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Impacts of Contemporaneous Air Pollution Exposure on Cognitive Performance in Kenya
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ABSTRACT

We estimate the short-term cognitive effects of fine particulate matter (PM2.5) exposure using highly time-resolved, individual-level data collected during cognitive testing in Kenya. By linking real-time portable monitor readings to Harmonized Cognitive Assessment Protocol (HCAP) scores, we identify acute impacts of pollution on general and domain-specific cognition. Higher PM2.5 exposure during testing is associated with lower cognitive performance, particularly in memory, executive function, and visuospatial tasks. Nonlinear models suggest threshold effects, with larger declines 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 PM2.5 levels below Kenya's annual regulatory threshold of 35 $\mu g/m^3$, 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.

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1 Introduction

Air pollution exposure is a growing global public health challenge (Abate 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 robust body of literature has established associations between exposure to fine particulate matter ($PM_{2.5}$) and increased mortality (Anderson, 2020; Arceo et al., 2016; Pozzer et al., 2023), respiratory conditions (Wu et al., 2022; Guarnieri and Balmes, 2014; Shin et al., 2021), cardiovascular diseases (de Bont et al., 2022), and neurological disorders (Shi et al., 2020, 2021). More recently, researchers have begun examining the immediate cognitive impacts 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).

Despite growing evidence linking air pollution to cognitive impairment, existing research predominantly focuses on high-income countries with monitoring infrastructure (Roth, 2021; La Nauze and Severnini, 2025; Krebs and Luechinger, 2024). Evidence from low-resource settings, particularly in Sub-Saharan Africa, remains scarce, largely due to limited monitoring systems, weaker regulatory frameworks (Fuller and Amegah, 2022), and limited data from cognitive assessments. Many commonly used cognitive instruments are not adapted to local languages or contexts and often test only a narrow domain such as executive functioning or fluid intelligence (e.g., Raven's Matrices). Consequently, there is limited understanding of how acute pollution exposure affects cognitive performance in settings characterized by different educational backgrounds, occupational demands, and environmental exposures (Ebenstein et al., 2016; Zhang et al., 2018; Bedi et al., 2021).

To address this gap, we leverage new data from Kenya collected as part of the fifth round of the Kenya Life Panel Survey (KLPS-5). The KLPS is a long-running longitudinal study that originally tracked participants of a randomized school-based deworming program in rural western Kenya (Miguel and Kremer, 2004). The most recent round includes an innovative module, the Cognitive Plus (C+) module, designed to measure mid-life cognitive performance and environmental risk factors, including exposure to air pollution. The C+ Module draws on data from more than 5,000 individuals—many of whom have been surveyed for over two decades—with the aim of establishing a cognitive baseline for future aging and dementia research in a Sub-Saharan African population.

We analyze data from 5,320 respondents with highly time-resolved, real-time $PM_{2.5}$ measurements taken during cognitive assessments using Atmotube Pro sensors (Pujante Pérez et al., 2024). These portable devices capture exposure levels at the time and location of cognitive testing, providing more localized measures of short-term pollution exposure than fixed-site monitors or satellite-based estimates. Average $PM_{2.5}$ concentrations in our sample are about 15 μg/m^3, 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/m^3 (U.S. Environmental Protection Agency, 2025). This enables us to test whether short-term cognitive impacts arise even at "moderate" pollution levels from a regulatory perspective.

The study further 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. Cognitive scores are constructed using confirmatory factor analysis following validation work (Gross et al., 2025). This approach yields domain-specific and general indices that are comparable to HCAP-based studies while appropriately adapted to the Kenyan sample. This multidimensional set of assessments is rare in LMIC studies, which typically rely on more limited single-domain measures, and improves our ability to detect subtle changes in cognition due to environmental stressors.

To estimate the relationship between contemporaneous air pollution exposure and cognitive outcomes, we employ a fixed-effects regression model that includes extensive time fixed effects (for time-of-day, day-of-week, and month) as well as geographic fixed effects, and adds controls for individual characteristics (gender, age, education) and environmental factors (temperature, humidity, and survey location). This strategy leverages short-term, within-location variation in $PM_{2.5}$ to isolate plausibly exogenous exposure shocks, and the results remain robust across alternative specifications. We find that a 10 μg/m^3 increase in $PM_{2.5}$ leads to a statistically significant decline of 0.026 standard deviations in general cognitive ability ($p < 0.05$). Several biological mechanisms may explain this effect: particulate exposure can trigger neuroinflammation and oxidative stress, impair synaptic function (Power et al., 2016; Kang et al., 2021), and in severe cases compromise the blood–brain barrier (Sharma et al., 2009).

We also find suggestive evidence of nonlinear effects, with larger marginal declines in cognition at exposure levels above 30 μg/m^3, although not all differential effects are statistically significant. Effects on domain-specific scores vary, perhaps reflecting ceiling effects in this relatively young cohort (in our case, for certain orientation and language tasks).

We document heterogeneity by educational attainment: individuals with at least some secondary schooling exhibit an even larger 0.056 SD decline in general cognition per 10 μg/m^3

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 rare evidence on the pollution–cognition relationship in a low-resource Sub-Saharan African setting, addressing a major geographic gap (Fuller and Amegah, 2022). Second, by combining real-time personal exposure measurements with validated multi-domain cognitive assessments, it improves both exposure and outcome measurement. Third, it contributes to the literature on the dose–response relationship by documenting meaningful nonlinearities and heterogeneities in the pollution–cognition gradient. These patterns echo prior evidence of steeper cognitive declines at high pollution concentrations (Weuve et al., 2012; Chen et al., 2017; Zhang et al., 2018) and stronger short-term impairments under high cognitive load or in high-stakes contexts (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). While we view the observed impacts as moderate in magnitude, they are considerably larger among more educated individuals, suggest that pollution may undermine cognitive inputs critical for productivity and decision-making. The findings are especially relevant in Sub-Saharan Africa, where air pollution is rising with urbanization and industrial development, yet enforcement of air quality standards and monitoring infrastructure remain 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). 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 5,320 adults who participated in the 2023 KLPS-5 Cognitive Plus (C+) module. 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 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. This spatial dispersion introduces meaningful variation in pollution exposure and enhances the generalizability of the findings.

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, here called field officers (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 minutes, and mean $PM_{2.5}$ exposure over this full testing window serves as the primary exposure measure. Approximately 6.1% of observations (358 out of 5,878) 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, including indoor and outdoor assessments. The Atmotube Pro has demonstrated strong correlations with reference-grade monitors (R^2 = 0.70–0.93) (Pujante Pérez et al., 2024). Following recommended practice in studies using portable pollution monitors, the top 2.5% of $PM_{2.5}$ values were trimmed to minimize extreme outliers and sensor noise (for a related approach, see Li et al. (2023); Venuta et al. (2024)).

$PM_{2.5}$ exposure varied substantially, ranging from 1 to 432 μg/m^3 (mean = 15.4 μg/m^3, SD = 20.3 μg/m^3), with elevated values during Kenya's dry seasons (February–March and August) and in major urban areas such as Nairobi (Figure 1). More detailed season-by-region distributions appear in Appendix Figures S2 and S3. Average $PM_{2.5}$ concentrations in this Kenyan sample are relatively modest compared with many African settings. In

Uganda, for example, Bassi et al. (2024) report annual averages of about 40.8 μg/m^3 in 2018 and 29.1 μg/m^3 in 2019, with urban levels roughly 40% higher than rural areas, and similar pollution magnitudes are reported across other African countries, including Nigeria and Ghana (Bassi et al., 2024).

Importantly, day-to-day variation in pollution concentration is plausibly unrelated to individual characteristics and behaviors once rich geographic and temporal fixed effects are included. Consistent with this, $PM_{2.5}$ 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 (Table S14).

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 aging and cognition studies (e.g., LASI-DAD, HAALSI, HRS-HCAP[1]) and supports future harmonization of cognitive research across countries (Gross et al., 2023).

The battery spans five core domains: (1) orientation, (2) memory, (3) executive functioning and attention, (4) language and verbal fluency, and (5) visuospatial skills. Orientation was measured using items that assess awareness of time and place. Memory was evaluated with the Consortium to Establish a Registry for Alzheimer's Disease (CERAD) 10-Word List Learning task, the East Boston Memory Test (EBMT), and a Logical Memory test. Executive functioning and attention were assessed using Raven's Progressive Matrices, Similarities and Differences, the Token Test, Go–No-Go, Trail Making, and Symbol Cancellation. Language and fluency were captured through animal fluency and object-naming tasks, while visuospatial abilities were measured using CERAD Constructional Praxis, interlocking pentagons, and clock drawing. All assessments were administered in the respondent's preferred language using standardized scripts and intensive enumerator training to ensure consistency across interviewers. Further details on the adaptation and validation of this battery in the Kenyan context are provided in Gross et al. (2025).

Domain-specific cognitive scores and a general cognitive ability score were constructed using confirmatory factor analysis (CFA), a statistical technique that summarizes multiple

[1]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; and HRS-HCAP is the U.S. Health and Retirement Study's Harmonized Cognitive Assessment Protocol. All three implement the HCAP framework to facilitate cross-country comparability in cognitive aging research.

test items into broader cognitive domains. We directly utilize the constructed cognitive measures described in detail by Gross et al. (2025), who provide model fit statistics from confirmatory factor analyses and test measurement invariance by respondent characteristics using the same sample of respondents.

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[2]. Following the pre-analysis plan (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):

$$Y_{igt} = \beta_0 + \beta_1 \mathrm{PM}_{igt} + X_{igt}\theta + \alpha_g + \delta_t + \varepsilon_{igt} \tag{1}$$

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 1 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

[2]This empirical setting does not involve a staggered or phased rollout of the exposure or 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 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.

point estimates.[3]

Additionally, we explore potential non-linear effects by estimating models with categorical $PM_{2.5}$ exposure levels, using mutually exclusive bins of 0–10 μg/m^3, >10–20 μg/m^3, >20–30 μg/m^3, >30–40 μg/m^3, and >40 μg/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; Chen et al., 2017; Weuve et al., 2012; Bedi et al., 2021). These patterns may reflect nonlinear physiological responses, 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, accounting for these nonlinearities 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 mea-

[3]This analysis closely follows the pre-specified regression framework outlined in the pre-analysis plan (PAP) (Miguel et al., 2023). There are three main deviations. First, we exclude the 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. Second, we extend the prespecified model to incorporate nonlinearity and interaction analyses (as discussed below), to more fully characterize pollution–cognition relationships. 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 the small number 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. Table S13 demonstrates that the results are broadly robust across several alternative geographic fixed-effects constructions, including more granular specifications aligned with the PAP.

sure. 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 Severnini, 2025). Finally, 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.

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/m^3 increase in $PM_{2.5}$ is associated with a 2.6% SD decline in cognitive ability ($p < 0.05$).

To make sense of the magnitude, this effect is comparable to the effect of aging by 0.78 years, as inferred from the age coefficient in the same specification (-0.0332 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/m^3—the implied 7.8 to 10.4% 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 their 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 3.9% of a SD (Ebenstein et al., 2016). In the United Kingdom, a 10 μg/m^3 increase in indoor PM_{10} is associated with a 0.003 SD reduction in university exam scores, and exposures exceeding 75 μg/m^3 correspond to declines of about 0.21 SD (Roth, 2021). In applied performance settings, comparable magnitudes arise: a 10 μg/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).

Relative to prior work, the preferred estimate of a 0.026 SD decline in general cognitive performance per 10 μg/m^3 increase in contemporaneous $PM_{2.5}$ exposure is broadly consistent with the magnitudes documented in earlier studies. 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 S2–S6). 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. For example, in the preferred specification (col.

