Original Article

Fostering Sustainability in India: The Role of Human Capital in Mitigating Ecological Footprint

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Abstract

Earlier research has largely focused on the relationship between human capital and economic growth, with limited attention to its effect on the ecological footprint. This study fills that gap by investigating the impact of human capital on India's ecological footprint during the period 1980–1981 to 2020–2021, while controlling for economic growth and renewable energy consumption. Employing advanced econometric techniques, including autoregressive distributed lag, vector error correction model Granger causality, stability tests, and decomposition analysis, the findings confirm a long-run co-integrated relationship among variables. Results indicate that a 1% increase in human capital reduces the ecological footprint by 2.70% in the long-run and 0.38% in the short-run. The study also supports the environmental Kuznets curve hypothesis and demonstrates a significant negative impact of renewable energy consumption on the ecological footprint. Granger causality analysis reveals that human capital influences ecological footprint, economic growth, and renewable energy consumption without feedback effects. The study concludes that human capital is instrumental in reducing the ecological footprint, fostering economic growth and promoting renewable energy adoption in India. It emphasizes the need for targeted policy interventions to enhance human capital investment and drive sustainable development in India.

Keywords

Autoregressive distributed lag, ecological footprint, economic growth, human capital, renewable energy, VECM Granger causality

JEL Classification

Q5, J24, H52

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Introduction

Modern policies for global development are increasingly centered on the need to find a balance between economic growth and environmental sustainability. This focus has become critical as climate change and environmental degradation continue to threaten the ecosystems and the economies. The persistent environmental degradation drags down the economic growth and could result in a 10% reduction in global GDP by 2100 (United Nations, 2024). Environmental degradation, encompassing biodiversity loss and resource depletion, exacerbates climate risks and threatens the very foundations of social and economic stability (Wu et al., 2018). Dasgupta et al. (2002) argue that unchecked degradation of natural resources could lead to the collapse of industries dependent on those resources, reinforcing the importance of adopting sustainable development practices.

According to Solow (1991), sustainability means the ethical obligation to preserve the capacity of future generations to be at least as well off as we are. This concept is embedded in the 2030 Agenda for Sustainable Development, which promulgated the 17 Sustainable Development Goals (SDGs) in 2015. These goals aim to address climate change, protect the environment, and promote global economic and social progress through a cooperative framework. Metrics such as the ecological footprint, created by the Global Footprint Network, have become widely recognized for tracking environmental impacts. Unlike CO_2 emissions, which have dominated discussions on climate change, the ecological footprint provides a broader measure of human impact, encompassing various activities such as agriculture, mining, and manufacturing. Together with bio-capacity data, it offers valuable insights into the pressures human activities place on natural systems.

Across the globe, despite structural differences between nations, policies are being developed to enhance sustainability while fostering economic growth. One crucial factor in sustainable development is the role played by human capital, which includes the knowledge, skills, and health of a population. While extensive research links human capital to economic growth, its role in sustainability is less frequently explored. Recent studies suggest that higher levels of human capital are linked with a smaller ecological footprint, driven largely by technological innovation and environmentally friendly practices (World Bank, 2020a). Educated populations tend to engage in more sustainable behaviors, supporting policies that promote ecological balance.

India's socio-economic and resource profile presents a distinctive backdrop for analyzing the nexus between human capital and ecological footprint. The country's economic trajectory has seen notable shifts, particularly after the liberalization, privatization, and globalization reforms of the 1990s. Despite the economic advancements, various environmental challenges persist in India. India currently ranks third in ecological footprint globally, with 1.5 billion global hectares, while its bio-capacity is only 492 million global hectares, making it the sixth-largest ecological debtor globally (World Population Review, 2024). This ecological imbalance emphasizes the urgency of policy interventions to address environmental degradation. India's human capital profile faces persistent challenges, particularly in early childhood nutrition and education. Despite the introduction of the *National Education Policy* (2020), India is positioned at 116th on the human capital index globally, with a slight improvement in its score from 0.44 in 2018 to 0.49 in 2019 (World Bank, 2020b).

