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EXAMINING THE EFFECT OF ENVIRONMENTAL DEGRADATION AND HEALTH FINANCING ON HEALTH OUTCOMES: EVIDENCE FROM INDIA

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ABSTRACT

This study investigates the impact of environmental degradation, particularly CO2 emissions, and health financing on health outcomes in India from 2000 to 2021. Using life expectancy and under-5 mortality rate as proxies for health outcomes, the study explores how CO2 emissions, health expenditure, and economic growth influence these indicators. Principal Component Analysis (PCA) was employed to capture the variability in the dataset, followed by regression models to quantify the relationships. The results reveal a significant negative impact of CO2 emissions on life expectancy and a positive association with mortality rates. Health expenditure positively influences life expectancy and reduces mortality, highlighting the importance of adequate health financing. The models explain over 95% of the variance in both health outcomes. These findings underscore the need for policy interventions that reduce environmental pollution and increase health investment to improve public health and achieve sustainable development in India.

Keywords: Life expectancy, Mortality, Environmental degradation, Health Financing, Principal Component Regression.

1. INTRODUCTION

The worldwide political priorities concerning health have only recently started to include environmental issues; for a long time, public health and environmental protection have been considered somewhat separate concerns(Dong et al., 2018; Usman et al., 2019). However, communities and governments have gradually become aware of the importance of understanding the major impact of environmental degradation on human health, as well as the necessity of accurately estimating health costs associated with the quality of the environment. Over the past few decades, the world has undergone a significant economic expansion as a result of rapid industrialization and technological development, which led to environmental degradation. The most significant impediment to world sustainable development is environmental degradation caused by rising greenhouse gases (GHGs). Among the various GHGs, carbon dioxide (CO2) is the most prevalent, produced by industrialization, change in land use, consumption of natural resources and energy consumption(Alam et al., 2011; Franco et al., 2017). The harmful effects of environmental pollution on human health have increased the amount of healthcare expenditure and decreased the productivity of labour, which in turn have an enormous social cost burden that may generate greater economic pressure in future(Pandey et al., 2021; Vyas et al., 2023). Researchers and policy makers stated that increase in social cost due to high level of environmental pollution is one of the great challenges for long-term economic development. In global CO2 emission, India stands at the third position with 6.8% total emissions. In fact, the country submitted its Intended National Determined Contribution (INDC) in Paris climate conference stating that the

