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Breakdown the impact of air pollution along with socio-economic factors on public health using people perceptions: A case study of Rourkela, India

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ABSTRACT

Introduction: The effect of air ambient pollution on human health is a widely discussed subject among environmental experts and socio-economists worldwide. Despite a large number of research being conducted on the topic, the relationship between public health and air quality in Indian cities remains questionable. The study was carried out to assess the impact of air pollution on the health of people of different socio-economic section of the society.
Materials and methods: A cross-sectional survey was conducted among the residents of Rourkela city who were exposed to air pollution, and the logistic regression model was applied.
Results: The findings revealed that human health is significantly impacted by air pollution in terms of flu/fever (46%), runny nose/cold (36 %) and others respiratory and cardiovascular disease. The individuals who were breathing in polluted air were 10.65 times more likely to have gotten sick from air pollution (β=2.37; SE=0.33; $p<0.01$) when compared to the people who were not breathing in polluted air. In contrast, a rise of one unit in the AQI in Rourkela corresponds to an 8.4% higher chance of being ill due to air pollution-related diseases (β=0.08; SE=0.02; $p<0.01$). A high, rising linear trend (R^2=0.67) of mortality by major air pollution-related diseases was also recorded in Rourkela during the period of 2016–2022. Hence, it is evidenced that rising AQI values correspond to rising health hazards associated with air pollution in Rourkela.
Conclusion: The study's conclusions offer a thorough understanding of the negative impacts of air pollution, locals' perceptions of it, and the practical ramifications for local government when assessing more efficient approaches for reducing pollution.

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Introduction

Cities are frequently seen as hotspots for air pollution and associated health issues [1]. As urbanisation and industrialization increase, many Indian cities are witnessing a decline in air quality [2-3]. As per the findings [4], around 87% of the global populace lives in areas where air quality is lower than the World Health Organization (WHO)'s recommended threshold, particularly in low- and middle-income nations, globally. This has resulted in unprecedented air pollution episodes with severe health risk in cities like Beijing, Karachi, and New Delhi [5]. Furthermore, even if levels of exposure have decreased in high-income nations, current research shows that serious health consequences can still arise at these reduced exposure levels [6]. Previous research has addressed the effects of air pollution on human health as well as the fundamental mechanisms underpinning cellular activity [7-8]. According to WHO, outdoor air pollution causes 4.2 million premature deaths worldwide each year, accounting for 17% of all deaths and illnesses resulting from acute lower respiratory infections [9].

Premature mortality, sleep difficulties etc resulting due to respiratory and cardiovascular health issue are only a few of the effects of prolonged exposure to air pollutants such as particulate matter, SO_2, NO_2, and other gases on [10, 11]. People who already have health issues, like asthma, are more susceptible to the negative effects of air pollution since it can exacerbate their symptoms [12-14]. Air pollution is commonly associated with self-reported health symptoms such as fatigue, sleepiness, headaches, respiratory symptoms, and skin, nose, and eye irritation. Besides, millions of avoidable deaths unfavourable health impacts such as low birth weight, birth defects, and malignancies have been observed due to worsening air quality [15-19]. A long-term exposure to air pollution poses a serious risk factor for anaemia in the elderly [14] cause more than 6 million premature cardiac and respiratory deaths each year [6, 20]. However, these risks vary with socio-economic factors including the income of exposed individual of the society [21].

India's recent growth and development have put the environment at serious risk and are endangering public health. There has been much discussion particularly on the economic and social costs of air pollution due to its detrimental impacts on public health. However, diseases linked to air pollution cause a disproportionately high death and morbidity rate in Indian cities [22, 23]. According to some recent studies, more than 75% of Indians are exposed to pollution levels that are far higher than the country's National Ambient Air Quality Standards (NAAQS) [24, 25]. Despite this, there are relatively few air pollution monitoring facilities in urban areas, which results in a poor understanding of the spatial patterns of air pollution and its health impact on urban residents [26].

Ambient air pollution is preventable, and the diseases it causes can be avoided [2, 27]. In order to assist growing economies and overcome the setbacks of the past, wise leadership may help decouple prosperity from pollution [28]. The consequences of ambient air pollution on health have piqued the curiosity of many researchers. The majority of research on this topic is done on children, the elderly, low-income nations, nations outside of Europe, and usually in environments with higher air pollution levels [29, 30]. Furthermore, the exposure-response relationship has been used in certain research to investigate the harmful health impacts of air pollution [31]. Because mortality and morbidity data are easily obtainable and reliable, they have been the primary sources of health data used in these investigations [19]. There is still debate on the relationship between public health and air quality in Indian cities, despite a substantial number of studies having been done on the subject.

With the aid of a perception survey of the local residents of Rourkela, the current study uses a logistic regression model to examine the effects of air pollution and other socio-economic factors on public health. In this study, air pollution and other covariates were used as independent or explanatory variables, and health conditions (such as respiratory and cardiovascular issues linked to air pollution) were used as dependent variables. Additionally, the mortality trend associated with air pollution in Rourkela is shown to provide a comprehensive understanding of the consequences of air pollution on human health in the city. The research provide unique blend filed based observation for air quality estimation and both door to door resident survey and health department report to understand the health hazard of the air pollution in the city. The research will contribute to our understanding of the detrimental impacts of air pollution on health outcomes and offer valuable information to decision-makers as they assess increasingly refined approaches to pollution reduction.

Materials and methods

Study area

Rourkela is one of the major industrial cities, situated in the northern region of Odisha, India (Fig. 1). In the third phase of India's National Smart City Mission, it was designated as a smart city on September 20, 2016. In Odisha, it is the third-largest urban agglomeration

