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Key Points:
- Interaction between $PM_{2.5}$ levels above National Ambient Air Quality Standard and household air pollution, leads to a substantial rise in mortality observed for all age-groups
- Districts with $PM_{2.5}$ levels exceeding the National Ambient Air Quality Standard show an approximately two fold increase in the odds of mortality among children

Supporting Information:
Supporting Information may be found in the online version of this article.

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Air Pollution and Mortality in India: Investigating the Nexus of Ambient and Household Pollution Across Life Stages

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Abstract Air pollution in India is a foremost environmental risk factor that affects human health. This study first investigates the geographical distribution of ambient and household air pollution (HAP) and then examines the associated mortality risk. Data on fine particulate matter ($PM_{2.5}$) concentration has been extracted from the Greenhouse Gas Air Pollution Interactions and Synergies (GAINS) model. HAP, mortality and socio-demographic data were extracted from the National Family and Health Survey-5, India, 2019–2021. Regression models were applied to see the difference in age-group mortality by different pollution parameters. The districts with $PM_{2.5}$ concentration above the National Ambient Air Quality Standard (NAAQS) level of 40 μg/m^3 show a higher risk of neonatal (OR-1.86, CI 1.418–2.433), postneonatal (OR-2.04, CI 1.399–2.971), child (OR-2.19, CI 0.999–4.803) and adult death (OR-1.13, CI 1.060–1.208). The absence of a separate kitchen shows a higher probability of neonatal (OR: 1.18, CI 1.074–1.306) and adult death (OR-1.06, CI 1.027–1.088). The interaction between $PM_{2.5}$ levels above NAAQS and HAP leads to a substantial rise in mortality observed for neonatal (OR 1.19 CI 1.051–1.337), child (OR 1.17 CI 1.054–1.289), and adult (OR 1.13 CI 1.096–1.168) age groups. This study advocates that there is a strong positive association between ambient and HAP and mortality risk. $PM_{2.5}$ pollution significantly contributes to the mortality risk in all age groups. Children are more vulnerable to HAP than adults. In India, policymakers should focus on reducing the anthropogenic $PM_{2.5}$ emission at least to reach the NAAQS, which can substantially reduce disease burden and, more precisely, mortality.

Plain Language Summary Air pollution in India poses a significant threat to human health, as explored in this study. Using data from the Greenhouse Gas Air Pollution Interactions and Synergies model and the National Family and Health Survey-5, the research examines both ambient and household air pollution and their impact on mortality risk. Analyzing fine particulate matter ($PM_{2.5}$) concentration, the study finds that districts exceeding the National Ambient Air Quality Standard (NAAQS) of 40 μg/m^3 face increased mortality risks across all age groups, including neonatal, postneonatal, child, and adult deaths. Additionally, the absence of separate kitchens correlates with higher neonatal and adult mortality rates. The interaction between elevated $PM_{2.5}$ levels and household air pollution further amplifies mortality risks, particularly among neonates, children, and adults. The study underscores the urgent need for policymakers to mitigate anthropogenic $PM_{2.5}$ emissions to meet NAAQS standards, which could significantly reduce mortality and disease burden, particularly among vulnerable populations like children.

1. Introduction

Ambient air pollution is a foremost environmental risk factor that affects human health in various ways, leading to increased morbidity and mortality. There are strong shreds of evidence (Babatola, 2018; Mahapatra et al., 2020) that air pollution harms human health, and it is also growing and evolving rapidly (Babatola, 2018; Mahapatra et al., 2020). Today, air pollution is the most significant environmental issue for the whole world because air cannot be limited or restricted to a particular region; it circulates over the atmosphere, and the pollution is distributed universally. Air pollutants that are significantly associated with morbidity and mortality are nitrogen oxides (NO_x), carbon monoxide (CO), sulfur dioxides (SO_2), volatile organic compounds, and polycyclic aromatic hydrocarbons. However, it is fine particulate matter ($PM_{2.5}$), with an aerodynamic diameter ≤2.5 μm, which has been studied most intensively and used as a representative indicator of exposure to air pollution and its

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association with various morbidity conditions (Adhikary et al., 2024; Ailshire & Crimmins, 2014; Amoatey et al., 2020; Chen et al., 2017; Giannadaki et al., 2016; Héroux et al., 2015; Wu et al., 2018).

$PM_{2.5}$ is a complex mixture of organic and inorganic particles of tiny diameter, which enters the respiratory system by inhalation process and causes respiratory and cardiovascular diseases, central nervous system dysfunction, reproductive issues, and cancer (Anderson et al., 2012; Kampa & Castanas, 2008). The associated diseases are not just restricted to physiological outcomes but psychological as well, with people affected by air pollution (Braithwaite et al., 2019). The effect has been observed all over the globe; international reports have revealed an augmented risk of morbidity and mortality worldwide (Health Effects Institute, 2020; International Energy Agency, 2016; World Health Organization, 2016).

According to research on the global burden of air pollution, anthropogenic $PM_{2.5}$ causes 3.5 million cardiovascular deaths and 220,000 lung cancer deaths per year (Anenberg et al., 2010). In Sub-Saharan Africa, a 10 $\mu g/m^3$ increase in $PM_{2.5}$ concentration is linked to a 9% increase in infant mortality (Heft-Neal et al., 2018). The adverse effect is more prominent in large urban areas where vehicular emission is high, and it highly contributes to the degradation of air quality. Air pollution is very severe in low and middle-income countries due to a dense population and unplanned urbanization simultaneously with rapid industrialization (Mannucci & Franchini, 2017). Especially in countries with substantial economic and social disparities where the knowledge of sustainable environmental management is lacking, the air quality deteriorates faster than in high-income countries with better knowledge and awareness. Besides ambient air pollution, household pollution is also high due to unclean fuel use (wood, coal/lignite, crop wastes, charcoal, dung and kerosene) and the absence of separate kitchens among lower-income households. As a result, many premature deaths attributable to air pollution occur every year (Heft-Neal et al., 2018; Landrigan et al., 2018).

Indian cities rank high in air pollution on a global scale (Amann et al., 2017; Guttikunda et al., 2014; IQAir, 2021). The National Capital Territory of Delhi ranked the most polluted capital city based on data collated for 2021, and another 62 Indian cities are in the top 100 most polluted cities at the global level (IQAir, 2021). In Indian cities, every 10-unit rise in PM_{10} levels increases the risk of neonatal mortality by 6% and premature death by 8% (Mahapatra et al., 2020). In the National Capital Region (NCR) of Delhi, every 10 $\mu g/m^3$ increase in $PM_{2.5}$ exposure results in a 0.52% increase in non-trauma all-cause death (P. Joshi et al., 2021). The mortality risk associated with $PM_{2.5}$ exposure varies by age group. Long and short-term exposure to $PM_{2.5}$ is hazardous for children and the elderly. Increases in the exposure of 25 $\mu g/m^3$ were linked to a 0.8% increase in daily non-accidental deaths and a 1.5% increase in mortality among individuals aged 60 and above (Krishna et al., 2021).