Given the essence of sustainable development, this study bridges the research gap in three ways. First, while extensive research links human capital to economic growth (Alam, 2023; Maitra, 2016; Pelinescu, 2015; Sharma et al., 2020), its impact on ecological footprint remains underexplored (Apergis & Payne, 2010; Khan et al., 2022; Yao et al., 2019, 2020). Second, existing studies lack a country-specific analysis for India, despite its distinct socio-economic and environmental challenges. Third, prior research lacks a robust empirical framework. This study employs advanced econometric techniques, including novel autoregressive distributed lag (ARDL) and vector error correction model (VECM) Granger causality, to elucidate the human capital environment nexus.

Following this introduction, we move on to examine the existing literature. Next, the study's theoretical framework, empirical approach, and methodology are discussed. Subsequently, the results and discussion are presented. Lastly, the article concludes with a summary and the policy implications.

Literature Review

All the relevant literature reviewed demonstrated that human capital can affect environmental sustainability through the process of growth, awareness, and substituting efficient technology and innovation. In the following section, the studies are reviewed through the same links.

Human Capital (HC) and Economic Growth (EG)

The ground-breaking works by Schultz (1961) and Becker (1964) lay the groundwork for the role of human capital in economic theory by claiming that training and education raise labor productivity. Further insights into how human capital promotes innovation and maintains long-term economic growth are provided by Lucas (1988) and Romer (1990). These views are supported by empirical research, which shows that human capital proxied as skills, health, and education contributes greatly to economic growth (Ali et al., 2018; Barro, 1991; Krueger & Lindahl, 2001; Naik & Bairagya, 2023; Qazi et al., 2014; Wirajing et al., 2023). Furthermore, by increasing labor productivity, human capital accelerates transitory growth to a higher equilibrium production level (Mankiw et al., 1992). In the literature on environmental economics, studies have analyzed the relationship between economic growth and environmental quality. This has led to the emergence of seeking the relationship between economic growth and environmental quality through estimating EKC (Ahmad et al., 2016; Grossman & Kreuger, 1995; Jalil & Mahmud, 2009; Jayanthakumaran et al., 2011; Jena et al., 2022; Sinha & Bhattacharya, 2017; Stern, 2004; Tiwari, 2011). The results of the studies either accept the presence of inverted U-shaped EKC (Ahmed & Wang, 2019; Ahmed et al., 2020; Al-Mulali et al., 2016; Danish et al., 2019; Ghoshal & Bhattacharyya, 2008; Sinha & Bhattacharya, 2017; Zafar et al., 2019) or reject the presence of inverted U-shaped EKC (Dietzenbacher & Mukhopadyay, 2007; Jena et al., 2022).

Human Capital (HC) and Energy Consumption (EC)

Innovation and incorporation of efficient technology are facilitated by human capital, which will enhance the quality of the environment. Research shows that increased education and skills stimulate creativity and technological breakthroughs essential for the creation and application of renewable energy technology (Popp, 2019; Organization for Economic Co-operation and Development (OECD), 2020). Studies conducted by Hanushek and Woessmann (2008) and Grossman and Krueger (1995) demonstrate the importance of human capital in encouraging energy efficiency. Furthermore, according to Bloom et al. (2014), training and education raise people's environmental consciousness, which increases public support for laws and programs on renewable energy. Further empirical investigations also support the role of human capital in energy efficiency (Edziah et al., 2021; Marques & Fuinhas, 2011). Research indicates that nations possessing robust educational institutions and robust vocational training programs demonstrate success in incorporating renewable energy sources into their energy blend (Apergis &

Payne, 2010; Huang et al., 2020). Furthermore, research also supports the link between human capital and green innovation, with higher human capital stocks in some regions associated with higher rates of patent activity for renewable energy technology (Acemoglu et al., 2012; Johnstone et al., 2010). Stern (2004) highlights that investing in human capital results in a workforce with greater skills that can support the renewable energy industry, hence promoting sustainability and economic resilience. Additionally, the demand for skilled labor is linked to renewable energy. This means that human capital and renewable energy have a bidirectional relationship (International Labor Organization (ILO), 2019; Renner et al., 2008). Utilizing renewable energy sources could lower the carbon emissions (Danish et al., 2017; Dong et al., 2018). According to Yao et al. (2019), human capital increases the use of environment-friendly energy and consequently decreases the use of dirty energy consumption.

