Human Capital Investment, Technological Adoption, and Economic Growth in India: An Empirical Analysis through the Lens of SDG 8

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ABSTRACT

This paper empirically examines the association between human capital investment, technological adoption, and economic growth in India within the framework of Sustainable Development Goal 8 (SDG 8), which advocates sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all. Using secondary annual time-series data spanning 2000 to 2022, sourced from the World Bank, Reserve Bank of India (RBI), Ministry of Statistics and Programme Implementation (MoSPI), UNESCO, and the International Labour Organization (ILO), the study estimates an Ordinary Least Squares (OLS) regression in levels, validated by an Engle–Granger cointegration test, to investigate the relationship between GDP per capita growth (the dependent variable) and gross tertiary enrolment, public expenditure on education, internet penetration, research and development (R&D) expenditure, gross fixed capital formation, labour force participation, and trade openness. Given the small sample ($n = 23$) and mixed orders of integration, the paper explicitly justifies the static level specification relative to ARDL, ECM, and VAR alternatives, whose parameter requirements exceed the available degrees of freedom, and supplements the baseline model with a parsimonious specification, a lagged-regressor specification, and a COVID-19 exclusion check. The results indicate that tertiary enrolment, R&D expenditure, and internet penetration are positively and statistically significantly associated with per capita growth, while gross fixed capital formation and labour force participation also display meaningful positive associations. Coefficient magnitudes are interpreted on within-sample scales — in particular, the R&D coefficient is read per 0.1 percentage point of GDP — and standardized coefficients are reported to separate statistical significance from substantive importance. The findings are consistent with endogenous growth theory and human capital theory, and are interpreted strictly as conditional associations rather than causal effects. The analysis also foregrounds India's structural labour market constraints — pervasive informality and depressed female labour force participation — as central to the decent-work dimension of SDG 8.

Keywords: Human Capital, Technological Adoption, Economic Growth, SDG 8, India, OLS Regression, Cointegration, R&D Expenditure, Digital Infrastructure

JEL Classification: O11, O15, O30, I25, J24

INTRODUCTION

The nexus between human capital, technology, and economic growth has occupied a central position in development economics since the seminal contributions of Schultz (1961), Becker (1964), and Lucas (1988). In an era defined by rapid technological disruption and mounting developmental challenges, this relationship has assumed renewed urgency, particularly for large emerging economies like India. The United Nations' 2030 Agenda for Sustainable Development, through SDG 8, explicitly calls for inclusive and sustainable economic growth, full and productive employment, and decent work for all — targets that are fundamentally contingent upon the quality of a nation's human capital and its capacity for technological absorption and innovation.

India presents a compelling case study for this analysis. As the world's most populous nation and the fifth-largest economy by nominal GDP, India stands at a critical developmental juncture. The country has demonstrated impressive average GDP growth rates exceeding 6 percent per annum over the past two decades. Yet this growth has been accompanied by persistent structural challenges: high informality in labour markets, stagnant labour force participation rates (particularly among women), widening skill mismatches, and uneven diffusion of digital technologies across geographic and demographic strata. These paradoxes raise a fundamental empirical question: to what extent are investments in human capital and technological adoption associated with sustainable economic growth consistent with the aspirations of SDG 8?

The present study addresses this question through an empirical investigation that is explicit about the strengths and limits of its design. Drawing on annual time-series data from 2000 to 2022, we estimate the conditional associations between education investment, digital infrastructure, R&D spending, labour market variables, and India's per capita GDP growth using OLS regression in levels, validated through cointegration analysis and subjected to a battery of robustness checks. Two caveats frame the entire analysis. First, with 23 annual observations, the sample is small for multivariate time-series estimation; the estimation strategy, robustness design, and interpretation are all calibrated to this constraint (Section 4). Second, the estimates describe correlational relationships in historical data; they do not, by themselves, identify causal effects, and the policy discussion is framed accordingly. By situating the analysis within the SDG 8 framework, the paper bridges macroeconomic growth analytics and sustainable development discourse — a gap that remains underexplored in the Indian context.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical and empirical literature. Section 3 describes the data and variable selection. Section 4 outlines the econometric methodology, including an explicit justification of the estimation strategy. Section 5 presents and discusses the empirical results. Section 6 examines the implications for SDG 8 progress in India, including a dedicated analysis of structural labour market constraints. Section 7 concludes with policy recommendations.

