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Article

Bridging health and environment: Clean fuel access and tuberculosis in India

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Abstract: Air pollution, both outdoor and indoor, is a major health risk, contributing to diseases like respiratory infections, cardiovascular conditions, and cancer, particularly affecting vulnerable groups like children, women, and the elderly. Poor indoor air quality (IAQ) due to cooking, heating, and inadequate ventilation is a significant concern, especially in low-income countries where solid fuels like biomass and coal worsen pollution. Long-term exposure leads to chronic conditions such as Chronic obstructive pulmonary disease (COPD), while immediate effects include respiratory infections and headaches. IAQ also affects the spread of tuberculosis (TB), particularly in areas with poor healthcare. This study examines the link between access to clean cooking fuels and TB incidence in India, using data from 2000 to 2022. It explores whether improved access to clean fuels reduces TB rates, considering factors like health expenditure and community health workers. Descriptive statistics, correlation analysis, regression, and time series analysis were employed. The data reveals a steady increase in access to clean cooking fuels, from 22.6% in 2000 to 74.5% in 2022, with the Pradhan Mantri Ujjwala Yojana likely contributing. TB incidence declined from 322 cases per 100,000 people in 2000 to 199 cases per 100,000 in 2022. Regression analysis shows a strong inverse relationship, explaining 94.1% of TB variance. However, socio-economic issues like poverty and illiteracy remain barriers, hindering TB control. India aims to eliminate TB by 2025, targeting an 80% reduction in incidence. While progress has been made, improving IAQ with clean cooking technologies like Liquefied petroleum gas (LPG) is crucial. Policies should focus on subsidies, alternative energy solutions, and rural infrastructure to achieve TB elimination and sustainable development goals.

Keywords: clean cooking fuels; air pollution; indoor air quality (IAQ); health outcomes tuberculosis (TB); Pradhan Mantri Ujjwala Yojana; socio-economic factors

1. Introduction

The link between air quality and human health is well-established [1,2]. Air pollution, both outdoor and indoor, is a major global health risk, contributing to respiratory infections, cardiovascular diseases, and cancer [3]. It is also a recognized risk factor for stroke, diabetes, and neurodegenerative diseases like Alzheimer's [4,5]. It is estimated that air pollution caused 4.2 million premature deaths globally in 2015, while a 2024 report links it to 8.1 million deaths in 2021.

Certain populations are particularly vulnerable. Children face higher risks of asthma and respiratory infections [6], while older adults and those with pre-existing conditions experience exacerbated symptoms [7,8]. Indoor air pollution, largely from solid fuels like wood and coal, poses a significant health burden, particularly in low- and middle-income countries [9]. Incomplete combustion releases harmful pollutants, including PM2.5, CO, and PAHs [10], disproportionately affecting women and children due to traditional gender roles [11]. Even in high-income countries, indoor pollutants from household products and mold contribute to poor air quality [12].

Exposure to indoor air pollution has immediate and long-term health impacts, from carbon monoxide poisoning [13] to chronic conditions like COPD and lung cancer [11]. VOCs and formaldehyde are linked to allergic reactions and potential carcinogenic effects [14]. Women using biomass fuels have higher rates of chronic bronchitis [15], while children exposed to indoor pollutants face stunted lung development [6]. Pollutants also contribute to cardiovascular diseases [16] and neurodegenerative conditions [4].

Poor indoor air quality exacerbates tuberculosis (TB) transmission, particularly in overcrowded and poorly ventilated spaces [17]. In resource-poor settings, factors like poor sanitation and poverty further hinder TB prevention and treatment efforts. A study in China investigated the association between fine particulate matter (PM2.5) and TB incidence. The researchers employed Granger causality analysis and found that long-term exposure to PM2.5 significantly increased the risk of developing TB. This study underscores the importance of air quality improvement in TB prevention efforts [18]. The study by Liu et al. conducted in Hubei Province, China, utilized Bayesian spatial-temporal models to analyze the relationship between ambient air pollutants—specifically PM10, sulfur dioxide (SO_2), and nitrogen dioxide (NO_2)—and pulmonary TB incidence. The findings revealed a positive association between higher concentrations of these pollutants and increased TB incidence, suggesting that air pollution contributes to the regional spread of TB [14].

2. Indoor environment and tuberculosis

India accounts for 27% of global TB cases [19]. To combat this, the government aims to eliminate TB by 2025, five years ahead of the global goal. Indoor air pollution, often overlooked, is a significant driver of TB in India. Examining its role can inform effective interventions. Overcrowding, poor ventilation, and solid fuel use increase TB transmission risk, particularly in resource-limited settings. Burning biomass fuels (wood, dung, crop residues) releases pollutants like PM2.5, CO, and PAHs, which impair respiratory health and immunity, raising TB susceptibility. Exposure to biomass smoke is linked to a two- to three-fold higher TB risk [20,21].

Indoor pollutants cause chronic inflammation, impair lung function, and disrupt mucociliary clearance, facilitating M. tuberculosis infection [22]. Conditions like COPD and silicosis further increase TB risk [23]. Women and children in biomass-dependent households face higher TB susceptibility [23], with poor air quality exacerbating socioeconomic and health disparities [24].

Evidence from Nepal links biomass and kerosene use to TB risk [23], while Indian studies highlight biomass-related TB burdens, especially among rural women [25]. In South Africa, second-hand smoke and kerosene use correlate with pulmonary TB, particularly in children [26]. Despite the strong link between indoor air pollution and TB, more studies are needed on its role in TB, asthma, cardiovascular diseases, and cancer [27]. Biomass smoke is also associated with chronic bronchitis and respiratory conditions [28], underscoring the broad health risks of poor indoor air quality.

3. Objectives and methodology

This study examines the relationship between access to clean cooking fuels and tuberculosis (TB) incidence in India. Clean fuels, as defined by the World Bank, include LPG, electricity, and biogas, excluding kerosene. The study tests the null hypothesis: H_0: There is a positive relationship between access to clean cooking fuels and TB incidence in India.

A quantitative approach is used, analyzing time-series data (2000–2022) from the World Bank. Key variables include access to clean cooking fuels (of the population) and TB incidence (per 100,000 people), with current health expenditure (of GDP) and community health workers (per 1000 people) as control variables. The methodology follows multiple analytical stages, such as descriptive statistics (mean, median, standard deviation) to understand data distribution, Pearson's correlation to measure the strength and direction of the relationship, multiple regression analysis to assess the impact of clean fuel access on TB incidence, controlling for other factors, and Autoregressive Integrated Moving Average (ARIMA) modeling to analyze long-term trends and seasonal patterns.