Human Capital and Environmental Quality

Investments in human capital have been associated with lower CO_2 emissions, as shown by Yao et al. (2019, 2020, 2021) that investing in post-secondary education led to a reduction in CO_2 emissions between 50.1% and 65.8%. In Pakistan, increasing human capital through education resulted in a long-term decrease in carbon emissions without affecting economic growth (Bano et al., 2018). In emerging market economies, human capital is essential for cutting CO_2 emissions and enhancing environmental quality (Gnangoin et al., 2022). Depending on the sector and the country's climate policy, information and communication technology (ICT) lowers carbon emissions while human capital formation raises them, as seen in ASEAN economies (Hazwan, 2021). Increasing levels of human capital were shown to positively correlate with CO_2 emissions in China (Dong et al., 2022). Research highlights the significance of human capital in decreasing ecological footprint, stressing the impact of education on sustainable consumption patterns and environmental behaviors (Danish et al., 2019; Zafar et al., 2019). Enhanced human capital as a result of higher educational attainment has shown to lower ecological footprint (Ahmed & Wang, 2019; Ahmed et al., 2020). Chen et al. (2022) found a considerable reduction in ecological footprint with greater human capital, despite showing an increasing trend initially. Similar dynamic panel data methodologies are used in research and confirm the role of education in reducing environmental consequences in upper-middle and high-income countries; however, this has not yet been seen in low- and lower-middle-income countries (Al-Mulali et al., 2022). Utilizing the ARDL technique, the results showed that human capital affects economic growth along with ecological footprint both in the short and long-run (Danish et al., 2019). Likewise, Ahmed et al. (2020) concluded that human capital decreases environmental deterioration. Additionally, Zhang et al. (2021), using ARDL, found that human capital has a positive link with ecological footprint in Pakistan.

Theoretical Foundation, Empirical Framework, and Methodology

Theoretical Framework

The endogenous growth theory associated with Romer (1986, 1990) and Lucas (1988) positions human capital as the driver of innovation and sustained economic growth. Unlike exogenous models, it internalizes technological change, with knowledge production fueled by human capital, leading to increasing returns (Aghion & Howitt, 1998). Lucas (1988) emphasizes knowledge spillovers, reinforcing a self-sustaining growth cycle. Arrow (1962) further highlights the non-rivalrous nature of knowledge, ensuring continuous productivity gains. The nexus between human capital and environmental sustainability is critical. Human capital enhances environmental awareness, promotes green technology adoption, and improves resource management (Dasgupta et al., 2002; UNESCO, 2015). Educated individuals advocate for environmental policies, aligning with the SDGs. Human capital facilitates eco-innovation, driving renewable energy, energy-efficient systems, and sustainable agriculture (Popp, 2002). Human capital also strengthens environmental governance and institutional quality (Barbier, 2019). Educated societies demand accountability, fostering effective environmental regulations. Additionally, it shapes sustainable consumption behaviors, reducing ecological footprint (Chen et al., 2022). As Nelson and Phelps (1966) argue, skilled labor accelerates technology adoption, reinforcing economic growth while mitigating environmental degradation.

Empirical Framework and Methodology

Within the human capital theory, this research attempts to analyze how human capital affects the ecological footprint. Using ecological footprint (EFP) as the dependent variable and human capital index (HCI) as the independent variable, the model controls for economic growth and renewable energy use. The following model is used

$$\mathrm{EFP}_t = f\left(\mathrm{HC}_t, X_t\right) \tag{1}$$

EFP_t represents ecological footprint, HC_t represents human capital, and X_t is the vector of (Y_t, Y^2_t, RE_t), where Y is economic growth, Y^2 is the square of economic growth term, and RE is renewable energy consumption. The vector X accounts for omitted variable bias. Ecological footprint and human capital have been utilized in recent studies by Abbas et al. (2022), Ahmed and Wang (2019), Ahmed et al. (2020), Al-Mulali et al. (2016), Chen et al. (2022), Danish et al. (2019), Nathaniel et al. (2021), Zafar et al. (2019), and Zhang et al. (2021). The variable description and data sources are presented in Table 1. The empirical equation for the study is represented as:

$$\mathrm{EFP} = \beta_0 + \beta_1 Y + \beta_2 \mathrm{Y}^2 + \beta_3 \mathrm{HC} + \beta_4 \mathrm{RE} + \varepsilon_t \tag{2}$$

Table 1. Variable Description and Data Sources.