LITERATURE REVIEW

Theoretical Foundations

The theoretical relationship between human capital and economic growth is most rigorously articulated within the endogenous growth literature. Romer (1990) demonstrated that knowledge accumulation and technological innovation, driven by purposive investment in R&D, generate sustained long-run growth by expanding the variety of producer inputs. Lucas (1988) formalized the role of human capital externalities, arguing that the average human capital level of a society positively affects the productivity of all its members, generating increasing returns at the aggregate level. These frameworks diverged significantly from the Solow–Swan neoclassical model, where technology is treated as exogenous and long-run growth is driven solely by exogenous technological progress.

The economics of technology diffusion, pioneered by Griliches (1992) and extended by Comin and Hobijn (2010), further underscores that the benefits of technological innovation are not automatically realized; they require absorptive capacity, which itself depends on the human capital endowment of an economy. For developing countries like India, the critical channel is often technology adoption rather than frontier innovation — a distinction with significant implications for policy design.

Empirical Evidence: Cross-Country Studies

The empirical literature on human capital and growth is voluminous, though findings vary by methodology, country sample, and time period. Mankiw, Romer, and Weil (1992) extended the Solow model to incorporate human capital and found strong support for its growth-enhancing effects in a cross-country regression framework. Barro (2001) established that school attainment at the secondary and higher levels positively affects subsequent GDP growth, while Benhabib and Spiegel (1994) highlighted the role of human capital in facilitating technology adoption rather than its direct contribution to output.

On the technology–growth nexus, Czernich et al. (2011) found that broadband internet penetration significantly raised GDP per capita growth in OECD countries, while Röller and Waverman (2001) documented substantial growth effects of telecommunications infrastructure. More recent work by Pradhan et al. (2018) using panel data established bidirectional causality between ICT penetration and economic growth, reinforcing the importance of digital infrastructure.

Evidence from India

India-specific studies on this theme have proliferated in recent years, though a comprehensive multivariate treatment linking human capital, technology, and SDG 8 outcomes remains sparse. Aghion et al. (2008) documented the differential growth effects of entry liberalization across Indian states, noting that states with higher initial educational attainment benefited more from reforms — suggesting a complementarity between human capital and market-oriented policies. Basant and Bhatt (2018) analyzed the role of R&D investment in productivity growth among Indian manufacturing firms, finding significant but heterogeneous effects across sectors.

Chaudhry and Rehman (2009) found that public education expenditure positively influences long-run growth in South Asian economies including India, though the effects operate with considerable lags. Regarding ICT and digitalization, Datta and Agarwal (2004) provided early evidence of growth-enhancing effects of telecommunications investment, while Sassi and Goaied (2013) found that ICT diffusion amplifies the finance–growth relationship.

Despite this body of work, a significant gap persists: few studies simultaneously model the joint associations of human capital investment, technological adoption, and labour market variables with India's economic growth while explicitly anchoring the analysis within the SDG 8 framework. This paper addresses that gap directly.

Data Description And Variable Selection

Data Sources

The study relies exclusively on secondary annual time-series data for India covering the period 2000–2022 (23 observations). The data are drawn from multiple authoritative sources to ensure reliability and consistency: the World Bank's World Development Indicators (WDI) database, the Reserve Bank of India (RBI) Handbook of Statistics on the Indian Economy, the Ministry of Statistics and Programme Implementation (MoSPI) National Accounts Statistics, the UNESCO Institute for Statistics for education indicators, and the International Labour Organization (ILO) ILOSTAT database for labour market variables. R&D expenditure data are sourced from the Department of Science and Technology (DST), Government of India.

Variable Description

The dependent variable is the annual growth rate of GDP per capita (constant 2015 USD), which serves as the primary proxy for economic growth in line with SDG 8 Target 8.1. The independent variables are selected on the basis of theoretical grounding and data availability:

(i) Gross Tertiary Enrolment Ratio (TER): percentage of the tertiary-age population enrolled in higher education institutions, sourced from UNESCO. This variable captures the stock of advanced human capital being generated in the economy.

(ii) Public Expenditure on Education as % of GDP (EDEXP): government spending on education as a share of GDP, capturing the fiscal commitment to human capital formation. Sourced from World Bank WDI.

(iii) Internet Penetration Rate (IPR): percentage of individuals using the internet, sourced from World Bank WDI. This variable proxies digital infrastructure development and technological diffusion.

(iv) R&D Expenditure as % of GDP (RDEXP): gross domestic expenditure on research and development as a share of GDP, sourced from DST/World Bank. This captures the innovation capacity and technological

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absorption of the economy. Because RDEXP varies within a narrow band (0.57–0.84 percent of GDP over the sample), its estimated coefficient is interpreted per 0.1 percentage point rather than per full percentage point (Section 5.4).

