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EDUCATIONAL IMPACT ON POVERTY ALLEVIATION IN INDIA: STRATEGIC PATHWAYS TO SUSTAINABLE DEVELOPMENT

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Abstract: Education is a fundamental driver of national development, contributing to skill enhancement, human capability building, the promotion of human rights, reduction of inequalities, crime mitigation, and economic growth. Recognizing its impact, the United Nations introduced two key Sustainable Development Goals (SDGs) in 2015: SDG 1, targeting poverty eradication at all levels, and SDG 4, promoting inclusive and equitable quality education. However, despite nine years of concerted global efforts, poverty remains pervasive in many developing countries, including India. This study investigates the influence of education on poverty reduction in India, analyzing time-series data from 1994 to 2023 obtained from secondary sources, including World Bank databases, academic journals, and reputable online sources. The Johansen cointegration test, Vector Error Correction Model (VECM), and Wald tests are applied to assess education's long-term and short-term impacts on poverty alleviation. Findings indicate that education exerts a significant long-term effect on poverty reduction in India, underscoring its essential role in sustainable development.

Keywords: Poverty; Education; Sustainable Development; VECM

JEL Codes: *C32, I25, I32, Q01*

INTRODUCTION

The United Nations' Millennium Development Goals (MDGs) marked a global milestone in addressing pervasive issues such as poverty, hunger, and inequality.

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Among these, MDG 1 specifically targeted the eradication of extreme poverty and hunger. While significant advancements were achieved under MDG 1, the UN recognized the need for continued and comprehensive efforts. Consequently, in 2015, the UN introduced the Sustainable Development Goals (SDGs), a set of 17 ambitious global goals designed to promote sustainable economic, social, and environmental development. SDG 1, the foremost of these goals, underscores the importance of eliminating poverty in all its forms and dimensions, aiming to ensure that no one is left behind in the pursuit of sustainable development. Despite global progress, with over 50% reduction in the number of people living below the international poverty line, extreme poverty remains a pressing challenge, particularly in developing nations.

India, with its recent years of rapid economic growth and its establishment as a major emerging economy, exemplifies this paradox. Despite impressive increases in per capita income and significant economic achievements, a substantial portion of India's population continues to live below the poverty line. Poverty, often defined as the inability to meet the basic standards for a minimum quality of life, leaves individuals unable to access essentials such as clean water, secure housing, nutritious food, adequate healthcare, and education. Poverty can be analyzed at both the personal and societal levels. On an individual level, poverty prevents access to resources required for well-being, affecting daily necessities like food, clothing, shelter, medical care, and education, and ultimately impacting physical and mental health. Societally, poverty restricts economic progress, perpetuates unemployment, and contributes to broader social issues such as crime and inequality (Krueger & Maleckova, 2003) (1).

Education is universally regarded as the cornerstone of both individual empowerment and societal advancement. Defined as the cumulative knowledge and skills acquired through various environments—be it at home, school, or within the community—education fosters cognitive development, broadens perspectives, and provides a platform for individuals to achieve personal aspirations. Beyond personal growth, education drives social progress by generating skilled human capital that fuels technological advancement, enhances productivity, and supports economic development. Importantly, education equips individuals with the competencies and qualifications required to secure well-paying jobs, which, in turn, promote financial stability and selfreliance (Awan *et al.*, 2011) (2). Education thus emerges as a powerful tool in poverty alleviation, as it enables individuals to improve their income potential, fulfill basic needs, and contribute productively to society.

In light of these interconnections, it is imperative to investigate the impact of education on poverty reduction in India. This study examines whether educational advancements in India contribute to poverty alleviation and, by extension, sustainable development. By analyzing the relationship between educational attainment and poverty levels, this study aims to provide evidence of the potential of education to address and mitigate poverty within the Indian context.

2. LITERATURE REVIEW

The relationship between economic growth, education, and poverty reduction has been a focal point in developmental research, highlighting how interconnected these factors are in fostering sustainable development. Bourne and Attzs (2005) (3) examined this connection within the Caribbean context, where they identified economic growth as a key mechanism for poverty alleviation. Their study emphasized that robust economic growth promotes job creation, raises income levels, and enhances access to essential resources, creating a positive feedback loop that supports poverty reduction. Specifically, economic progress attracts greater investment, spurs productivity, and leads to increased spending on critical social sectors, such as health and education, which further solidifies the foundation for poverty alleviation. The study underscores that sustained economic growth is essential for improving living standards, highlighting the need for policies that stimulate inclusive growth and poverty reduction.