3 in Appendix Tables S2–S6), a 10 μg/m^3 increase is associated with a 0.022 SD decline in executive function ($p < 0.05$), and a 0.024 SD decline in visuospatial skills ($p < 0.01$). In contrast, there is no significant association with memory, orientation, or language. This likely at least partially reflects ceiling effects: for instance, many participants achieved near-perfect orientation scores (which is not surprising for a mid-life sample), limiting variation (Gross et al., 2025).

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; Sukumaran et al., 2024). These pathways provide a plausible mechanism for the domain-specific cognitive effects observed in the data.

4.2 Non-Linear Impacts of Contemporaneous Air Pollution on Cognitive Test Scores

To explore potential non-linearities, we first examine the raw relationship between general cognitive scores and contemporaneous $PM_{2.5}$ exposure. Figure 2 presents a binned scatterplot of unadjusted cognitive performance against measured $PM_{2.5}$ concentrations. The fitted non-parametric LOESS curve reveals a negative gradient: cognitive scores remain relatively stable at low to moderate exposure levels but decline once concentrations exceed roughly 10 μg/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. Figure 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 percent of the $PM_{2.5}$ distribution to reduce the influence of outliers, and Appendix Figure S4 and S5 confirms similar results using the full untrimmed sample.

Regression results provide statistical evidence of non-linearity using categorical exposure bins (Table 1, col. 4). Relative to the reference category (<10 μg/m^3), cognitive scores decline by 0.052 SD at 10–20 μg/m^3 ($p < 0.10$), 0.054 at 20–30 μg/m^3 (not significant), 0.087 SD at 30–40 μg/m^3 ($p < 0.10$), and 0.106 SD above 40 μg/m^3 (not significant). The overall dose-response pattern appears to be monotonic, indicating that cognitive declines intensify at higher pollution levels, consistent with threshold effects. There are similar non-linear patterns across cognitive subdomains (in col. 4 of Appendix Tables S2-S6): $PM_{2.5}$ levels at 10–20 μg/m^3 are associated with declines of 0.055 SD in memory ($p < 0.10$), 0.037 SD in visuospatial skills ($p < 0.10$); $PM_{2.5}$ levels at 30–40 μg/m^3 are associated with declines of 0.093 SD in visuospatial skills ($p < 0.01$); $PM_{2.5}$ levels above 40 μg/m^3 are associated with declines of 0.127 SD in executive function ($p < 0.10$), 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 echo prior research documenting non-linear responses to air pollution. For instance, Weuve et al. (2012) find faster cognitive decline among older adults at higher levels of chronic PM exposure, while Chen et al. (2017) report stronger memory and executive function impairments above 35 μg/m^3. 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, the observed non-linearities imply that the cognitive risks of air pollution may be underestimated when relying 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 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. Figure 4 plots residualized general cognitive performance against residualized $PM_{2.5}$ exposure, stratified by subgroup and trimming the top 2.5% of observations (and Appendix Figure S6 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. Panels A, B, and D show broadly similar exposure–response patterns across gender, age, and rural–urban residence, with subgroup curves largely overlapping. Panel C, however, shows a clearer separation between respondents with and without secondary schooling, the latter of whom exhibit consistently higher residualized cognition across the exposure distribution and a steeper negative slope at some $PM_{2.5}$ levels. The higher average residual cognitive scores for respondents with secondary education is consistent with prior evidence from Gross et al. (2025), who show that general cognitive performance is strongly correlated with education but only weakly with age in midlife. Interestingly, urban and rural respondents exhibit nearly overlapping exposure–response profiles, with similar slopes and average residualized cognitive scores.

These patterns are confirmed in Table 2, which formally estimates interaction effects. Individuals with at least some secondary schooling experience significantly larger cognitive losses as $PM_{2.5}$ increases: for every 10 μg/m^3 increase in pollution, they exhibit a decline in general cognitive scores that is approximately 0.055-0.056 SD larger than their less-educated peers (cols. 3 and 5), while the effect for those with less than secondary schooling is close to zero and not statistically significant. In other words, the effect of $PM_{2.5}$ exposure on cognitive performance appears to be concentrated almost entirely among the more educated in this Kenyan sample. In contrast, there are no statistically significant interaction effects with gender, age, or urban/rural residence (despite these being relatively precise estimates).

There are several other statistically significant interaction effects in specific domains—underscoring that pollution susceptibility varies meaningfully across cognitive domains, and that subgroup differences must be interpreted in light of the specific mental processes involved in each task—although, once again, heterogeneity by education is the most robust pattern across several domains (Appendix Tables S7 - S11).

What could explain the larger effects among more educated individuals? One plausible explanation is task engagement. More educated respondents may process information more deeply and exert greater cognitive effort during testing, which could increase their susceptibility to pollution-induced disruption. The mental effort required to perform well on tasks involving executive control, reasoning, or working memory may expose these individuals to greater marginal impairment from transient exposure. This interpretation is consistent with empirical evidence showing that air pollution appears to have larger cognitive impacts under high cognitive load, and among higher-ability individuals in high-stakes settings. For example, Krebs and Luechinger (2024) show that acute NO_x exposure reduced performance among trained players but not novices in an online arithmetic training game, while Ebenstein et al. (2016) find that temporary increases in $PM_{2.5}$ on exam days in Israel reduced student performance, with downstream effects on educational attainment and earnings. By contrast, Zhang et al. (2018) report greater vulnerability among less-educated elderly adults in China. The difference may reflect contextual and methodological contrasts: the Kenyan study sample here is relatively young, healthy, and economically active, with high cognitive engagement during testing. Moreover, the use of highly time-resolved, person-level exposure measurements in this study captures short-term spikes that may interact differently with cognitive function than chronic exposure metrics used in some prior research.

An alternative and more speculative explanation is differential adaptation. More educated individuals may have been less chronically exposed to high pollution levels over time—due to differences in residential location, occupation (i.e., indoor versus outdoor work), or lifestyle—and thus may lack the physiological or behavioral adaptation mechanisms that mitigate acute exposure effects. As a result, transient pollution shocks may have more pronounced cognitive consequences for those with lower cumulative exposure histories. This hypothesis is supported by emerging research on exposure–susceptibility interactions in neurotoxicology, which highlights that individuals with less long-term exposure can be more vulnerable to short-term pollution episodes (Clougherty and Kubzansky, 2009). Relatedly, recent epidemiological evidence suggests that concentration–response relationships may be steeper at lower exposure levels, implying disproportionately larger impacts for those less adapted to polluted environments (Shi et al., 2021). That said, as noted above, individual characteristics including education are not significantly correlated with $PM_{2.5}$ exposure in this sample conditional on time and geographic fixed effects (Appendix Table S14).

Overall, these findings identify educational attainment as a consistent moderator of the cognitive effects of $PM_{2.5}$ exposure. Contrary to the assumption that air pollution harms primarily the most socioeconomically disadvantaged, these results instead suggest that short-term pollution can impair performance among higher-functioning individuals engaged in cognitively intensive activities. These heterogeneous effects highlight the need for regulatory frameworks that account for not just health risks, but also productivity and human capital losses across the socioeconomic spectrum.

4.4 Robustness and Sensitivity Checks

Next, we 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, and (4) whether the results are sensitive to alternative constructions of geographic fixed effects.

4.4.1 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 S12). The lagged measure reflects ambient conditions recorded shortly before the interview, but the spatial correspondence between this lagged exposure and the respondent's exact location varies. 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 vicinity rather than a precise prior exposure at the 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 both contemporaneous and lagged $PM_{2.5}$ coefficients are marginally significant.) Although this exercise is imperfect due to potential spatial misalignment in the lagged measure in some cases, 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 S7 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 $r = 0.52$. 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 necessarily approximate—robustness check supporting the temporal specificity of the contemporaneous measure.

4.4.2 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.

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 minutes 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 S12), show that only the immediate measure predicts cognitive performance, while the estimated effect of lagged exposure is small and not statistically significant. 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.

4.4.3 Exposure and Socioeconomic Selection

To assess potential confounding by socioeconomic status, we regress individual-level $PM_{2.5}$ exposure on education, gender, and age (Appendix Table S14). As noted above, once geographic and temporal fixed effects are included, none of these characteristics significantly predict contemporaneous $PM_{2.5}$ levels, and the coefficients on secondary education and age are close to zero. This pattern suggests that short-term exposure during testing is conditionally uncorrelated with observable socioeconomic status, alleviating concerns that measured pollution differences simply reflect systematic differences across demographic groups. It also supports interpreting the heterogeneity by education (Table 2) as mainly stemming from differences in vulnerability rather than differences in exposure.

4.4.4 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 S13 re-estimates the preferred specification using four increasingly coarse or granular geographic fixed-effects constructions, 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 S14 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.

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 setting of rural, urban and peri-urban areas in Sub-Saharan Africa 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, suggesting that the cognitive costs of exposure may be underestimated in conventional cost–benefit analyses of air quality policies.

From a policy perspective, the findings support targeted interventions that reduce short-term exposure during cognitively demanding activities. Low-cost mitigation strategies, such as mobile air quality alerts, temporary clean-air shelters in schools and markets, or targeted subsidies for indoor filtration, could improve cognitive outcomes. These results also underscore the need to incorporate cognitive functioning into the welfare analysis of pollution regulation, particularly in LMIC settings where these issues have rarely been examined.

Several limitations merit discussion. Although the $PM_{2.5}$ exposure data are both temporally and spatially precise, some degree of measurement error remains possible. Because the Atmotube relies on optical light scattering, 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). Classical measurement error due to sensor lag or imperfect alignment between recorded and inhaled air is likely to attenuate estimates toward zero. We also address potential non-classical error by controlling for interview location (indoors vs. outdoors), and the robustness checks described above suggest that any residual error is likely to attenuate estimates toward zero. In addition, although we examine both contemporaneous and lagged exposure, the precise neurocognitive timing window may vary across individuals, introducing further attenuation bias. As such, the main estimates likely represent lower bounds on the true cognitive impacts of acute pollution exposure. Other limitations include limited external validity to other age groups, including children or older adults; ceiling effects in some cognitive domains (especially orientation); and the inability to assess interactions between pollution and co-occurring stressors such as heat or financial strain.

Future research could usefully examine the dynamic effects of repeated pollution exposure on cognitive functioning over time, using longitudinal designs with repeated testing and real-time exposure measurement. These findings highlight the potential value of incorporating fine-grained temporal resolution into future environmental health studies. Additional work is also needed to flexibly model non-linear exposure–response relationships and to identify potential threshold effects. Finally, understanding how pollution interacts with other stressors, such as heat or financial strain, and how cognitive vulnerability varies across population subgroups can help target mitigation strategies to those most at risk.