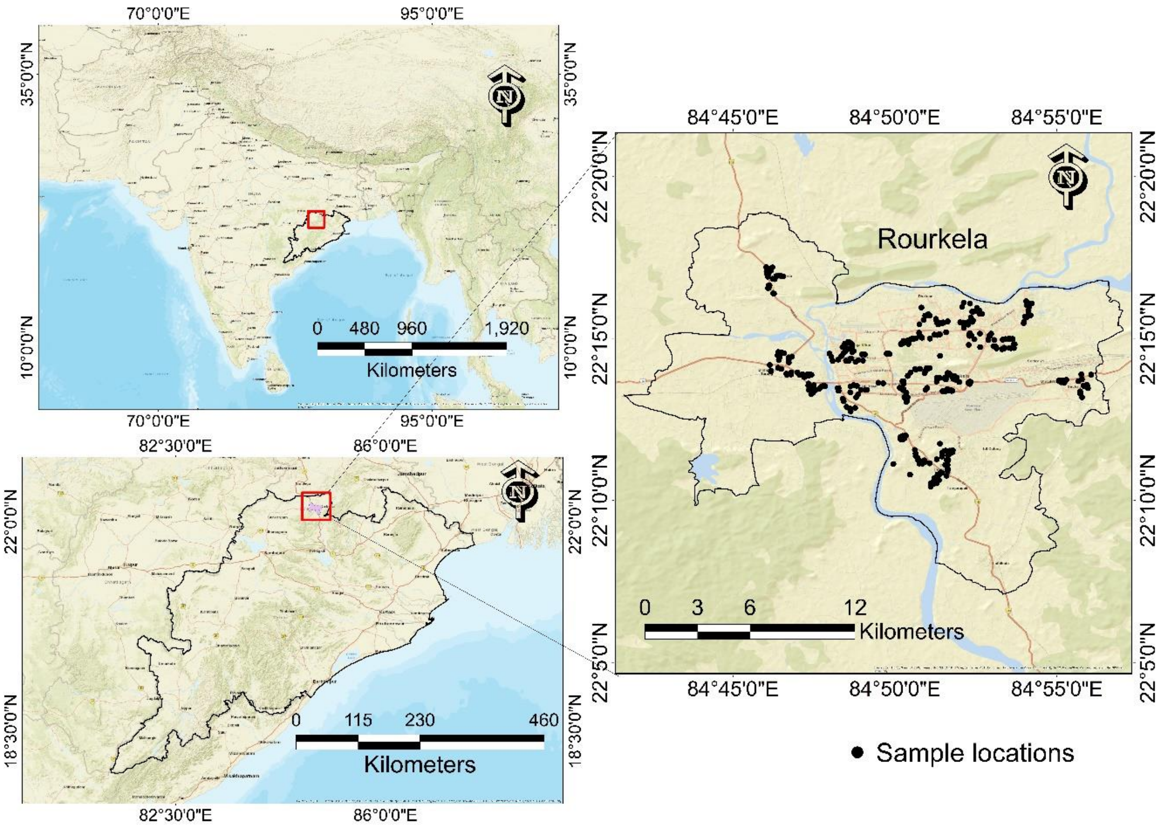

Fig. 1. Location map of the study area with sampling points for perception survey

The Rourkela Municipal Corporation (RMC) is situated at a height of 219 metres above mean sea level and spans around 274 square kilometres. The city is surrounded by the rivers Koel, Sankha, and Brahmani. According to the 2011 Indian census, the total population of the city is 5.52 lakh. The name "Steel City of Odisha" is frequently applied to the city because of the location of the massive Rourkela steel factory and its considerable production of iron and steel. In addition, the city is home to several medium-sized industries, including refractories, explosives, cement, chemicals, and sponge iron mills and 291625 number of registered vehicles from January 2011 to December 2022. As a result, a variety of air pollutants are constantly emitted from numerous sources, worsening the city's ambient air quality.

Data collection

The present study used field survey based primary data to explore the influence of ambient air pollution on public health in Rourkela Municipal Corporation (RMC) region. In order to do this, a comprehensive study of people's perceptions utilising a questionnaire survey (a cross-sectional survey) has been carried out. The questionnaire has included 26 questions covering various socioeconomic aspects of the local dwellers of Rourkela city. During survey, 417 local respondents of various ages were selected using clustered random sampling during December 2022. The sample size was determined using the Eq. 1 [32, 33].

$$\frac{N.Z^2.P.\ (1-P)}{E^2.(N-1)+Z^2.P.\ (1-P)} \quad (1)$$

Where, N is population size (Total population of Rourkela city is more than 5.2 lakhs as per the census of 2011), E is margin of error (±5% is considered in this study), Z is confidence level (95% is considered in the present study) and P is expected proportion (0.5 is used for maximum variability).

Therefore, for a population of 520,000 or more, a sample size of approximately 385 is sufficient for a 95% confidence level and a 5% margin of error. This sample size ensures that the survey results will be statistically significant and representative of the population. In this study, 417 samples have been collected for implementing logistic regression to estimate the impact of air pollution on human health.

- Standardizing data collection and survey protocol were designed for the use of epicollect tools for the survey.
- To ensure the internal consistency the dataset was alienated into two halves and compare the responses between the halves.

Determination of AQI

In order to show the true state of ambient air pollution levels in the city, we included AQI (air quality index) ground data as the primary explanatory variable in the second logistic regression model. The index is determined by calculating the levels of various air pollutants present in the ambient air, such as ground-level ozone, sulphur dioxide, nitrogen dioxide, and particle matter [34, 35]. We obtained AQI values from six sites that monitored the air quality in Rourkela under the Odisha State Pollution Control Board (SPCB) in 2022.

Initially, the data from continuous air quality monitoring stations of SPCB was averaged over 24 h (one day) was used. The final AQI map was prepared using average of such daily measurements taken thrice a week for the study period. The AQI map (Fig. 2) of the city was prepared using the IDW (inverse distance weighted) method in the ArcGIS environment. AQI readings for each respondent's location within the city were then extracted from this AQI map.

Logistic regression analysis

This study used binary logistic regression models to analyze the impact of ambient air pollution on public health in Rourkela city. Logistic regression models the probability of an outcome according to individual attributes. As probability is a ratio, the actual quantity to be represented is the logarithm of the likelihood provided by [36, 37]. Both models use the logistic function to model the probability of a binary outcome. The main difference lies in the context and interpretation of the variables.

Binary Logistic Regression: In binary logistic regression, there can be multiple independent variables (X_1, X_2, ..., X_n). The formula extends to accommodate multiple predictors and the formula can be written as mentioned in Eq. 2 [38, 39].

$$P(Y = 1/X) = \frac{1}{1+e- \beta_0+\beta_1 X_1+\beta_2 X_2 \ldots\ldots+\beta_n X_n} \quad (2)$$

Here, P(Y=1/X) represents the probability of the dependent variable (Y) being 1 given the values of the independent variables (X). e is the base of the natural logarithm (approximately equal to 2.71828). β0 represents the reference group, which is defined by those groups that represent the reference point of each variable $X_{1 \ldots n}$. In our study, we used the first category of each explanatory variable as the reference category to interpret the model. The intercept term (β0) in logistic regression sets the baseline probability and influences the initial position of the logistic curve, providing a reference point for interpreting the effects of the independent variables on the outcome. B_1, β_2,...,β_n are the coefficients of the independent variables X_1, X_2, ..., X_n, respectively.

This study implemented two binary logistic regression models, namely Model-1 and Model-2. The data concerning the health impact caused by air pollution serves as the dependent variable (Y) in the models under consideration. Meanwhile, the key explanatory variable encompasses aspects related to air quality, incorporating both the public perception of air quality in the first model and ground-level Air Quality Index (AQI) in the second model. Additionally, other socio-economic variables such as gender, age group, economic conditions, availability of medical facilities, smoking habits, exposure time, and governmental efforts are included as independent variables (X_1, X_2, ..., X_n). These variables collectively constitute the factors examined within these models.