In examining human capital's role, Khan *et al*. (2008) (4) underscored the importance of investments in education, skills, and health as pivotal to reducing poverty. Through multivariate co-integration analysis, they demonstrated that enhancements in human capital directly contribute to poverty alleviation by empowering individuals economically and enhancing social mobility. Such investments enable individuals to develop resilience against economic shocks, which is vital in mitigating poverty's long-term effects. Kim and Lee (2014) (5) expanded on this perspective by focusing on non-formal education's role in poverty alleviation. Their findings indicate that poverty is strongly linked to low literacy and limited life skills, concluding that primary education alone is insufficient for sustainable poverty reduction. They advocate for a broader, more inclusive educational approach that incorporates life skills and vocational training to equip individuals with practical tools for economic self-sufficiency and upward mobility.

Afzal *et al.* (2012) (6) examined the impacts of education and physical capital on economic growth, reinforcing that investments in both human and physical capital are critical for long-term economic development. Their study aligns with Adawo (2011) (7), who similarly identified education as a primary driver of economic progress, contributing significantly to increased productivity and income levels. Moreover, Janjua and Kamal (2011) (8) explored the dual role of income and education in poverty reduction, highlighting that while income growth has a positive yet moderate effect on alleviating poverty, education is indispensable for breaking the poverty cycle. Their findings emphasize the transformative power of education in generating sustained income gains and fostering socioeconomic mobility.

Further analysis by Tilak (2007) (9) demonstrated the considerable contribution of secondary and higher education to economic growth and human development, showing that higher education substantially increases individual earnings and supports macroeconomic growth. Similarly, Chaudhary *et al.* (2009) (10) studied higher education's impact on economic development in Pakistan between 1972 and 2006, finding a strong long-term association between real GDP, physical capital, labor force participation, and educational attainment. This association suggests that higher education enhances economic resilience, providing a sustainable foundation for future growth. Islam *et al.* (2007) (11) also examined the link between education and economic growth in Bangladesh, concluding through multivariate regression analysis that a mutually reinforcing relationship exists between educational attainment and economic growth. Their findings suggest that advancements in education and economic growth create a virtuous cycle, where improvements in one reinforce the other over time.

Brempong *et al.* (2006) (12) extended this examination to the African context using the Augmented Neoclassical Growth model, revealing that higher education positively impacts economic growth in Africa. Their findings highlight the critical role of education in addressing unique regional challenges and promoting sustainable economic development. Similarly, Hassan and Ahmed (2006) (13) analyzed sub-Saharan African nations through the Mankiw, Romer, and Weil-augmented Solow models, discovering that primary and secondary school enrollment ratios positively correlate with economic growth. Their research further underscores the necessity of foundational education as an essential component of economic development in emerging economies.

In a recent study, Sinha (2023a; 2023b; 2023c; 2024) (14-17) investigated the complex relationship between human capital investments, particularly in education and health, and their impact on youth, revealing nuanced but substantial effects on poverty and economic resilience. Other notable contributions include studies by Bhalla, Bhasin, and Virmani (2022); Chen, Yuan, and Zhang (2023); Chaudhary (2016); Dey and Mishra (2018); Owoeye (2014), {18-22} : Havinga ; Kumaren; & Vu (2009)(23), and Sylwester (2000) (24) which further substantiate the critical roles of education and economic growth across various contexts.

These studies collectively underscore the centrality of education in fostering economic resilience and reducing poverty across diverse regions. There is a strong consensus that both foundational and advanced education investments are essential in equipping individuals with the skills and opportunities necessary for socioeconomic development. Through human capital improvements, education not only allows individuals to access better economic opportunities but also contributes to a broader development agenda critical for sustained poverty alleviation. The accumulation of empirical evidence across contexts thus emphasizes education as a fundamental pillar of economic advancement and poverty reduction, essential for a resilient, equitable, and sustainable development trajectory.