In the Indian context, studies are available on air pollution and mortality risk at the regional level (P. Joshi et al., 2021; Krishna et al., 2021). Earlier studies in the Indian context are either micro-level (regional) or have some methodological limitations. Mahapatra et al. (2020) established the associations between child mortality risk and air pollution. However, their study integrated the city-level pollution data with district-level mortality estimation. Because district size is bigger than cities in population and space, such integration may not reveal the actual intensity of air pollution. Second, most of the earlier studies investigated either the role of household air pollution (HAP) or the role of ambient air pollution separately (Chowdhury & Dey, 2016; P. Joshi et al., 2021; Naz et al., 2016). Though there are several studies conducted in India on air quality and health behavior among children and adults (Lakshmi et al., 2013; Naz et al., 2016; Pandey et al., 2021), none have explored the association between ambient and HAP with mortality across different age groups. The exposure to poor air quality depends on a number of factors, and hence, the intensity of the negative impact of poor quality can affect children and adults differently. In addition to that, the 19% increase in the use of clean fuel in India under the Pradhan Mantri Ujjwala Yojana (PMUY) scheme (IIPS & ICF, 2017, 2021) could have influenced the pollution effect on health at a regional level. The availability of new and nationally representative data for mortality and air quality from the National Family and Health Survey-5 (NFHS-5) in 2019–2021 and the Greenhouse Gas Air Pollution Interactions and Synergies (GAINS) model, respectively, allows studying the association of mortality risk by different age groups with household and ambient air pollution. Thus, using a nationally representative large-scale survey data set, the present study investigated the association of ambient and household air quality with neonatal, postneonatal, child, and adult mortality in India.

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2. Methods

2.1. Data on Ambient $PM_{2.5}$ Concentration for 2020 in India

This study extracts the district-level data on fine particulate matter ($PM_{2.5}$) concentration from the GAINS model. Subsequently, we integrate this high-resolution environmental data with the comprehensive NFHS-5 data set, which furnishes socio-demographic and health-related information for individuals across all 707 districts of India. The GAINS model assesses strategies that reduce emissions of multiple air pollutants and greenhouse gases at the least cost and minimize their harmful effects on human health, ecosystems and climate change (Amann et al., 2011, 2020; Klimont et al., 2017). The model follows the pathways of the emissions from their sources to their impacts in the scenario analysis mode and provides estimates of the costs and environmental benefits of alternative emission control strategies. The model provides $PM_{2.5}$ for different emission scenarios in India. In the current study, we have used district-level concentrations of $PM_{2.5}$ for the base version of the emission scenario. Further details on modeling procedures are provided in Supporting Information S1. Modeled $PM_{2.5}$ concentrations are frequently utilized in health impact analysis due to their numerous advantages over monitored $PM_{2.5}$ data. The scarcity and limited coverage of $PM_{2.5}$ monitoring data, particularly in rural and remote areas of India, are evident. For instance, the National Air Quality Monitoring Program by the Government of India established 703 monitoring stations across 307 cities and towns, with a notable concentration in urban areas, leaving rural regions with no coverage (Balakrishnan et al., 2014; Gordon et al., 2018). This imbalance in data distribution may contribute to exposure misclassification in large-scale modeling and epidemiological studies, particularly given the substantial health impact of HAP in rural areas. Models, such as the GAINS model, effectively address the limited availability of monitoring data, offering comprehensive information over broader regions. Modeled concentrations provide finer spatial and temporal resolution, offering detailed insights into $PM_{2.5}$ levels at specific locations and times, thereby improving accuracy in health risk assessments. Moreover, modeling proves to be a more cost-effective approach for extensive areas and prolonged durations, relying on efficient computer simulations. Recent advancements in accuracy have been made as models now consider various factors influencing $PM_{2.5}$ concentration.

2.2. Data on Household Air Quality

The type of fuel used for cooking, availability of separate kitchens, and availability of ventilation, if cooked within a household, were all used to determine HAP. These three variables were used as a proxy measure of HAP. The amount of pollution emitted by households is directly proportional to the kind of energy used for cooking, with unclean fuels producing more pollution per cooked meal than liquid or gaseous fuels. As a result, the household fuel use pattern could be used to assess HAP. NFHS-5 compiled information on cooking fuel, asking, "What sort of fuel does your household mostly use for cooking?." Electricity, Liquefied Petroleum Gas (LPG) and natural gas, biogas, kerosene, coal and lignite, biomass (including charcoal, wood, straw/shrubs/grass, agricultural residues, animal manure), and others were included in a complete list of different types of cooking fuels used in the household. We divided household fuel consumption into two categories: (a) clean fuels, that is, electricity, LPG, natural gas, and biogas, and (b) unclean fuels, that is, kerosene, coal and lignite, biomass. It is worth mentioning that the trend of using liquid fuels (i.e., kerosene) for cooking is decreasing, and only 0.4% of households use kerosene for cooking as per recent NFHS-5 (IIPS & ICF, 2021). Households utilizing clean fuels were projected to be less exposed to HAP as compared to households using biomass fuels, exposed to higher pollution levels inside.

Prior research showed that the availability of separate kitchens is linked with HAP. "Do you have a separate area that is utilized as a kitchen?" was another of the questions in the NFHS-5 that elicited information on exposure to cooking fuels. A separate kitchen was generated as a variable and was dichotomized into houses with a separate kitchen (coded "0") and households without a separate kitchen (coded "1"). Households without a separate kitchen are thought to be more susceptible to HAP. Another question was asked if the households lack a separate kitchen, "Does the room used for cooking have any ventilation?." Ventilation status was generated as a variable and dichotomized into houses with proper ventilation (coded "0") and households without ventilation (coded "1").

2.3. Data on Mortality

Two different files from NFHS-5 data were used in this study for mortality estimation. For neonatal, postneonatal, and child mortality (1–5 years), we used birth history information available from the women's questionnaire. In the women's questionnaire, there were two questions: (a) "Have you ever given birth to a boy or girl who was born alive but later died?" and (b) "How old was (NAME) when he/she died?." Neonatal, postneonatal, and child mortality were estimated using these question's responses. The household roster questionnaire asked, "Did any usual member of this household die since January 2016?" and adult mortality (15 and above) was estimated using the responses from that question. The NFHS-5 collected data from 724,115 women and 101,879 men, while the individual response rate for males was 92%, and for women, it was 97%. Further, the survey provides information on 232,920 children under the age of 5 years, along with the details of 636,699 household characteristics, such as the type of cooking fuel used, with a response rate of 98%. To generate the mortality variable in binary form, we have reshaped the household member file and got a final sample size of 2,145,231 for analyzing adult mortality and for analyzing child mortality, we got a sample size of 232,920.