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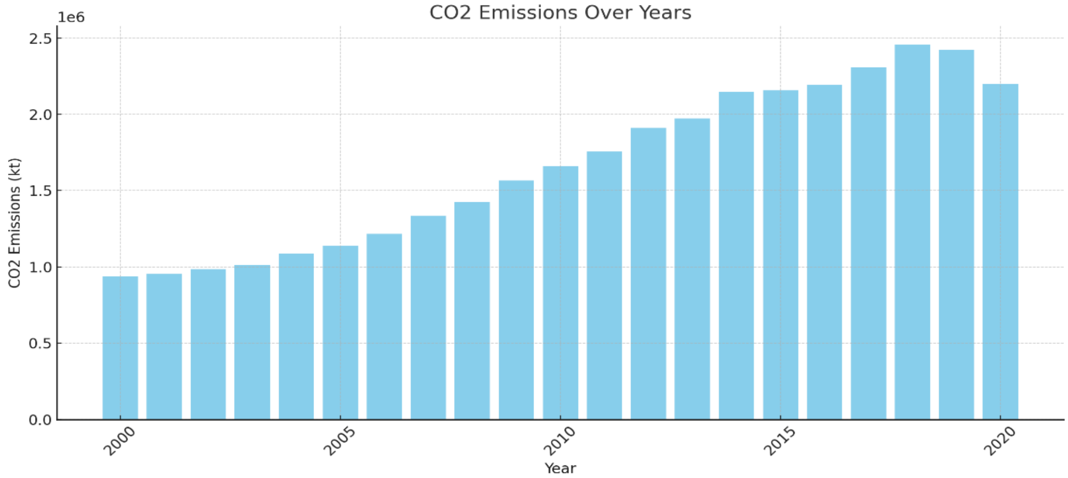
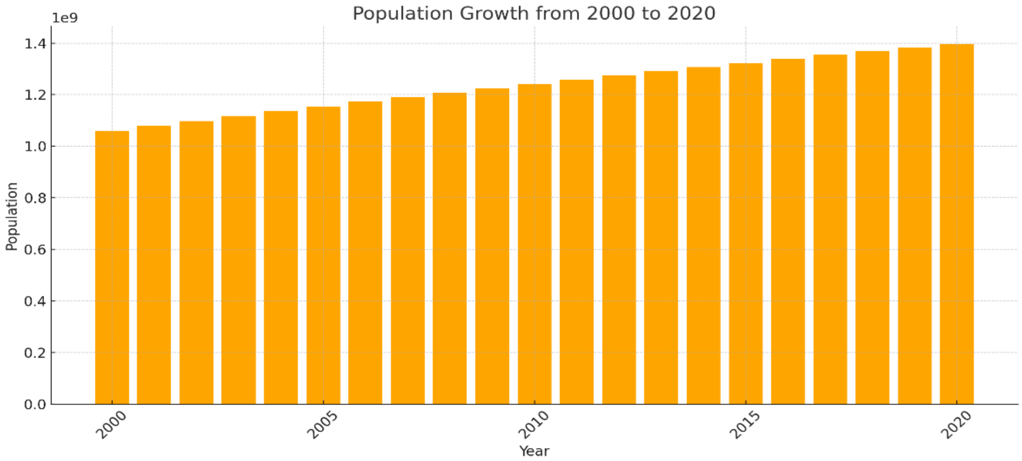
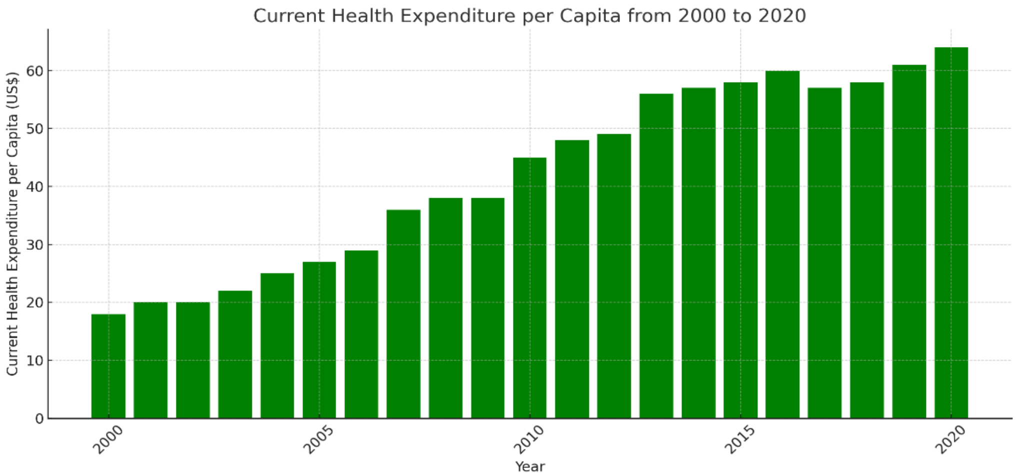
country has to reduce emissions intensity of its GDP by 45 percent by 2030, from 2005 level (Chaturvedi et al., 2021). Besides, the country has also witnessed a tremendous increase in health issues which have consequently increased the health expenditures. Figure 1a demonstrates the CO_2 emission, Fig. 1b total population, and Fig. 1c health expenditures patterns of India from 2000 to 2020, showing that CO_2 emission, population, and health expenditures have increased over the last few years.



(a) Carbon emission of India



(b) Total population of India



(c) Health Expenditure

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Figure1: Carbon emission of India, total population of India, health expenditures of India Source: World Bank, 2023.

The health expenditure in India to be precise has to be expanded to cater for the health issues related to environmental degradation, population growth, and lack of facilities. To successfully manage the issue, India needs massive environmental reforms (e.g., India's environment (protection) third amendment rules, 2023) to mitigate carbon level to protect human development and to minimize the funds spent on health treatment plans. In the study, we consider CO2 gas on the investigation of the impact of human health in India in term of mortality and life expenditure. More healthcare problems add to the health care financing both in developing and developed countries with a goal of improving the population's health outcomes (Sirag et al., 2017). The high healthcare-related issues place a lot of pressure on the government which has to squeeze the budget to cater for them and provide better treatment facilities (Chokshi et al., 2016). The increase in healthcare spending suggests that environmental conditions affect human health.