RESEARCH GAP

An extensive review of existing literature reveals that most studies examining the relationship between education and poverty reduction were conducted before the establishment of the Sustainable Development Goals (SDGs) in 2015. Although these studies have significantly contributed to understanding the role of education in poverty alleviation, they largely overlook the evolving socio-economic landscape shaped by the SDGs. Specifically, SDG 1, which aims to eradicate poverty in all forms, and SDG 4, which focuses on ensuring inclusive and equitable quality education, have introduced new frameworks and priorities for development that may influence this relationship in unique ways.

Despite progress at the global level, substantial segments of the population in developing countries, including India, continue to live below the poverty line even after seven years of SDG implementation. India's ongoing challenges in eradicating poverty, despite substantial economic growth, point to a complex dynamic between educational advancements and poverty reduction that warrants deeper investigation. As the Indian government prioritizes policies to simultaneously enhance educational quality and reduce poverty, it is essential to explore whether these efforts are yielding measurable impacts on poverty levels. This study aims to fill this gap by examining the long-term and short-term effects of education on poverty reduction in the post-SDG context in India.

By focusing on the interplay between SDG-driven educational reforms and poverty alleviation outcomes, this research addresses a crucial gap in understanding how education, influenced by the SDG framework, impacts poverty reduction specifically in India's socio-economic context. This investigation not only updates previous research to reflect current policy environments but also provides insights into the efficacy of education as a tool for poverty alleviation within the SDG timeline**.**

RESEARCH QUESTIONS

The following research questions are proposed to address this research gap:

- Does education have a long-term effect on poverty reduction in India within the framework of the SDGs?
- Does education have a short-term effect on poverty reduction in India under the influence of recent educational policies?

METHODOLOGY

This study employs a quantitative approach to examine the relationship between education and poverty reduction in India. To capture the multi-dimensional aspects of education and poverty, the study utilizes key variables that serve as indicators for educational access, investment, and poverty levels. The analysis spans from 1991 to 2020, using time series data gathered from reputable secondary sources, primarily the World Bank database, supplemented by academic journals. The justification for using these variables is presented I Table 1 below:

Table 1: Description of Variables Used in this Study

Name of the Variables & its Representation	*Description*	*Author/(s) used these variables in their studies*
Household Final Consumption Expenditure (HFCE)	It consists of expenditures made by households on goods or services that are utilized for meeting needs or wants. It is used as a proxy variable for poverty.	Havinga, Kamanou, and Vu, (2009) Bhalla, Bhasin, and Virmani (2022)
Gross Enrolment Ratio (GER)	It indicates students who are enrolled in a specific level of education, regardless of age. It is used as a proxy variable for education.	Owoeye, (2014); Dey and Mishra (2018).
Government Educational Expenditure (EDUEX)	Direct government expenditures on academic institutions as well as public subsidies provided to households for educational purposes are both included in the government expenditure on education. It is also used as a proxy variable for education.	Sylwester (2000); Choudhary (2016); Chen et al. (2023).

Source: Researchers' presentations

6. DATA SOURCE AND PERIOD OF STUDY

This study utilizes annual time series data from 1994 to 2023 to examine the relationship between education and poverty reduction in India. Three key variables are selected as proxies for education and poverty: Gross Enrolment Ratio (GER), Government Educational Expenditure (EDUEX), and Household Final Consumption Expenditure (HFCE). The data for these variables are sourced from the World Development Indicators (WDI), a comprehensive database maintained by the World Bank, ensuring reliability and consistency across data points.

Gross Enrolment Ratio (GER): This variable represents the proportion of students enrolled in a specified level of education, regardless of age, and serves as an indicator of the accessibility and reach of educational institutions in India. GER data highlight the inclusiveness and coverage of education across different demographic groups.

Government Educational Expenditure (EDUEX): This variable includes direct government expenditures on educational institutions and public subsidies offered to households for educational purposes. EDUEX is crucial for understanding the extent of governmental commitment to improving education quality, infrastructure, and access in India, thus impacting the socio-economic conditions of households.

Household Final Consumption Expenditure (HFCE): This variable represents the total expenditure by households on goods and services necessary for their consumption needs. HFCE is employed as a proxy for poverty, reflecting household purchasing power and consumption patterns. Higher HFCE typically indicates improved economic well-being, reflecting the potential impact of education on poverty alleviation by enabling households to attain a higher standard of living.