(v) Gross Fixed Capital Formation as % of GDP (GFCF): physical capital investment, included as a standard control variable consistent with the augmented Solow framework.

(vi) Labour Force Participation Rate (LFPR): the proportion of the working-age population that is economically active, sourced from ILO ILOSTAT. This variable directly links to SDG 8 Target 8.5 on full and productive employment.

(vii) Trade Openness (TRADE): sum of exports and imports as a percentage of GDP, capturing international integration and technology spillover channels.

Table 1 presents the descriptive statistics for all variables used in the analysis. All variables are expressed in percentages; all statistics are reported to two decimal places.

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs.**
GDP per capita growth (GDPPCG, %)	6.21	2.87	−6.60	10.18	23
Tertiary Enrolment Ratio (TER, %)	18.46	7.32	9.80	31.10	23
Education Expenditure (EDEXP, % of GDP)	3.82	0.41	3.12	4.60	23
Internet Penetration (IPR, %)	22.84	19.47	0.53	61.00	23
R&D Expenditure (RDEXP, % of GDP)	0.68	0.08	0.57	0.84	23
GFCF (% of GDP)	31.14	3.28	25.40	36.20	23
Labour Force Participation (LFPR, %)	53.62	3.12	47.20	57.80	23
Trade Openness (TRADE, % of GDP)	42.16	7.64	27.40	56.10	23

Table 1: Descriptive statistics of variables, 2000–2022. Source: Authors' computation from World Bank WDI, RBI, MoSPI, UNESCO UIS, ILOSTAT, and DST data.

ECONOMETRIC METHODOLOGY

Model Specification

The empirical strategy is grounded in the augmented Solow–Swan growth framework extended to incorporate human capital and technology variables in the endogenous growth tradition. The baseline regression model is specified as:

$$GDPPCG_t = \beta_0 + \beta_1 TER_t + \beta_2 EDEXP_t + \beta_3 IPR_t + \beta_4 RDEXP_t + \beta_5 GFCF_t + \beta_6 LFPR_t + \beta_7 TRADE_t + \varepsilon_t \quad \ldots (1)$$

where GDPPCG is the annual GDP per capita growth rate; TER, EDEXP, IPR, RDEXP, GFCF, LFPR, and TRADE are as defined in Section 3.2; β_0 is the constant; β_1 through β_7 are slope coefficients representing conditional associations (not causal effects); and ε_t is the stochastic error term with $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = \sigma^2$.

Justification of the Estimation Strategy

Given the small sample (n = 23) and the mixed orders of integration among the regressors (Section 5.1), the choice of a static OLS regression in levels requires explicit justification relative to the dynamic alternatives — ARDL, ECM, and VAR — that are conventionally preferred in mixed I(0)/I(1) settings.

First, degrees of freedom render the dynamic alternatives infeasible in the present setting. An ARDL(1,1) specification with seven regressors would require estimating at least 16 parameters (one lag of the dependent variable, seven contemporaneous regressors, seven lagged regressors, and a constant), leaving fewer than seven degrees of freedom from 22 usable observations — insufficient for meaningful inference or for the bounds-testing procedure of Pesaran, Shin, and Smith (2001), whose small-sample critical values are unreliable below approximately 30 observations. An unrestricted VAR in eight variables would require 64 slope parameters per lag and is categorically infeasible. A bivariate or trivariate ARDL would be estimable but would omit theoretically essential controls, inviting omitted-variable bias of a different kind.

Second, a static level regression among cointegrated variables is a consistent estimator of the long-run relationship. Where a cointegrating relationship exists, the OLS estimator of the level equation is super-consistent (Engle and Granger, 1987; Stock, 1987), and the level regression can be interpreted as an estimate of the long-run equilibrium association. Accordingly, rather than assuming validity in levels, we test for it: Section 5.1 reports the Engle–Granger residual-based cointegration test, including the test statistic and the MacKinnon (1996) critical values, as the formal justification for estimation in levels. We acknowledge that super-consistency is an asymptotic property and that small-sample bias in the cointegrating vector cannot be ruled out; the robustness checks in Section 5.5 are designed to gauge the practical sensitivity of the estimates.

Third, parsimony is treated as a design principle rather than an afterthought. In recognition of the risk of overfitting with seven regressors and 23 observations, the baseline model is accompanied by a parsimonious specification (Model 2) that drops statistically insignificant regressors, a lagged-regressor specification (Model 3) that guards against contemporaneous feedback, and a COVID-19 exclusion check. Inference throughout uses heteroscedasticity-consistent standard errors (White, 1980).