The protocol for the NFHS-5 survey, including the content of all the survey questionnaires, was approved by the IIPS Institutional Review Board and the ICF Institutional Review Board. The US Center for Disease Control and Prevention (CDC) also reviewed the protocol. While collecting information, informed consent was taken from the respondents.

2.4. Confounding Variables

Several socio-economic and demographic variables were considered as possible confounding factors in the risk of death. Sex of person/child (male, female), social group (Scheduled Caste—SC, Scheduled Tribe—ST, Other Backward Classes—OBC, and General), wealth quintile (low, medium-low, medium, medium-high, and high) of the household, religion (Hindu, Muslim, and Others), place of residence (urban and rural), region (North, Central, North-East, West, East and South).

The wealth quintile was employed as a proxy indicator of living standards. Various consumer products (e.g., vehicles, bicycles, radio, television) and dwelling features (e.g., drinking water, sanitation facilities, housing materials) were used to construct the wealth quintile. Each individual was given a score based on principal component analysis, which was then divided into five quintiles, each representing 20% of the respondents and ranging from low (value 1) to high wealth (value 5).

2.5. Data Analysis

In the present study, we have undertaken a rigorous integration of $PM_{2.5}$ exposure data for 2020, derived from the GAINS model, with the NFHS-5 data set at the district level. The NFHS-5 data set offers invaluable retrospective information concerning death events occurring within the preceding 5 years. For our analysis, we specifically leveraged $PM_{2.5}$ exposure data for a single temporal point in 2020. One of the primary concerns when integrating pollution data with health outcomes is the reliability of such an integration, given that $PM_{2.5}$ concentrations can exhibit temporal variability. To address this concern and assess the robustness of our integrated data set, we conducted an in-depth examination of the correlation between $PM_{2.5}$ concentrations across a two-decade span from 2000 to 2020 in Figure 1. To accomplish this, we obtained $PM_{2.5}$ concentration data from the GAINS model for 5 distinct years: 2000, 2005, 2010, 2015, and 2020. Then, we examined the correlation patterns between the $PM_{2.5}$ concentration levels in different years for each primary sampling unit (PSU). Remarkably, our analysis revealed a strong and positive correlation, exceeding 0.99, among the $PM_{2.5}$ concentration levels across different years within the specified clusters. This robust correlation is indicative of the stability and consistency of $PM_{2.5}$ concentrations within these clusters over the analyzed time period. The correlation matrix depicting these findings is presented in Figure 1, and it was constructed utilizing the "*ggpairs*" function from the "*GGally*" package in the R software environment (Baxter, 2016). Within the context of NFHS-5, a cluster is defined as either a PSU or a segment thereof. A total of 22 families were randomly selected within each chosen rural and urban cluster using systematic sampling techniques. It is pertinent to note that NFHS-5 encompasses a total of 30,456 surveyed clusters, of which 30,197 cluster locations were made available for our analysis. These findings underscore the reliability and robustness of our integrated data set, paving the way for meaningful investigations into the association between $PM_{2.5}$ exposure and mortality outcomes within the context of the NFHS-5 data set.

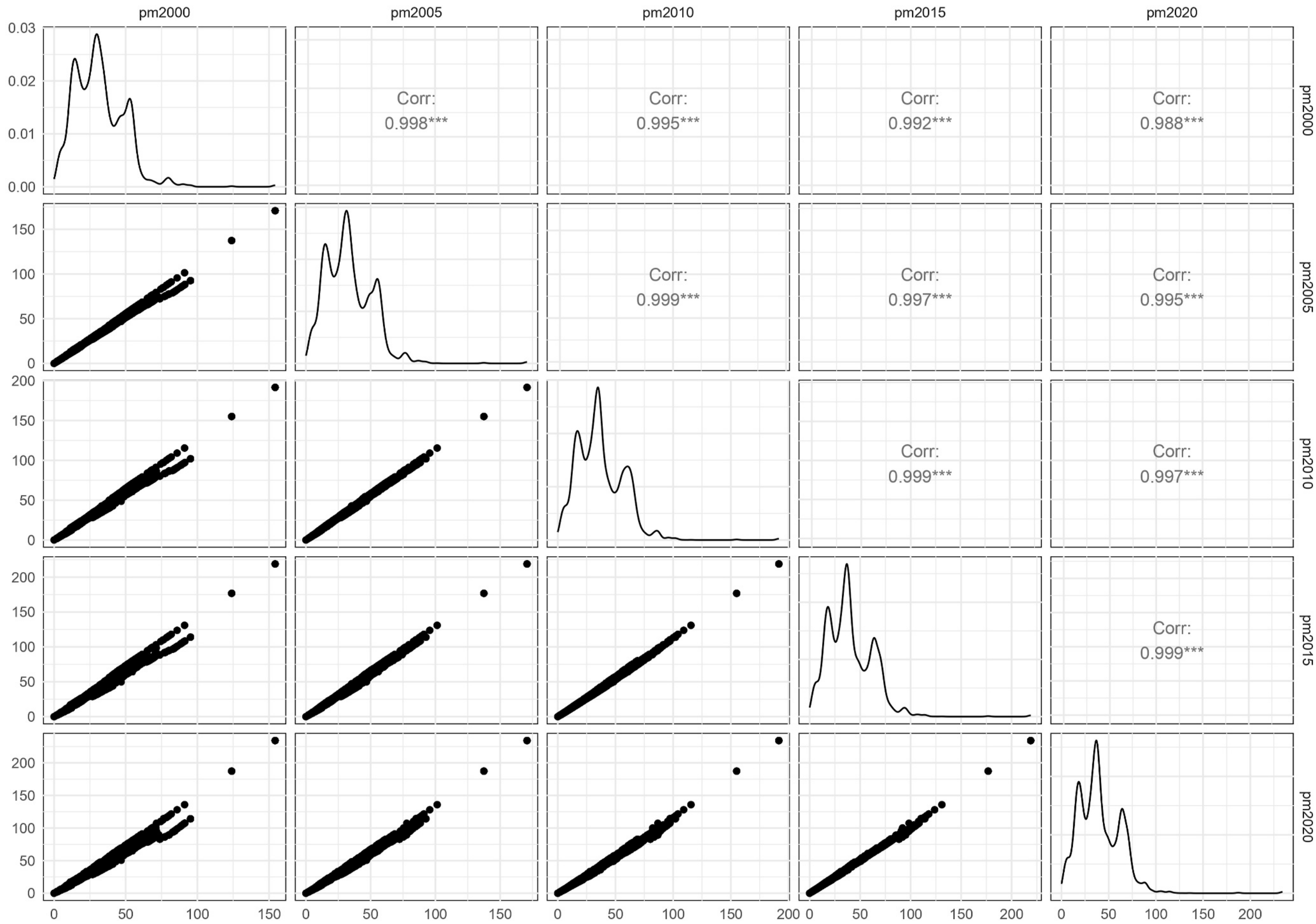

Figure 1. Correlation matrix of $PM_{2.5}$ concentration across different years (2000–2020) among clusters across the country. The values on the *X* and *Y* axes represent $PM_{2.5}$ concentrations, measured in micrograms per cubic meter (μg/m³) of air.