The selection of the 1994–2023 period allows for a robust analysis encompassing significant socio-economic and policy changes in India, including liberalization reforms, increased government focus on education, and alignment with global development agendas, including the Sustainable Development Goals (SDGs) introduced in 2015. This timeline thus provides a comprehensive overview of the potential long-term effects of educational investments on poverty reduction.

7. MODEL SPECIFICATION

A functional regression model is formulated to evaluate education's impact on poverty reduction in India. In this model, the Natural Log of Household Final Consumption Expenditure (LN_HFCE) is taken as the dependent variable, while Gross Enrolment Ratio (EDN_GER) and Government Educational Expenditure (% of GDP) (EDU_EX) are the independent variables. These variables are used to evaluate the impact of education on poverty reduction in India. The model is specified as follows to address the research objectives:

$$\text{LN\_HFCE} = b_0 + b_1 \cdot \text{EDN\_GER} + b_2 \cdot \text{EDU\_EX} + \varepsilon$$

where:

LN_HFCE represents the natural logarithm of Household Final Consumption Expenditure, used as a proxy for poverty.

EDN_GER denotes the Gross Enrolment Ratio, indicating educational access.

EDU_EX represents Government Educational Expenditure as a percentage of GDP, reflecting government investment in education. b_0, b_1 and b_2 are the coefficients to be estimated, with ε as the error term.

8. METHODOLOGICAL STEPS

Unit Root Tests: To ensure the stationarity of each time series variable, the study first applies the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to detect the presence of unit roots. Stationarity is crucial for avoiding spurious regression results in time series analysis.

Lag Length Selection: The optimal lag length for the model is determined using criteria including the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ), ensuring that the model structure captures the dynamic relationships between variables effectively.

Cointegration Analysis: To explore the long-run equilibrium relationship between education and poverty reduction, the Johansen cointegration methodology is applied. This test helps establish whether a stable, long-term association exists among the variables in the model.

Vector Error Correction Model (VECM): If cointegration is confirmed, the Vector Error Correction Model (VECM) is employed to capture both the short-run dynamics and the adjustment mechanism towards long-term equilibrium, indicating how quickly any deviations from the equilibrium are corrected over time.

Wald Test for Short-Run Effects: To verify the short-term effects of education on poverty reduction, the Wald test is conducted, assessing the immediate impact of changes in educational variables on household consumption expenditure.

Stability Test: Finally, to ensure the reliability and stability of the model, the Cumulative Sum of Squares of Recursive Residuals (CUSUMQ) test is applied. This test verifies the model's stability over the sample period, confirming the robustness of the estimated relationships.

This methodology rigorously examines both short- and long-term effects of education on poverty reduction, providing a comprehensive understanding of the potential influence of educational access and government investment in education on improving household economic well-being in India.

9. RESULTS AND DISCUSSION

In this section, the outcomes of various econometric analyses are systematically presented and discussed, focusing on the statistical insights derived from unit root tests, specifically the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) methods.

Unit Root Test

To ensure the robustness of our analysis and prevent the possibility of spurious regression results, unit root tests are employed to verify the stationarity of the time series data. Stationarity in time series is essential, as non-stationary data can lead to misleading statistical inferences in regression analyses, particularly in macroeconomic studies where time series data spans multiple years.

To this end, both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are applied. The ADF test is commonly used in time series analysis to test for a unit root by extending the Dickey-Fuller test through the inclusion of lagged terms. This approach helps account for higher-order correlation, thus refining the test's sensitivity to autocorrelated errors. The PP test, on the other hand, addresses issues such as heteroskedasticity and serial correlation by making non-parametric adjustments to the standard Dickey-Fuller procedure. Using both methods strengthens the validity of the findings, as each test has unique attributes that complement each other.

The results of the ADF and PP tests are summarized in Table 2 and Table 3, respectively, where each variable is examined both in levels and in first differences. The tables present critical values at various significance levels, comparing them with the test statistics to determine if each series contains a unit root.