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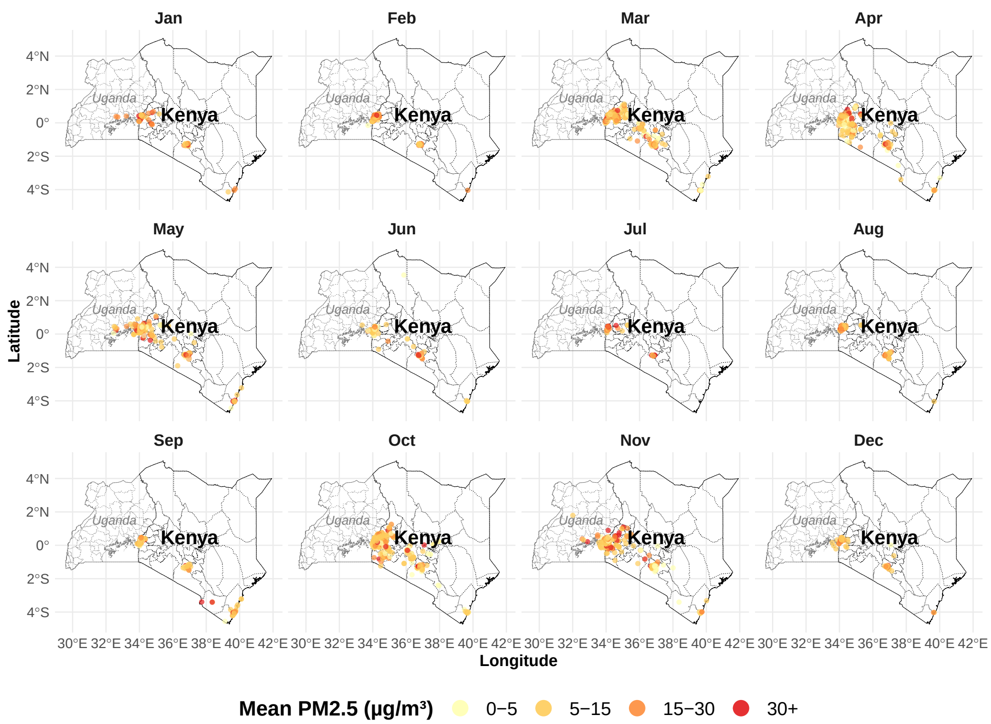
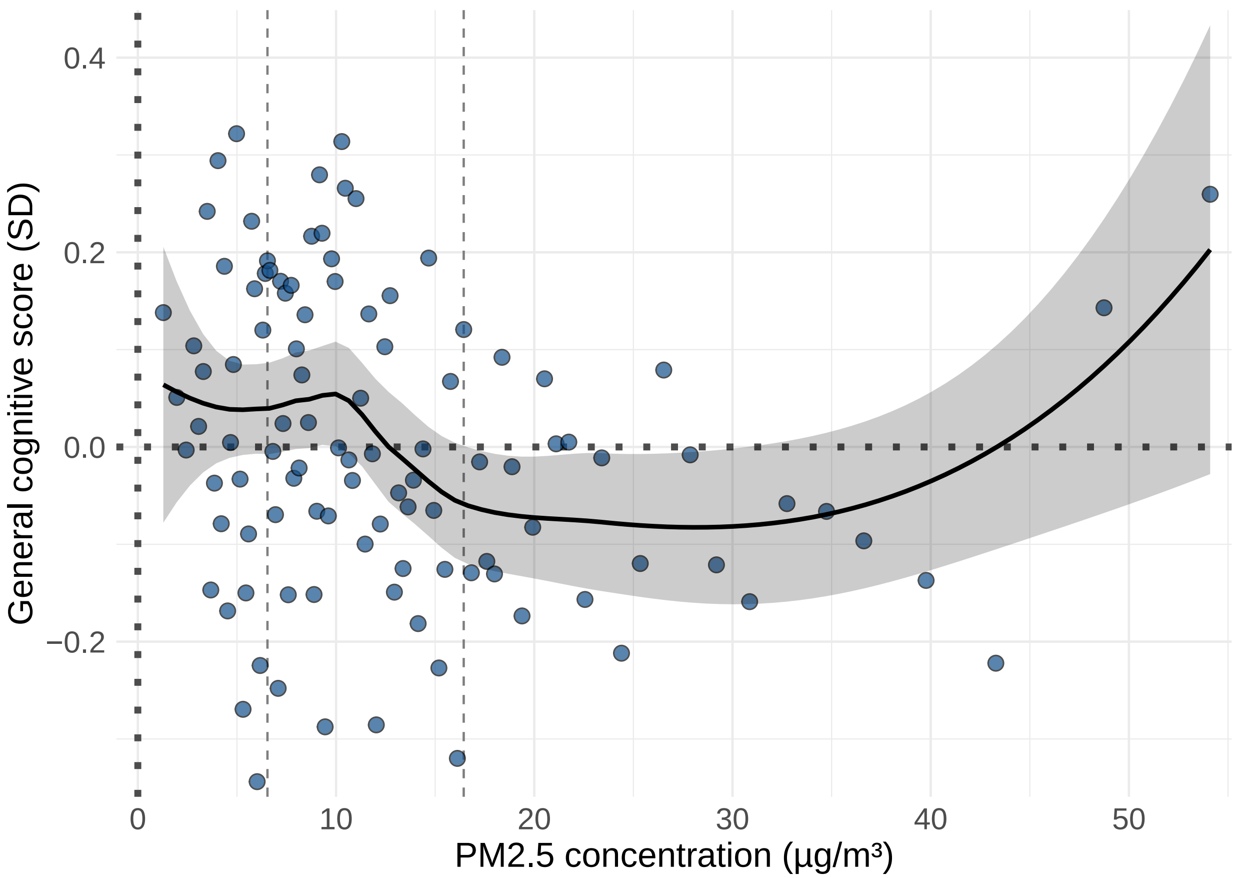
Figure 1: Spatial and Temporal Variation of $PM_{2.5}$ Exposure



Town	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
Busia Rural	45	534	418	138	120	37	21	462	463	96	117	38	2489
Busia Urban	31	30	15	11	32	5	4	33	8	7	6	8	190
Central	0	1	12	6	16	6	0	8	6	8	11	3	77
Coast	2	0	2	2	3	0	0	0	16	2	5	0	32
Eastern KE	1	0	5	8	3	2	0	0	1	12	7	2	41
Kampala (Uganda Urban)	1	0	0	0	4	0	0	0	0	0	1	0	6
Kisumu	4	0	0	49	11	0	0	0	0	53	7	0	124
Mombasa	1	1	82	17	11	4	0	1	90	11	6	2	226
Nairobi	30	264	35	71	82	36	18	333	48	53	79	19	1068
Nakuru	0	0	55	2	1	3	0	0	0	40	5	0	106
Nyanza	1	3	2	87	19	8	0	2	0	75	23	2	222
Other City (Kenya)	1	1	0	0	15	3	0	0	0	0	9	3	32
Other Rural (Kenya)	3	0	0	0	30	2	1	0	0	0	58	1	95
Rift Valley	3	2	36	24	20	2	1	1	6	50	28	2	175
Western	5	3	75	20	11	2	2	0	0	92	11	2	223
Total	128	839	737	435	378	110	47	840	638	499	373	82	5106

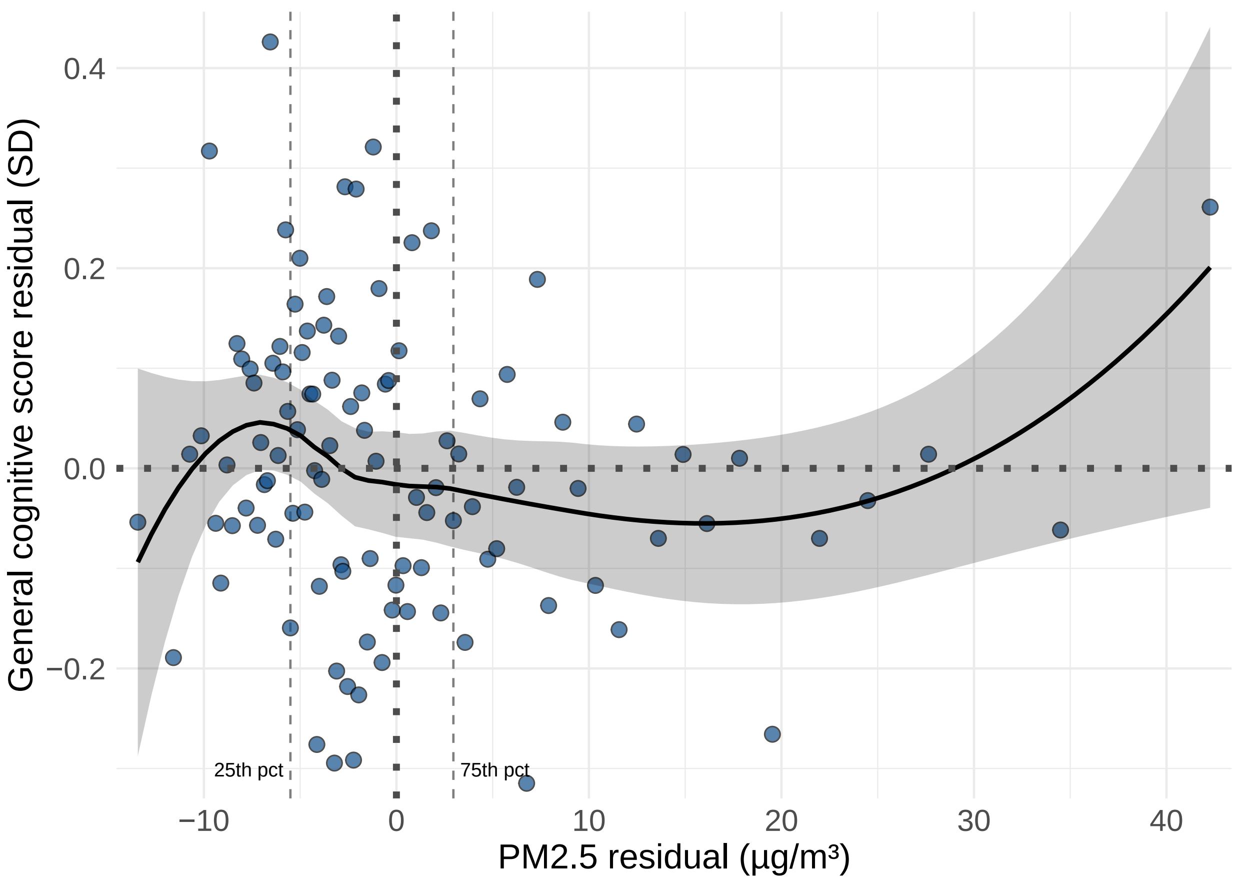
Notes: This figure displays the spatial distribution of individual mean $PM_{2.5}$ exposures recorded in Kenya and Uganda from January through December. Each dot represents a single reading corresponding to an individual's average exposure during their survey period within the given month. GPS locations outside the Kenyan and Ugandan country boundaries were excluded. The color gradient indicates the $PM_{2.5}$ concentration levels (0–5, 5–15, 15–30, 30+ $\mu g/m^3$). The table below summarizes the number of observations in each town for the corresponding months.