Descriptive death estimates for each age group are presented based on different characteristics independently ($PM_{2.5}$, cooking fuel, separate kitchen, ventilation status) using proper sample weight; the proportion of death among children and adult populations was calculated using a bivariate percentage distribution based on the relevant predictors and confounding factors, and the differences were then assessed using Pearson's chi-square statistic.

Logistic regression models estimate mortality and the effect of all the different independent variables combined. This investigates the association between ambient, household pollution and neonatal, postneonatal, child (1–5 years) and adult mortality. The logistic regressions estimated the probability of death as:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots \beta_i x_i + \epsilon,$$

where p is the likelihood of occurrence of death; $x_1, x_2, x_3, \ldots x_i$ refers to the independent variables; $\beta_0, \beta_1, \beta_2, \beta_3, \ldots \beta_i$ refer to the coefficients or effects of the independent variables in the death prevalence; and ϵ is the error term.

We introduced the socio-economic and demographic factors (such as sex, social group, religion, wealth quintile, place of residence, and region of residence) in the model to estimate the net effect of ambient and HAP on the risk of neonatal, postneonatal, child death, and adult death.

In our analysis, we conducted a comprehensive examination of the relationship between two key environmental factors, namely $PM_{2.5}$ and HAP, in relation to age-specific mortality rates. Moreover, we investigated whether an

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interaction effect exists between these two parameters and how this interaction is associated with mortality outcomes.

First, we dichotomized the $PM_{2.5}$ exposure variable into a binary classification:

a. $PM_{2.5}$ Below NAAQS: This category includes areas with $PM_{2.5}$ levels lower than the NAAQS threshold, which is set at 40 μg per cubic meter. These areas are considered to have relatively better ambient air quality.
b. $PM_{2.5}$ Above NAAQS: This category encompasses regions with $PM_{2.5}$ levels that exceed the NAAQS threshold, indicating poorer ambient air quality.

Additionally, we constructed another variable to represent HAP, which takes into account the use of unclean fuel and the absence of a separate kitchen facility within households. This variable characterizes HAP based on the presence or absence of these factors:

a. No HAP: This category comprises households that do not use unclean fuel and have a separate kitchen facility, indicating relatively cleaner indoor air quality.
b. HAP: This category encompasses households that either use unclean fuel or do not have a separate kitchen or use unclean fuel and also lack a separate kitchen, signifying a higher level of indoor air pollution.

To explore the interaction between ambient and HAP in relation to mortality, we created four distinct groups:

a. $PM_{2.5}$ Below NAAQS with No HAP: This group represents areas with both cleaner ambient air ($PM_{2.5}$ below NAAQS) and cleaner indoor air (no HAP).
b. $PM_{2.5}$ Below NAAQS with HAP: This group includes areas with cleaner ambient air ($PM_{2.5}$ below NAAQS) but elevated household pollution levels (HAP present).
c. $PM_{2.5}$ Above NAAQS with No HAP: This group consists of regions with poorer ambient air quality ($PM_{2.5}$ above NAAQS) but cleaner indoor air (no HAP).
d. $PM_{2.5}$ Above NAAQS with HAP: This group characterizes areas with both elevated ambient air pollution ($PM_{2.5}$ above NAAQS) and increased household pollution levels (HAP present).

Again, in the analysis, we have adjusted the effects of potential confounders as mentioned in the earlier analysis. By categorizing and examining these four groups, we assessed how the combined effects of ambient and HAP contribute to age-specific mortality patterns and further understand the association between these factors and their potential impact on health outcomes.

All statistical analysis has been carried out using the STATA 14 software (StataCorp, 2021), and the distribution of $PM_{2.5}$ level, utilization of unclean fuel and unavailability of separate kitchens were shown in the maps were created using ArcMap version 10.3.

3. Results

3.1. District Level Variation in Ambient $PM_{2.5}$, Unclean Fuel Used in the Kitchen and Absence of Separate Kitchen in India

In Figure 2 (Section 1), we present a comprehensive depiction of ambient $PM_{2.5}$ concentrations across India. Notably, the figure vividly illustrates that the ambient $PM_{2.5}$ levels exhibit a substantially high concentration in the districts situated within the Indo-Gangetic Plain (IGP) region, the geographic location of which is delineated in Figure 2 (Section 4). Within the IGP region, we observe localized clusters characterized by markedly higher ambient $PM_{2.5}$ concentrations, particularly over the NCR and its proximate districts, as well as in the southern districts of West Bengal. Conversely, our analysis reveals a noteworthy reduction in fine particulate matter pollution in the northern districts with higher elevations, encompassing states such as Arunachal Pradesh, Sikkim, Uttarakhand, Himachal Pradesh, Jammu and Kashmir, and Ladakh. Additionally, the districts of Kerala, the western districts of Karnataka, and the select southern districts of Tamil Nadu exhibit relatively lower ambient $PM_{2.5}$ concentrations.

In Figure 2 (Section 2), we show the prevalence of unclean cooking fuel usage throughout India. The northern, central, and eastern regions of the country display notably elevated levels of unclean fuel utilization in households. Specifically, the districts in the northern region, with the exception of Ladakh and certain areas in Punjab and Haryana, exhibit a higher prevalence of unclean cooking fuel adoption. Moreover, this pattern extends to