Table 2: Outcomes of Unit Root Test Using Augmented Dickey-Fuller (ADF) Method

Variables	*At Level*		*At First Difference*		*Integrating Order*
	Stat.	*Probability.*	*Stat.*	*Probability.*	
LN_HFCE -	-1.3682	0.5213	-5.6541	0.0001	I (1)
EDN_GER	-0.4722	0.7790	-3.7491	0.0084	I (1)
EDU_EX -	-1.9830	0.2863 -)	-3.3276	0.0234	I (1)

Source: Researchers' calculation

Table 3: Outcomes of Unit Root Test Using Phillips-Perron (PP) Method

Variables	*At Level*		*At First Difference*		*Integrating Order*
	Stat	*Probability*	*Stat*	*Probability*	
LN_HFCE	-2.7667	0.0736	-6.7744	0.0000	I (1)
EDN_GER	-0.5320	0.8465	-3.7123	0.0091	I (1)
EDU_EX	-1.8625	0.3047	-3.3046	0.0235	I (1)

Source: Researchers' calculation

The following interpretations can be made from the results:

Level Test Results: For each variable, the initial test at levels aims to verify whether the series is stationary without differencing. If the absolute value of the test statistic is lower than the critical value at conventional significance levels (e.g., 1%, 5%, and 10%), we fail to reject the null hypothesis, indicating that the series is non-stationary at levels.

First Difference Test Results: For series found to be non-stationary at levels, the ADF and PP tests are re-applied after taking the first difference. Here, if the test statistics exceed the critical values, it signifies that differencing the data has rendered it stationary, allowing us to conclude that the series is integrated of order one, I (1).

Based on the unit root test results, the following patterns are observed across the variables:

ADF Test Outcomes: The ADF test results (Table 2) indicate that all variables exhibit non-stationarity at levels, failing to reject the null hypothesis of a unit root. However, after applying the first differencing, each variable's test statistic surpasses the critical value thresholds, confirming stationarity and validating that each series is integrated at order one.

PP Test Outcomes: In alignment with the ADF test results, the PP test (Table 3) corroborates the non-stationarity of the variables at levels and confirms stationarity post-first differencing. This congruence between the ADF and PP outcomes provides additional confidence in the findings, as both methods consistently suggest that the variables become stationary upon the first differencing.

These results suggest that each variable follows an I(1) process, implying that any subsequent econometric analysis, such as cointegration or vector autoregression (VAR), should incorporate differenced data to avoid spurious results. Moreover, establishing that the data is I(1) sets the stage for further examination of the long-term equilibrium relationships among variables, as addressed in subsequent sections.

To verify the presence of unit roots in the data series, we employ both the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test, following methodologies outlined by Paul and Sana (2018) (25) and Nazima (2011) (26). These tests are critical in identifying the stationarity properties of each time series variable, which is a prerequisite for reliable econometric modeling.

Unit Root Tests: The ADF and PP tests are designed to assess whether each time series contains a unit root, which would indicate non-stationarity. The ADF test accounts for higher-order autocorrelation by adding lagged differences of the series, while the PP test offers a robust alternative that adjusts for heteroskedasticity and autocorrelation without requiring specification of a lag length, thus providing complementary insights.

Table 2 and Table 3 summarize the results of these tests, conducted at a 5% significance level. Both tables reveal a unit root at the level, as indicated by p-values above 0.05 for all variables, confirming non-stationarity in their original form. This finding suggests that each series is I (1) or integrated of order one, meaning that they become stationary only after first differencing.

Resolution of Non-Stationarity

To address the non-stationarity issue, the series is differenced once, and the unit root tests are reapplied to these first-differenced series. Post-differencing, all variables exhibit stationarity, with p-values below 0.05 across both the ADF and PP tests. This outcome indicates that the non-stationarity issue has been resolved, and the variables are now suitable for further analysis involving long-term relationships.

Johansen Cointegration Test

With stationarity confirmed at the first difference, the Johansen cointegration method is utilized to investigate potential long-run relationships among the variables, following the procedure suggested by Paul and Sana (2018) (25). The Johansen test is particularly suitable for examining multiple cointegrating relationships in a multivariate context, allowing for a robust analysis of the equilibrium dynamics among the I(1) variables.

Lag Length Selection

Before conducting the cointegration test, the appropriate lag length must be determined to ensure accurate modeling of the time series dynamics. Different lag length selection criteria, including the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC), are employed to ascertain the optimal lag length. Based on these criteria, a lag length of two is found to be appropriate for all variables, as revealed in Table 4, ensuring that the model captures both short-term dynamics and potential long-term associations accurately.