Figure 2: Cognition vs. $PM_{2.5}$ Exposure (Trimmed Top 2.5%)



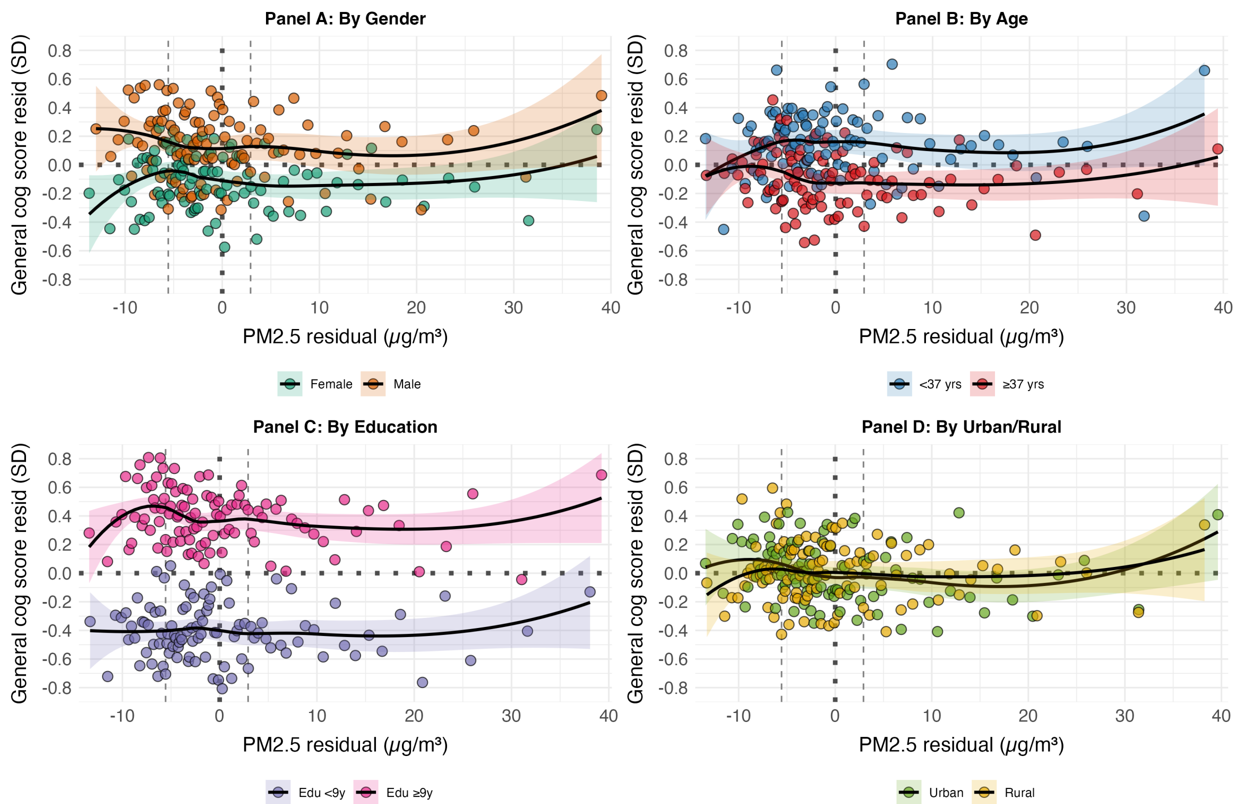
Notes: This figure presents a binned scatterplot of raw general cognitive performance (y, in SD units) against raw $PM_{2.5}$ concentrations (x, in $\mu g/m^3$). Observations with $PM_{2.5}$ in the top 2.5% of the full-sample distribution were first excluded to remove extreme outliers. The remaining data were then sorted into equal-sized bins of 50 based on their raw $PM_{2.5}$ values. Each point plots the bin's mean $PM_{2.5}$ concentration and mean general cognitive score. 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 any non-linear association between pollution and cognition.

Figure 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) against residualized $PM_{2.5}$ concentrations (x). Observations with raw $PM_{2.5}$ values in the top 2.5% of the full-sample distribution were first dropped to remove extreme outliers. Both $PM_{2.5}$ and cognitive scores were then residualized by regressing on hour-of-day, day-of-week, month, and geographic fixed effects; the x-axis therefore shows each bin's average deviation from its predicted mean. The remaining data were sorted into equal-sized bins of 50 based on that $PM_{2.5}$ residual. Each point plots the bin's mean $PM_{2.5}$ residual ($\mu g/m^3$) and 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 any non-linear association.

Figure 4: 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) against residualized $PM_{2.5}$ (x) within each subgroup (gender, age, education, and urban/rural). Observations with raw $PM_{2.5}$ in the top 2.5% of the full-sample distribution were first excluded to remove extreme outliers. Both $PM_{2.5}$ and cognitive scores were then residualized by regressing 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, the cleaned data were sorted into equal-sized bins of 50 based on $PM_{2.5}$ residuals. Each point plots the bin's mean $PM_{2.5}$ residual ($\mu g/m^3$) and 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 any non-linear association.

Table 1: Association Between Contemporaneous $PM_{2.5}$ Exposure and Cognition

	(1) General Cognitive	(2) General Cognitive	(3) General Cognitive	(4) General Cognitive
Mean PM2.5	-.0032***	-.0024*	-.0026**	
	(.0007)	(.0012)	(.0010)	
PM2.5 10-20 µg/m^3				-.0520*
				(.0266)
PM2.5 20-30 µg/m^3				-.0539
				(.0419)
PM2.5 30-40 µg/m^3				-.0867*
				(.0418)
PM2.5 above 40 µg/m^3				-.1061
				(.0667)
Interviewed Outdoor	.2052***	.1719***	.0882*	.0885*
	(.0562)	(.0517)	(.0480)	(.0492)
Female			-.1580***	-.1574***
			(.0502)	(.0504)
Age			-.0332***	-.0333***
			(.0034)	(.0034)
Any Secondary Schooling			.7623***	.7624***
			(.0220)	(.0222)
Geographic and Time FE		YES	YES	YES
Number Observations	5187	5187	5056	5056
Adjusted R-squared	.010	.039	.211	.211

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on a general cognitive index, measured as a standardized index with mean zero and unit standard deviation. The general cognitive index is constructed using confirmatory factor analysis (see Gross et al. (2025)) and incorporates multiple cognitive domains. 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) does not include fixed effects. Columns (2), (3), and (4) include hour-of-day, day-of-week, month, and geographic fixed effects. $PM_{2.5}$ exposure is modeled both as a linear term and in categorical bins (10–20 μg/m^3, 20–30 μg/m^3, 30–40 μg/m^3, and above 40 μg/m^3) to explore potential non-linear effects. Statistical significance is denoted as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

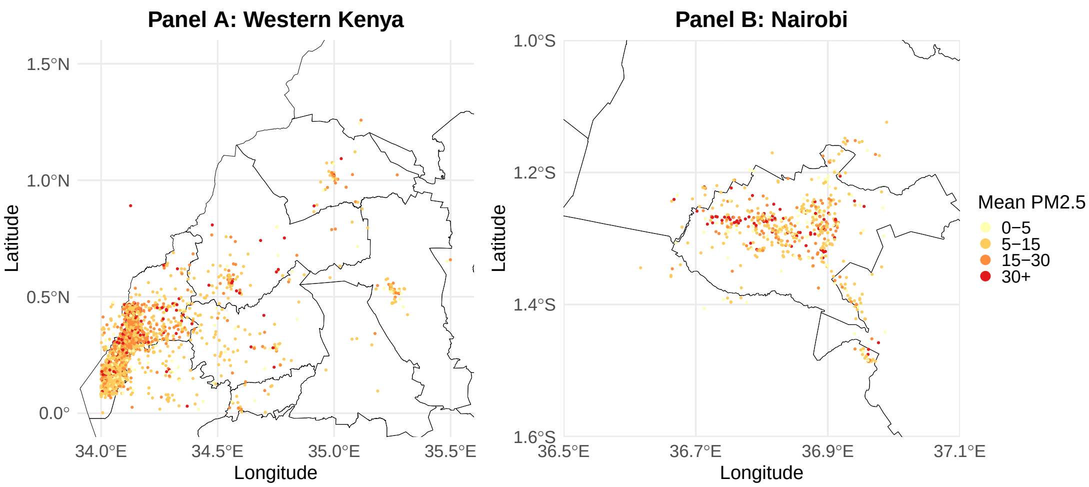
Table 2: Interaction Effects on General Cognitive Scores

	(1) General Cognitive	(2) General Cognitive	(3) General Cognitive	(4) General Cognitive	(5) General Cognitive
Mean PM2.5	-.0033**	-.0020	.0003	-.0039***	.0006
	(.0014)	(.0021)	(.0019)	(.0013)	(.0021)
Female	-.1753**	-.1387**	-.1571***	-.1574***	-.1461**
	(.0600)	(.0517)	(.0507)	(.0503)	(.0566)
Female x PM2.5	.0014				.0007
	(.0014)				(.0011)
Age $\geq$ 35		-.1375**			-.1242**
		(.0482)			(.0468)
Age $\geq$ 35 * PM2.5		-.0007			-.0016
		(.0032)			(.0030)
Any Secondary Schooling	.7623***	.7904***	.8344***	.7624***	.8615***
	(.0220)	(.0215)	(.0535)	(.0220)	(.0505)
Any Secondary Schooling $\times$ PM2.5			-.0056**		-.0055**
			(.0023)		(.0021)
Rural				-.0944	-.0866
				(.0846)	(.0877)
Rural x PM2.5				.0022	.0012
				(.0018)	(.0016)
Geographic and Time FE	YES	YES	YES	YES	YES
Number Observations	5056	5056	5056	5056	5056
Adjusted R-squared	.211	.207	.211	.211	.207

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on a general cognitive index, with interactions by gender, age, education, and rural residence. The general cognitive index is constructed using confirmatory factor analysis (see Gross et al. (2025)) and is standardized to have mean zero and unit standard deviation. 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, the interview setting (indoor vs. outdoor) to account for potential environmental confounders. All regressions also include hour-of-day, day-of-week, month, and geographic fixed effects. 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.

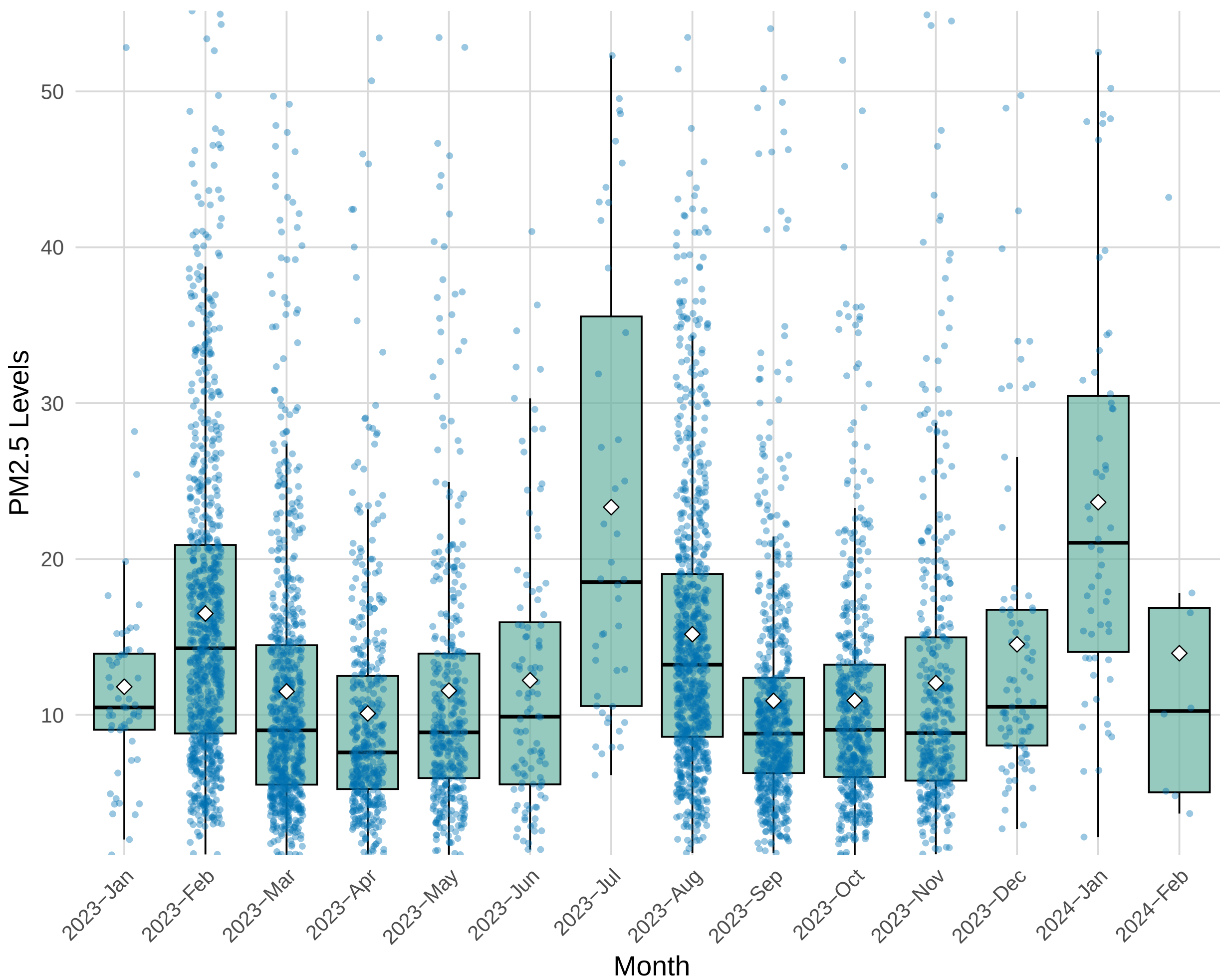
Supplemental Material

Figure S1: Spatial Distribution of Mean $PM_{2.5}$ Levels in Western Kenya and Nairobi