Indicators (Variables)	Symbol	Measurements	Data Source
Ecological footprint	EFP	Total ecological footprint per person	Global Footprint Network (2023)
Human capital index	HCI	Human capital index based on years of schooling and assumed rate of return	Feenstra et al. (2015)
Economic growth	*Y*	GDP per capita constant 2015 $	World Bank (2022c)
Square of economic growth	Y^2	Square of GDP per capita	Authors' estimation
Renewable energy	RE	Renewable energy consumption	World Bank (2022d)

The expected sign of economic growth and the square of economic growth are in EKC fashion. The expected sign of renewable energy is negative, and the sign of human capital is to be determined. Following Shahbaz et al. (2012), log-linear specification of our empirical equation is modeled as follows:

$$\ln\text{EFP} = \beta_0 + \beta_1 \ln Y + \beta_2 \ln Y^2 + \beta_3 \ln\text{HC} + \beta_4 \ln\text{RE} + \varepsilon_t \tag{3}$$

Unit Root Test

In this study, we used the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests to evaluate the stationary properties of the data. The ADF test is based on the following equation:

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \sum\nolimits_{j-1}^{k} d_j \Delta Y_t + \varepsilon_t \tag{4}$$

In the equation, ε_t represents the pure white noise error term, Δ denotes the difference operator, Y_t is a time series, α_0 is the constant, and k is the optimum number of lags of the dependent variable. The ADF test checks whether the estimated coefficients are equal to zero. It provides a cumulative distribution of ADF statistics. The variable is said to be stationary if the value of the coefficients δ is below the critical values. Accordingly, the PP is based on the following equation:

$$\Delta Y_t = \alpha + p^* Y_{t-1} + \varepsilon_t \tag{5}$$

ARDL Bound Testing Approach

The ARDL bounds approach created by Pesaran and Pesaran (1997), Pesaran and Shin (1999), and Pesaran et al. (2001) was used to investigate the long- and short-run dynamics between the variables, instead of other conventional techniques. Compared to previous co-integration techniques, the ARDL methodology offers numerous benefits. According to Pesaran and Shin, ARDL may be applicable regardless of whether the underlying variables are mutually co-integrated, 1(0), or 1(1). Better small sample attributes have been computed using the ARDL technique (Huang, 2020). Even if the explanatory variables in the ARDL process are endogenous, the results can still be estimated. The following is the formulation of the empirical ARDL equation:

$$\begin{aligned}\Delta\text{EFP}_t = \beta_0 + \beta_{1k}\sum_{k=1}^{n}\Delta\text{EFP}_{t-k} + \beta_{2k}\sum_{k=1}^{n}\Delta Y_{(t-k)} + \beta_{3k}\sum_{k=1}^{n}\Delta Y^2{}_{(t-k)} + \beta_{4k}\sum_{k=1}^{n}\Delta\text{HC}_{(t-k)} \\ + \beta_{5k}\sum_{k=1}^{n}\Delta\text{RE}_{(t-k)} + \lambda_1\text{EFP}_{(t-1)} + \lambda_2 Y_{(t-1)} + \lambda_3 Y^2_{(t-1)} + \lambda_4\text{HC}_{(t-1)} + \lambda_5\text{RE}_{(t-1)} + \varepsilon_{1t}\end{aligned} \tag{6}$$

where Δ implies the first difference, β_o indicates the constant term, ε is the residuals, $\beta_1\, \beta_2, \beta_3, \beta_4$, and β_5 are the short-run coefficients, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$, and λ_5 implies the long-run coefficients. The study estimates the long-run relationship between the variables by conducting null hypothesis testing of no co-integration $H_O = \lambda_{1=}\lambda_{2=}\lambda_{3=}\lambda_{4=}\lambda_5 = 0$ against the alternative hypothesis. The values of the F-statistic determine the co-integration. The critical value, given by Pesaran et al. (2001), indicates whether to accept or reject the null hypothesis. If the F-statistic values lie within the critical values, the result will be inconclusive, while in case the *F*-statistic lies above the critical values, the result will be considered conclusive. However, lower than the critical values means no co-integration. This study used the Akaike information criterion (AIC) for lag length selection.