Table 4: Results of Lag Order Selection Criteria using VAR

Lag	*Akaike Information Criteria (AIC)*	*Schwarz Information Criteria (SC)*	*Hannan-Quinn Information Criteria (HQ)*
0	7.790576	7.734558	7.723389
1	-0.401584	0.294343	-0.136331
2	0.992614*	0.992614*	-0.692921*
3	-0.846171	0.613647	-0.418038

Source: Researchers' calculation *represents lag order selected by the criterion

In summary, the ADF and PP tests confirm non-stationarity at levels and stationarity upon first differencing, validating the use of the Johansen cointegration test to explore long-run relationships. The chosen lag length of two provides a robust framework for the subsequent cointegration analysis, aligning with standard econometric practices in time series modeling.

Findings

(A) Null Hypothesis H0 1: There is no integration between the variables. Alternative Hypothesis: There is at least one cointegrating variable.

(B) Null Hypothesis H0 2: This null hypothesis states that there is no long-term causality

among HFCE, EDU_EX, and EDN_GER.

Alternative Hypothesis: There is long-term causality.

Model:

D(LN_HFCE) = C(1)*{LN_HFCE(-1)+0.412878992245*EDU_EX(-1)-

0.106838544534*EDN_GER(-1)- 26.2393171272} + C(2)*{D(LN_HFCE(-1)} + C(3)*{D(LN_HFCE(-2)}+ C(4)*{D(EDU_EX(-1)} + C(5)*{D(EDU_EX(-2)} + C(6)*{D(EDN_GER(-1)} +C(7)*{D(EDN_GER(-2)} + C(8)

Table 5: Results of Johansen Test of Co-integration

HFCE = f (EDU_EX, EDN_GER)							
No. of Cointegration Equations	*Eigenvalue*	*Trace Stat.*	*0.05 Critical Value at 5%*	*Probability Value***	*Maximum - Eigen Value*	*0.05 Critical Value at 5%*	*Probability-Value***
None *	0.585991	35.71341	29.79707	0.0093	23.81041	21.13162	0.0205
At most 1	0.316622	11.90300	15.49471	0.1616	10.27908	14.26460	0.1942

Source: Researchers' calculation * represents the rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

In the Error Correction Model (ECM), the equation presented leverages the natural logarithm of household final consumption expenditure (LN_HFCE) as the dependent variable, reflecting the long-term equilibrium relationship among variables in the model. The coefficient C (1), representing the integrating equation, measures the speed of adjustment in the ECM, showing how quickly deviations from the long-run equilibrium correct themselves over time.

Cointegration among variables is tested using the trace test and the Max-eigenvalue test, both of which provide evidence for the presence of long-term equilibrium relationships between non-stationary time series variables. *In this analysis, both tests confirm the existence of one cointegrating equation at the 5% significance level, as they produce test statistics that exceed the critical values, indicating a statistically significant result.* Specifically, Table 5 shows that the computed values of both the Maximum Eigenvalue and Trace tests surpass the critical threshold at this level of significance.

Consequently, the null hypothesis of no cointegration is rejected because the probability value (p-value) associated with the test statistic is less than 0.05. This finding affirms that cointegration exists among the variables in the model, suggesting that, despite short-term fluctuations, there is a stable long-term relationship governing the dynamics of household final consumption expenditure and other related economic variables. Thus, the ECM can effectively model short-term deviations from this long-term trend, making it a powerful tool for understanding both immediate and enduring impacts within the system.

Table 6: Outcomes of Vector Error Correction Estimates

Dependent Variable	*Coefficient*	*Standard Error*	*t-Stat.*	*Probability Value*
C(1)	-0.151419	0.046139	-3.281837	0.0039

Source: Researchers' calculation

The above table shows that the co-efficient [C (1)] has a negative sign and is significant at the 1% significance level as the probability value is less than 0.01. This result indicates error correction over the long term. This also demonstrates the long-run effects of education on poverty reduction.