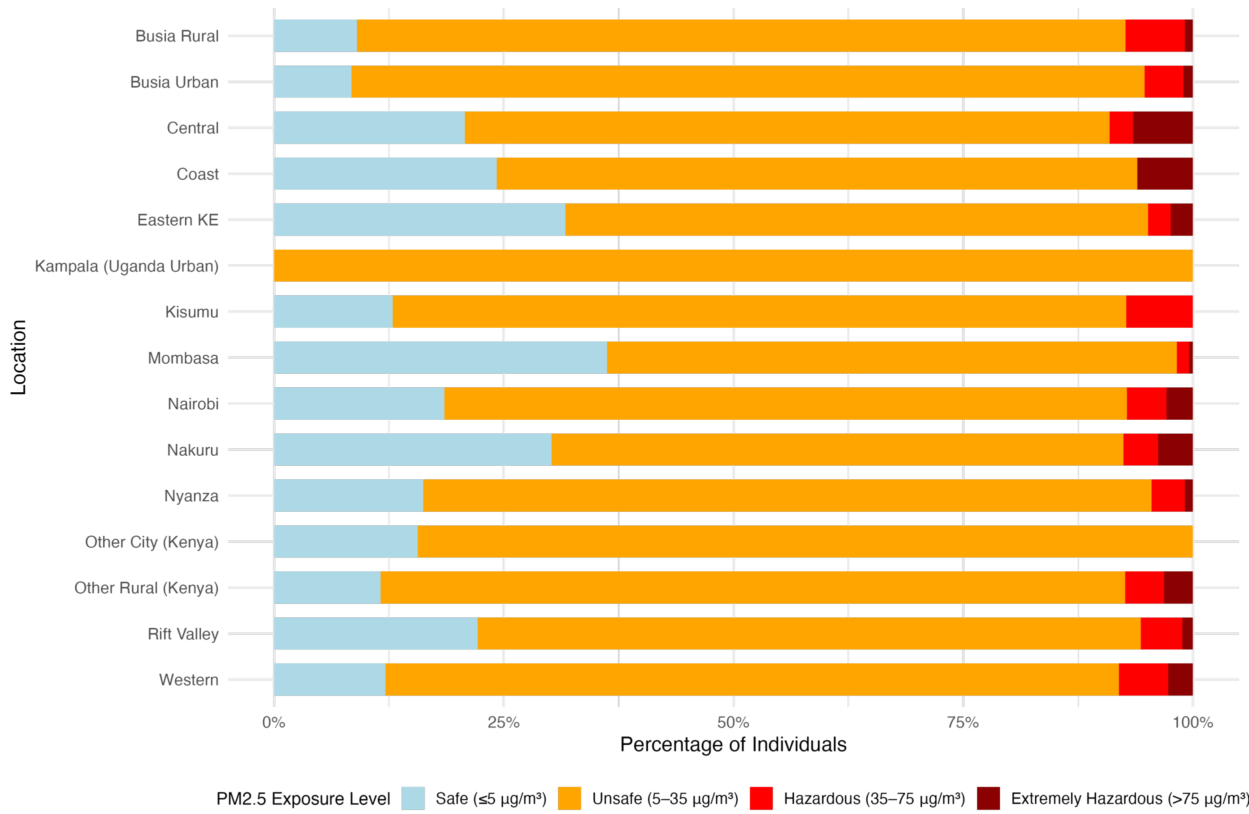
Notes: This figure focuses on $PM_{2.5}$ levels in two key regions of Kenya: Western Kenya (Panel A) and Nairobi (Panel B). Each point represents individual $PM_{2.5}$ measurements, with colors indicating concentration levels (0–5, 5–15, 15–30, 30+ $\mu g/m^3$).

Figure S2: Monthly Distribution of $PM_{2.5}$ Concentrations (Trimmed Top 2.5%)



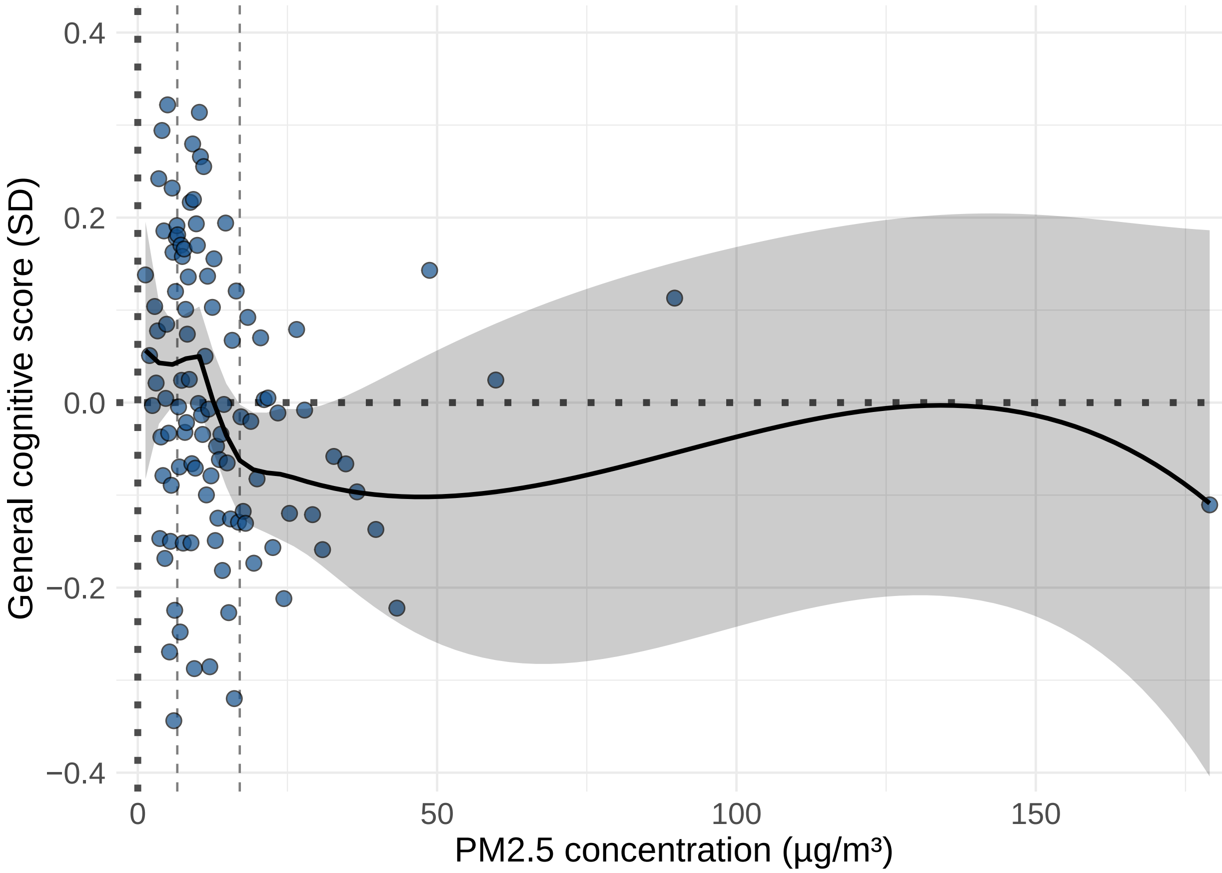
Notes: This figure presents the monthly distribution of $PM_{2.5}$ levels, with data trimmed at the top 2.5% to remove extreme values. Each box plot represents the spread of daily $PM_{2.5}$ levels within each month. The black horizontal line inside each box indicates the median $PM_{2.5}$ level for that month, while the white diamonds indicate the mean $PM_{2.5}$ level for each month. The green bars (boxes) represent the interquartile range (IQR), covering the middle 50% of the data.The whiskers extend up to 1.5×IQR, capturing most of the variation in daily $PM_{2.5}$ levels. The overlaid blue dots represent individual daily $PM_{2.5}$ values.

Figure S3: Share of Population Exposed to Unsafe Air Pollution, by Region



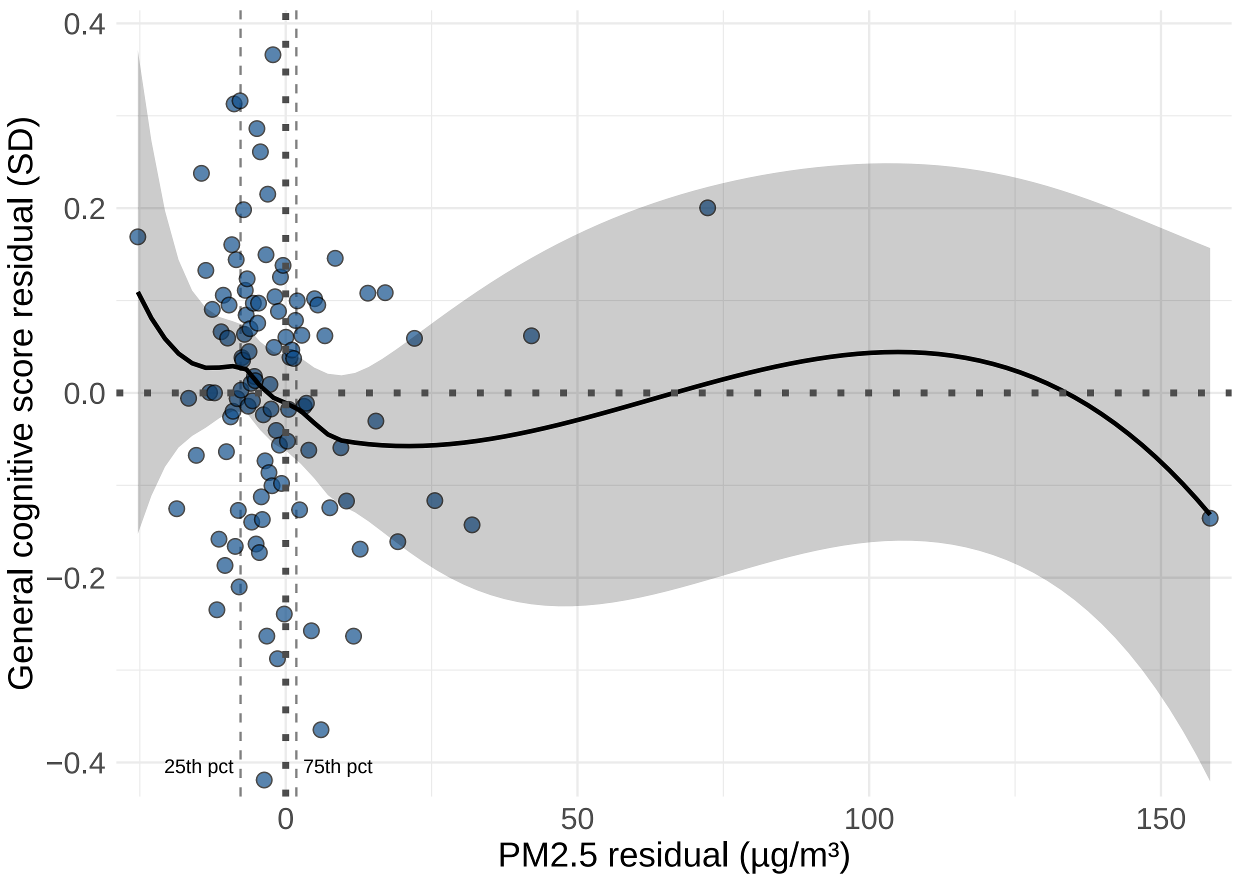
Notes: This figure presents the share of people exposed to varying levels of $PM_{2.5}$ pollution across different regions, categorized using the WHO guideline and Kenya's nationally established ambient air quality standards. The classification is as follows: Safe (5 $\mu g/m^3$) (Light Blue): Concentrations at or below the WHO annual guideline of 5 $\mu g/m^3$. Moderate (5–35 $\mu g/m^3$) (Orange): Concentrations above the WHO guideline but below Kenya's annual ambient air quality standard of 35 $\mu g/m^3$. Hazardous (35–75 $\mu g/m^3$) (Red): Concentrations exceeding Kenya's annual limit of 35 $\mu g/m^3$, indicating elevated long-term health risks. Extremely Hazardous (¿75 $\mu g/m^3$) (Dark Red): Concentrations exceeding Kenya's 24-hour ambient limit of 75 $\mu g/m^3$, indicating severe short-term exposure risks. Each bar represents the percentage of exposed individuals within a given town or region.