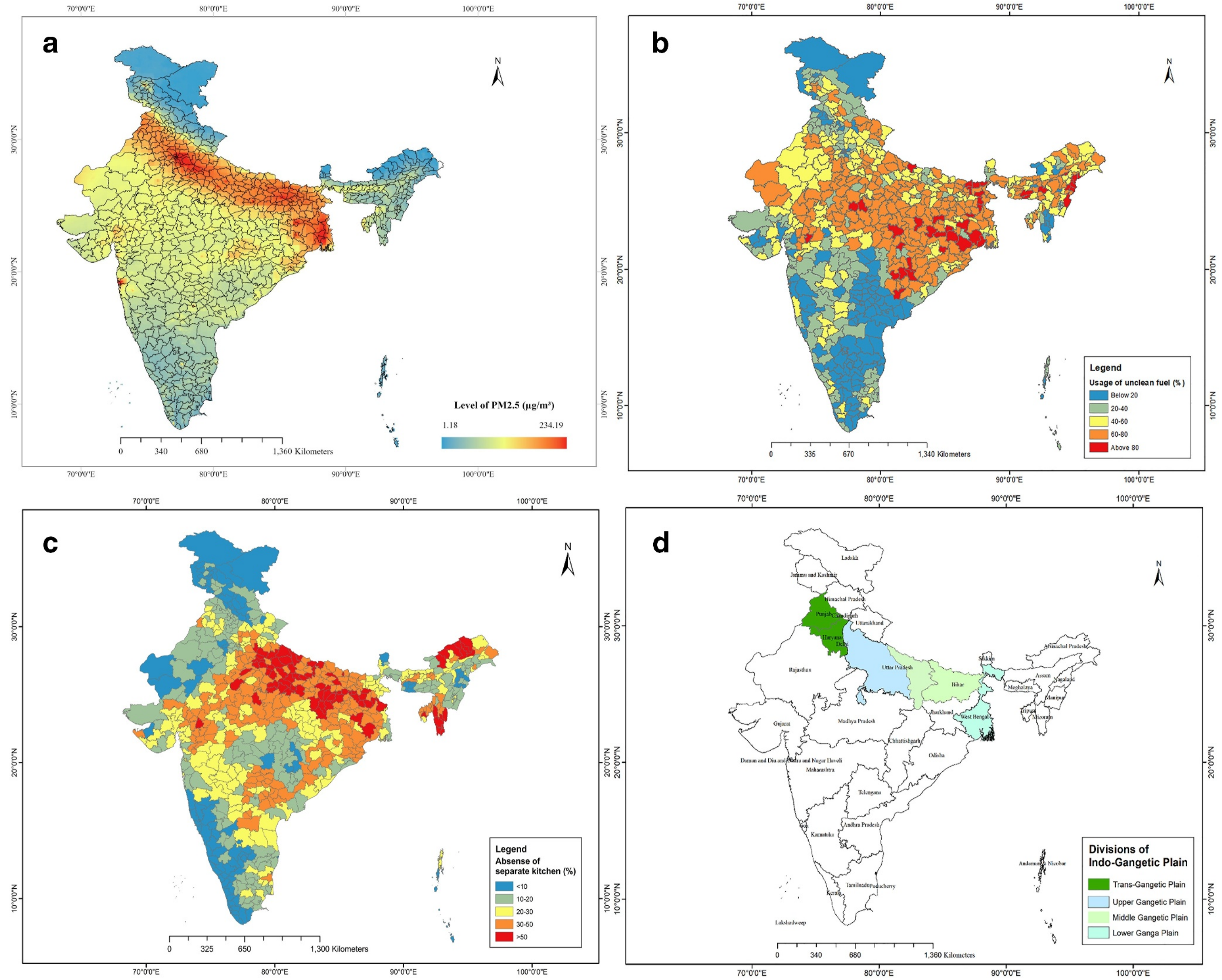

Figure 2. Distribution of pollution parameters (Subfigures: (a) Concentration of ambient $PM_{2.5}$ across districts in India, 2020; (b) Usage of unclean fuel across districts in India, 2019–2021; (c) Absence of separate kitchens in households across districts in India, 2019–2021; (d) Map of India showing its States/UTs and Indo-Gangetic Plain [IGP] region).

encompass the central, eastern, and northeastern parts of India. In stark contrast, the majority of southern districts exhibit a substantial preference for clean fuel sources within households for cooking purposes.

Figure 2 (Section 3) also offers a visual representation of the prevalence of households lacking a separate kitchen facility. The spatial distribution observed in this figure closely mirrors the patterns identified in Figure 2 (Section 2), where regions characterized by heightened unclean fuel utilization coincide with a greater prevalence of households lacking dedicated cooking areas. Notably, the central part of India exhibits a marginally improved situation in terms of separate kitchen availability. Most prominently, districts in Gujarat, Uttar Pradesh, Bihar, Madhya Pradesh, Jharkhand, Odisha, Telangana, Arunachal Pradesh, Tripura, southern West Bengal, and Mizoram report a higher proportion of households without a designated kitchen for cooking.

Furthermore, it is noteworthy that the entirety of the middle and lower Gangetic plain, in addition to the central regions of India, exhibits a clustering of districts characterized by a simultaneous dearth of clean fuel usage and the absence of separate kitchen facilities, even as ambient $PM_{2.5}$ concentrations remain markedly elevated throughout the broader IGP region.