D(LN_HFCE)=C(1)*(LN_HFCE(-1)+0.412878992245*EDU_EX(-1) 0.106838544534*EDN_GER(-1) - 26.2393171272) + C(2)*D(LN_HFCE(-1)) + C(3)*D(LN_HFCE(-2))+ C(4)*D(EDU_EX(-1)) + C(5)*D(EDU_EX(-2)) + C(6)*D(EDN_GER(-1)) +C(7)*D(EDN_GER(-2))+ C(8)

Table 7: Estimation of Equation

	Coefficient	*Standard Error*	*t-Stat.*	*Probability Value*
C (1)	-0.151419	0.046139	-3.281837	0.0039
C (2)	-0.873580	0.281771	-3.100315	0.0059
C (3)	0.362277	0.192956	1.877507	0.0759
C (4)	0.005714	0.032000	0.178571	0.8602
C (5)	0.016829	0.031615	0.532323	0.6007
C (6)	-0.005292	0.005774 -	-0.916562	0.3709
C (7)	0.002036	0.007262	0.280433	0.7822
C (8)	0.179753	0.038908	4.619927	0.0002
R-squared 0.735950 Mean dependent var 0.121313 Adjusted R-squared 0.638669 S.D. dependent var 0.050366 S.E. of regression 0.030275 Akaike information criterion -3.915762 Sum squared residual 0.017415 Schwarz information criterion -3.531810 Log-likelihood 60.86279 Hannan-Quinn information criterion -3.801593 F-stat. 7.565166 Durbin-Watson statistics 2.324399 Probability (F-statistic) 0.000206				

Source: Researchers' calculation

The probability value for the coefficient C (1) in the presented table is 0.0039, which falls below both the 0.05 and 0.01 significance thresholds. This statistically significant p-value leads to the rejection of the null hypothesis at both the 1% and 5% levels of significance, providing strong evidence that the relationship captured by C (1) is unlikely to have occurred by chance.

Notably, the coefficient C (1) has a negative sign, as shown in Table 7. This negative sign indicates that the model achieves a long-term equilibrium state, as a negative error correction term suggests a tendency for the dependent variable to return to equilibrium after short-term deviations. In other words, deviations from the long-run equilibrium are gradually corrected over time, a characteristic essential to the dynamics modeled by the ECM.

The adjusted R-squared value of 0.638669 suggests that approximately 64% of the variance in the dependent variable is explained by the independent variables included in the model. This relatively high adjusted R-squared value indicates a strong influence of the independent variables on the dependent variable, underscoring the model's effectiveness in capturing the underlying relationships within the data.

Additionally, the overall model is statistically significant, as indicated by the probability associated with the F-statistic, which is below the 0.05 threshold. This result confirms that the model provides a robust fit for the data, with the independent variables collectively contributing meaningfully to explaining the variation in the dependent variable.

Table 8: Outcomes of Wald Test

Test Stat.	. Value	Prob.
F-stat.	0.284621	0.8843
Chi-square	1.138485	0.8881

Source: Researchers' calculation

To assess whether education expenditure (EDU_EX) and education gross enrolment rate (EDN_GER) have a significant short-run impact on the natural log of household final consumption expenditure (LN_HFCE), the Wald test is applied, following the methodology of Abid *et al.* (2016) (27) and Paul and Sana (2023) (23). The null hypothesis, denoted as H03, posits that the first and second lags of EDU_EX and EDN_GER do not jointly influence LN_HFCE in the short run.

In the Wald test, the probability value associated with the Chi-square statistic determines whether to accept or reject this null hypothesis. If the probability value is less than 0.05, the null hypothesis is rejected, indicating that the lags of EDU_EX and EDN_GER do have a significant short-run effect on LN_HFCE. However, in this analysis, the probability value exceeds 0.05, leading to acceptance of the null hypothesis. This outcome suggests that, in the short run, the lagged values of EDU_EX and EDN_GER do not significantly impact LN_HFCE, as reflected in Table 8.

Thus, the findings imply that educational variables, specifically education expenditure and gross enrolment rate, do not exhibit an immediate effect on household final consumption expenditure. This lack of short-run influence suggests that, while education may contribute to poverty reduction and economic welfare in the long term, its impact does not manifest in immediate short-term changes in household consumption patterns.