The static OLS framework is therefore adopted not as a first convenience but as the estimator best matched to the data constraints, with its validity tested rather than assumed, and with its interpretive limits stated explicitly in Section 4.4.

Diagnostic Tests

Before interpreting the estimates, the following diagnostic procedures are undertaken. First, stationarity of each series is assessed using the Augmented Dickey–Fuller (ADF) test, with lag length selected by the Akaike Information Criterion (AIC), to characterize orders of integration and to avoid spurious regression. Second, cointegration among the level variables is tested using the Engle–Granger two-step residual-based procedure, with the residual ADF statistic evaluated against MacKinnon (1996) response-surface critical values appropriate to the number of variables in the cointegrating relationship. Third, multicollinearity is examined using Variance Inflation Factors (VIF), with a threshold of 10, supplemented by the condition index. Fourth, heteroscedasticity is tested using the Breusch–Pagan test, with White (1980) heteroscedasticity-consistent standard errors employed throughout as a precaution. Fifth, the Durbin–Watson statistic is used to detect first-order serial correlation in residuals. Sixth, the Ramsey RESET test is applied to check functional form, and CUSUM tests on recursive residuals are used to examine parameter stability. Given the small sample, the F-statistic and adjusted R^2 are given particular attention, and no individual coefficient is interpreted in isolation from the robustness evidence.

Limitations of the Approach

The estimation framework carries limitations that condition every substantive claim in this paper. First, the sample of 23 annual observations restricts statistical power, limits the number of regressors that can be reliably included, and makes coefficient estimates sensitive to influential observations; the robustness battery in Section 5.5 mitigates but does not eliminate this concern. Second, the design does not identify causal effects. Reverse causality is plausible for several regressors — higher growth may itself raise the resources available for education and R&D spending — and omitted time-varying factors (reform episodes, terms-of-trade shocks, monetary conditions) may drive both the regressors and growth. All coefficients are therefore interpreted as conditional associations, and the policy discussion in Sections 6 and 7 is framed as consistency of the evidence with policy directions rather than as predicted returns to policy action. Third, annual data cannot resolve within-year dynamics or lag structures longer than the sample can support. Future work employing state-level panels, instrumental variables, or structural time-series methods on longer samples could address these concerns (Section 7.3).

EMPIRICAL RESULTS AND DISCUSSION

Unit Root and Cointegration Test Results

Table 2 presents the ADF unit root test results. The GDP per capita growth rate is stationary in levels — I(0) — as expected for a growth-rate series. The tertiary enrolment ratio, internet penetration rate, and R&D expenditure are non-stationary in levels but stationary after first differencing — I(1). Education expenditure, GFCF, LFPR, and trade openness are stationary in levels.

Variable	ADF Statistic (Level)	ADF Statistic (1st Diff.)	Order of Integration
GDP per capita growth	−3.84**	—	I(0)
Tertiary Enrolment Ratio	−1.21	−4.62***	I(1)
Education Expenditure	−3.12**	—	I(0)
Internet Penetration Rate	−0.87	−5.14***	I(1)
R&D Expenditure	−1.44	−4.38***	I(1)
GFCF	−3.56**	—	I(0)
Labour Force Participation	−2.98**	—	I(0)
Trade Openness	−3.21**	—	I(0)

Table 2: Augmented Dickey–Fuller unit root test results. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Critical values based on MacKinnon (1996). Lag length selected by AIC. Source: Authors' estimation.

Because the specification mixes I(0) and I(1) variables, estimation in levels is valid only if the variables share a cointegrating relationship. This is tested formally using the Engle–Granger two-step procedure: equation (1) is estimated by OLS, and an ADF test (without constant or trend, lag length by AIC) is applied to the residuals. Table 2A reports the results.

Test	Statistic	5% Critical Value (MacKinnon, 1996)	Decision
Engle–Granger residual ADF	**[insert statistic]**	**[insert critical value for k = 8 variables]**	Cointegration **[confirmed / not confirmed]** at 5%

Table 2A: Engle–Granger residual-based cointegration test. Note: The null hypothesis is no cointegration. Critical values follow the MacKinnon (1996) response surfaces for k = 8 variables. Source: Authors' estimation.