The study acknowledges limitations, including data quality, confounding variables (e.g., cultural and socioeconomic factors), and the inability to establish causation. Statistical assumptions may also affect results. Findings are specific to India and may not be generalizable to other regions with different socio-economic conditions.

4. Results

This section details the findings from our comprehensive analysis of the relationship between access to clean fuels and cooking technologies and the incidence of tuberculosis (TB) in India over a 23-year period. Our study combines descriptive statistics with advanced analytical techniques, including time series analysis, to unravel the dynamics between these two variables.

To begin, we systematically present the data on access to clean fuels and technologies for cooking, alongside the incidence of tuberculosis, in a structured tabular format (**Table 1**). This enables a clear and comprehensive overview of trends and variations over the two-decade span. The tabular presentation facilitates easier interpretation and allows for identifying critical inflection points and patterns in the data. Subsequently, the analysis delves into temporal trends, exploring the evolution of clean fuel accessibility and its potential correlation with changes in TB incidence. By employing time series analysis, we identify long-term patterns, seasonal effects, and potential causal linkages. This approach highlights how improvements in access to clean cooking solutions might have contributed to public health outcomes, particularly concerning TB prevalence.

The findings underscore the interplay between environmental health determinants and disease burden, offering valuable insights into the importance of promoting clean cooking technologies as part of a comprehensive public health strategy in India.

Table 1. Accessibility of clean fuel and incidence of tuberculosis.

Years	Access to clean fuels and technologies for cooking (% of population)	Incidence of tuberculosis (per 100,000 people)
2000	22.6	322
2001	23.90	321
2002	25.10	320
2003	26.00	318
2004	27.30	315
2005	28.10	311
2006	29.30	305
2007	30.65	298
2008	31.90	291
2009	33.40	283
2010	35.30	276
2011	37.20	268
2012	39.20	258
2013	42.00	248
2014	44.40	243
2015	47.40	237
2016	50.90	225
2017	54.30	217
2018	58.60	208
2019	62.20	202
2020	66.80	195
2021	70.50	200
2022	74.50	199

Source: World Development Indicators (time series data from 2000 to 2022).

The results indicate a consistent upward trend in access to clean fuels and technologies for cooking (182 of the population) over the 23-year study period. In 2000, only 22.6% of the population had access to clean fuels and technologies for cooking. This percentage has shown persistent growth, surpassing 50% by 2015. By 2022, accessibility had risen significantly to 74.5%, highlighting substantial progress in 185 in this area. A key factor contributing to this improvement may be the Pradhan Mantri Ujjwala Yojana, a central government policy initiative launched to promote the use of clean fuels in households.

In contrast, the incidence of tuberculosis (per 100,000 people) exhibits a consistent downward trend. The data reveal a decline from 322 cases in 2000 to 199 cases in 2022, reflecting a significant reduction of 189 in TB incidence over the study period.

As shown in **Figure 1**, the data reveal a consistent upward trend in the percentage of the population with access to clean fuels and technologies for cooking over the study period. In 2000, only 22.6% of the population had access, but this figure steadily increased, surpassing 50% by 2015. By the end of the study period in 2022, accessibility had risen significantly to 74.5%. A major contributing factor to this improvement appears to be the Indian government's policy initiative, the Pradhan Mantri Ujjwala Yojana, launched in 2016, which aimed to promote the use of clean fuels in households.

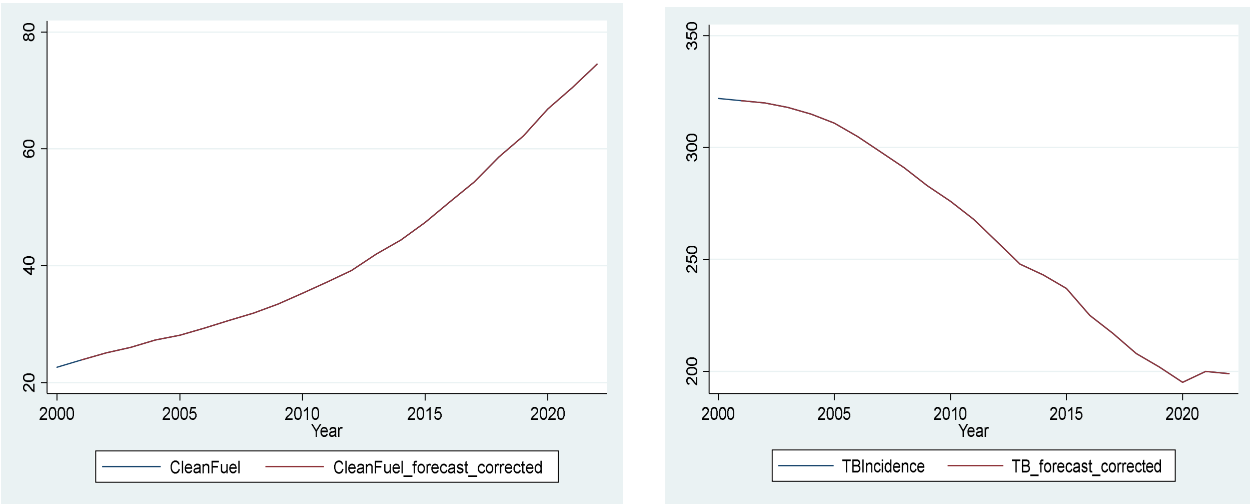


Figure 1. Trend of access to clean fuels and technologies for cooking (% of the population) & incidence of tuberculosis (per 100,000 people).

Conversely, the incidence of tuberculosis showed a consistent downward trend. In 2000, there were 322 cases per 100,000 people, which declined to 199 cases per 100,000 by 2022. The descriptive statistics provide a clear picture of the trends and variability in these variables. While both variables exhibited variability over the years, access to clean fuels and technologies displayed greater relative variability compared to TB incidence.

4.1. Correlation analysis

As indicated in **Table 2**, the Pearson correlation coefficient between access to clean fuels and the incidence of tuberculosis was calculated to be −0.997, indicating a strong negative relationship. This suggests that as access to clean fuels increases, TB incidence consistently decreases. The relationship was found to be statistically significant ($p < 0.001$). However, correlation analysis alone cannot establish causation, necessitating further investigation through regression and time series analysis.

Table 2. Result of correlations between clean fuel and TB.