These models were assessed based on various model fit criteria. The omnibus tests of model coefficients showed significant incremental fit for both models, with p-values less than 0.05 [38]. This indicates that the models perform significantly better than the null model. Additionally, the Hosmer & Lemeshow goodness of fit tests yielded non-significant results, suggesting that the models fit the data well [40]. The Nagelkerke pseudo-R-square values indicated that the independent variables in Model-1 and Model-2 have moderate to good explanatory power. Moreover, the -2 log likelihood values were smaller in better fitting models. The percentage of correctness in predicting outcomes increased from block 0 to block 1 in both models, demonstrating the suitability of the regression models for predictive analysis. In summary, both Model-1 and Model-2 of the logistic regression were found to be statistically significant, with good model fit and predictive capability, making them suitable for further analysis and interpretation [41].

Dependent variable

In both models, public health conditions (respiratory and cardiovascular) affected by ambient air pollution are used as dependent variables. This dichotomy variable was measured by asking respondents whether or not they got sick from any air pollution-related disease in the last 24 months. After a thorough review of the literature and discussions with medical professionals, a number of respiratory and cardiovascular conditions were chosen and included in the questionnaire survey as potential health effects of exposure to ambient air pollution.

Independent variables

By asking respondents if they felt that the ambient air in their area—which they breathe—was polluted, we were able to incorporate ambient air pollution-related data into model-1. This dichotomy variable (Yes or No) is used as the key explanatory variable in the first model. While, annual average AQI ground data was incorporated as key explanatory variable for model-2.

Other demographic information (age, gender, and household annual income), exposure-related information (outdoor exposure time, smoking habits, and separate kitchen), and governmental strategy-related information (government medical facilities and government effort) that are associated with health were also analysed. To optimise the fit of our final empirical model, we combined age group (Young age = 1, Middle age = 2, and Old age = 3), exposer time to ambient air pollution (Slightly exposed = 1, Moderately exposed = 2, and Heavily exposed = 3), household income (Low income = 1, Medium income = 2, and High income = 3), smoking habits (Regular smoking = 1, Sometime smoking = 2, and Never smoking = 3), and available government medical facilities (Good =1, Moderate = 2, and Poor = 3) into three categories. On the other hand, gender (Male = 1 and Female = 0), availability of separate kitchen (Yes = 1 and No = 0), and satisfaction with governmental efforts (Yes = 1 and No = 0) are categorised in a dichotomous manner.

Results and discussion

Spatial variation of AQI in Rourkela city

Air pollution concentrations in ambient air are measured and reported using the AQI, a numerical scale. It shows possible health issues related to air quality and acts as an indication of pollution levels or air cleanliness. In this study, AQI is incorporated as a key explanatory variable in Model-2 to enhance the robustness of the analysis.

This study utilizes the annual AQI data for 2022, as the household survey was conducted in December of the same year. Fig. 2 illustrates the spatial variation of the annual mean AQI across Rourkela city. The AQI values for 2022 in the city ranged from 96 to 122, indicating that the air quality fell within the "moderate" category. The highest AQI levels were recorded in the southwestern region of the city, particularly in the Kalunga industrial area, due to emissions from numerous industries. This region is characterized by a large, unplanned industrial setup, including iron and steel, chemical, and other small- to medium-scale industries, which continuously emit air pollutants, thereby elevating AQI levels in the city's atmosphere.

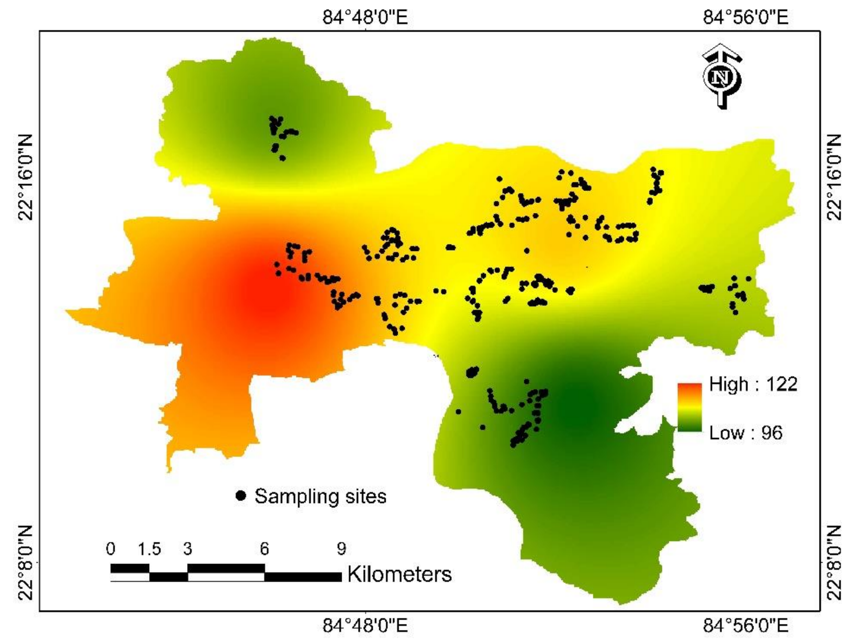

Fig. 2. Spatial variation of annual average AQI (2022) and sample sites of perception survey in Rourkela

The central, northern, and northeastern parts of Rourkela have experienced moderate AQI levels throughout the entire year. Central and northern Rourkela are primarily characterized by the presence of the Rourkela Steel Plant and heavy traffic. Although the steel plant is well-planned, vehicular emissions from dense traffic serve as the dominant source of air pollution in this region. In contrast, the southeastern part of the city, particularly the Soneparbat region, has recorded the lowest AQI levels in Rourkela. This region has a sparse concentration of industries and minimal vehicular movement, which contributes to improved air quality and lower AQI values in the ambient air.

Air quality and pollution sources: perspectives from respondents

Understanding the experience and opinion of local residents regarding air quality, primary sources of pollution, and associated health effect is essential for an effective an inclusive pollution management strategy from public health point of view. According to the responses gathered from residents, approximately 41% perceived the air quality in Rourkela as moderate, while 18.5% and 1.9% categorized it as poor or severe, respectively. In contrast, about 26% and 12% of respondents considered the air quality to be satisfactory or good, as depicted in Fig. 3. The findings suggest a notable concern among residents regarding the air quality in Rourkela, with a significant proportion perceiving it as moderate to poor.