The objective of this study is to determine the impact of public health expenditure and environmental pollution on health outcomes in India. The research questions to be answered from which the hypotheses were drawn are: what impact does public health expenditure (PHE) have on the health of Indians? Does environmental pollution have a significant effect on the health of Indians?

This paper is structured into five sections, following this introductory section is section two which contain review of literature, section three deals with the methodology of the study as section four details out the descriptive and inferential analyses of data, section five concludes the study with summary of findings and policy implications.

2. **LITERATURE REVIEW**

2.1 *Nexus between carbon dioxide emissions and health outcomes*

The association between CO_2 emissions and health outcomes are examined in this section. Sirag et al. (2017) showed show a negative relationship between CO_2 emissions and health outcomes which include life expectancy at birth and under-5 mortality rate, still these results remain inclusive in Sub-Saharan African countries. The study by Rahman and Alam (2021) investigated whether there is the impact of health expenditure (public and private), CO_2 emissions, energy consumption, sanitation facilities, and economic growth on the health status in the SAARC-BIMSTEC region and whether their will have the long-term and short-term associations or causality for the period of 2000 to 2015. The study revealed that the CO_2 emissions significantly reduce the health status (proxied as life expectancy at birth) and it also observed the bidirectional causality between health status, and health expenditures (both public and private), and carbon emissions. Das and Debanth (2023) examined the net impact of CO_2 emissions on life expectancy in India using a panel autoregressive distributed lag (ARDL) model for the period of 1991 to 2018. The study found the existence of a long-run and quadratic relationship between life expectancy and CO_2 emission. The study finds that India has already surpassed its optimal atmospheric concentration of CO_2 and thereby suggests adopting CO_2 reduction strategies. The study by Li et al. (2023) explores the nexus between CO_2 emission, energy consumption, mortality, life expectancy, and GDP in the top five carbon-emitting countries by using time series data from 1975 to 2015 by using panel vector auto-regression model. The results demonstrated that strong positive correlation between CO2 emissions and energy consumption. It also reflects a weak correlation with mortality and life expectancy in Japan and Russia. Mortality rate and life expectancy rate of

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China, U.S., Russia, India, and Japan show relevant policy changes with economic policies of each country.

2.2 *Nexus between health expenditure and health outcomes*

Nixon and Ulmann (2006) found that increases in health care expenditure are significantly associated with large improvements in infant mortality but only marginally in relation to life expectancy in 15 members of the European Union from 1980 to 1995. By using the fixed effects model, Arthur and Oaikhenan (2017) discovered health expenditure has a significant but inelastic effect on health outcomes in SSA, reducing mortality rates and improving life expectancy at birth. Rahman et al. (2018) found that an increase of total health expenditures had no impact on life expectancy at birth while total health care expenditure significantly reduced infant mortality rates. Similarly, Kiross et al. (2020) showed that Both public and external health care spending showed a significant negative association with infant and neonatal mortality. However, private health expenditure was not significantly associated with either infant or neonatal mortality in sub-Saharan Africa countries. Polcyn et al. (2023) found that higher rates of energy use and healthcare spending lead to better health outcomes for Asian countries over the long run. CO_2 emissions are shown to be harmful to human health. Among all the factors influencing life expectancy in Asian countries, healthcare spending is the most influential. Khan et al. (2024) revealed that there is a one-way causal relationship between government performance, health spending, and SDGs to life expectancy in the short term. Sultana et al. (2024) analyzed the impact of healthcare expenditure on health outcomes, specifically focusing on the reduction in different mortality rates and the transmission of various infectious diseases using Vector Autoregression with Exogenous Variables (VARX) model for 1990–2019. Results showed per capita health expenditure and the number of doctors showed a significant positive impact on life expectancy and maternal and child health. Also, the government's annual budget on the health sector and number of doctors had a significant positive impact on lowering deaths by Diphtheria, Cholera, Tuberculosis, and Malaria diseases.