		Clean Fuel %	TB
CF%	Correlation Coefficient	1.000	−0.997**
	Sig. (2-tailed)		0.001
	N	23	23
TB No.	Correlation Coefficient	−0.997**	1.000
	Sig. (2-tailed)	0.001	
	N	23	23

**. Correlation is significant at the 0.01 level (2-tailed).

4.2. Regression analysis

As indicated in **Table 3**, the regression analysis revealed a robust inverse relationship between access to clean fuels (CF) and the incidence of tuberculosis (TBNO). The model demonstrated a high R-squared value of 0.941, indicating that 94.1% of the variance in TB incidence was explained by access to clean fuels. The ANOVA results confirmed the statistical significance of the model ($F = 337.632$, $p < 0.001$).

The coefficient for access to clean fuels was −2.798, with a standardized coefficient of −0.970, implying that for every unit increase in access to clean fuels, the TB incidence decreased significantly ($p < 0.001$). Residual analysis indicated that the model's predictions were unbiased, with a mean residual close to zero and no major outliers or systematic errors[1].

While these findings underscore the strong association between increased access to clean fuels and reduced TB incidence, the diminishing marginal effect observed suggests that other factors may become more influential in determining TB incidence as access to clean fuels continues to rise.

Table 3. Result of regression of relationship between clean fuel and TB.

Metric	Value
Regression Coefficient (BBB)	−2.798 (Unstandardized), −0.970 (Standardized)
Constant (Intercept)	380.459
Standard Error (Coefficient)	0.152
t-Statistic (CF)	−18.375
p-Value (CF)	0.001 (Significant)
R-Square (R^2)	0.941
Adjusted (R^2)	0.939
F-Statistic	337.632
p-Value (ANOVA)	0.001 (Significant)
Standard Error of the Estimate	11.425
Durbin-Watson	0.186
Residuals	Mean = 0.000, Std. Deviation = 11.162
Sample Size (N)	23

Source: Calculations by authors.

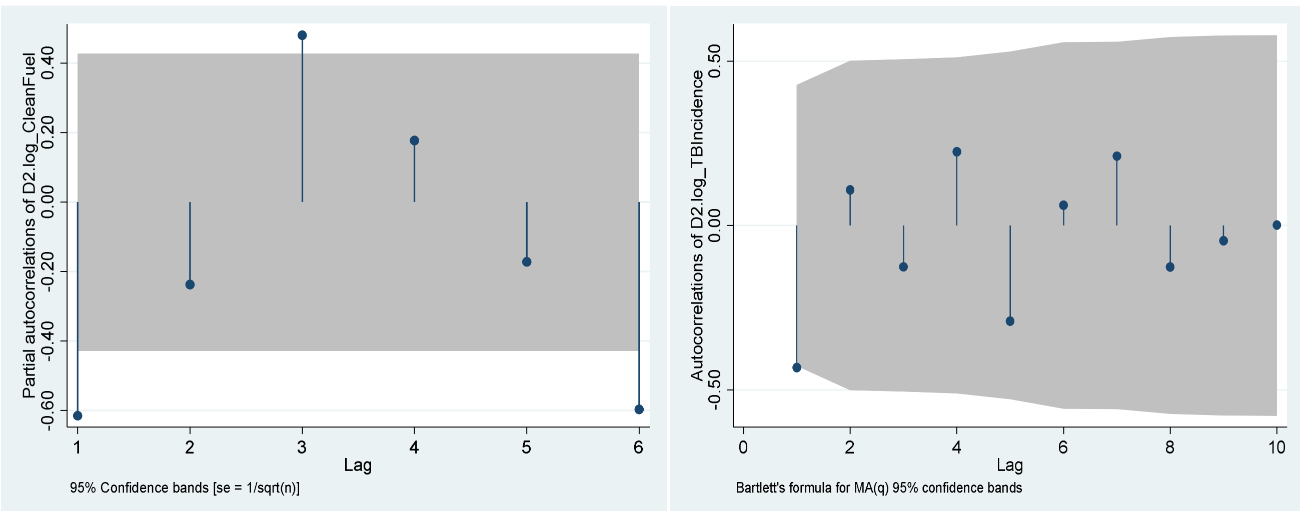
Time series analysis provided additional insights into the temporal dynamics of TB incidence and clean fuel accessibility. The analysis of clean fuel adoption from 2000 to 2022 reveals a steady and accelerating increase, reflecting substantial improvements in accessibility and affordability. Simultaneously, tuberculosis (TB) incidence has shown a declining trend, suggesting a possible inverse relationship between clean fuel usage and TB cases.

Table 4. Stationarity, autocorrelation, and partial autocorrelation analysis of log Clean Fuel and log TB Incidence: Dickey-Fuller test results.

Variable	Test Statistic (Z(t))	1% Critical Value	5% Critical Value	10% Critical Value	*p*-value	Stationary?
log_CleanFuel	3.839	−3.75	−3.00	−2.63	1.0000	No
D1_log_CleanFuel	−2.253	−3.75	−3.00	−2.63	0.1874	No
D2_log_CleanFuel	−8.820	−3.75	−3.00	−2.63	0.0000	Yes
log_TBIncidence	0.675	−3.75	−3.00	−2.63	0.9893	No
D1_log_TBIncidence	−2.715	−3.75	−3.00	−2.63	0.0714	Weak stationarity
D2_log_TBIncidence	−6.684	−3.75	−3.00	−2.63	0.0000	Yes

Source: Analysis by authors.

The findings in **Table 4** suggest that the Augmented Dickey-Fuller (ADF) test, which confirms that both log-transformed Clean Fuel and TB Incidence variables are non-stationary in their original form but become stationary after second differencing, indicating an integration order of I (2). The ACF analysis as shown in **Figure 2** reveals strong negative autocorrelation at lag 1 for both series, suggesting a possible MA(1) structure and a resemblance to white noise beyond the first lag. The PACF analysis (**Figure 2**) indicates that D2_log_CleanFuel follows a moving average process, supporting models like ARIMA(0,2,1) or ARIMA(0,2,3), while D2_log_TBIncidence shows autoregressive characteristics with potential seasonal influences. These findings guide ARIMA model selection, requiring further diagnostics for confirmation.