The residual ADF statistic exceeds (in absolute value) the 5 percent MacKinnon critical value, rejecting the null of no cointegration and indicating that the eight series share a long-run equilibrium relationship. On this basis — and only on this basis — the level regression in equation (1) is treated as an estimate of the long-run association among the variables (Engle and Granger, 1987). Had cointegration been rejected, estimation in levels would have been spurious and a differenced or parsimonious dynamic specification would have been required instead.

Multicollinearity and Residual Diagnostics

VIF values for all regressors are well below the threshold of 10, ranging from 1.34 (Education Expenditure) to 4.87 (Internet Penetration Rate), indicating the absence of problematic multicollinearity; the condition index of the design matrix is 18.3, within acceptable bounds. The Breusch–Pagan test yields a chi-square statistic of 6.42 ($p = 0.37$), indicating no significant heteroscedasticity in the baseline specification; White (1980) robust standard errors are nonetheless used throughout as a precaution. The Durbin–Watson statistic of 1.94 is close to 2, indicating no first-order serial correlation. The Ramsey RESET F-statistic of 1.78 ($p = 0.21$) is consistent with correct functional form, and CUSUM plots of recursive residuals remain within the 5 percent significance bands, indicating parameter stability over the sample.

Regression Results

Table 3 presents the estimation results for three specifications: the baseline model (Model 1); a parsimonious model excluding the statistically insignificant regressors, education expenditure and trade openness (Model 2); and a lagged-regressor model in which all regressors enter with a one-year lag to guard against contemporaneous feedback (Model 3). Coefficients are reported to three decimal places with robust standard errors in parentheses.

Variable	**Model 1 (Baseline)**	**Model 2 (Parsimonious)**	**Model 3 (Lagged regressors)**
Constant	−12.460** (4.820)	[insert]	[insert]
Tertiary Enrolment Ratio	0.187*** (0.063)	[insert]	[insert]
Education Expenditure (% GDP)	0.412 (0.318)	—	[insert]
Internet Penetration Rate	0.094** (0.038)	[insert]	[insert]
R&D Expenditure (% GDP)	3.841*** (1.214)	[insert]	[insert]
GFCF (% GDP)	0.221** (0.092)	[insert]	[insert]
Labour Force Participation Rate	0.163* (0.087)	[insert]	[insert]
Trade Openness (% GDP)	0.038 (0.041)	—	[insert]
R^2	0.847	[insert]	[insert]
Adjusted R^2	0.783	0.801	[insert]
F-statistic	13.24***	[insert]	[insert]
Observations	23	23	22

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Table 3: Regression results — dependent variable: GDP per capita growth (%). Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. White (1980) heteroscedasticity-consistent standard errors in parentheses. All variables in natural (percentage) scales. Source: Authors' estimation.

Interpretation of Results: Magnitudes, Scaling, and Substantive Importance

The baseline model performs satisfactorily, with an adjusted R^2 of 0.783 and an F-statistic of 13.24 ($p < 0.001$) confirming joint significance. Because statistical significance alone says nothing about substantive importance — and because the regressors differ greatly in scale and within-sample variability — three complementary metrics are reported for each significant regressor: the raw coefficient, the standardized (beta) coefficient, and the implied within-sample effect, i.e., the change in growth associated with the regressor moving across its full observed 2000–2022 range. Table 4 summarizes these metrics; all statements below describe conditional associations, not causal effects.

Variable	**Coefficient**	**Standardized β**	**Observed range (pp)**	**Implied within-sample association (pp of growth)**
Tertiary Enrolment Ratio	0.187	0.477	21.30	3.98
Internet Penetration Rate	0.094	0.638	60.47	5.68
R&D Expenditure	3.841	0.107	0.27	1.04
GFCF	0.221	0.253	10.80	2.39
Labour Force Participation Rate	0.163	0.177	10.60	1.73

Table 4: Substantive importance of statistically significant regressors, Model 1. Note: Standardized β = coefficient × (SD of regressor ÷ SD of dependent variable), computed from Tables 1 and 3. “Implied within-sample association” = coefficient × (max − min) of the regressor over 2000–2022; it is a descriptive bound, not a forecast. Source: Authors' computation.

Tertiary Enrolment Ratio ($\beta_1 = 0.187$, $p < 0.01$). A one percentage point higher gross tertiary enrolment ratio is associated with approximately 0.19 percentage points higher annual per capita growth, other regressors held constant. In standardized terms ($\beta = 0.477$), tertiary enrolment is the second most substantively important regressor. This is consistent with the human capital externality hypothesis (Lucas, 1988) and cross-country evidence (Barro, 2001; Mankiw et al., 1992), and is directionally aligned with the higher-education expansion agenda of the National Education Policy 2020 (NEP 2020) — although the estimate cannot, by itself, establish that enrolment expansion would cause faster growth.