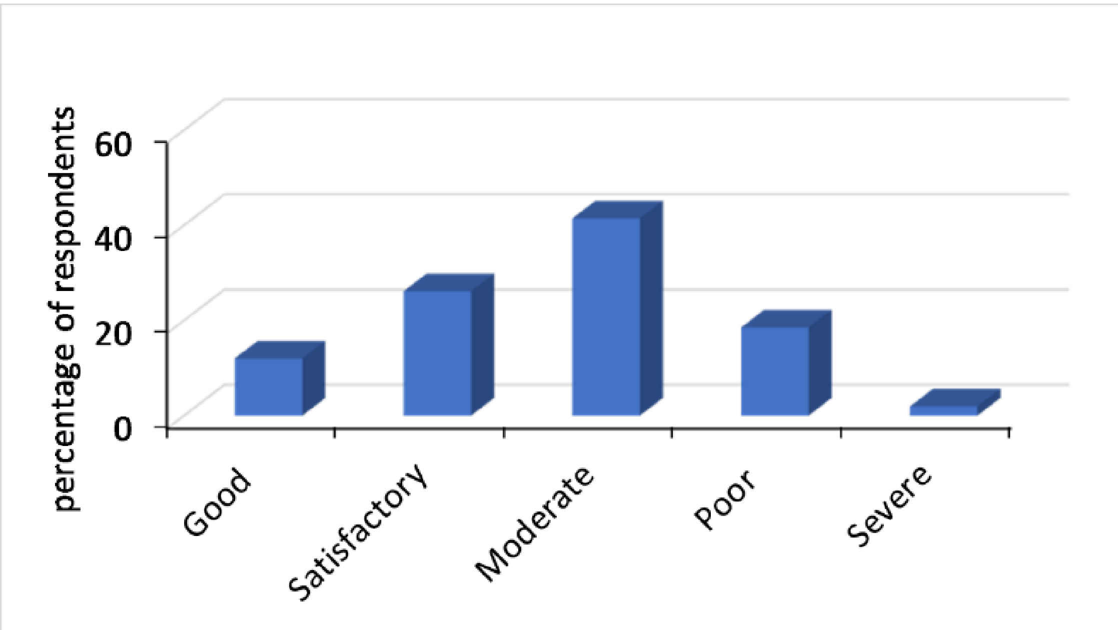

Fig. 3. Status of air quality in Rourkela as per respondents

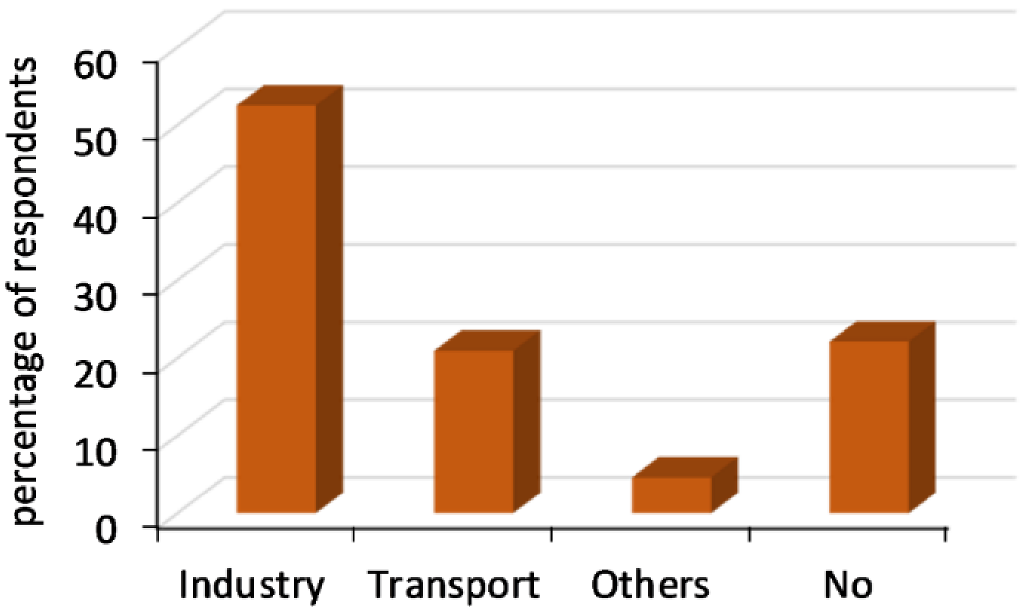

Fig. 4. Major sources of air pollution in Rourkela

Industrial emissions, primarily from the iron, steel, and chemical sectors, are identified as the primary contributors to air pollution, aligning with the city's status as an industrial centre. The transportation sector also plays a significant role in pollution, likely due to vehicular emissions from increased mobility associated with industrial activities and urbanization. Almost 3 lakhs of new motor vehicles were registered in Rourkela regional transport office during the last decade which were continuously adding air pollutants to the ambient air of the city. The presence of other pollution sources, such as construction activities and agricultural practices, highlights the multifaceted nature of air pollution challenges in Rourkela. Fig. 4 shows the major sources of air pollution in Rourkela city.

In Rourkela, the primary sources of air pollution are predominantly attributed to industrial activities, accounting for 52.5% of the pollution burden. This includes emissions from industries involved in iron, steel, chemicals, fertilizers, cement, and brick production, reflecting the city's status as a significant industrial centre in Odisha. Transportation also plays a substantial role, contributing 30% to the overall pollution levels, likely due to vehicular emissions from increased mobility associated with industrial growth and urbanization. Other sources, such as construction activities, agricultural waste burning, and brick kilns, collectively contribute 4.6% to the pollution load. Surprisingly, 22% of respondents believed that the city's ambient air was not polluted, indicating a potential gap in awareness or perception regarding air quality issues in Rourkela.

Demographic description of the respondents involved in the perception study

The demographic description of respondents in our perception study is outlined in Table 1, providing a comprehensive overview of the participants' characteristics. Among the total (417) respondents, 74.1% were male and 25.9% were female.

Table 1. Descriptive statistics for variables used in the regression models

Variables	Frequency (N)/Median	Percentage (%)/Range
Age		
Young	125	30
Middle	227	54.4
Old	65	15.6
Gender		
Male	309	74.1
Female	108	25.9
Outdoor exposure		
Slightly exposed	229	54.9
Moderately exposed	124	29.7
Heavily exposed	64	15.3
Annual household income		
Low income	161	38.6
Medium income	132	31.7
High income	124	29.7
Governmental medicinal facilities		
Good	281	67.4
Moderate	96	23
Poor	40	9.6
Smoking habits		
Regular	57	13.7
Sometime	48	11.5
Never	312	74.8
Availability of separate kitchen		
No	104	24.9
Yes	313	75.1
Enough government effort		
No	259	62.1
Yes	158	37.9

Table 1. Continued

Variables	Frequency (N)/Median	Percentage (%)/Range
Breathing in polluted air		
No (Not polluted)	105	25.2
Yes (Polluted)	312	74.8
AQI	110.58	97.03-122
Got sick by air pollution in last 24 months (dependent variable)		
No	151	36.2
Yes	266	63.8

The study surveyed respondents across various age groups and categorised them into three major age groups on the basis of prior literature. 30% of the total respondents belonged to the young age group (0–35), 54.4% were from the middle age group (36–59 years), and 15.6% were old (60 years or more) people. Respondents exposed to outdoor air pollution are sorted into three categories. About 54.9% of those surveyed were marginally exposed to ambient air pollution, defined as spending on average less than an hour each day travelling or engaging in any other activity outside of their home.