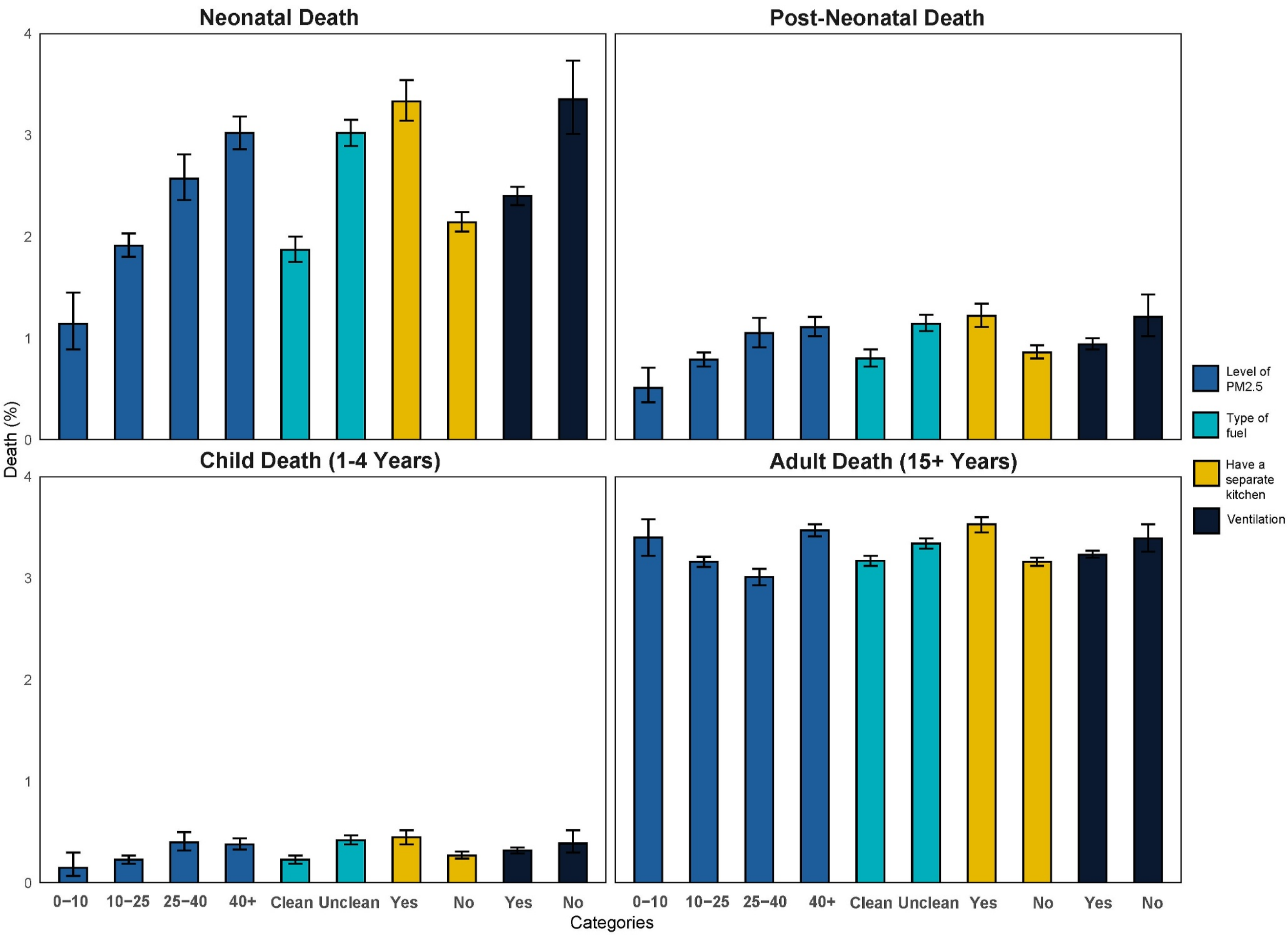

Figure 3. Percentage of deaths for each age group based on different pollution parameters independently, India, 2019–2021.

3.2. Descriptive Estimates of Neonatal, Postneonatal, Child, and Adult Deaths by Exposure Variables and Other Relevant Covariates

With an increased level of concentration of ambient $PM_{2.5,}$ the death rate among different age groups (neonatal, postneonatal, child and adult) also shows an increasing trend in Figure 3. The unclean fuel used for cooking in the households also shows a higher level of death in each category (3.02%, 1.14%, 0.42%, and 3.34%), respectively, for neonatal, postneonatal, child, and adult deaths. The absence of separate kitchens also shows a higher level of death among children (3.33%, 1.12%, and 0.38%, 3.53%, respectively, for neonatal, postneonatal, and child and adult deaths). Similarly, lack of ventilation in the house also shows higher mortality rates (3.35%, 1.21%, 0.3%, and 3.39%, respectively, for neonatal, postneonatal, and child and adult deaths).

Table 1 shows that neonatal and adult death is higher among male children (2.68% and 3.68%, respectively) than among females; however, there is no such significant difference in postneonatal and child death by gender. Neonatal and adult deaths are higher among Hindus than non-Hindus. No statistically significant difference was found in the postneonatal and child deaths among different religious communities. Among the social classes, the scheduled caste community shows a higher prevalence of death in each age group. An increasing rate of neonatal, postneonatal, child, and adult deaths was found with a decreasing wealth index. Death in each age group is highest among the people in the lowest wealth category, and vice versa. The rural residence shows a higher level of death risk in every age group than its urban counterpart.

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Table 1
Proportion of Deaths by Background Characteristics of Sample, India, 2019–2021

Variables	Neonatal death *n* (%)	Post neonatal death *n* (%)	Child death (1–5) *n* (%)	Adult death *n* (%)
Sex		#	#	
Male	3,232 (2.68)	1,232 (1.02)	400 (0.33)	38,687 (3.68)
Female	2,427 (2.16)	1,073 (0.96)	378 (0.34)	28,227 (2.58)
Religion		#	#	
Hindu	4,476 (2.62)	1,714 (1.00)	580 (0.34)	53,490 (3.28)
Muslim	736 (2.20)	297 (0.89)	96 (0.29)	6,422 (2.51)
Christian	285 (1.51)	200 (1.06)	74 (0.39)	3,596 (2.44)
Others	162 (1.71)	94 (0.99)	28 (0.29)	3,408 (3.09)
Social groups				
SC	1,408 (2.94)	533 (1.11)	192 (0.40)	13,860 (3.34)
ST	1,040 (2.21)	577 (1.22)	207 (0.44)	10,586 (2.73)
OBC	2,237 (2.51)	808 (0.91)	279 (0.31)	26,149 (3.26)
Others	787 (2.06)	308 (0.81)	80 (0.21)	13,938 (3.10)
Wealth index				
Poorest	1,986 (3.13)	869 (1.37)	350 (0.55)	14,915 (3.41)
Poorer	1,506 (2.77)	595 (1.09)	191 (0.35)	15,128 (3.26)
Middle	991 (2.20)	388 (0.86)	117 (0.26)	13,801 (3.12)
Richer	758 (1.94)	297 (0.76)	74 (0.19)	12,277 (2.97)
Richest	418 (1.35)	156 (0.51)	46 (0.15)	10,795 (2.78)
Place of residence				
Urban	832 (1.76)	362 (0.77)	122 (0.26)	15,427 (2.85)
Rural	4,827 (2.60)	1,943 (1.05)	656 (0.35)	51,489 (3.21)
Region				
North	858 (1.99)	349 (0.81)	114 (0.26)	12,091 (2.70)
Central	2,033 (3.36)	813 (1.34)	276 (0.46)	16,698 (3.32)
East	1,356 (3.00)	449 (0.99)	155 (0.34)	12,134 (3.62)
NE	573 (1.67)	331 (0.97)	120 (0.35)	6,964 (2.43)
West	399 (1.94)	146 (0.71)	59 (0.29)	7,001 (3.06)
South	440 (1.50)	217 (0.74)	54 (0.18)	12,028 (3.48)
Cooking Fuel				
Solid fuel	3,471 (2.83)	1,442 (1.18)	513 (0.42)	31,608 (3.14)
Clean fuel	1,868 (1.88)	766 (0.77)	231 (0.23)	35,308 (3.10)
Separate kitchen				
No	1,921 (3.16)	729 (1.20)	259 (0.43)	15,614 (3.35)
Yes	2,464 (2.06)	1,003 (0.84)	319 (0.27)	37,038 (3.04)
Ventilation			#	#
Yes	5,080 (2.37)	2,085 (0.97)	707 (0.33)	62,453 (3.12)
No	579 (3.10)	220 (1.18)	71 (0.38)	4,463 (3.13)
Level of $PM_{2.5}$ ($\mu g/m^3$)				
0–10	171 (1.16)	89 (0.60)	31 (0.21)	4,456 (2.71)
10–25	2,145 (2.06)	993 (0.95)	306 (0.29)	30,768 (3.01)

Table 1
Continued

Variables	Neonatal death *n* (%)	Post neonatal death *n* (%)	Child death (1–5) *n* (%)	Adult death *n* (%)
25–40	1,139 (2.62)	432 (0.99)	162 (0.37)	12,394 (3.16)
40+	2,198 (3.14)	786 (1.13)	279 (0.40)	18,963 (3.41)

Note. The difference in death between sub-categories of independent variables is statistically significant at a 95% confidence level; chi-squared p value <0.05 for all variables except the variables with a # symbol.