Figure S4: Cognition vs. $PM_{2.5}$ Exposure (Untrimmed)



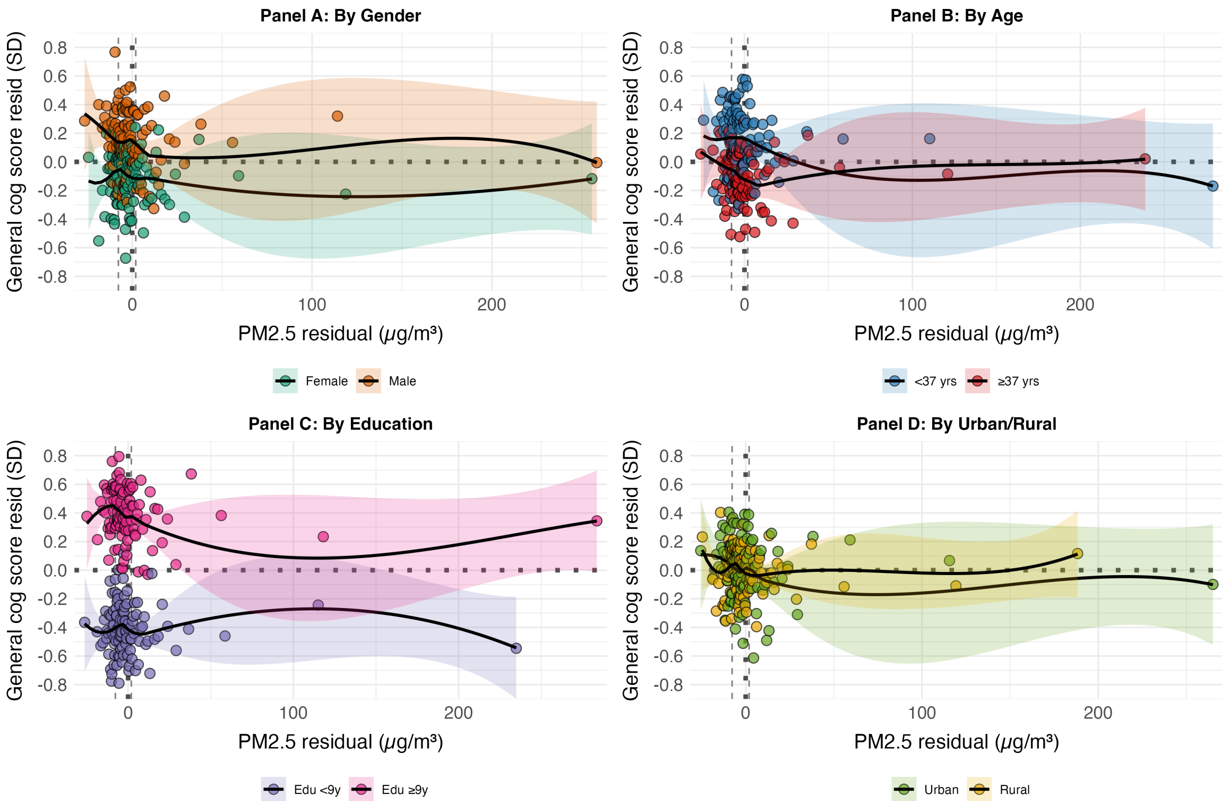
Notes: This figure presents a binned scatterplot of raw general cognitive performance (y, in SD units) against raw $PM_{2.5}$ concentrations (x, in $\mu g/m^3$). The data were sorted into equal-sized bins of 50 based on their raw $PM_{2.5}$ values. Each point plots the bin's mean $PM_{2.5}$ concentration and mean general cognitive score. 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 any non-linear association between pollution and cognition.

Figure S5: Residualized Cognition vs. $PM_{2.5}$ Exposure (Untrimmed)



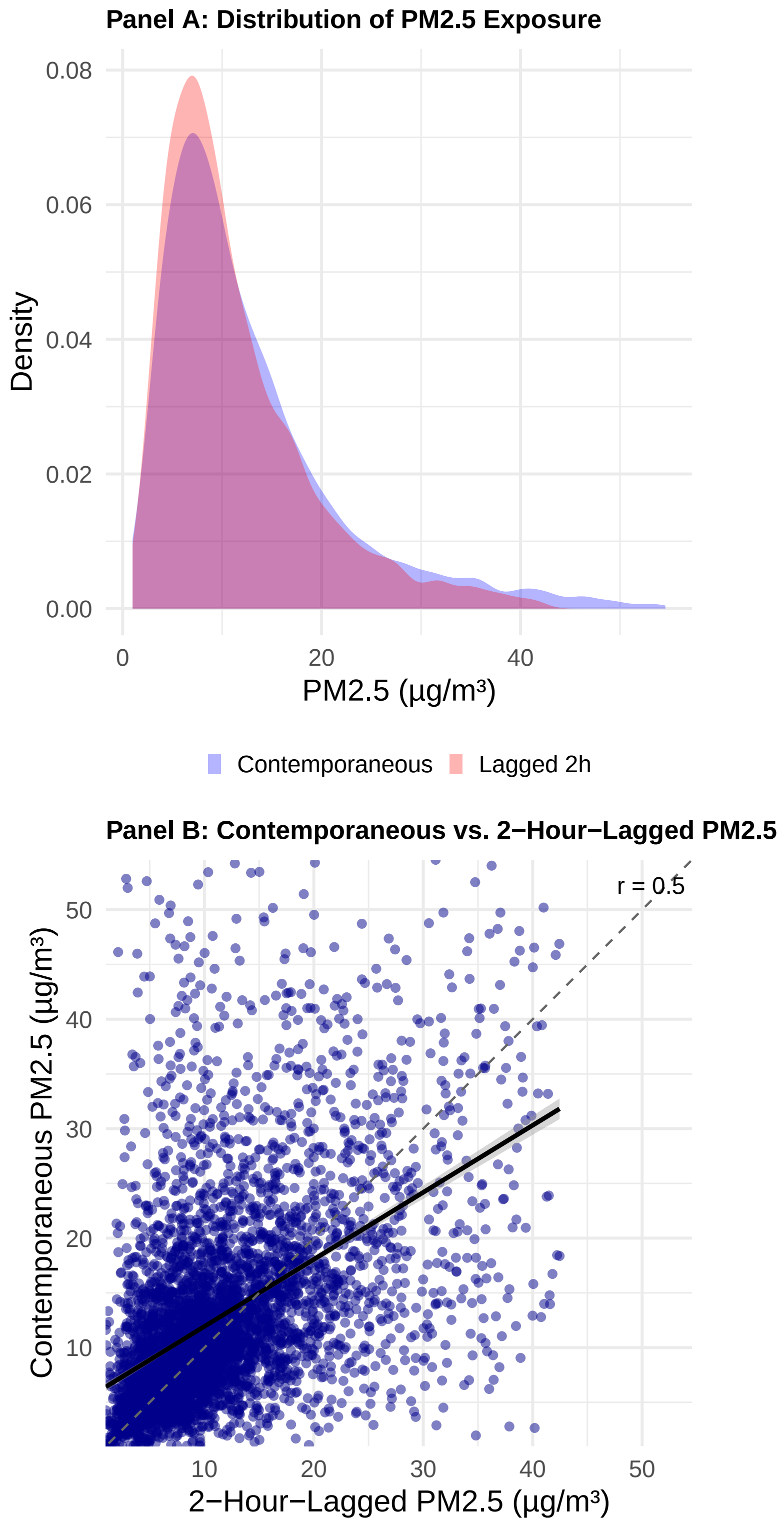
Notes: This figure presents a binned scatterplot of residualized general cognitive performance (y) against residualized $PM_{2.5}$ concentrations (x). Both $PM_{2.5}$ and cognitive scores were then residualized by regressing on hour-of-day, day-of-week, month, and geographic fixed effects; the x-axis therefore shows each bin's average deviation from its predicted mean. The data were sorted into equal-sized bins of 50 based on that $PM_{2.5}$ residual. Each point plots the bin's mean $PM_{2.5}$ residual ($\mu g/m^3$) and 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 any non-linear association.

Figure S6: Residualized Cognition vs. $PM_{2.5}$ Exposure, By Subgroup (Untrimmed)



Notes: Panels A–D show binned scatterplots of residualized general cognitive performance (y) against residualized $PM_{2.5}$ (x) within each subgroup (gender, age, education, and urban/rural). Both $PM_{2.5}$ and cognitive scores were then residualized by regressing 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, the data were sorted into equal-sized bins of 50 based on $PM_{2.5}$ residuals. Each point plots the bin's mean $PM_{2.5}$ residual ($\mu g/m^3$) and mean 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 any non-linear association.

Figure S7: Relationship Between Contemporaneous and 2-Hour Lagged $PM_{2.5}$ Exposure



Notes: Panel A shows kernel density estimates of contemporaneous (blue) and 2-hour-lagged (red) $PM_{2.5}$ exposures, each computed after dropping the top 2.5% of raw $PM_{2.5}$ values. Panel B plots 2-hour-lagged $PM_{2.5}$ (x-axis) against contemporaneous $PM_{2.5}$ (y-axis) in the same trimmed sample. The solid line is the fitted ordinary least squares trend (with 95% CI), and the annotated Pearson's r quantifies the correlation.