2.3 *Nexus between economic growth and health outcomes*

Gupta and Mitra (2004) discovered that economic growth and health status are positively correlated and have a two-way relationship, suggesting that better health enhances growth by improving productivity, and higher growth allows better human capital formation in the Indian states. However, Mohapatra (2017) study using panel cointegration and granger causality technique revealed economic growth was found to affect infant mortality rate (IMR) only in the long run but no effect in the short run in 16 major Indian states. Verma & Usmani (2019) analyzed the relationship between health and economic growth in India from 1985 to 2015 and found that there is bilateral causality between GSDP and IMR. However, Ogunjimi and Adebayo (2019) examined the relationship among health expenditure, health outcomes and economic growth in Nigeria and found no causality between real GDP and infant mortality. (Salahuddin et al., 2020) found economic growth and FDI have negative significant effects on both indicators of child health outcomes, i.e., infant mortality rate and child mortality rate under 5 in both the short run and the long run in the South Africa from 1985 to 2016, using Autoregressive Distributed Lag (ARDL) model. Kaur (2023) examined the causal linkage among government health expenditure, health status and economic growth in India for the time period of 1981 to 2016 by using the Toda–Yamamoto causality test. The findings of the study revealed there existed unidirectional causal relationship running from government health expenditure to gross domestic product—GDP (economic growth); GDP

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(economic growth) to life expectancy; government health expenditure to infant mortality rate and infant mortality rate to life expectancy.

3. **Theoretical framework, data and methodology**

3.1 *Data and model specification*

The current study investigates impact of environmental degradation and health financing in health outcomes. So, the first part explores the relationship between life expectancy, a positive indicator of health outcomes, environmental degradation, health financing and economic growth, and the second part explores the relationship between mortality rate (under 5) which a negative indicator of health outcomes, environmental degradation, health financing and economic growth for India. The study uses the annual data for 21 years from 2000 to 2021. Table 1 highlights the names of variables, symbols, units of measurement and data source used in the study.

Table 1: Variable description

Variables	Description	Measurement	Source
le	Life expectancy at birth, total	Years	World Development Indicators of World Bank, 2021
mr	Mortality rate, under-5	Per 1,000 live births	World Development Indicators of World Bank, 2021
co2	CO_2 emissions	Metric tons per capita	World Development Indicators of World Bank, 2021
he	Current health expenditure per capita	current US$	World Development Indicators of World Bank, 2021
gdp	GDP per capita	constant 2015 US$	World Development Indicators of World Bank, 2021

In this study, the following equations were used to evaluate the relationship between life expectancy and mortality rate (under 5), environmental degradation, health financing and economic growth shown in equations (1) and (2).

Model 1:

$$le = \alpha_0 + \alpha_1\, co2 + \alpha_2\, he + \alpha_3\, gdp + \varepsilon_t$$

Model 2:

$$mr = \alpha_0 + \alpha_1\, co2 + \alpha_2\, he + \alpha_3\, gdp + \varepsilon_t$$

In the subsequent equations, in Model 1, dependent variable is life expectancy (le), and independent variables are carbon dioxide emission (co2), health expenditure (he) and economic growth (gdp) in Model 2, mortality rate of children under age of 5 years (mr) is the dependent variable and independent variables are carbon dioxide emission (co2), health expenditure (he) and economic growth (gdp). In Models 1 and 2, α_0 depicts intercept and α_1, α_2 and α_3 depict the slope coefficients of co2, he and gdp respectively. The subscript ε_t is the error term in both regression models, which are normally distributed, where t is the time period (2000–2021). According to the environmental economics literature, CO2 emissions should have negative effect on life expectancy, but its positive effect on mr. The he stands for the per capita health expenditure. The he should have either a positive or no effect on life expectancy, but it also reduces mortality. According to the growth model, economic growth should reduce mr and increases le as people have more income for better lifestyle, facilities and awareness about health care.