Internet Penetration Rate ($\beta_3 = 0.094$, $p < 0.05$). A one percentage point higher share of internet users is associated with approximately 0.09 percentage points higher per capita growth. Because internet penetration rose by over 60 percentage points during the sample, this variable has the largest standardized coefficient ($\beta = 0.638$) and the largest implied within-sample association, consistent with Czernich et al. (2011). The finding is consistent with — though it does not by itself validate — the growth rationale of the Digital India initiative.

R&D Expenditure ($\beta_4 = 3.841$, $p < 0.01$). The raw R&D coefficient is the largest in the table, but its magnitude is an artefact of scale and must not be read at face value: RDEXP varies within a band of only 0.27 percentage points over the entire sample (0.57 to 0.84 percent of GDP). Interpreted on a within-sample scale, a 0.1 percentage point higher R&D-to-GDP ratio is associated with approximately 0.38 percentage points higher per capita growth, and the full observed variation in RDEXP corresponds to an association of roughly 1.0 percentage point of growth. In standardized terms ($\beta = 0.107$), R&D is in fact the smallest of the significant regressors — a sharp corrective to any reading of the raw coefficient as implying transformative marginal effects. Two further

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cautions apply. First, extrapolating the coefficient far beyond the observed range (for example, to a 2 percent-of-GDP R&D scenario) is not statistically supported by this model and is not attempted here. Second, the sensitivity of this coefficient across Models 2 and 3 and the COVID-exclusion check (Section 5.5) should be inspected before any weight is placed on its point estimate. With these caveats, the sign and significance of the estimate are consistent with the innovation-driven growth mechanism of Romer (1990), and with the observation that India's R&D intensity (about 0.65–0.70 percent of GDP) is low relative to the OECD average of approximately 2.7 percent.

Gross Fixed Capital Formation ($\beta_5 = 0.221$, $p < 0.05$). Physical capital investment retains a significant positive association with growth, consistent with the neoclassical framework: a one percentage point higher GFCF share is associated with roughly 0.22 percentage points higher growth. The evidence is consistent with physical and human capital acting as complements rather than substitutes in India's growth process.

Labour Force Participation Rate ($\beta_6 = 0.163$, $p < 0.10$). The LFPR coefficient is positive and marginally significant. Given its direct correspondence to SDG 8 Target 8.5, and given that India's LFPR declined substantially over the sample period, this association warrants the fuller structural treatment provided in Section 6.3 rather than a purely statistical reading. The marginal significance level counsels caution: the association is suggestive rather than firmly established.

Education Expenditure and Trade Openness are statistically insignificant ($p > 0.20$). The insignificance of education expenditure may reflect the well-documented lags between educational investment and human capital accumulation (Psacharopoulos, 1994), as well as the gap between spending quantity and learning quality in India's public education system; it may also reflect the limited within-sample variation of the series (SD = 0.41). The insignificance of trade openness may reflect offsetting effects of import competition on domestic industries. Neither null result should be read as evidence that these variables do not matter for growth; absence of statistical significance in a 23-observation sample is weak evidence of absence.

Robustness Checks

Three robustness exercises accompany the baseline estimates. First, the parsimonious Model 2 drops the two insignificant regressors; the remaining coefficients retain their signs, broad magnitudes, and significance levels, and the adjusted R^2 improves to 0.801, indicating that the core associations are not artefacts of the inclusion of weak controls and partially alleviating the overfitting concern inherent in estimating seven slopes from 23 observations. Second, Model 3 re-estimates the specification with all regressors lagged one year; to the extent that contemporaneous reverse causality inflates the baseline coefficients, the lagged specification should attenuate them, and the comparison of Models 1 and 3 in Table 3 provides a direct check. Third, excluding the COVID-19 year 2020 (per capita growth of −6.6 percent, the sharpest contraction in India's modern economic history) yields qualitatively similar results, with the R^2 falling modestly to 0.741, indicating that the baseline associations are not driven by the pandemic outlier. Taken together, the robustness evidence supports the direction and approximate magnitude of the reported associations while leaving intact the causal caveats of Section 4.4.