Table S1: Descriptive statistics

	Num. Obs.	Mean	SD	Min	Max
Panel A: Cognitive Measurements					
General Cognitive	5320	0.00	1.00	-4.60	3.37
Orientation	5320	0.00	1.00	-6.85	0.72
Memory	5320	0.00	1.00	-4.19	3.50
Executive Function	5320	0.00	1.00	-4.16	2.90
Language	5320	0.00	1.00	-3.72	2.35
Visuospatial	5320	0.01	0.99	-2.79	1.26
Panel B: Atmotube					
Current PM2.5 (µg/m^3)	5320	15.35	20.28	1.00	432.19
Lagged Mean PM2.5 (2-hour lag, µg/m^3)	5263	13.40	15.27	1.00	368.55
Humidity (%)	5320	46.17	10.87	5.68	96.29
Temperature (°C)	5320	30.10	6.71	18.41	89.24
Panel C: Socioeconomic Factors					
Interviewed Outdoors	5320	0.29	0.45	0.00	1.00
Female	5320	0.56	0.50	0.00	1.00
Age (in 2023)	5300	37.16	2.53	28.00	47.00
Any secondary schooling	5207	0.52	0.50	0.00	1.00

Notes: This table presents descriptive statistics in three panels. Panel A reports the mean, standard deviation, and range for general cognitive performance and subdomain scores, which were standardized to have mean 0 and SD 1 in the full sample prior to merging with the Atmotube data. Panel B reports the mean, standard deviation, and range for Atmotube-derived environmental measures. Panel C reports the mean, standard deviation, and range for key socioeconomic characteristics.

Table S2: Association between contemporaneous $PM_{2.5}$ exposure and orientation

	(1) Orientation	(2) Orientation	(3) Orientation	(4) Orientation
Mean PM2.5	.0007	-.0002	-.0003	
	(.0016)	(.0015)	(.0015)	
PM2.5 10-20 µg/m³				.0077
				(.0363)
PM2.5 20-30 µg/m³				.0439
				(.0399)
PM2.5 30-40 µg/m³				-.0259
				(.0708)
PM2.5 above 40 µg/m³				.0349
				(.0756)
Interviewed Outdoor	.0490	.1203***	.0782**	.0793**
	(.0601)	(.0219)	(.0283)	(.0286)
Female			-.1065*	-.1059*
			(.0583)	(.0592)
Age			-.0126***	-.0125***
			(.0023)	(.0024)
Any Secondary Schooling			.2765***	.2767***
			(.0202)	(.0200)
Geographic and Time FE		YES	YES	YES
Number Observations	5187	5187	5056	5056
Adjusted R-squared	.002	.040	.063	.063

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on an orientation index, measured as a standardized index with mean zero and unit standard deviation. The orientation index is constructed using confirmatory factor analysis (see Gross et al. (2025)) and forms part of the broader cognitive battery. 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) does not include fixed effects. Columns (2), (3), and (4) include hour-of-day, day-of-week, month, and geographic fixed effects. $PM_{2.5}$ exposure is modeled as a linear term in columns (1)–(3), and in categorical bins (10–20 $\mu g/m^3$, 20–30 $\mu g/m^3$, 30–40 $\mu g/m^3$, and above 40 $\mu g/m^3$) in column (4) to examine potential non-linear effects. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S3: Association between contemporaneous $PM_{2.5}$ exposure and memory

	(1) Memory	(2) Memory	(3) Memory	(4) Memory
Mean PM2.5	-.0031***	-.0024	-.0024	
	(.0008)	(.0015)	(.0015)	
PM2.5 10-20 µg/m³				-.0550*
				(.0305)
PM2.5 20-30 µg/m³				-.0549
				(.0423)
PM2.5 30-40 µg/m³				-.0670
				(.0682)
PM2.5 above 40 µg/m³				-.0889
				(.0591)
Interviewed Outdoor	.1293***	.1129***	.0722*	.0727*
	(.0388)	(.0372)	(.0366)	(.0377)
Female			.0047	.0055
			(.0416)	(.0418)
Age			-.0312***	-.0314***
			(.0034)	(.0034)
Any Secondary Schooling			.6013***	.6013***
			(.0220)	(.0221)
Geographic and Time FE		YES	YES	YES
Number Observations	5187	5187	5056	5056
Adjusted R-squared	.004	.027	.131	.131

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on an memory index, measured as a standardized index with mean zero and unit standard deviation. The memory index is constructed using confirmatory factor analysis (see Gross et al. (2025)) and forms part of the broader cognitive battery. 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) does not include fixed effects. Columns (2), (3), and (4) include hour-of-day, day-of-week, month, and geographic fixed effects. $PM_{2.5}$ exposure is modeled as a linear term in columns (1)–(3), and in categorical bins (10–20 μg/m^3, 20–30 μg/m^3, 30–40 μg/m^3, and above 40 μg/m^3) in column (4) to examine potential non-linear effects. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S4: Association between contemporaneous $PM_{2.5}$ exposure and executive function

	(1) Executive Function	(2) Executive Function	(3) Executive Function	(4) Executive Function
Mean PM2.5	-.0026***	-.0017	-.0022**	
	(.0007)	(.0011)	(.0009)	
PM2.5 10-20 µg/m³				-.0283
				(.0228)
PM2.5 20-30 µg/m³				-.0428
				(.0300)
PM2.5 30-40 µg/m³				-.0662
				(.0469)
PM2.5 above 40 µg/m³				-.1272*
				(.0686)
Interviewed Outdoor	.2306***	.1817***	.0768	.0768
	(.0557)	(.0534)	(.0462)	(.0469)
Female			-.2884***	-.2884***
			(.0396)	(.0399)
Age			-.0328***	-.0328***
			(.0046)	(.0046)
Any Secondary Schooling			.6902***	.6905***
			(.0152)	(.0152)
Geographic and Time FE		YES	YES	YES
Number Observations	5187	5187	5056	5056
Adjusted R-squared	.012	.035	.197	.196

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on an executive function index, measured as a standardized index with mean zero and unit standard deviation. The executive function index is constructed using confirmatory factor analysis (see Gross et al. (2025)) and forms part of the broader cognitive battery. 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) does not include fixed effects. Columns (2), (3), and (4) include hour-of-day, day-of-week, month, and geographic fixed effects. $PM_{2.5}$ exposure is modeled as a linear term in columns (1)–(3), and in categorical bins (10–20 $\mu g/m^3$, 20–30 $\mu g/m^3$, 30–40 $\mu g/m^3$, and above 40 $\mu g/m^3$) in column (4) to examine potential non-linear effects. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S5: Association between contemporaneous $PM_{2.5}$ exposure and language

	(1) Language	(2) Language	(3) Language	(4) Language
Mean PM2.5	-.0016	-.0003	-.0002	
	(.0009)	(.0011)	(.0009)	
PM2.5 10-20 µg/m³				-.0235
				(.0280)
PM2.5 20-30 µg/m³				-.0052
				(.0394)
PM2.5 30-40 µg/m³				-.0322
				(.0307)
PM2.5 above 40 µg/m³				.0115
				(.0638)
Interviewed Outdoor	.1547*	.1173*	.0635	.0638
	(.0744)	(.0662)	(.0653)	(.0654)
Female			-.0694	-.0686
			(.0457)	(.0454)
Age			-.0114***	-.0115***
			(.0032)	(.0032)
Any Secondary Schooling			.6207***	.6206***
			(.0250)	(.0254)
Geographic and Time FE		YES	YES	YES
Number Observations	5187	5187	5056	5056
Adjusted R-squared	.006	.030	.130	.129

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on an language index, measured as a standardized index with mean zero and unit standard deviation. The language index is constructed using confirmatory factor analysis (see Gross et al. (2025)) and forms part of the broader cognitive battery. 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) does not include fixed effects. Columns (2), (3), and (4) include hour-of-day, day-of-week, month, and geographic fixed effects. $PM_{2.5}$ exposure is modeled as a linear term in columns (1)–(3), and in categorical bins (10–20 $\mu g/m^3$, 20–30 $\mu g/m^3$, 30–40 $\mu g/m^3$, and above 40 $\mu g/m^3$) in column (4) to examine potential non-linear effects. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S6: Association between contemporaneous $PM_{2.5}$ exposure and visuospatial skills

	(1) Visuospatial	(2) Visuospatial	(3) Visuospatial	(4) Visuospatial
Mean PM2.5	-.0023***	-.0022**	-.0024***	
	(.0006)	(.0008)	(.0008)	
PM2.5 10-20 µg/m³				-.0368*
				(.0207)
PM2.5 20-30 µg/m³				-.0535
				(.0415)
PM2.5 30-40 µg/m³				-.0928***
				(.0219)
PM2.5 above 40 µg/m³				-.1214**
				(.0494)
Interviewed Outdoor	.1626***	.1364***	.0354	.0352
	(.0368)	(.0428)	(.0344)	(.0351)
Female			-.3200***	-.3200***
			(.0293)	(.0296)
Age			-.0074*	-.0075*
			(.0038)	(.0038)
Any Secondary Schooling			.5312***	.5314***
			(.0158)	(.0157)
Geographic and Time FE		YES	YES	YES
Number Observations	5187	5187	5056	5056
Adjusted R-squared	.006	.012	.119	.119

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on an visuospatial index, measured as a standardized index with mean zero and unit standard deviation. The visuospatial index is constructed using confirmatory factor analysis (see Gross et al. (2025)) and forms part of the broader cognitive battery. 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) does not include fixed effects. Columns (2), (3), and (4) include hour-of-day, day-of-week, month, and geographic fixed effects. $PM_{2.5}$ exposure is modeled as a linear term in columns (1)–(3), and in categorical bins (10–20 μg/m^3, 20–30 μg/m^3, 30–40 μg/m^3, and above 40 μg/m^3) in column (4) to examine potential non-linear effects. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S7: Interaction Effects on Orientation

	(1) Orientation	(2) Orientation	(3) Orientation	(4) Orientation	(5) Orientation
Mean PM2.5	-.0033**	.0013	-.0008	-.0018	-.0053
	(.0015)	(.0033)	(.0018)	(.0024)	(.0033)
Female	-.1770**	-.0971	-.1066*	-.1059*	-.1717**
	(.0681)	(.0591)	(.0583)	(.0583)	(.0655)
Female x PM2.5	.0055**				.0058***
	(.0019)				(.0018)
Age $\geq$ 35		.0028			-.0113
		(.0386)			(.0370)
Age $\geq$ 35 * PM2.5		-.0019			-.0007
		(.0031)			(.0030)
Any Secondary Schooling	.2765***	.2915***	.2654***	.2766***	.2654***
	(.0201)	(.0190)	(.0343)	(.0201)	(.0327)
Any Secondary Schooling $\times$ PM2.5			.0009		.0020
			(.0017)		(.0019)
Rural				-.0943*	-.0977*
				(.0448)	(.0461)
Rural x PM2.5				.0023	.0023
				(.0027)	(.0029)
Geographic and Time FE	YES	YES	YES	YES	YES
Number Observations	5056	5056	5056	5056	5056
Adjusted R-squared	.064	.062	.063	.063	.063

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on an orientation index, with interactions by gender, age, education, and rural residence. The orientation index, standardized at mean zero and unit standard deviation, is constructed using confirmatory factor analysis (see Gross et al. (2025)) and forms part of the broader cognitive battery. 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, the interview setting (indoor vs. outdoor) to account for potential environmental confounders. All regressions also include hour-of-day, day-of-week, month, and geographic fixed effects. 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.