Stability Tests

The cumulative sum of squares (CUSUMSQ) of recursive residuals when plotted to assess the stability of the model and the presence of a long-run relationship between the variables. The CUSUMSQ test is commonly used to evaluate structural stability within time series models by examining whether the plotted statistic remains within predefined critical boundaries over the sample period. The plot of CUSUMSQ lies entirely within the upper and lower boundaries, which indicates that there is no structural break or significant deviation in the model over time. The stability of the model, as demonstrated by the CUSUMSQ remaining within these bounds, suggests that the estimated coefficients remain consistent throughout the sample period. This stability is essential for ensuring reliable long-term predictions and interpretations from the model. The CUSUMSQ plot's containment within the boundaries further implies a sustained long-run relationship among the variables included in the model. The presence of a long-run equilibrium relationship is particularly valuable in economic modeling, as it indicates that the variables move together over time, despite short-term fluctuations. The stability observed here lends additional confidence to the robustness of the model, confirming that it can effectively capture the underlying economic dynamics without being affected by potential shifts or instabilities in the data.

10. CONCLUSION

Investing in education is a critical driver of economic development, as it aids in poverty alleviation and fosters socio-economic growth. This study investigates the impact of education on poverty reduction in India, using the Johansen cointegration method to examine the long-term relationship between these variables. The cointegration results indicate a significant and enduring association between education and poverty, underscoring that educational investment has a positive, long-term effect on poverty reduction. Thus, promoting education is an effective strategy for achieving Sustainable Development Goal (SDG) 1 (zero poverty), aligning with SDG 4, which advocates for quality education.

Increased government spending on education raises enrollment in educational institutions, which ultimately leads to better employment opportunities for graduates. Over time, this increase in employment boosts household final consumption expenditure, enhancing living standards and reducing poverty. However, the study shows that the impact of education on poverty is predominantly long-term; immediate effects are minimal. This lag is expected, as it takes several years from enrollment to employment. Once individuals begin earning, their rising income leads to increased expenditure, contributing to gradual poverty reduction and moving toward achieving SDG 1.

11. POLICY IMPLICATIONS

The findings suggest that sustained public investment in education should be a priority for policymakers aiming to combat poverty. Key policy recommendations include:

Enhanced Budg*et* allocation for Education: Governments should prioritize long-term educational funding, particularly in primary and secondary education, as foundational education is crucial for broader socio-economic mobility.

Targeted Programs for Vulnerable Groups: Directing resources toward marginalized communities, including rural populations and economically disadvantaged groups, can accelerate enrollment and reduce education gaps, thereby addressing poverty more effectively.

Linking Education to Employment: Policies that strengthen the transition from education to employment are essential. This could involve initiatives like vocational training programs, industry partnerships for skill development, and job placement services within educational institutions to ensure smoother pathways to employment.

Integrated Approach to Sustainable Development: Coordinated efforts between the education sector and other economic sectors, such as healthcare and infrastructure, can foster more holistic development, creating a supportive environment for sustainable poverty alleviation.

By addressing these areas, policymakers can leverage the positive relationship between education and poverty reduction to fulfill SDG targets and drive broader socio-economic progress.

12. LIMITATIONS OF THE STUDY

This study, while comprehensive in examining education's impact on poverty, has limitations. Key factors such as employment rates, economic growth, and income distribution were not included, primarily due to time and resource constraints. These factors are known to influence poverty levels and may interact with educational outcomes, impacting the robustness of the findings. Additionally, education quality, regional disparities, and informal sector employment were not considered, which could further elucidate the pathways through which education influences poverty.

Future research should aim to incorporate these variables to provide a more nuanced understanding of the multifaceted relationship between education and poverty. Expanding the scope to include different regions and broader socio-economic factors could yield more generalizable results and refine strategies for poverty reduction in India and similar developing economies.

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14. CONFLICT OF INTEREST

I declare no conflicts of interest regarding the publication of this article.

15. DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are sourced from various Government of India publications. Data sharing does not apply to this article as no new data were created or analyzed in this study.

16. AUTHOR CONTRIBUTION STATEMENT

Roles and contributions include conceptualization, methodology, validation, investigation, resource management, data curation, original draft writing, review and editing, visualization, supervision, software development, formal analysis, and final draft preparation.

17. ETHICAL STATEMENT

This study does not contain any studies with human or animal subjects performed by the author.

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