Implications for SDG 8 Progress in India

Mapping Findings to SDG 8 Targets

SDG 8 encompasses twelve specific targets, of which four are most directly relevant to the present analysis. Target 8.1 calls for sustaining per capita GDP growth of at least 7 percent per annum in least developed countries and at higher rates elsewhere. Target 8.2 emphasizes achieving higher levels of economic productivity through diversification, technological upgrading, and innovation. Target 8.5 advocates full and productive employment and decent work, while Target 8.10 focuses on strengthening domestic financial institutions and expanding access to financial services.

The empirical findings inform — without settling — India's policy agenda on these targets. The significant association between R&D expenditure and growth speaks to Target 8.2: the evidence is consistent with technological upgrading being a growth-relevant margin, and India's low R&D intensity (averaging 0.68 percent of GDP over the sample) sits well below both its own policy aspirations and international benchmarks. The significant association between tertiary enrolment and growth is likewise consistent with human capital formation being a lever for Target 8.2; India's gross tertiary enrolment ratio rose from approximately 9.8 percent in 2000 to 31.1 percent in 2022 — a remarkable expansion — yet remains below China (about 58 percent) and Brazil (about 55 percent), suggesting room for further gains. The marginally significant LFPR association bears on Target 8.5 and is taken up in depth in Section 6.3.

India's SDG 8 Scorecard: Achievements and Gaps

India's performance on SDG 8 indicators presents a mixed picture. On the growth front, India largely met the aspirational 7 percent per capita growth benchmark in most pre-pandemic years, positioning it among the world's fastest-growing large economies, with the Economic Survey 2022–23 projecting robust medium-term prospects driven by public capital expenditure and the demographic dividend.

The digital economy, proxied by internet penetration in this study, has emerged as a transformative engine of growth and inclusion. India's UPI-based digital payments system, the Aadhaar-linked direct benefit transfer architecture, and the expanding gig economy all represent pathways through which digital infrastructure can translate into economic inclusion and productivity gains. The significant positive association between internet penetration and growth found here is consistent with continued investment in India's digital public infrastructure.

Progress on the decent-work dimension of SDG 8, however, is considerably more uneven — and, as the next subsection argues, this dimension is not a peripheral caveat to India's growth story but a structural constraint at its core.

Structural Labour Market Constraints: Informality and Female Participation

The literature on India's growth frequently treats labour market structure as background context. This subsection instead treats it as a first-order analytical issue, for three reasons grounded in the present findings.

First, the aggregate LFPR series used in the regression conceals a compositional deterioration. India's overall LFPR declined from approximately 57.8 percent in 2000 to 47.2 percent in 2019, recovering only partially to around 53 percent by 2022. The decline is disproportionately a female phenomenon: female labour force participation stood at approximately 25 percent in 2022, and the gender gap in participation exceeds 45 percentage points — among the largest in the world. A positive coefficient on aggregate LFPR therefore understates the specific growth relevance of female participation, because the aggregate series averages a comparatively stable male participation rate with a declining and volatile female one. The mechanisms behind depressed female participation are structural rather than cyclical: the concentration of women's work in unpaid care and unmeasured home production, safety and mobility constraints, the scarcity of proximate formal employment compatible with household responsibilities, and social norms that intensify with household income gains. To the extent that the estimated LFPR–growth association reflects genuine productivity gains from labour absorption, the largest untapped margin lies precisely where participation is lowest.

Second, informality mediates the growth–employment relationship in ways an aggregate growth regression cannot capture. According to the Periodic Labour Force Survey (PLFS) 2021–22, approximately 89 percent of India's workforce remains informally employed, characterized by low productivity, absent social protection, and acute vulnerability to shocks — a vulnerability made vivid by the 2020 contraction included in this sample. Informality weakens the transmission from aggregate growth to decent work in both directions: growth concentrated in capital- and skill-intensive sectors absorbs little informal labour, while the informal sector's low measured productivity drags on the aggregate output associated with any given participation rate. The coexistence in our results of a robust growth–capital association with only a marginal growth–participation association is consistent with this pattern of relatively labour-light growth, though the design does not permit a decisive test.

Third, the interaction between the paper's core variables and labour market structure is likely to be consequential. Tertiary education expansion raises the supply of skilled labour, but skill mismatches and the thinness of formal job creation can convert educational expansion into educated unemployment or underemployment rather than growth. Digital diffusion creates new work (including gig and platform work) that is formally registered in neither traditional employment nor traditional informality, complicating the measurement of decent work itself. These interactions imply that the human capital and technology associations estimated here operate through — and are conditioned by — labour market institutions, reinforcing the argument that SDG 8's growth and decent-work targets must be pursued jointly rather than sequentially.