3.3. Association of Ambient and Household Air Quality With Neonatal, Postneonatal, Child and Adult Death

Table 2 presents the binary logistic regression model results for assessing the association between mortality across different life stages with ambient and HAP separately. It is observed that the concentration level of $PM_{2.5}$ is associated with an increased likelihood of neonatal, postneonatal, and child mortality. When the $PM_{2.5}$ concentration level is less than 10 μg/m^3 in the reference category, the probability of neonatal death is almost two times higher (OR 1.86 CI 1.418–2.433) in the $PM_{2.5}$ level above the national ambient air quality standard (NAAQS) of 40 μg/m^3. Similarly, the likelihood of postneonatal and child death is also higher (OR 2.04 CI 1.399–2.971; OR 2.219 CI 0.999–4.803, respectively) when the $PM_{2.5}$ level crosses the NAAQS level. The type of cooking fuel does not show a statistically significant association for any category of death, though there is an increasing likelihood of death among children from households using unclean fuels for cooking. Households

Table 2
Differential Associations of Ambient and Household Air Quality With Deaths in India, 2019–2021

	Neonatal death	Postneonatal death	Child death	Adult death
Variables/models	Odds ratio (CI)	Odds ratio (CI)	Odds ratio (CI)	Odds ratio (CI)
$PM_{2.5}$ level (μg/m^3)				
0–10 ®	1.00	1.00	1.00	1.00
10–25	1.49***	1.49**	1.40	0.97
	(1.150–1.936)	(1.040–2.125)	(0.654–2.993)	(0.915–1.032)
25–40	1.69***	1.90***	2.23**	0.98
	(1.279–2.244)	(1.286–2.819)	(1.017–4.942)	(0.915–1.046)
40+	1.86***	2.04***	2.19**	1.13***
	(1.418–2.433)	(1.399–2.971)	(0.999–4.803)	(1.060–1.208)
Cooking Fuel				
Clean Fuel®	1.00	1.00	1.00	1.00
Unclean fuel	1.09*	0.95	1.03	0.85***
	(0.986–1.206)	(0.819–1.108)	(0.781–1.370)	(0.826–0.856)
Separate kitchen				
Yes®	1.00	1.00	1.00	1.00
No	1.18***	1.08	1.11	1.06***
	(1.074–1.306)	(0.934–1.260)	(0.851–1.452)	(1.027–1.088)
Ventilation				
Yes®	1.00	1.00	1.00	1.00
No	1.02	0.99	0.82	0.96
	(0.900–1.165)	(0.802–1.293)	(0.582–1.145)	(0.911–1.006)
Cons.	0.01***	0.01***	0.00***	0.01***
	(0.010–0.019)	(0.006–0.014)	(0.002–0.010)	(0.013–0.016)

Note. Data are given as odds ratio (95% CI); Models were adjusted for other Socio-economic and demographic variables [Sex, residence, religion, social group, wealth index, region]. ® Reference category; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3
Interaction of Ambient $PM_{2.5}$ With Household Air Quality and Their Association With Mortality

Interaction	Neonatal death Odds ratio (95% CI)	Postneonatal death Odds ratio (95% CI)	Child death Odds ratio (95% CI)	Adult death Odds ratio (95% CI)
$PM_{2.5}$ below NAAQS with no HAP®	1.00	1.00	1.00	1.00
$PM_{2.5}$ below NAAQS with HAP	1.04 (0.962–1.135)	1.06 (0.931–1.202)	1.04 (0.974–1.114)	1.04 (1.021–1.065)***
$PM_{2.5}$ above NAAQS with no HAP	1.19 (1.051–1.337)***	1.03 (0.836–1.264)	1.17 (1.054–1.289)**	1.13 (1.096–1.168)***
$PM_{2.5}$ above NAAQS with HAP	1.25 (1.142–1.372)***	1.32 (1.136–1.523)***	1.29 (1.196–1.390)***	1.17 (1.139–1.206)***

Note. ® Reference category; *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$; Models were adjusted for sex, social group, religion, place of residence (rural/urban), wealth, and region.

without any separate kitchen for cooking reveal a higher likelihood of neonatal death (OR 1.18 CI 1.074–1.306). Again, Table 1 shows that when the fine particulate matter pollution level crosses the NAAQS level of 40 $\mu g/m^3$, the mortality risk among adults increases substantially (OR 1.13 CI 1.060–1.208). The model also discloses that using unclean fuel leads to a lower risk of adult death (OR 0.85 CI 0.826–0.856). At the same time, households without a separate kitchen show higher odds of adult death (OR 1.06 CI 1.027–1.088). The status of ventilation does not show any significant association with death in any category.

The results of the interaction analysis presented in Table 3 demonstrate the interaction between $PM_{2.5}$ levels below the NAAQS and HAP, indicating an increase in mortality risk across all age groups. When we examined the interaction between $PM_{2.5}$ levels above NAAQS and HAP, we found that there is a substantial increase in mortality observed for neonatal (OR 1.19 CI 1.051–1.337), child (OR 1.17 CI 1.054–1.289), and adult (OR 1.13 CI 1.096–1.168) age groups. However, no significant change in postneonatal mortality is evident. Furthermore, the presence of both ambient and HAP exhibits the highest chance of death for each age group.

4. Discussion

Currently, India is in a phase of industrialization and its development process, and thus, the level of ambient air pollution in its cities is also increasing significantly. From 1990 to 2019, there has been a 115% increase in fine particulate matter pollution, leading to approximately 1 million premature deaths in 2019 (Pandey et al., 2021). The present study explored the correlation between neonatal, postneonatal, child, and adult mortality with ambient and HAP using the most recent data. In India, the whole IGP region shows a very high concentration of $PM_{2.5}$. Simultaneously, indicators of household air quality, such as usage of clean fuel and availability of separate kitchens, are very low in the middle and lower Ganga plain as well as in the districts of central India. The Gangetic Plain in India experiences higher $PM_{2.5}$ levels due to multiple factors. Extensive agricultural practices, including the burning of crop residues, release significant amounts of smoke and particulate matter into the air. Additionally, the region's industrial centers and manufacturing hubs emit pollutants through the burning of fossil fuels and industrial processes. The high population density, urbanization, and vehicular traffic further contribute to emissions and pollution (Jain et al., 2021; Jat & Gurjar, 2021). The limited utilization of cleaner cooking fuel in these regions can be explained by the more convenient availability of inexpensive and easily accessible traditional fuels, known as unclean cooking fuel. Forest-rich areas like Madhya Pradesh, Odisha, and other northeastern states offer abundant firewood as an easily accessible Unclean Fuel option. Similarly, in the IGP, agricultural crop residue and animal dung are readily available as unclean fuel. These readily available and cost-effective unclean fuel options contribute to the lower adoption of clean fuel in these areas (Gupta et al., 2020; J. Joshi & Bohara, 2017).

