive function: an analysis of the english longitudinal study of ageing cohort. *Environ. Health* 23 (1), 35.
- World Health Organization, 2021. WHO Global Air Quality Guidelines: Particulate Matter (PM_{2.5} and PM₁₀), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide. World Health Organization, Geneva.
- Wu, K., Ho, H.-C., Su, H., Huang, C.-H., Zheng, H., Zhang, W., Cheng, J., et al., 2022. A systematic review and meta-analysis of intraday effects of ambient air pollution and temperature on cardiorespiratory morbidities: First few hours of exposure matters to life. *EBioMedicine* 86, 104345.
- Yao, Y., Wang, K., Xiang, H., 2022. Association between cognitive function and ambient particulate matters in middle-aged and elderly Chinese adults: Evidence from the China health and retirement longitudinal study (CHARLS). *Sci. Total Environ.* 828, 154297.
- Yao, Z., Zhang, W., Ji, X., Weng, W., 2023. Short-term exposure to air pollution and cognitive performance: New evidence from China's college english test. *Environ. Resour. Econ.* 85 (1), 211–237.
- Ye, W., Campbell, D., Johnson, M., Balakrishnan, K., Peel, J.L., Steenland, K., Underhill, L.J., Rosa, G., Kirby, M.A., Díaz-Artiga, A., McCracken, J., Thompson, L.M., Clark, M.L., Waller, L.A., Chang, H.H., Wang, J., Dusabimana, E., Ndagijimana, F., Sambandam, S., Pillarisetti, A., 2024. Exposure contrasts of women aged 40–79 years during the household air pollution intervention network randomized controlled trial. *Environ. Sci. Technol.* 59 (1), 69–81.
- Yin, B., Fang, W., Liu, L., Guo, Y., Ma, X., Di, Qian, 2024. Effect of extreme high temperature on cognitive function at different time scales: A national difference-in-differences analysis. *Ecotoxicol. Environ. Safety* 275, 116238.
- Zhang, X., Chen, X., Zhang, X., 2018. The impact of exposure to air pollution on cognitive performance. *Proc. Natl. Acad. Sci.* 115 (37), 9193–9197.
- Zhang, X., Chen, X., Zhang, X., 2024. Temperature and low-stakes cognitive performance. *J. Assoc. Environ. Resour. Econ.* 11 (1), 75–96.
- Zheng, T., Bergin, M.H., Johnson, K.K., Tripathi, S.N., Shirodkar, S., Landis, M.S., Sutaria, R., Carlson, D.E., 2018. Field evaluation of low-cost particulate matter sensors in high-and low-concentration environments. *Atmospheric Meas. Tech.* 11 (8), 4823–4846.
- Zhou, J., Wang, H., Huebner, G., Zeng, Y., Pei, Z., Ucci, M., 2023. Short-term exposure to indoor PM_{2.5} in office buildings and cognitive performance in adults: An intervention study. *Build. Environ.* 233, 110078.