Respondents who were moderately (average 1 to 5 h stayed outside the home) and heavily exposed (more than 5 h outside the home) were 29.7% and 15.3%, respectively. Household income was summed into three categories: low (annually less than 1 lakh), medium (1 to 5 lakhs), and high (more than 5 lakhs). In this perception study, 38.6%, 31.7%, and 29.7% of respondents belonged to low, medium, and high-income groups, respectively. Perceptions regarding governmental medicinal facilities were distributed as good (67.4%), moderate (23%), and poor (9.6%). In terms of smoking habits, 13.7% reported regular smoking, 11.5% smoked occasionally, and 74.8% were non-smokers. The availability of a separate kitchen was noted for 75.1% of respondents, whereas 24.9% did not have this facility. Interestingly, almost 60% of the total respondents believed that the government was not putting enough effort into controlling air pollution, while a substantial majority, 74.8% of the total respondents agreed that they were breathing in highly polluted ambient air. About 64% of respondents agreed that they were affected by air pollution and got sick from air pollution-related respiratory and cardiovascular diseases within the last 24 months. These kinds of responses are sufficient to get researchers interested in learning more about how air pollution affects public health in industrial cities like Rourkela. These demographic details provide a comprehensive understanding of the participant profile and their perceptions related to air pollution and public health.

Air pollution-related diseases

Two key questions were included in the questionnaire to assess the effects of air pollution on local residents' health. The first question asked participants if they had fallen ill due to air pollution in the past two years,

with response options being "Yes" or "No." The second question requested respondents to mark specific diseases they attributed to air pollution from a list identified through literature review.
Fig. 5 illustrates the distribution of air pollution-related diseases reported by respondents. Among the participants in the study conducted in Rourkela, 64% (266 individuals) acknowledged being affected by various air pollution-related diseases, contrasting with the 36% who disagreed with this perception. The distribution of these reported air pollution-related diseases is as follows: 46% (193 individuals) experienced flu/fever, 36% (142 individuals) reported runny nose/cold symptoms, 17% (72 individuals) suffered from eye/nose/throat irritation, 11% (44 individuals) had skin infection/rash issues, 8% (34 individuals) experienced respiratory allergies to dust and pollen, 7% (31 individuals) had shortness of breath, 4% (16 individuals) faced asthma attacks, while heart disease and bronchitis each affected 1.4% of the respondents (4 individuals each). These findings highlight a range of health impacts attributed to air pollution in the surveyed population, with respiratory and dermatological issues being the most prevalent.

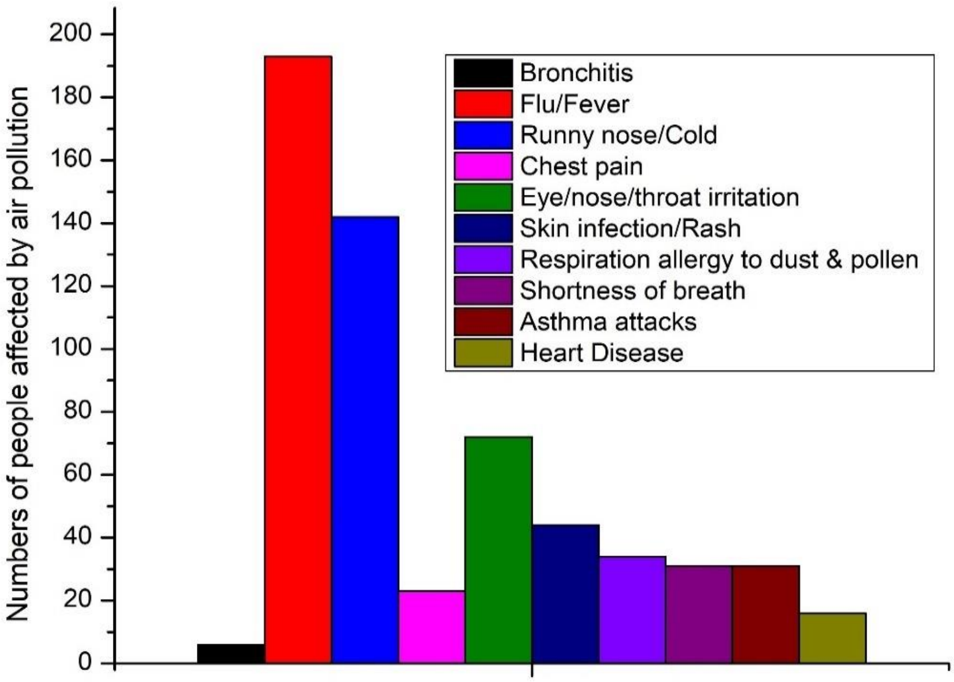

Fig. 5. Respondents affected by various air pollution related diseases

The findings reveal a significant proportion of the population in Rourkela attributing their health issues to air pollution. Notably, flu/fever and runny nose/cold were the most commonly reported ailments, affecting nearly half of the respondents. These results align with previous studies highlighting the respiratory and dermatological effects of air pollution [27, 41]. Furthermore, the presence of respiratory allergies, asthma attacks, and cardiovascular problems underscores the diverse health impacts of poor air quality. The higher prevalence of respiratory symptoms like shortness of breath and bronchitis among a smaller subset of respondents suggests a subset of individuals may be more vulnerable to air pollution's effects, consistent with existing literature on susceptibility factors.

Modeling health impact of air pollution

To examine our research questions regarding the perceptions of people about the impact of ambient air pollution on public health, two binary logistic regression models were run in SPSS (Model-1 and Model-2). In both models, the explanatory variables are regressed on the dependent variable (respiratory and cardiovascular health condition) using binary logistic regression. The first model used ambient air pollution-related data (Yes or No) acquired by people's perceptions as a key explanatory variable, whereas, in the second model, we used AQI ground data as a key explanatory variable. Thereafter, the study compared the results of both models to comprehend the impact of air pollution and other covariates on the respiratory and cardiovascular health problems of the local residents of the city. A trustworthy picture of how air pollution affects public health conditions is being obtained by utilising data linked to air pollution from both perception studies and ground AQI.

Model fit criteria for implemented binary logistic regression

The omnibus test facilitates the evaluation of the potential influence of the independent variables on the dependent variable. It is an illustration of the incremental fit. The null hypothesis (H0) states that the model does not exhibit incremental fit. Considering that the model's fit is significantly better than the null model (p values<0.05), the null hypothesis has been rejected in this instance [42].

A goodness of fit test, the Hosmer & Lemeshow test, compares the estimated model against one that has perfect fit. The test's null hypothesis (H0) suggests that the model fits perfectly [40]. Because the Hosmer and Lemeshow test is not statistically significant in this case, the null hypothesis is not rejected [model-1: x^2 (8) = 5.741, p = > 0.05, and model-2: x^2 (8) = 12.783, p = > 0.05], which shows that the models fit perfectly.