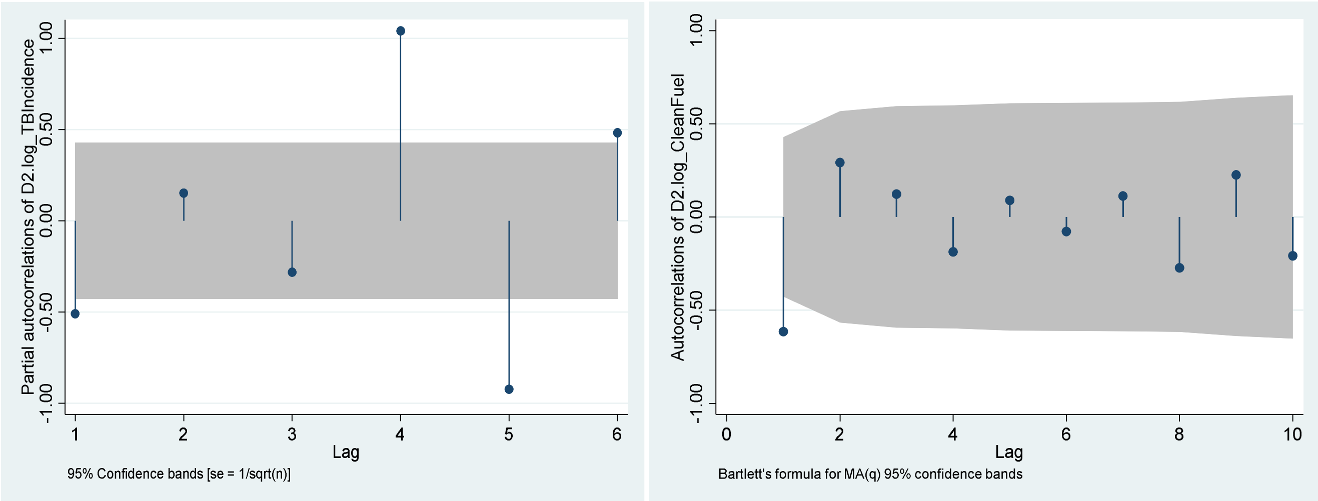


Figure 2. Correlational function and partial auto-correlation function.

Source: Analysis by authors.

ARIMA modeling of clean fuel accessibility and TB incidence.

The ARIMA(1,1,2) model effectively captures the time-series patterns of clean fuel accessibility and TB incidence from 2000 to 2022. For clean fuel, the model indicates strong persistence, with past values significantly influencing future trends. For TB incidence, the model captures both short-term fluctuations and long-term trends, showing that past TB levels have a lasting impact. The high log-likelihood and significant Wald χ^2 test confirm a good model fit for both variables, providing valuable insights into their temporal dynamics.

Table 5. Residual analysis summary of ARIMA(1,1,2) models for clean fuel accessibility and TB incidence.

Model Component	**Clean Fuel (ARIMA 1,1,2)**	**TB Incidence (ARIMA 1,1,2)**
Observations	23	23
Log Likelihood	43.0322	54.1384
Wald χ^2	618.37	Significant
p-value (χ^2 test)	< 0.001	< 0.001
Differencing Order (I)	1	1
AR(1) Coefficient	0.996 ($p < 0.001$)	0.988 ($p < 0.001$)
MA(2) Coefficient	1	0.6546 ($p = 0.025$)
Constant	3.709 ($p < 0.001$)	5.5499 ($p < 0.001$)
Residual Variance (σ)	0.029	0.0202

Source: Analysis by authors.

Residual diagnostics in **Table 5** confirm that the ARIMA(1,1,2) models for clean fuel accessibility and TB incidence are well-specified, with residuals exhibiting white noise behavior and no significant lagged dependencies. The ACF and PACF plots as **Figure 3** show that all autocorrelations fall within 95% confidence bands, indicating no misspecification. With no large spikes suggesting unaccounted dependencies, the models are statistically sound and reliable for forecasting trends.

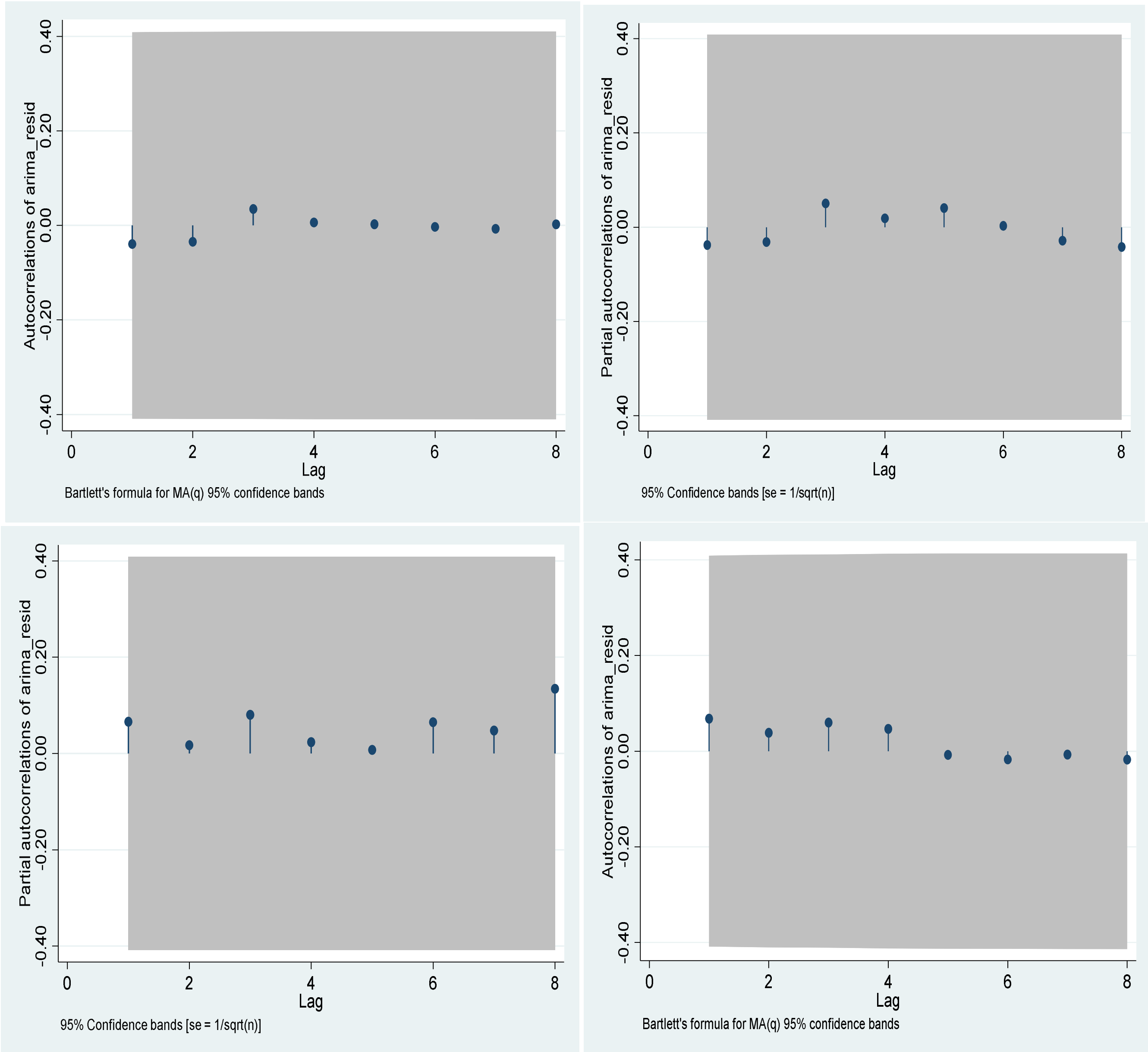


Figure 3. Auto-correlation function and partial autocorrelation functions of residual test.