Table S8: Interaction effects on memory

	(1) Memory	(2) Memory	(3) Memory	(4) Memory	(5) Memory
Mean PM2.5	-.0027	-.0043*	-.0006	-.0047**	-.0045
	(.0022)	(.0024)	(.0016)	(.0018)	(.0039)
Female	-.0035	.0244	.0053	.0052	.0170
	(.0606)	(.0421)	(.0418)	(.0418)	(.0517)
Female x PM2.5	.0006				.0006
	(.0018)				(.0013)
Age $\geq$ 35		-.1512**			-.1426**
		(.0553)			(.0567)
Age $\geq$ 35 * PM2.5		.0023			.0017
		(.0042)			(.0043)
Any Secondary Schooling	.6013***	.6297***	.6454***	.6012***	.6659***
	(.0220)	(.0199)	(.0344)	(.0219)	(.0326)
Any Secondary Schooling $\times$ PM2.5			-.0034*		-.0028
			(.0016)		(.0016)
Rural				-.0951	-.0912
				(.0881)	(.0882)
Rural x PM2.5				.0037	.0029
				(.0025)	(.0024)
Geographic and Time FE	YES	YES	YES	YES	YES
Number Observations	5056	5056	5056	5056	5056
Adjusted R-squared	.131	.127	.131	.131	.127

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on an memory index, with interactions by gender, age, education, and rural residence. The memory index, standardized at mean zero and unit standard deviation, is constructed using confirmatory factor analysis (see Gross et al. (2025)) and forms part of the broader cognitive battery. 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, the interview setting (indoor vs. outdoor) to account for potential environmental confounders. All regressions also include hour-of-day, day-of-week, month, and geographic fixed effects. 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.

Table S9: Interaction effects on executive function

	(1) Executive Function	(2) Executive Function	(3) Executive Function	(4) Executive Function	(5) Executive Function
Mean PM2.5	-.0018	-.0015	.0028	-.0019	.0082**
	(.0012)	(.0018)	(.0017)	(.0018)	(.0033)
Female	-.2789***	-.2704***	-.2870***	-.2873***	-.2396***
	(.0480)	(.0415)	(.0404)	(.0396)	(.0502)
Female x PM2.5	-.0007				-.0022*
	(.0014)				(.0011)
Age $\geq$ 35		-.1470***			-.1172***
		(.0337)			(.0339)
Age $\geq$ 35 * PM2.5		-.0009			-.0030*
		(.0016)			(.0017)
Any Secondary Schooling	.6902***	.7162***	.8137***	.6910***	.8514***
	(.0153)	(.0148)	(.0536)	(.0150)	(.0527)
Any Secondary Schooling $\times$ PM2.5			-.0095***		-.0103***
			(.0027)		(.0026)
Rural				-.1607*	-.1451
				(.0809)	(.0853)
Rural x PM2.5				-.0003	-.0018
				(.0021)	(.0019)
Geographic and Time FE	YES	YES	YES	YES	YES
Number Observations	5056	5056	5056	5056	5056
Adjusted R-squared	.197	.193	.199	.197	.196

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on an executive function index, with interactions by gender, age, education, and rural residence. The executive function index, standardized at mean zero and unit standard deviation, is constructed using confirmatory factor analysis (see Gross et al. (2025)) and forms part of the broader cognitive battery. 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, the interview setting (indoor vs. outdoor) to account for potential environmental confounders. All regressions also include hour-of-day, day-of-week, month, and geographic fixed effects. 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.

Table S10: Interaction effects on language

	(1) Language	(2) Language	(3) Language	(4) Language	(5) Language
Mean PM2.5	-.0026*	.0055**	.0006	-.0005	.0038
	(.0014)	(.0021)	(.0015)	(.0012)	(.0031)
Female	-.1262**	-.0640	-.0691	-.0695	-.1108**
	(.0446)	(.0469)	(.0460)	(.0457)	(.0494)
Female x PM2.5	.0044*				.0037
	(.0021)				(.0021)
Age $\geq$ 35		.0304			.0258
		(.0391)			(.0403)
Age $\geq$ 35 * PM2.5		-.0068**			-.0064**
		(.0023)			(.0024)
Any Secondary Schooling	.6207***	.6298***	.6406***	.6205***	.6494***
	(.0250)	(.0266)	(.0455)	(.0251)	(.0485)
Any Secondary Schooling $\times$ PM2.5			-.0015		-.0015
			(.0017)		(.0017)
Rural				.0181	.0187
				(.0825)	(.0833)
Rural x PM2.5				.0004	.0002
				(.0012)	(.0012)
Geographic and Time FE	YES	YES	YES	YES	YES
Number Observations	5056	5056	5056	5056	5056
Adjusted R-squared	.130	.130	.130	.129	.129

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on an language index, with interactions by gender, age, education, and rural residence. The language index, standardized at mean zero and unit standard deviation, is constructed using confirmatory factor analysis (see Gross et al. (2025)) and forms part of the broader cognitive battery. 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, the interview setting (indoor vs. outdoor) to account for potential environmental confounders. All regressions also include hour-of-day, day-of-week, month, and geographic fixed effects. 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.

Table S11: Interaction effects on visuospatial skills

	(1) Visuospatial	(2) Visuospatial	(3) Visuospatial	(4) Visuospatial	(5) Visuospatial
Mean PM2.5	-.0032**	-.0011	-.0014	-.0046**	-.0026
	(.0012)	(.0036)	(.0023)	(.0017)	(.0029)
Female	-.3390***	-.3182***	-.3197***	-.3207***	-.3306***
	(.0467)	(.0301)	(.0295)	(.0295)	(.0430)
Female x PM2.5	.0015				.0009
	(.0018)				(.0014)
Age $\geq$ 35		-.0448			-.0422
		(.0789)			(.0721)
Age $\geq$ 35 * PM2.5		-.0016			-.0019
		(.0043)			(.0037)
Any Secondary Schooling	.5312***	.5333***	.5557***	.5304***	.5529***
	(.0158)	(.0163)	(.0520)	(.0156)	(.0512)
Any Secondary Schooling $\times$ PM2.5			-.0019		-.0016
			(.0038)		(.0038)
Rural				.0735	.0770
				(.1122)	(.1140)
Rural x PM2.5				.0034	.0031
				(.0027)	(.0029)
Geographic and Time FE	YES	YES	YES	YES	YES
Number Observations	5056	5056	5056	5056	5056
Adjusted R-squared	.119	.119	.119	.119	.119

Notes: This table presents the estimated effects of $PM_{2.5}$ exposure on an visuospatial index, with interactions by gender, age, education, and rural residence. The visuospatial index, standardized at mean zero and unit standard deviation, is constructed using confirmatory factor analysis (see Gross et al. (2025)) and forms part of the broader cognitive battery. 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, the interview setting (indoor vs. outdoor) to account for potential environmental confounders. All regressions also include hour-of-day, day-of-week, month, and geographic fixed effects. 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.

Table S12: Robustness Checks using $PM_{2.5}$ exposure from the previous 2 hours window

	(1) General Cognitive	(2) Orientation	(3) Memory	(4) Executive Function	(5) Language	(6) Visuospatial
Mean PM2.5	-.0025*	-.0000	-.0025	-.0021**	-.0003	-.0016
	(.0012)	(.0016)	(.0017)	(.0009)	(.0011)	(.0009)
Lagged Mean PM2.5	.0003	-.0004	.0005	.0002	.0008	-.0015**
	(.0010)	(.0011)	(.0010)	(.0007)	(.0010)	(.0007)
Interviewed Outdoor	.0867*	.0765**	.0708*	.0778*	.0606	.0382
	(.0470)	(.0273)	(.0370)	(.0435)	(.0631)	(.0343)
Female	-.1521***	-.1033*	.0111	-.2844***	-.0672	-.3174***
	(.0473)	(.0547)	(.0397)	(.0362)	(.0440)	(.0291)
Age	-.0330***	-.0130***	-.0308***	-.0330***	-.0116***	-.0073*
	(.0034)	(.0023)	(.0035)	(.0046)	(.0030)	(.0038)
Any Secondary Schooling	.7612***	.2820***	.5993***	.6876***	.6194***	.5338***
	(.0233)	(.0198)	(.0234)	(.0153)	(.0271)	(.0169)
Number Observations	5001	5001	5001	5001	5001	5001
Adjusted R-squared	.210	.064	.130	.195	.130	.119

Notes: This table presents a robustness check using $PM_{2.5}$ exposure from the previous two hours to examine the sensitivity of the estimated effects on cognitive performance. Although the target window is the full two hours prior, the Atmotube device was occasionally powered off earlier in the day (e.g., before fieldwork began), resulting in a shorter pre-interview window; the mean available lookback period is approximately 101 minutes. 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, as well as hour-of-day, day-of-week, month, and geographic fixed effects. Standard errors, clustered at the geographic level, are reported in parentheses. Statistical significance is denoted as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table S13: Robustness to Alternative Geographic Fixed Effects

	(1) General Cognitive	(2) General Cognitive	(3) General Cognitive	(4) General Cognitive
Mean PM2.5	-.0026**	-.0028**	-.0025**	-.0019*
	(.0010)	(.0011)	(.0011)	(.0010)
Interviewed Outdoors	.0882*	.1010**	.0925*	.0898*
	(.0480)	(.0466)	(.0467)	(.0459)
Female	-.1580***	-.1534***	-.1460**	-.1431**
	(.0502)	(.0505)	(.0493)	(.0486)
Age	-.0332***	-.0332***	-.0343***	-.0348***
	(.0034)	(.0034)	(.0041)	(.0041)
Any Secondary Schooling	.7623***	.7680***	.7667***	.7690***
	(.0220)	(.0201)	(.0200)	(.0188)
Geographic FE	Approach 1	Approach 2	Approach 3	Approach 4
Number Observations	5056	5051	5056	5056
Adjusted R-squared	.211	.209	.205	.201

Notes: This table reports estimates of the General Cognitive Index under four alternative definitions of geographic fixed effects. Approach 1 uses the original geographic classification shown in Figure 1, which distinguishes major urban areas (Busia Urban, Kisumu, Mombasa, Nairobi, Nakuru, Kampala), Busia Rural, the primary Kenyan provincial regions (Western, Nyanza, Coast, Central, Eastern, Rift Valley, North Eastern), and residual "Other City" and "Other Rural" categories. Approach 2 replaces this with fixed effects for each Kenyan county represented in the sample (41 distinct counties). Approach 3 instead uses fixed effects based on a coarser categorization, including Busia Town, Eldoret, Kisumu, Mombasa, Nairobi, Nakuru, Kampala, an "Other City/Large Town" group, and a rural category. Approach 4 replaces these classifications with a simple urban–rural fixed effect. All specifications control for mean temperature, mean humidity, and the interview setting (indoor vs. outdoor), and include hour-of-day, day-of-week, and month fixed effects. Standard errors are clustered at the Approach 1 geographic level and reported in parentheses. Statistical significance is denoted as: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table S14: Associations between individual characteristics and current $PM_{2.5}$ exposure

	(1) Mean PM2.5	(2) Mean PM2.5	(3) Mean PM2.5	(4) Mean PM2.5
Any Secondary Schooling	-.0402	-.0936	-.0200	-.0140
	(.2461)	(.2671)	(.2314)	(.2310)
Female	.0310	-.0291	.0750	.1140
	(.1447)	(.1317)	(.1292)	(.1342)
Age	-.0530	-.0568	-.0545	-.0654
	(.0339)	(.0346)	(.0349)	(.0375)
Geographic FE	Approach 1	Approach 2	Approach 3	Approach 4
Number Observations	5056	5051	5056	5056
Joint F-Test (p-value)	.429	.392	.412	.305
Adjusted R-squared	.158	.159	.155	.149

Notes: This table reports balance tests that examine whether contemporaneous $PM_{2.5}$ exposure varies systematically with observable individual characteristics (education, gender, and age). Each column estimates a version of the regression in which mean $PM_{2.5}$ is regressed on these characteristics, controlling for mean temperature, mean humidity, and the interview setting (indoor vs. outdoor). All specifications also include hour-of-day, day-of-week, and month fixed effects. The four approaches differ only in how geographic fixed effects are defined, where the various approaches are defined in Table S13. Standard errors, clustered at the Approach 1 geographic level, are shown in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.