The Nagelkerke pseudo-R-square, which is a modified version of the Cox and Snell, has a range of 0 to 1. Based on the Nagelkerke pseudo-R-square, the independent variables may account for 47 percent and 35.5 percent of the variations in the dependent variables of model 1 and model 2, respectively. The percentage of correctness in a binary logistic regression model indicates how well the model fits the data. It denotes the extent to which the chosen model can predict the observed outcomes. It is necessary to raise the percentage of correctness from block 0 to block 1. In this study, the percentage of correctness in model 1 increased from 63.8% to 78.9%, while it increased from 63.8% to 74.6% in model 2. It demonstrates the suitability of our regression model for further prediction. From the above-mentioned model fitting criteria, it could be concluded that both of our logistic regression models (model-1 and model-2) are statistically significant and fit for predictive analysis.

Assessing air pollution's impact on public health

Table 2 illustrates the results of the first logistic regression model (Model-1) used to assess the likelihood that respondents had fallen sick over the previous 24 months as a result of ambient air pollution. Since human health is affected by a number of environmental, demographic, and socioeconomic factor, their underlying es intricacy need to be investigated. Ambient air pollution related data (whether or not respondents breathe in polluted air), which is obtained through a perception study in dichotomous form, is used as a key explanatory variable in this model. This model also incorporates a few more socioeconomic and demographic factors to see if they have an impact on the capacity to predict the potential health effects of air pollution.

Table 2. Logistic regression (model-1) predicting health impact of air pollution

Independent Variables	Categories	β	S.E.	Sig.	Exp (β)	95% C.I. for EXP(B)	
						Lower	Upper
Gender	Female (Omitted)						
	Male	-0.275	0.315	0.382	0.759	0.410	1.408
Age	Young						
	Middle	-0.351	0.293	0.230	0.704	0.397	1.249
	Old	1.126*	0.482	0.020	3.082	1.198	7.930
Outdoor exposure	Slightly exposed (Omitted)						
	Moderately exposed	0.380	0.303	0.209	1.462	0.808	2.646
	Highly exposed	1.539**	0.452	0.001	4.658	1.919	11.305
Annual family income	Low Income (Omitted)						
	Medium Income	-0.765*	0.336	0.023	0.465	0.241	0.900
	High Income	-1.193**	0.333	0.000	0.303	0.158	0.583
Separate kitchen	No (Omitted)						
	Yes	-0.733*	0.355	0.039	0.481	0.240	0.964
Smoking habits	Regular smoker (Omitted)						
	Sometime smoker	-0.709	0.610	0.245	0.492	0.149	1.626
	Never smoker	-1.221**	0.480	0.011	0.295	0.115	0.756
Medical facilities	Good (Omitted)						
	Moderate	0.939*	0.330	0.004	2.558	1.341	4.880
	Poor	0.627	0.548	0.252	1.873	0.640	5.480
Government Efforts	Not enough (Omitted)						
	Enough	-0.619*	0.275	0.024	0.539	0.314	0.923
Air pollution	No (Omitted)						
(Breathing in polluted air)	Yes	2.365**	0.328	0.000	10.647	5.603	20.233

Note: *= < 0.05, **= < 0.01

According to the results of model-1, air pollution is a significant predictor of health impact with a 95% confidence interval. The respondents who did not reported poor air quality in their locality or region for which AQI is within the safe limit were treated as the reference group in this case. When compared to those who did not breathe in polluted air, those who were exposed to it had a 10.65-fold higher likelihood of becoming ill due to air pollution ($\beta = 2.37$; SE = 0.33; $p < 0.01$). In Rourkela, gender is not a significant predictor of health conditions, but male respondents were about 24% less likely to have respiratory and cardiovascular health problems in comparison to female respondents ($\beta = -0.28$; SE = 0.32; $p > 0.05$). The majority of women spend a significant amount of time in the kitchen, practising cooking on a daily basis, which may expose them to high levels of indoor air pollution.

Age is a significant predictor of health conditions. Middle-aged people have a 30% lower likelihood of getting sick ($\beta = -0.35$; SE = 0.29; $p > 0.05$), whereas older people have a 3.08-time higher likelihood of getting sick ($\beta = 1.13$; SE = 0.48; $p < 0.05$) from air pollution related diseases compared to young people. According to prior studies, the health condition of elderly people is more vulnerable to respiratory and cardiovascular disease compared to other age groups [29-30]. The model likewise supports this statement. The outdoor exposure time is also an important factor that can control human health [9, 43].

As ambient air pollution exposure time increases, the likelihood of a person being affected by air pollution-related health issues drastically increases. Moderately exposed people have a 46% higher probability of getting sick ($\beta = 0.38$; SE = 0.30; $p > 0.05$), while highly exposed groups have a 4.7 higher likelihood of getting sick ($\beta = 1.54$; SE = 0.45; $p < 0.01$) by air pollution-induced diseases in comparison to slightly exposed groups. High-income people can access better facilities to prevent outdoor air pollution compared to lower-income people [25]. In the first model, household income is negatively associated with air pollution-related health problems and is a highly significant predictor of health conditions. Individuals in the medium-income ($\beta = -0.77$; SE = 0.34; $p < 0.05$) and high-income ($\beta = -1.19$; SE = 0.33; $p < 0.01$) groups are 15% and 25% less likely, respectively, to get ill from an air pollution-related illness than those in the low-income group. Separate kitchens in households were significantly and negatively associated with the air pollution-related health issues in Rourkela, which are directly related to indoor air pollution. Individuals who have a separate kitchen in their households were 52% less likely to be affected by air pollution-related diseases compared to households that have no separate kitchen ($\beta = -0.73$; SE = 0.36; $p < 0.05$). Smoking habits may also be an important factor that can cause respiratory health issues in human bodies [6].

In the present study, regular smokers were treated as a reference group. According to our model, people who are not regular smokers but smoke occasionally have a 51% lower likelihood of getting sick ($\beta = -0.71$; SE = 0.61; $p > 0.05$) from air pollution compared to regular smokers. On the other hand, people who never smoke have almost 70% less probability of getting sick ($\beta = -1.22$; SE = 0.48; $p < 0.01$) from air pollution-related respiratory and cardiovascular diseases. Governmental medical facilities are also a substantial factor that helps to prevent the health issues of human beings [19]. People who were getting moderate medical facilities had 2.6 times the probability of getting sick due to air pollution-related diseases compared to people getting good medical facilities ($\beta = -0.94$; SE = 0.33; $p < 0.01$). On the other side, poor medical facilities were insignificantly related to air pollution-related health issues. The overall government effort to control air pollution is also significant but negatively interrelated to air pollution-induced health issues. Individuals from the area where the government was putting in enough effort to reduce air pollution had a 46% less likelihood of getting sick ($\beta = -0.62$; SE = 0.28; $p < 0.05$) from air pollution-related diseases compared to individuals living in the area where the government is not taking enough measures to stop air pollution-related issues.