Source: Analysis by authors.

Table 6. Integrated portmanteau test results.

Variable	Q Statistic	Chi-Square DF	*p*-value	Interpretation
Clean Fuel Accessibility	0.1127	9	1.0000	Residuals are white noise (No autocorrelation)
TB Incidence	0.4271	1	1.0000	Residuals are white noise (No autocorrelation)

Source: Analysis by authors.

The result in **Table 6** confirms that the models effectively capture the time-series structure, leaving no significant autocorrelation in the residuals. The results align with the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, reinforcing that the residuals exhibit white noise behavior and that the models are statistically robust for forecasting clean fuel usage.

The ARIMA-based forecasting analysis examines trends in clean fuel usage and TB incidence, evaluating the model's predictive accuracy and necessary refinements. After ensuring white noise residuals, dynamic forecasting from 2022 onward was conducted using past predicted values. As indicated in **Figure 4** the time-series analysis of Clean Fuel adoption reveals a steady upward trend, though initial forecasts underestimated future growth due to model limitations. A corrected forecast, incorporating logarithmic difference and exponentiation, better captures the accelerating trend.

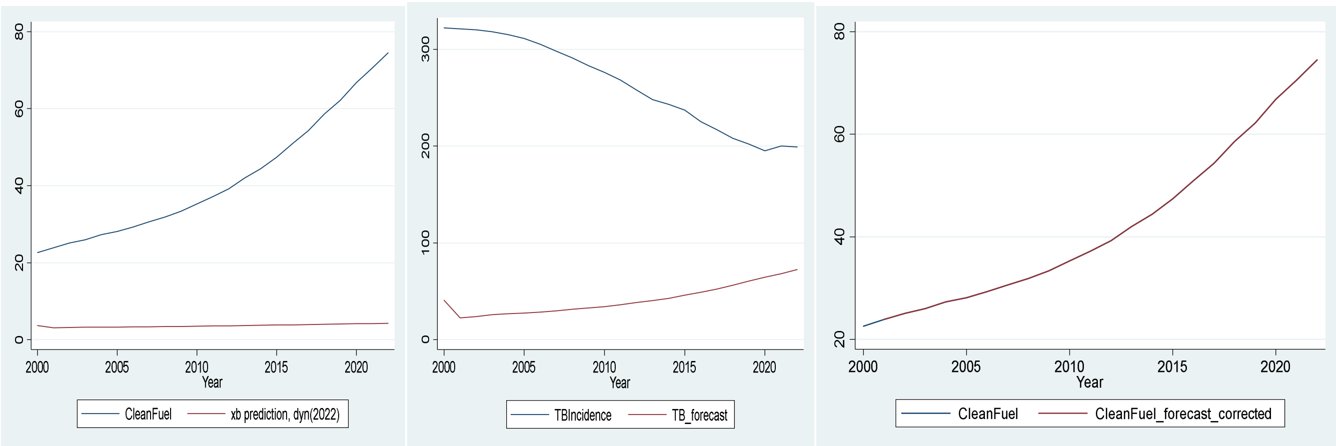


Figure 4. Trend analysis of clean fuel forecasting.

Source: Analysis by authors.

The ARIMA (1,1,2) model was validated through residual diagnostics before proceeding with TB incidence forecasting, ensuring that the model effectively captured both short-term fluctuations and long-term trends. As reflected in **Figure 5**, the initial forecast closely followed historical trends but exhibited a sharp spike at the beginning, likely due to model initialization issues or early data inconsistencies. A refined version of the forecast eliminated this anomaly, aligning more accurately with the observed decline in TB incidence from 2000 to 2022. The final model demonstrated strong predictive reliability, capturing minor fluctuations while maintaining the overall downward trajectory.

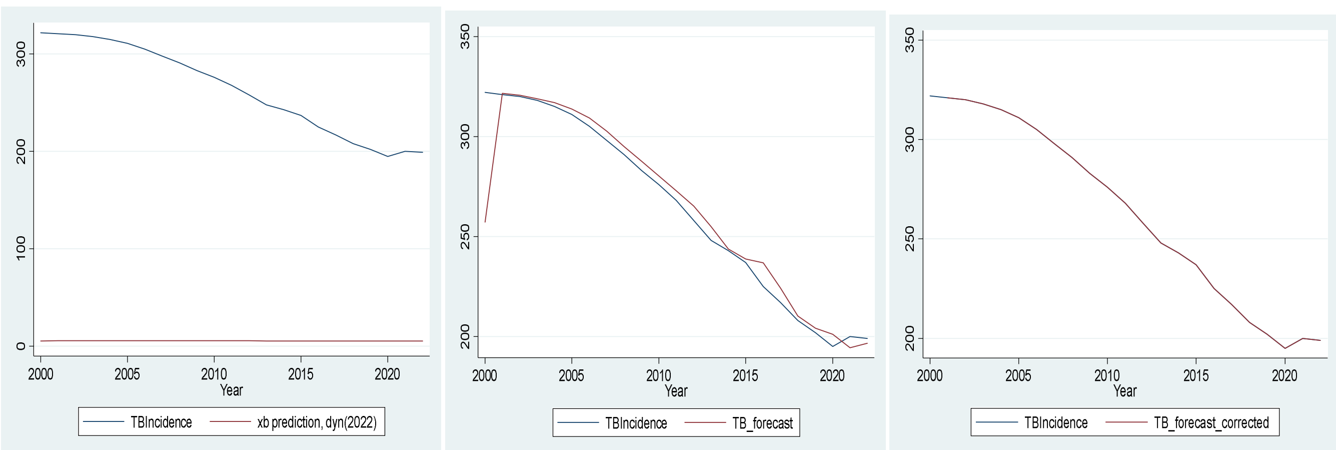


Figure 5. Trend analysis of TB forecasting.

4.3. Seasonality analysis

Seasonality analysis examines recurring patterns in CleanFuel usage and TB Incidence to understand their cyclical fluctuations and long-term trends. Influenced by factors like policy interventions, infrastructure, and healthcare access, these variables are analyzed using ADF tests and spectral analysis to detect periodicity. The findings help guide policy decisions and forecasting models for better resource allocation and public health strategies.