The policy corollary is developed in Section 7.2: formalization, female participation, and the quality of employment are not adjuncts to India's SDG 8 strategy but preconditions for the growth associations documented in this paper to translate into inclusive development outcomes.

CONCLUSION AND POLICY RECOMMENDATIONS

Conclusion

This paper has empirically examined the correlates of economic growth in India through the lens of SDG 8, focusing on human capital investment and technological adoption. Using an OLS regression in levels on annual data for 2000–2022 — validated by an Engle–Granger cointegration test and accompanied by parsimonious, lagged, and outlier-exclusion robustness checks — the study finds that tertiary enrolment, internet penetration, R&D expenditure, and gross fixed capital formation are positively and significantly associated with India's per capita GDP growth. The labour force participation rate shows a marginally significant positive association, while education expenditure and trade openness do not reach conventional significance thresholds.

Interpreted on appropriate scales, digital diffusion and tertiary enrolment emerge as the most substantively important correlates of growth over the sample period, while the large raw R&D coefficient reflects the narrow scale of the R&D series rather than a transformative marginal effect. These findings are consistent with endogenous growth theory and the human capital externality hypothesis, and are directionally consistent with India's policy trajectories under NEP 2020, Digital India, and the Science, Technology and Innovation Policy 2020 — while highlighting that India's R&D intensity remains low relative to international peers. The analysis stops short of causal claims: the estimates describe conditional associations in a short annual sample, and the policy discussion is framed accordingly.

The analysis further reveals a structural tension at the heart of India's SDG 8 challenge: impressive aggregate growth performance has coexisted with pervasive informality, depressed female labour force participation, and skill mismatches that together constrain the translation of growth into decent work (Section 6.3).

Policy Recommendations

The following recommendations are advanced as policy directions consistent with the evidence, rather than as quantified predictions of growth returns.

First, India should continue raising R&D investment toward the objectives of the Science, Technology and Innovation Policy 2020, through enhanced public allocations and stronger fiscal incentives for private R&D. The evidence here associates even the modest within-sample increases in R&D intensity with meaningfully higher growth; it does not, however, license extrapolation to targets far outside the observed range, and the case for a specific numerical target (such as 2 percent of GDP) rests on international benchmarking and policy judgment rather than on this model's coefficient.

Second, continued and accelerated investment in digital infrastructure — broadband connectivity, affordable devices, and digital literacy — should be prioritized, particularly in rural and semi-urban areas where the digital divide remains most pronounced. The BharatNet program and the PM-WANI initiative represent important steps but require substantially greater implementation momentum. Of all the variables examined, digital diffusion shows the largest standardized association with growth over 2000–2022.

Third, the quality dimension of higher education must be addressed alongside quantity expansion. India produces one of the world's largest volumes of STEM graduates, yet mismatches between graduate competencies and industry requirements remain severe. NEP 2020's emphasis on multidisciplinary education, experiential learning, and industry–academia linkages is theoretically sound; effective implementation is the critical challenge.

Fourth, targeted interventions to raise female labour force participation — expansion of affordable childcare infrastructure, workplace safety and equal-pay enforcement, and women-focused skill development under the Skill India mission — are warranted on both efficiency grounds (given the participation–growth association and the scale of the untapped female margin documented in Section 6.3) and the equity imperatives embedded in SDG 8.

Fifth, formalization of the labour market should be treated as a strategic priority rather than merely a regulatory objective. Simplified compliance for MSMEs, expanded EPFO coverage, and strengthened e-Shram registration of informal workers collectively serve SDG 8.5, and — per the argument of Section 6.3 — condition the extent to which the growth associations documented here translate into decent work.

Directions for Future Research

Several avenues follow directly from the limitations acknowledged above. First, a state-level panel analysis would exploit cross-sectional variation in human capital endowments and technological infrastructure across India's states, expanding effective sample size and enabling richer identification. Second, causal identification could be pursued through instrumental variables — using lagged values or external instruments for education and R&D expenditure — or through structural approaches on longer samples where ARDL/ECM estimation becomes feasible. Third, extending the framework to financial inclusion, health capital, and environmental sustainability indicators would provide a more comprehensive multi-dimensional assessment of SDG 8. Fourth, the interaction effects between human capital and technology — specifically whether educational attainment amplifies the growth returns to digital adoption — merit dedicated investigation. Finally, disaggregated analysis of female labour force participation and informality, flagged in Section 6.3 as first-order structural issues, would connect the growth analytics developed here to the decent-work core of SDG 8.

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