This study has revealed a significant and constant positive association between ambient $PM_{2.5}$ pollution and neonatal, postneonatal, child and adult mortality. Our findings show that exposure to ambient $PM_{2.5}$ (natural and anthropogenic) has an adverse effect on child health or, more precisely, on child mortality. The probability of neonatal and postneonatal and child (1–5 years) death appeared to be almost two-fold and more than two-fold higher, respectively, in the districts of India where the $PM_{2.5}$ concentration is up to the NAAQS level. Our findings are consistent with earlier research that has found a link between air pollution and newborn fatalities (Goyal et al., 2019; Karimi & Shokrinezhad, 2020; Kotecha et al., 2020; Lin et al., 2004). The findings are also consistent with the studies conducted in the context of both high-income (Hajat et al., 2007; Kotecha et al., 2020) and middle or low-income (Goyal et al., 2019; He et al., 2022; Lin et al., 2004) countries. Several studies have also examined the impact of coarse particles PM_{10} (all particles with an aerodynamic diameter of 10 μm or smaller) on child mortality (Hajat et al., 2007; Kotecha et al., 2020; Mahapatra et al., 2020). A study utilizing daily time series data on 10 England cities also shows a positive association between PM_{10} and infant mortality in most cities (Hajat et al., 2007).

Rising fine particulate pollution levels (i.e., $PM_{2.5}$) are expected to have a considerable influence on rising adult death rates, according to our pollution and adult mortality analyses. The regression analysis findings reveal that they are consistent with earlier empirical studies conducted in high (Pope et al., 1995; B. Wang et al., 2020; Y. Wang et al., 2017) and low and middle-income (He et al., 2022; Li et al., 2018; Liu et al., 2022) countries. $PM_{2.5}$ has a significant positive connection, indicating that growing $PM_{2.5}$ pollution levels contribute to increased adult mortality rates in India.

For adult mortality, a negative association was found with unclean fuel usage. The finding is contradictory to other studies regarding the type of cooking fuel and health or mortality (Lakshmi et al., 2013; Naz et al., 2016; Padhi & Padhy, 2008; Sk et al., 2020; Upadhyay et al., 2015). The death risk is produced using the NFHS-2019-21 data set, which provides information on dead members of a household since 2016. The Government of India launched a flagship programme—"Pradhan Mantri Ujjwala Yojana" (PMUY), in May 2016 to provide clean fuel to the rural and deprived households of the country (www.pmuy.gov.in, n.d.). Since the launch of the programme to the date of the survey, clean fuel usage has increased substantially in India. According to NFHS, clean fuel usage has increased by 19% from NFHS-2015-16 (clean fuel usage 40%) to NFHS-2019-21 (clean fuel usage 59%) (IIPS & ICF, 2017, 2021). LPG coverage tremendously increased with the launch of PMUY, reaching almost all households by April 2019. This drastic change might have affected the mortality prediction by using cooking fuel. It is worth discussing that despite the increasing coverage of clean fuel in recent years, a sizable portion of the scheme's below-poverty line recipients did not continue using the service after the initial refill, mostly for financial reasons (Pandey et al., 2021; Sethi & Deep, 2018; The Hindu, 2018). Thus, it is quite possible that some households may answer that they have a clean fuel facility, but they are still using unclean fuels. This may modify the outcome of our analysis.

The unavailability of a separate kitchen in households predicts neonatal and adult mortality positively, which is consistent with previous studies (Naz et al., 2016; Sk et al., 2020). The adjusted odds for neonatal death are higher than the adults because a newborn child is always supposed to stay indoors. Thus, the exposure is higher for them than for other adult household members. Apart from that, newborns are more vulnerable to $PM_{2.5}$ exposure than adults.

The interaction analysis was conducted to elucidate the extent of the association of $PM_{2.5}$ and household air quality with mortality. The results demonstrate that $PM_{2.5}$ exhibits a stronger association with mortality across various life stages. Notably, when HAP is considered in conjunction with ambient pollution, this association is further heightened. While HAP alone does not exhibit a substantial association with mortality, a modest association is still evident. Importantly, the combined presence of both household and ambient air pollution demonstrates a significantly elevated association with mortality, regardless of age group.

This study has utilized the district-wise $PM_{2.5}$ concentration data from the GAINS model. Further, the $PM_{2.5}$ data were integrated with a nationally representative household and individual-level survey data set, NFHS-2019-21. In the absence of real cohort data, we estimated the net association between air quality indicators and mortality risk. As our data is cross-sectional and does not document the migration history of dead individuals, we cannot capture actual years of exposure at the time of death, particularly for adult deaths. Although reliable lifetime personal air pollution exposure estimates would be ideal for many research objectives, such data is not available in India and is unfeasible for a large sample. However, these limitations are not applicable for neonatal, post-neonatal, and childhood mortality since their place of residence at the time of the survey or at death is not likely to differ much from the place of birth. Another limitation of our study is that we cannot infer a causal relationship because of the cross-sectional nature of the data set. It is much worth mentioning that the GAINS data used in this study does not take into account the COVID-19 lockdown impacts on air quality, as the study was completed in 2019.

Despite data limitations, our findings demonstrate that ambient and HAP has a harmful effect on human health and, succinctly, on mortality. Since the effect of air pollution on human health is a gradual and long-term process, it is not so visible, and common people always underrate the consequences. So, increasing awareness among the people in vulnerable areas where the usage of clean fuel and availability of separate kitchens is low is very crucial so that common people can also try to maintain healthy household air quality. Forgetting about WHO air quality guidelines, in India, policymakers should focus on reducing the anthropogenic $PM_{2.5}$ emission at least to reach the NAAQS, which can substantially reduce disease burden and, more precisely, premature deaths.

Conflict of Interest

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

Data Availability Statement

NFHS-2019-21 data (IIPS & ICF, 2021) is used in the study and the data is publicly available on the DHS Program repository and can be downloaded from https://dhsprogram.com/data/dataset/India_Standard-DHS_2020.cfm?flag=0. Data on $PM_{2.5}$ were extracted from the Greenhouse Gas—Air Pollution Interactions and Synergies (GAINS) model (Amann et al., 2011), developed by the pollution management group at International Institute for Applied System Analysis (IIASA). The $PM_{2.5}$ data is publicly available on the GAINS Online website and can be downloaded via https://gains.iiasa.ac.at/gains/impacts.INN/index.menu?page=1706. All the statistical analysis were performed using Stata version 14 (StataCorp, 2021). The bar graph (Figure 3) presented in the article is created using R software and the code to produce this graph is publicly available (Adhikary, 2024) in the Zenodo repository and can be accessed through https://zenodo.org/records/11036903. The maps in the article ware created using ArcGIS desktop version 10.8.2 (Esri, 2021), the software is available at https://www.esri.com/en-us/arcgis/products/index.

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