In the second model (Table 3), AQI is used as a key explanatory variable to predict the impact of air pollution on human health in Rourkela. The Air Quality Index (AQI) is a type of data that is observed from the ground and indicates the degree of pollution or cleanliness of the air in a given area [44]. Therefore, it will offer trustworthy assistance in estimating how air pollution will affect people's health [45, 46]. Model 2 indicates that in Rourkela, the Air Quality Index (AQI) is a significant controlling factor that is positively correlated with health issues due to air pollution. One unit increase in AQI indicates 8.4% more likelihood of getting sick ($\beta = 0.08$; SE = 0.02; $p < 0.01$) by air pollution-related disease in Rourkela. Hence, it has been established that rising AQI corresponds to rising health risks associated with air pollution in Rourkela.

Table 3. Logistic regression (model-2) predicting health impact of air pollution

Independent Variables	Categories	B	S.E.	Sig.	Exp(B)	95% C.I. for EXP(B)	
						Lower	Upper
Gender	Female (Omitted)						
	Male	-0.170	0.293	0.562	0.844	0.475	1.497
Age	Young						
	Middle	-0.091	0.271	0.737	0.913	0.536	1.554
	Old	1.077*	0.424	0.011	2.936	1.278	6.744
Outdoor exposure	Slightly exposed (Omitted)						
	Moderately exposed	0.232	0.280	0.408	1.261	0.729	2.181
	Highly exposed	0.727	0.389	0.062	2.069	0.965	4.435
Annual family income	Low Income (Omitted)						
	Medium Income	-0.725*	0.308	0.019	0.484	0.265	0.886
	High Income	-1.367**	0.308	0.000	0.255	0.139	0.466
Separate kitchen	No (Omitted)						
	Yes	-0.934**	0.332	0.005	0.393	0.205	0.753
Smoking habits	Regular smoker (Omitted)						
	Sometime smoker	-0.543	0.550	0.323	0.581	0.198	1.706
	Never smoker	-1.158**	0.432	0.007	0.314	0.135	0.732
Medical facilities	Good (Omitted)						
	Moderate	0.915**	0.306	0.003	2.497	1.370	4.551
	Poor	1.063*	0.518	0.040	2.895	1.048	7.994
Government Efforts	Not enough (Omitted)						
	Enough	-1.133**	0.248	0.000	0.322	0.198	0.524
Air pollution (AQI)		0.080**	0.023	0.000	1.084	1.037	1.133

Note: *= < 0.05, **= < 0.01

As per model-2, females are 16 % more likely than males to become ill from respiratory and cardiovascular disorders linked to air pollution. Older people are more vulnerable to ambient air pollution compared to the middle and young age groups. When compared to younger age groups, those over 60 have a 2.9-fold increased risk of being ill due to air pollution (β = -1.08; SE = 0.42; $p < 0.05$). It's interesting to note that this model does not show any substantial correlation between the amount of time spent outside and health problems due to air pollution, but the prediction's direction is theoretically sound. When compared to persons who are slightly exposed to air pollution, those who are moderately exposed have a 26 % higher risk of being ill (β = 0.23; SE = 0.28; $p > 0.05$), and those who are severely exposed have an almost two-fold higher likelihood (β = 0.73; SE = 0.39; $p > 0.05$).

According to this model, yearly household income significantly predicts the health problems caused by air pollution. A lower likelihood of health problems is associated with higher household income, and vice versa. Medium- and high-income group people had almost 52% (β = -0.73; SE = 0.30; $p < 0.05$) and 75% (β = -1.37; SE = 0.30; $p < 0.01$) less likelihood of getting sick, respectively, compared to low-income group people. When it came to the availability of a separate kitchen, those who had one in their home had a 61% lower chance of suffering from a disease linked to air pollution (β = -0.93; SE = 0.33; $p < 0.01$) than those who did not. Smoking habits can be a key factor that has a direct impact on an individual's respiratory system. Model 2 shows that compared to regular smokers, occasional smokers have a 42 percent lower probability of being ill from air pollution (β = -0.54; SE = 0.55; $p > 0.05$), and never smokers have a 69 percent lower likelihood (β = -1.16; SE = 0.43; $p < 0.01$) of falling ill. Another important element that contributes to the prevention of health problems due to air pollution is the availability of government medical services. Individuals with access to moderate medical facilities had a 2.5-fold higher likelihood of experiencing health issues due to air pollution (β = 0.92; SE = 0.31; $p < 0.01$) as compared to those with access to good medical facilities. Conversely, individuals with inadequate access to quality medical facilities had a 2.9-fold increased risk of having diseases linked to air pollution (β = -1.06; SE = 0.52; $p < 0.05$) than those with decent medical facilities. The government's effort to reduce air pollution related health issues was also a highly significant factor in predicting the impact of air pollution on human health. In Rourkela, those who believe that their local government is making a sufficient effort to reduce air pollution have a 68 percent lower chance of becoming ill from it (β = -1.13; SE = 0.25; $p < 0.01$) than those who believe that their local government is not making a sufficient effort to reduce air pollution.

From the above discussion, it can be concluded that air pollution is a major threat to public health in Rourkela. Each model indicates that air pollution is the key factor behind the deterioration of human health (respiratory and cardiovascular health systems). Age, outdoor exposure times, household income, an individual's smoking habits, and the availability of a separate kitchen have a significant effect on determining the human health condition [47-49]. Additionally, standard medical facilities and appropriate government efforts to eliminate air pollution can minimise respiratory and cardiovascular health risks [50, 51].

Trends of total mortality by air pollution induced diseases in Rourkela

Air pollution can have serious and detrimental consequences for people's health, causing a number of health issues and, in certain situations, even increasing mortality [30]. It is noteworthy that the precise influence of air pollution on mortality may differ depending on the kind and quantity of pollutants present, as well as personal vulnerability and additional environmental elements [19, 30]. Following a comprehensive review of previous research, a number of diseases related to air pollution were identified and used in this study to illustrate the trends and patterns of air pollution-related mortality in Rourkela city. The necessary data has been collected from the public health office of Rourkela Municipal Corporation (RMC). Fig. 6 shows the total number of deaths in Rourkela city from 2016 to 2022 that were recorded as a result of serious diseases associated with air pollution.