After witnessing a long-run relationship among the variables, the study used the following empirical equation for long-run coefficient estimation:

$$\Delta \mathrm{EFP}_t = \delta_0 + \delta_1 \sum_{i=1}^{0} \mathrm{EFP}_{t-\mathrm{k}} + \delta_2 \sum_{i=1}^{0} Y_{t-\mathrm{k}} + \delta_3 \sum_{i=1}^{0} Y_{i-\mathrm{k}}^2 + \delta_4 \sum_{i=1}^{0} \mathrm{HC}_{t-\mathrm{k}} + \delta_5 \sum_{i=1}^{0} \mathrm{RE}_{t-\mathrm{k}} + \mu_t \tag{7}$$

In case of a long-run relationship, the study estimates the short-run coefficients by employing the following empirical equation:

$$\Delta \mathrm{EFP}_t = \varphi_0 + \varphi_1 \sum_{i=1}^{0} \Delta \mathrm{EFP}_{t-k} + \varphi_2 \sum_{i=1}^{0} \Delta Y_{t-1} + \varphi_3 \sum_{i=1}^{0} \Delta Y_{t-1}^2 + \varphi_4 \sum_{i=1}^{0} \Delta \mathrm{HC}_{t-1} + \varphi_5 \sum_{i=1}^{0} \Delta \mathrm{RE}_{t-1} + \mathrm{n}\mathrm{EC}_{t-1} + \mu_t \tag{8}$$

The error correction term (ECT) depicts the speed of adjustment required to restore the long-run equilibrium after witnessing a short-run shock.

VECM (Granger Causality)

The inability of the ARDL test to show the direction of causality is one of its limitations. The study employs the Granger causality technique (Granger, 1988) to determine the directional relationship among the variables under examination. A negative and significant ECM coefficient indicates a long-run equilibrium relationship, while short-run causality is assessed using the *F*-value from the Wald test. Accordingly, the study formulates the following VECM framework:

$$\begin{bmatrix} \Delta \ln \mathrm{EFP}_t \\ \Delta \ln \ Y_t \\ \Delta \ln \ Y^2{}_t \\ \Delta \ln \mathrm{HC}_t \\ \Delta \ln \mathrm{RE}_t \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \end{bmatrix} = \begin{bmatrix} \beta_{11,k} & \beta_{12,k} & \beta_{13,k} & \beta_{14,k} & \beta_{15,k} \\ \beta_{21,k} & \beta_{22,k} & \beta_{23,k} & \beta_{24,k} & \beta_{25,k} \\ \beta_{31,k} & \beta_{32,k} & \beta_{33,k} & \beta_{34,k} & \beta_{35,k} \\ \beta_{41,k} & \beta_{42,k} & \beta_{43,k} & \beta_{44,k} & \beta_{45,k} \\ \beta_{51,k} & \beta_{52,k} & \beta_{53,k} & \beta_{54,k} & \beta_{55,k} \end{bmatrix} \times \begin{bmatrix} \Delta \ln \mathrm{EFP}_{t-1} \\ \Delta \ln Y_t \\ \Delta \ln Y^2{}_t \\ \Delta \ln \mathrm{HC}_t \\ \Delta \ln \mathrm{RE}_t \end{bmatrix} + \ldots + \begin{bmatrix} \beta_{11,m} & \beta_{12,m} & \beta_{13,m} & \beta_{14,m} & \beta_{15,m} \\ \beta_{21,m} & \beta_{22,m} & \beta_{23,m} & \beta_{24,m} & \beta_{25,m} \\ \beta_{31,m} & \beta_{32,m} & \beta_{33,m} & \beta_{34,m} & \beta_{35,m} \\ \beta_{41,m} & \beta_{42,m} & \beta_{43,m} & \beta_{44,m} & \beta_{45,m} \\ \beta_{51,m} & \beta_{52,m} & \beta_{53,m} & \beta_{54,m} & \beta_{55,m} \end{bmatrix}$$
$$\times \begin{bmatrix} \Delta \ln \mathrm{EFP}_{t-1} \\ \Delta \ln Y_t \\ \Delta \ln Y^2{}_t \\ \Delta \ln \mathrm{HC}_t \\ \Delta \ln \mathrm{RE}_t \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ n_3 \\ n_4 \\ n_5 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \end{bmatrix} \times \left(\mathrm{ecm}_{t-1}\right) + \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \\ \mu_{3t} \\ \mu_{4t} \\ \mu_{5t} \end{bmatrix}$$