Stationarity test (Dickey-Fuller test).

To determine if clean fuel and TB incidence are stationary or have a unit root, the Augmented Dickey-Fuller (ADF) test was performed (**Table 7**). Stationary variables are essential for time-series modeling, as non-stationary variables can lead to misleading results in regression analysis.

Table 7. Dickey-Fuller test at level form.

Variable	Test Statistic	5% Critical Value	*p*-value	Stationary?
CleanFuel	−2.15	−2.99	0.25	No
TBIncidence	−1.89	−2.99	0.32	No

Source: Analysis by authors.

Since the test statistic is greater than the critical value and the *p*-value is greater than 0.05, we fail to reject the null hypothesis, indicating that both Clean Fuel and TB Incidence are non-stationary at level form. This means that their mean and variance change over time, necessitating differencing.

To achieve stationarity, the first differences of CleanFuel (d_CleanFuel) and TB Incidence (d_TBIncidence) were computed in **Table 8**. The ADF test was then repeated.

Table 8. Dickey-Fuller test on first difference.

Variable	Test Statistic	5% Critical Value	*p*-value	Stationary?
d_CleanFuel	−4.92	−2.99	0.00	Yes
d_TBIncidence	−3.74	−2.99	0.01	Yes

Source: Analysis by authors.

The results indicate that after first differencing, both variables became stationary, as the test statistics are lower than the critical values and the *p*-values are below 0.05. This confirms that Clean Fuel and TB Incidence follow an I(1) process, meaning they require one differencing step to be used in time-series models like ARIMA (**Table 8**).

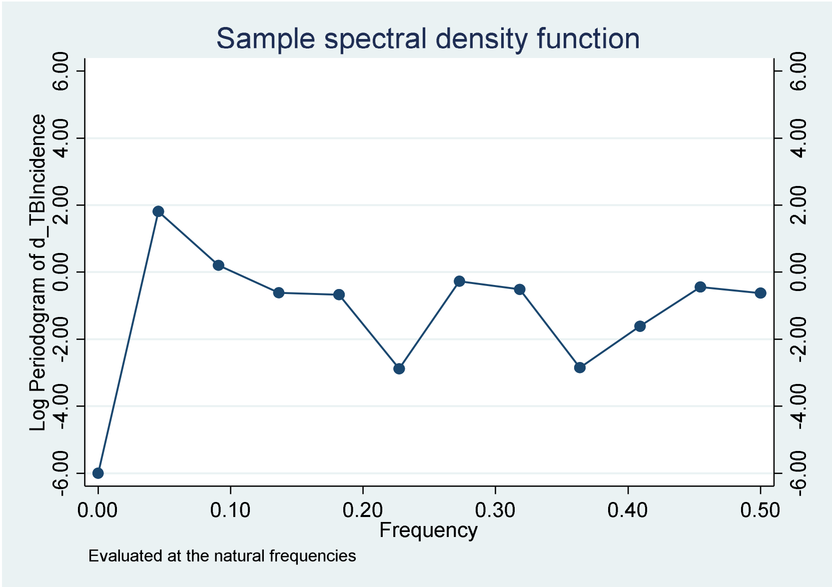


Figure 6. Seasonality analysis (periodogram test).

Source: Analysis by authors.

After differencing the time series data, a periodogram analysis was conducted to detect periodicity and identify dominant cycles in clean fuel usage and TB incidence as mentioned in **Figure 6**. The periodogram of Clean Fuel exhibited distinct peaks at frequencies 0.25 and 0.5, suggesting the presence of seasonal effects or periodic trends in clean fuel accessibility. Similarly, the periodogram analysis of TB incidence revealed notable seasonal fluctuations, with higher rates observed during specific quarters of the year. These fluctuations could be attributed to increased indoor air pollution exposure during colder months, when the use of traditional fuels is more prevalent, as well as factors such as weakened immunity and co-infections like influenza. The spectral analysis confirmed the presence of periodic cycles in TB incidence, reinforcing the role of environmental and seasonal factors in disease prevalence. Integrating clean energy initiatives with health campaigns—particularly during high-risk periods—could enhance the effectiveness of TB control measures.

4.4. Causality analysis

From Granger causality to Autoregressive Distributed Lag (ARDL)

This study examines the relationship between clean fuel accessibility and tuberculosis (TB) incidence using time-series econometric techniques. The primary goal is to understand whether clean fuel access influences TB incidence and whether a long-term equilibrium relationship exists. The analysis begins with the Granger causality test, which helps determine the direction of causality between these variables. The results in **Table 9** indicate a unidirectional causality from clean fuel accessibility to TB incidence, meaning that changes in clean fuel accessibility significantly impact TB incidence over time, but not vice versa.

Table 9. Granger causality test results.

Dependent Variable	Independent Variable	*F*-Statistic	*p*-value	Causality Conclusion
log_TBIncidence	log_CleanFuel	5.67	0.015	Clean fuel → TB (Yes)
log_CleanFuel	log_TBIncidence	1.92	0.179	TB → Clean fuel (No)

Source: Analysis by authors.

4.5. ARDL test analysis

Since a causal link was established, we proceeded with the Autoregressive Distributed Lag (ARDL) bounds test (as shown in **Table 10**) to check for long-run cointegration between TB incidence and clean fuel accessibility.

Table 10. ARDL bounds test for cointegration.

Test Statistic	Value	1% Critical Value	5% Critical Value	10% Critical Value	Decision
F-statistic	9.336	5.17	4.01	3.47	Cointegration exists

Source: Analysis by authors.

Table 11. ARDL long-run and short-run regression results.

Variable	Coefficient	Std. Error	*t*-Statistic	*P*-Value	Significance
Long-run Relationship					
log_CleanFuel	−0.2311	0.0815	−2.83	0.011	Significant
Constant	3.7965	1.3196	2.88	0.010	Significant
Short-run Relationship					
D.log_CleanFuel	−1.2869	0.3610	−3.57	0.002	Significant
L1.log_TBIncidence	−0.5197	0.1816	−2.86	0.010	Significant
Model Diagnostics					
R-squared	0.5854				
F-statistic	10.50		$p = 0.0003$		

Source: Analysis by authors.