3.2 *Methodology*

Principal component analysis (PCA) is one of the oldest techniques examined by Pearson (1901) while Hotelling (1933) explains the mathematical procedure for computing it. It is the simplest technique to carry out as it does not require any particular assumption to fulfil before analyzing the data. The analysis required to take n variables

$$x_1, x_2, x_3 \ldots\ldots\ldots\ldots x_n$$

and search a composition of these variables to produce uncorrelated indices

$$y_1, y_2, y_3 \ldots\ldots\ldots\ldots y_n$$

These linear combinations are ordered in such a way that captures the highest amount of variation in it, captures the second highest mass of variation and so on. The objective of creating these linear combinations is to extract such components whose variances is large among all components, thus neglecting the low variance components we extract those one which effectively describe the variation in data set.

The procedure of principle component analysis consists of following steps; Starting with the set of n variables for p individuals, extract i^{th} principal components expressed as linear combinations of original variables $x_1, x_2, x_3 \ldots\ldots\ldots\ldots x_n$

,

$$y_1 = b_{11}x_1 + b_{12}x_2 + b_{13}x_3 + \ldots\ldots\ldots\ldots + b_{1n}x_n$$
$$y_2 = b_{21}x_1 + b_{22}x_2 + b_{23}x_3 + \ldots\ldots\ldots\ldots + b_{2n}x_n$$
$$.$$
$$.$$
$$Y_i = b_{i1}x_1 + b_{i2}x_2 + b_{i3}x_3 + \ldots\ldots\ldots\ldots + b_{in}x_n$$

These components varies as much as possible subject to the constraint that

$$b_{11}^2 + b_{12}^2 + b_{13}^2 + \ldots\ldots\ldots\ldots + b_{1n}^2 = 1$$
$$b_{21}^2 + b_{22}^2 + b_{23}^2 + \ldots\ldots\ldots\ldots + b_{2n}^2 = 1$$
$$b_{i1}^2 + b_{i2}^2 + b_{i3}^2 + \ldots\ldots\ldots\ldots + b_{in}^2 = 1$$

The method also includes calculation of the eigenvalues of the symmetric sample covariance matrix such that the diagonal elements present the variances of original variables and off diagonal elements are covariance of variables. The eigenvalues are in fact variances of the principal components and they sorted as

$$\omega_1 \geq \omega_2 \geq \omega_3 \geq \cdots \geq \omega_i \geq 0$$

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Now discard the components capturing low proportion of variation in the data i.e. extract those ones holding 90% of the variation of the data set. So, this is the methodology that has been used for empirical results and to realize the objectives of the study.

4. **Results and discussions**

4.1 *Descriptive statistics and correlation*

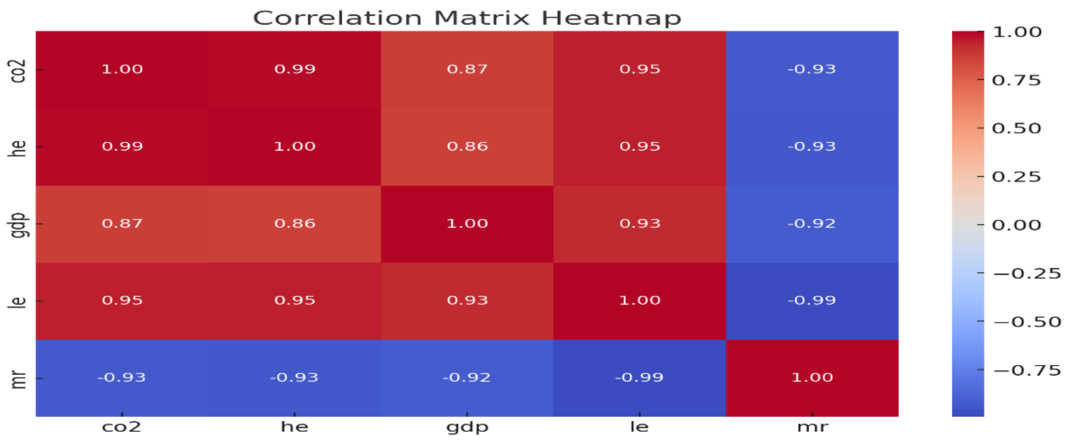
Table 2 provides summary statistics for five variables across 22 observations, highlighting differences in central tendencies and variability. CO2 emissions average 1.304 units with low variability (standard deviation 0.315), while health expenditure averages 41.592 units with larger variation (standard deviation 15.181). GDP has a mean of 1306.343 units and substantial variation (standard deviation 407.481). Life expectancy is relatively consistent, averaging 67.073 years with low variability (standard deviation 2.618). In contrast, the mortality rate shows notable variation, averaging 59.495 with a standard deviation of 18.297. Overall, the dataset reflects significant differences in the spread of values for economic and health-related indicators.