where, ecm_{t-1} is the lagged ECT, which is produced from the long-run association, and Δ is the difference operator. Using the *t*-test statistic, the significance of the coefficient of the lagged ECT is used to determine the long-term causality. The direction of short-term causality is demonstrated by the presence of a meaningful link in the variables' first difference. The direction of short-term causality between the variables is tested using the joint X^2 statistic for the first-differenced lagged independent variables, where t denotes the time period, $t - 1$ denotes the time period's lagged values, and ε denotes the residual term.

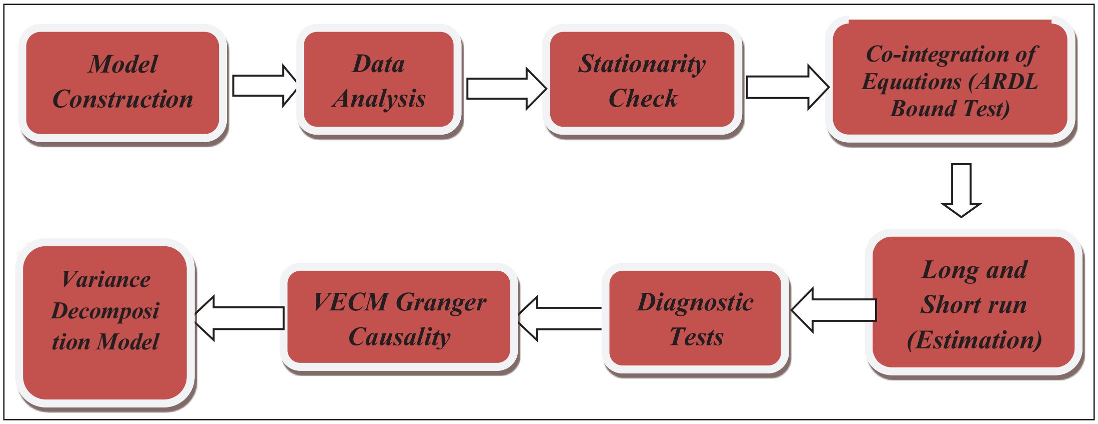

Figure 1. Flowchart of Research Design and Methodological Framework.

Note: ARDL: Autoregressive distributed lag; VECM: Vector error correction model.

Stability of the Short-run Model

The cumulative sum (CUSUM) and CUSUM of the square test on the recursive residuals are used to assess the stability of the model in the short-run. While the CUSUM of squares test can identify abrupt changes from the constancy of regression coefficients, the CUSUM test can identify systematic changes from the regression coefficients (Brown et al., 1975). To examine the robustness of the causal relationships in the investigation, the variance decomposition method has been utilized. The research design and methodological framework are presented in a flowchart (Figure 1).

Results and Discussion

Preliminary Analysis

The descriptive statistics presented in Table 2, ecological footprint (EFP), show an average value of 0.797705 with a range between 0.574696 and 1.082215, highlighting significant environmental degradation. Notably, the ecological footprint has the smallest deviation from its mean, with a standard deviation of 0.154701, indicating high stability. Human capital (HC) demonstrates a steady increase from 0.246860% in 1980 to 0.783902% in 2020, indicating consistent improvements. Economic growth (y) maintained a mean of 6.689921, was further propelled by the LPG reforms. Renewable energy (RE) has an average value of 15.72059, with a range between 15.32177 and 18.24608 during the sample period.