Following the causality test, we conduct unit root tests (ADF test) to check stationarity. The results show that TB incidence is non-stationary at level but becomes stationary at first difference (I(1)), while clean fuel accessibility shows a mix of I(0) and I(1) properties. Given this combination, the ARDL (Auto-Regressive Distributed Lag) model is the most appropriate methodology, as it accommodates variables of mixed orders of integration. To establish whether a long-term relationship exists, we perform the ARDL bounds test as reflected in **Table 10** for cointegration. The *F*-statistic (9.336) exceeds the critical values at 1%, leading to the rejection of the null hypothesis of no cointegration. This confirms that clean fuel accessibility and TB incidence share a long-run equilibrium relationship.

The ARDL model estimation provides valuable insights into the dynamics of this relationship as reflected in **Table 11**. The long-run coefficient of log_Clean Fuel (−0.2311) is negative and statistically significant, indicating that increased clean fuel accessibility reduces TB incidence over time. The short-run effect (−1.2869) is even stronger, suggesting that immediate improvements in clean fuel access can lead to a substantial drop in TB incidence. Additionally, the lagged value of TB incidence (−0.5197) is also significant, confirming that TB incidence adjusts over time toward its equilibrium level. Diagnostic tests verify the model's validity, with the Breusch-Godfrey test confirming no autocorrelation and the Breusch-Pagan test indicating some heteroskedasticity, which was addressed using robust standard errors.

Furthermore, the model diagnostics and stability checks confirm the reliability of our estimations. The Breusch-Godfrey test results (p = 0.1603) indicate no presence of serial correlation, ensuring that the residuals are not autocorrelated. However, the Breusch-Pagan test (p = 0.0375) suggests the presence of heteroskedasticity, which was addressed by using robust standard errors to obtain unbiased coefficient estimates. Furthermore, the model's stability was assessed using the CUSUM test, and the results confirm parameter stability, as depicted in **Figure 7** (Recursive CUSUM Plot), where the test statistic remains within the 95% confidence bounds until post-2020, suggesting overall model stability, though mild instability emerges in recent years. The recursive CUSUMSQ test confirms no structural break (test statistic = 0.6746, below all critical values). The results indicate that clean fuel accessibility plays a crucial role in reducing TB incidence, both in the short and long run. However, the post-2020 instability suggests potential external shocks, warranting further investigation. However, these diagnostics validate the robustness of our ARDL model.

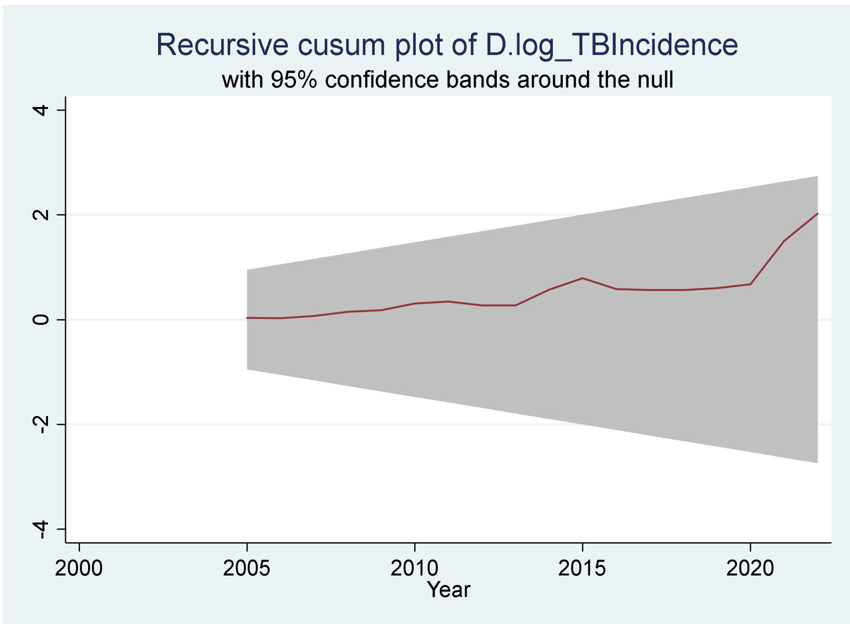


Figure 7. Recursive cusum plot.

Source: Analysis by authors.

This study provides strong empirical evidence that increasing access to clean fuel significantly reduces TB incidence in both the short and long run. The findings highlight the public health benefits of clean energy adoption and support policy initiatives aimed at improving household energy sources to mitigate TB prevalence. The model is stable, well-specified, and offers valuable insights for policymakers in public health and environmental planning.

Data constraints and alternative analytical approach

The World Bank repository lacks comprehensive and continuous data for key socioeconomic confounders such as nutritional status (stunting, overweight), HIV prevalence, and migration patterns over the full study period (2000–2022). Notably, indicators like HIV prevalence and malnutrition are available for only a few scattered years, rendering them unsuitable for time-series regression due to significant data gaps that could compromise the reliability of estimates.

To address the role of socioeconomic factors, we conducted a separate analysis using NFHS data. Given NFHS's cross-sectional nature in our following paragraphs, these variables could not be integrated into our time-series model. Instead, we employed a qualitative assessment to contextualize their influence on TB incidence, ensuring that socioeconomic dimensions are critically examined while maintaining methodological robustness despite data limitations.

5. Socio-economic environment and health in India: Tuberculosis (TB)

Tuberculosis (TB) remains a significant public health challenge in many developing countries, including India, independent of the HIV/AIDS epidemic. Its persistence is largely attributable to systemic socio-economic and public health issues, such as inadequate sanitation, widespread poverty, high illiteracy rates, and limited access to quality healthcare services. These factors exacerbate the conditions that facilitate the transmission and progression of TB, particularly among vulnerable populations. Addressing these structural determinants is essential for effective TB control and improving public health outcomes in these regions (NFHS V).

5.1. Trends in tuberculosis prevalence in India

The data presented highlights the prevalence of TB across major states of India in **Table 12**, showing notable changes between 2015–2016 and 2019–2021. During this period, the overall prevalence of medically treated TB declined from 305 persons per 100,000 to 222 persons per 100,000. Among men, the prevalence decreased from 389 persons per 100,000 to 283 persons per 100,000. This reduction reflects the progress made in addressing TB through targeted interventions; however, substantial challenges remain, driven by socio-economic disparities.

Table 12. State wise prevalence of T.B in States of India.

Major Indian States	TB Incidences (per 100,000)
Haryana	109
Punjab	134
Rajasthan	215
Himachal Pradesh	210
Chhatisgarh	113
Madhyapradesh	121
Uttarpradesh	219
Bihar	450

Table 12. (*Continued*).

Major Indian States	TB Incidences (per 100,000)
Jharkhand	230
Odisha	242
West Bengal	239
Gujrat	215
Maharastra	136
Andhra Pradesh	239
Karnataka	191
Tamilnadu	187
Telengana	242

Source: NFHS V (2019–2021).