(Note: ANM- Anaemia, BRI- Birth injury, BRAS- Bronchitis-asthma, CLD- Chronic liver disease, HRD- Heart diseases, PNM- Pneumonia, T.B- Tuberculosis)

Over the past seven years, the leading causes of air quality related death in Rourkela have been heart disease (1361), pneumonia (578), chronic liver disease (452), anaemia (211), tuberculosis (202), asthma, and birth injuries related to air pollution (22). In Rourkela, the AQI is mostly dominated by the high concentration of particulate matter (PM_{10} and $PM_{2.5}$). This may be the cause of the higher rate of heart disease-related deaths in the city. In our research site, high blood pressure is related to long-term exposure to air pollution and is a risk factor for cardiovascular or heart-related disorders [6, 10]. Furthermore, air pollution can impair respiratory health, increasing a person's susceptibility to respiratory illnesses like pneumonia and bronchitis [52, 53].

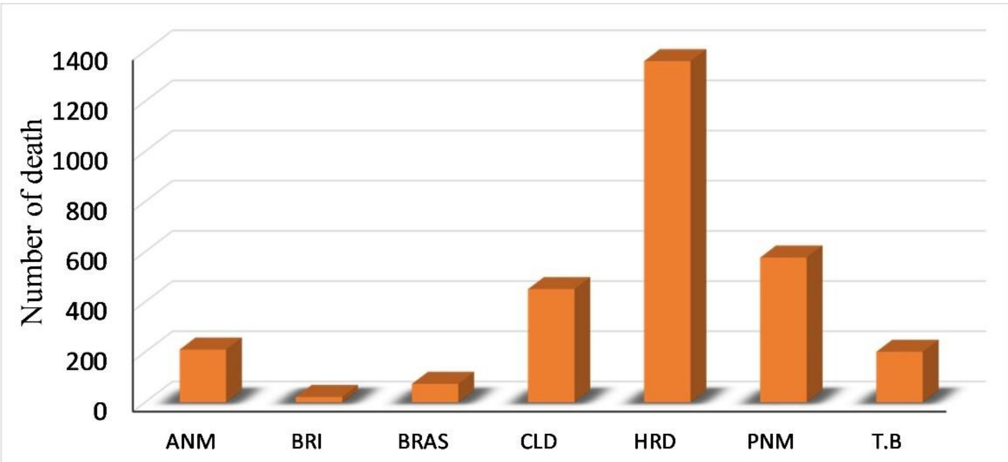

Fig. 6. Air pollution related disease wise total deaths during 2016-2022 in Rourkela

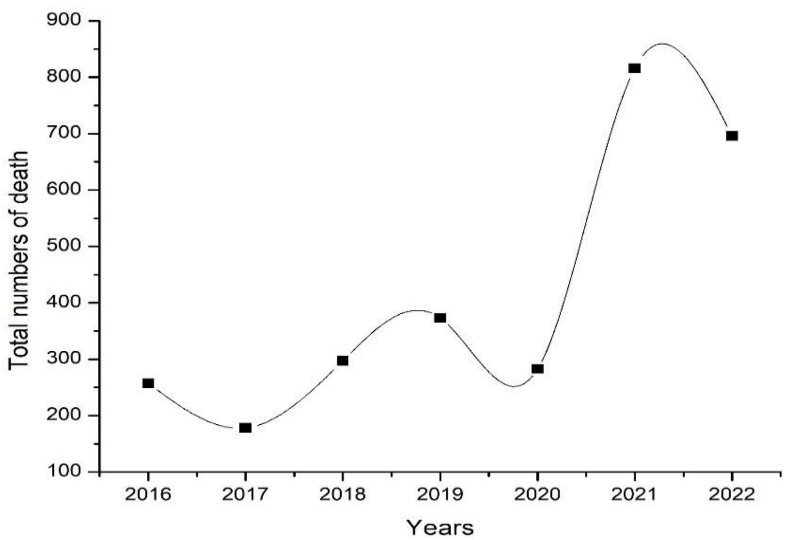

Fig. 7. Trend of annual mortality by air pollution related diseases in Rourkela

Being one of the leading industrial cities in eastern India, Rourkela is growing rapidly and so as the air pollutants, including particulate matter, sulphur dioxide, nitrogen oxides, and volatile organic compounds (VOCs), from various anthropogenic activities [13-14]. Following that, Rourkela's ambient air quality is steadily declining, which has a detrimental effect on people's health both directly and indirectly. Fig. 7 shows the year-wise trend of the total number of deaths due to major air pollution-related diseases in Rourkela city during 2016–2022. A high rising trend (R^2 = 0.67) of mortality by major air pollution-related diseases was found in Rourkela during 2016–2022. The maximum number of deaths (806) was recorded in 2021, while the minimum number of deaths (178) was caused by air pollution in 2017. A sharp decline in this trend is recorded in 2020, the year of COVID-19 restriction. While the stringent COVID-19 lockdown periods in 2020 caused numerous challenges for human society, they also had a positive side in that they helped reduce emissions of ambient air pollutants from a variety of sources, including traffic and industrial emissions. This could be a possible reason behind the decline in mortality from air pollution-related diseases in the city in 2020. There are a number of interrelated causes that contribute to the high and increasing trend in mortality from diseases linked to air pollution, most of which are caused by several anthropogenic activities, including industrialization [54]. Consequently, there is a pressing need to address the trend of increased mortality from diseases associated with air pollution [10]. This calls for a multifaceted strategy that includes enforcing strict environmental laws, advancing cleaner technology, implementing sustainable urban planning techniques, and fostering international collaboration to address transboundary pollution challenges [47].

Conclusion

The ambient air pollution is becoming a more serious public health issue in Rourkela where fast economic growth has coincided with environmental degradation. This study utilizes logistic regression model to assess the impact of air pollution on human health across different socioeconomic strata, based on the perceptions of local residents. The finding reveals that human health is significantly impacted by air pollution in terms of the occurrence of cardiovascular and respiratory disorders. When compared to those who did not breathe in polluted air and those who were exposed to it had a 10.65-fold higher likelihood of becoming ill due to air pollution (β = 2.37; SE = 0.33; $p < 0.01$). On the other hand, a rise of one unit in the AQI in Rourkela corresponds to an 8.4% increase in the risk of getting sick due to air pollution-related diseases (β = 0.08; SE = 0.02; $p < 0.01$). At the 0.05 significance level, all Independent variables representing socio-economic factors of the resident show statistically significant associations with respiratory symptoms, as indicated by their p-values (Sig. < 0.05). Therefore, it is evidenced that an increase in AQI means an increase in air pollution-related health risks among the resident of Rourkela and more especially to those who are socio-economically weak or vulnerable. Furthermore, a high rising linear trend (R^2 = 0.67) of mortality by major air pollution-related diseases was also found in Rourkela during the period of 2016–2022. The results of the study deciphered the role of socio-economic factors that made resident more vulnerable to the air pollution related health hazard. This may assist stakeholders to formulate necessary measures to become more resilient to health issue raised due to air pollution.

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Competing interests

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

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Ethical considerations

"Ethical issues (Including plagiarism, Informed Consent, misconduct, data fabrication and/ or falsification, double publication and/ or submission, redundancy, etc) have been completely observed by the authors."

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