Table 2: Variable descriptive statistics

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
co2	22	1.304	0.315	0.884	1.791
he	22	41.592	15.181	18.502	63.748
gdp	22	1306.343	407.481	755.482	1941.815
le	22	67.073	2.618	62.669	70.910
mr	22	59.495	18.297	32.6	91.7

Figure 2 depicts the correlation matrix heatmap where, high positive correlations (near 1) are indicated in deep red, while strong negative correlations (near -1) appear in blue. Notably, CO2 emissions, health expenditure, GDP, and life expectancy are highly positively correlated with each other, particularly with correlations of around 0.95 between life expectancy and both CO2 and health expenditure. Mortality rate, however, shows a strong negative correlation with all other variables, especially with life expectancy (−0.99), indicating that as life expectancy increases, the mortality rate tends to decrease. Overall, the matrix shows strong interrelationships among economic and health indicators, with mortality standing in opposition to the other variables.

Figure 2: The Correlation Heatmap



4.2 *Principal Component Analysis*

Table 3 show that the first principal component (PC1) explains the majority of the variance (94.67%), indicating that most of the data's variability can be captured by this component. PC2 adds 3.53% more, bringing the cumulative variance explained to 98.20%. PC3 accounts for 1.50%, while the remaining two components contribute very little (0.22% and 0.07%). Overall, the first component is sufficient to explain almost all the variance in the dataset.

Table 3: Principal Component

Principal Component	Eigen Value	Proportion of Variance Explained	Cumulative Variance Explained
PC1	4.959	94.67%	94.67%
PC2	0.185	3.53%	98.20%
PC3	0.079	1.50%	99.70%
PC4	0.012	0.22%	99.92%
PC5	0.004	0.07%	100.00%

Table 4 shows that in PC1, CO2 emissions, health expenditure, GDP, and life expectancy all have strong negative contributions, while mortality rate has a strong positive contribution, indicating an inverse relationship with the other variables. In PC2, GDP dominates with a high positive contribution, while CO2 emissions and health expenditure contribute negatively. PC3 is primarily driven by mortality rate and GDP with strong positive loadings, while life expectancy opposes these variables. Overall, PC1 captures a general trend among most variables, PC2 is largely influenced by GDP, and PC3 reflects the relationship between mortality rate and GDP.

Table 4: Loading Analysis

Variable	PC1	PC2	PC3
co2	-0.4486	-0.4350	0.3407
he	-0.4473	-0.4996	0.2141
gdp	-0.4325	0.7306	0.5197
le	-0.4558	0.0842	-0.4157
mr	0.4516	-0.1424	0.6287

The regression analysis shows a highly significant relationship between life expectancy and the first principal component (PC1) as depicted in table 5. The intercept value of 67.115 indicates the baseline life expectancy, while the negative coefficient of -1.145 for PC1 suggests that as PC1 increases, life expectancy decreases. Both the intercept and PC1 are statistically significant with very low p-values (<0.001). The model fits the data extremely well, with an R-squared value of 0.978, explaining 97.8% of the variance in life expectancy. Additionally, the F-statistic confirms the overall significance of the model. The Durbin-Watson statistic of 1.976 suggests no autocorrelation in the residuals, and the condition number (2.106) indicates no multicollinearity issues. The low mean squared error (MSE) and its standard deviation show the model has a strong predictive accuracy.