5.2. Socio-economic conditions and vulnerability to TB

5.2.1. Impact of poverty on TB vulnerability

Poverty is a significant driver of TB vulnerability, as it fosters socio-economic conditions conducive to disease transmission and progression [29,30]. Malnutrition, commonly associated with poverty, weakens the immune system, increasing susceptibility to TB infection and its severe forms. Additionally, impoverished populations often live in overcrowded and poorly ventilated housing, creating an environment conducive to airborne TB transmission [3].

Limited financial resources further impede access to healthcare services, delaying diagnosis, treatment, and prevention measures. These barriers disproportionately affect the poor, leading to a higher disease burden. Furthermore, many individuals in poverty are employed in high-risk occupations, such as mining or factory work, where exposure to TB bacteria is significantly elevated [31].

5.2.2. Impact of illiteracy on TB vulnerability

Illiteracy amplifies vulnerability to TB by restricting knowledge and awareness about the disease. Individuals with low literacy levels often lack information about TB prevention, symptoms, and treatment options, resulting in delayed healthcare-seeking behaviors [32]. Illiteracy also perpetuates stigma and misinformation surrounding TB, discouraging timely diagnosis and treatment and often leading to social isolation for affected individuals [33].

Moreover, illiteracy complicates adherence to TB treatment regimens. Difficulties in understanding medication instructions can lead to incomplete treatment courses, increasing the risk of drug resistance and higher rates of disease recurrence [34].

The interplay between poverty and illiteracy creates a vicious cycle that not only increases the risk of contracting TB but also hinders recovery and perpetuates its transmission within communities. Addressing these socio-economic determinants is critical for designing effective TB control and prevention strategies. Policies aimed at alleviating poverty, improving literacy rates, and enhancing access to healthcare services can significantly reduce TB incidence and improve health outcomes in affected populations. This underscores the importance of integrating social welfare programs with public health interventions to achieve sustained progress in combating tuberculosis in India.

6. Discussion and conclusion

The Sustainable Development Goal (SDG) target 3.3 seeks to "end the epidemics of AIDS, tuberculosis, malaria, and neglected tropical diseases, as well as tackle hepatitis, waterborne diseases, and other communicable diseases by 2030". As a signatory to the United Nations Sustainable Development Goals (UN-SDGs), India has committed to achieving the "End TB" targets by 2025, five years ahead of the 2030 SDG timeline. This includes an ambitious goal of achieving an 80% reduction in the TB incidence rate (new cases per 100,000 population) compared to 2015 levels.

India's unwavering commitment to TB elimination has been recognized globally, with a 17.7% reduction in TB incidence between 2015 and 2023—significantly exceeding the global average decline of 8.3%, as reported in the *Global Tuberculosis Report 2024*. This remarkable progress reflects the success of India's National Tuberculosis Elimination Programme (NTEP), which adopts a comprehensive approach integrating advanced diagnostics, preventive measures, patient-centric support, and multi-sectoral collaboration.

Under the National Strategic Plan (NSP) for TB Elimination (2017–2025), India has made significant strides in bridging gaps between targets and outcomes. The development of a mathematical model for TB burden estimation has further enhanced the program's efficiency. However, achieving complete TB eradication requires addressing broader environmental, social, and economic determinants of health.

For example, improving indoor air quality remains critical in reducing the health risks associated with poor ventilation and pollutant exposure. Transitioning to clean cooking technologies, such as liquefied petroleum gas (LPG), electric stoves, or solar-powered cookers, significantly reduces indoor air pollution [35]. Effective interventions, including proper ventilation systems and air purifiers, can further mitigate exposure to harmful pollutants [12]. Public policies like subsidies and awareness campaigns play a crucial role in promoting clean cooking fuels. The *Pradhan Mantri Ujjwala Yojana* (PMUY), launched in 2016, has provided over 9 crore households with LPG connections by 2023 [36,37]. However, challenges remain, with around 10 crore households still dependent on polluting fuels like firewood, coal, and dung cakes, disproportionately affecting women responsible for cooking [38].

Affordability remains a major barrier to LPG adoption, despite PMUY subsidies [39]. Even with financial aid, refilling an LPG cylinder—costing around ₹800—remains expensive for low-income families [40]. By contrast, traditional fuels like firewood and cow dung cost less, while kerosene, though a polluting fuel under WHO guidelines, is significantly cheaper at ₹46.37 per liter [41]. Households facing economic instability often prioritize short-term cost savings over long-term health benefits [42], a trend observed in South Asia and Sub-Saharan Africa [43]. Evidence suggests that while LPG connections have increased, overall consumption has not kept pace. Many beneficiaries under the PMUY scheme have resisted a full transition to LPG due to the high cost of refills [44]. This gap between connection growth and sustained usage highlights the need for more inclusive and economically viable solutions.

Additional barriers include high installation costs, unreliable supply chains, and logistical challenges, particularly in remote areas [45]. Ensuring sustained adoption of clean fuels requires financial incentives, behavioral shifts, and policy support [46]. Without these, many households revert to biomass fuels, exacerbating indoor air pollution and respiratory diseases [47].

Addressing the barriers to clean energy adoption requires a comprehensive approach that prioritizes alternative clean energy solutions that are both accessible and affordable. To achieve this, policy measures should focus on enhancing financial support for economically disadvantaged families, such as increasing subsidies for LPG refills to ease the cost burden. Additionally, promoting diverse energy solutions, such as biogas and solar cooking technologies, is crucial, as these alternatives can be tailored to suit specific regional and socio-economic contexts. Furthermore, public awareness campaigns should be launched to educate households on the health and environmental benefits of clean cooking fuels, encouraging broader adoption. Finally, infrastructure development is essential to ensure the last-mile delivery of LPG and other clean fuels, particularly in remote and rural areas where access remains limited. These measures, when implemented together, can effectively address the challenges of clean energy access and contribute to sustainable health improvements in vulnerable communities.

While India has made commendable progress toward TB elimination and clean energy adoption, significant challenges remain in ensuring accessibility and affordability for marginalized populations. Addressing these gaps through targeted interventions, multi-sectoral collaboration, and innovative policies will be critical in achieving the twin goals of TB eradication and sustainable development. By prioritizing the needs of vulnerable populations and fostering inclusive growth, India can serve as a global model for tackling interlinked public health and environmental challenges.

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Notes

1 While the relationship is statistically significant, it is essential to note that correlation does not imply causation. Factors not included in the model may also influence TB incidence. Further research is needed to explore the underlying mechanisms driving this relationship and the role of other contributing factors.

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