Table 3: Principal Component Regression (Model 1)

Variable	Coefficient	Std. Error	t-Statistic	p-value (Significance)
Intercept	67.115	0.093	720.644	<0.001
PC1	-1.145	0.045	-25.613	<0.001
R-squared 0.978			Durbin-Watson stat 1.976	
F-statistic 656.04			Prob (F-statistic) 8.53×10^{-14}	
Condition Number 2.106			Mean Squared Error (MSE) 0.0644	
Standard deviation of the MSE 0.254				

The regression analysis indicates a significant positive relationship between the first principal component (PC1) and mortality rate as depicted in table 6. The intercept of 59.046 suggests the baseline mortality rate when PC1 is zero, while the coefficient of 7.841 shows that an increase in PC1 leads to a rise in mortality. Both the intercept and PC1 are highly significant with p-values less than 0.001. The model explains 95.5% of the variance in mortality (R-squared = 0.955), and the F-statistic confirms the overall significance of the model. There is no indication of autocorrelation or multicollinearity issues, as suggested by the Durbin-Watson statistic (1.935) and condition number (2.106). The mean squared error (MSE) of 8.33 indicates that the model's predictions are reasonably accurate.

Table 6: Principal Component Regression (Model 2)

Variable	Coefficient	Std. Error	t-Statistic	p-value (Significance)
Intercept	59.046	0.918	64.296	<0.001
PC1	7.841	0.441	17.792	<0.001
R-squared 0.955			Durbin-Watson stat 1.935	
F-statistic 316.56			Prob (F-statistic) 1.71×10^{-11}	
Condition Number 2.106			Mean Squared Error (MSE) 8.33	
Standard deviation of the MSE 2.886				

Validity of the model

Some diagnostic tests are also performed to check if the errors are normal, homoskedastic and independent of the regressors, and that the linear specification of the model is correct. The results are presented in table 7, the Jarque–Bera statistic tests for normality. If the residuals are normally distributed, the Jarque–Bera statistics should not be significant. The Breusch–Godfrey LM test checks for serial correlation. The null hypothesis is no serial correlation. The ARCH LM tests for autoregressive conditional heteroskedasticity (ARCH) in the residuals. The null hypothesis is no ARCH. The Jarque–Bera test indicates that the residuals from the regression model are normally distributed. Moreover, the Breusch–Godfrey LM test suggests that the residuals do not exhibit autocorrelation. Finally, the ARCH LM test confirms the absence of heteroscedasticity in the residuals. In essence, these diagnostics suggest that the regression model's residuals adhere to the key assumptions of linearity, which is vital for the validity and interpretability of regression analyses.

Table 7: Diagnostics of the estimated principal component regression (Model 1)

Test statistics	Size	P-value
Jarque–Bera	5.831	0.054
Breusch–Godfrey LM	0.00069	0.979
ARCH LM	0.807	0.848

In table 8, the Jarque–Bera test indicates non-normality in the residuals, there is no evidence of autocorrelation or heteroscedasticity based on the Breusch–Godfrey and ARCH LM tests, respectively.

Table 8: Diagnostics of the estimated principal component regression (Model 2)

Test statistics	Size	P-value
Jarque–Bera	52.038	<0.001
Breusch–Godfrey LM	0.015	0.902
ARCH LM	0.830	0.842

5. CONCLUSION AND POLICY IMPLICATIONS

The study demonstrates a significant relationship between environmental degradation, health financing, and health outcomes in India. The results of the study reveal a strong and significant relationship between environmental degradation, health financing, and health outcomes in India. The analysis shows that an increase in CO_2 emissions is associated with a decrease in life expectancy and an increase in the mortality rate, underscoring the negative health impacts of environmental pollution. Health expenditure plays a positive role in improving life expectancy and reducing mortality rates, indicating the crucial role of health financing in mitigating the adverse effects of pollution and improving public health. The regression models demonstrate that CO_2 emissions, health expenditure, and GDP collectively explain over 95% of the variance in life expectancy and mortality. These results highlight the pressing need for policies that both address environmental degradation and invest in healthcare to improve health outcomes in India.

Based on the findings, policymakers in India should prioritize integrated strategies that tackle both environmental degradation and health financing to improve public health outcomes. Reducing CO_2 emissions through stricter environmental regulations, investment in renewable energy, and sustainable industrial practices is critical to improving life expectancy and reducing mortality rates. Additionally, expanding health expenditure is essential to counter the adverse effects of pollution, ensuring better healthcare access, infrastructure, and preventive care. Public health campaigns that raise awareness about the health risks of pollution, combined with targeted investments in healthcare, will be crucial in addressing the dual challenges of environmental degradation and growing healthcare demands. These policies will help India achieve its climate targets while improving the overall health and well-being of its population.

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