Stationarity Check

Before estimating the models, it is crucial to verify the stationarity of the variables to avoid spurious regression. Table 3 presents the results of the unit root test. The test statistics for all variables are below the critical values at the constant levels in their first differences, indicating that they are stationary. This finding meets the condition for using the ARDL model for co-integration analysis, as it ensures that the

Table 2. Descriptive Statistics.

	lnEFP	lnY	lnY²	lnHC	lnRE
Mean	0.797705	6.689921	45.00219	0.542782	15.72059
Median	0.766962	6.627367	43.92199	0.582216	15.64505
Maximum	1.082215	7.572668	57.34529	0.783902	18.24608
Minimum	0.574696	5.963142	35.55907	0.246860	15.32177
Std. dev.	0.154701	0.503318	6.805774	0.168590	0.440782
Skewness	0.432759	0.272341	0.351832	–0.262482	4.687676
Kurtosis	1.910056	1.794846	1.845398	1.701437	27.68993
Jarque–Bera	3.309213	2.988004	3.123260	3.351498	1,191.545
Probability	0.191167	0.224473	0.209794	0.187168	0.000000
Sum	32.70591	274.2868	1845.090	22.25406	644.5442
Sum sq. dev.	0.957293	10.13315	1852.743	1.136909	7.771537
Observations	41	41	41	41	41

Table 3. Unit Root Test Results.

	Augmented Dicky–Fuller *t*-statistic		Phillips–Peron *t*-statistic		Integration Order (I)
Variables	*C*	C&T	*C*	C&T	
LEFP	–4.758778*** (0.0004)	–4.722786*** (0.0026)	–4.679864*** (0.0005)	–4.661791*** (0.0031)	I(1)
LY	–3.237613** (0.0252)	–2.984462 (0.1493)	–3.239530** (0.0251)	–3.016428 (0.1409)	I(1)
LY²	–3.724094*** (0.0074)	–3.506073** (0.0526)	–3.746855*** (0.0070)	–3.403891* (0.0655)	I(1)
LHC	–8.344779*** (0.0000)	–8.616370*** (0.0000)	–8.359698*** (0.0000)	–8.860355*** (0.0000)	I(1)
LRE	–8.083752*** (0.0000)	–8.323339*** (0.0000)	–38.27824*** (0.0000)	–37.04305*** (0.0000)	I(1)

Note: ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively.

order of integration does not exceed 1 (i.e., $p \leq 1$). Consequently, the study proceeded with the ARDL approach and employed the VECM for causality analysis, given the integration order of the variables.

Lag Length Vector Autoregression (VAR) Model and Co-integration Analysis

In the ARDL estimation process, the initial step involves determining the lag order through the VAR model. Based on the AIC shown in Table 4, the ideal lag length for the model is (1). The estimated equations are detailed in Table 5. A lag length of one has been selected for the model, and the F-values are provided in Table 5, which are within the bounds for orders 1(0) and 1(1). The bounds test statistic value of $F = 5.58$, with critical values at the 5% significance level of 3.29 for 1(0) and 4.37 for 1(1), exceeds

Table 4. Lag Model Ecological Footprint (EFP).

Lag	LogL	LR	FPE	AIC	SC	HQ
0	19.06506	NA	0.023184	–0.926413	–0.883758	–0.911109
1	86.85279	128.6229*	0.000755*	–4.351425*	–4.266114*	–4.320816*
2	87.03291	0.332519	0.000787	–4.309380	–4.181413	–4.263467

Note: *Indicates lag order selected by the criterion.

Table 5. Co-integration Results of Autoregressive Distributed Lag (ARDL) Bound Test.

Estimated Model	*F*-stat.	Lag Order	Co-integration
LEFP/LY,LY^2,LHC,LRE	5.58*	(2,1,1,2,2)	Yes
LY/LEFP,LY^2,LHC,LRE	46.62*	(1,1,2,1,2)	Yes
LY^2/LY,LEFP,LHC,LRE	54.01*	(1,1,2,2,2)	Yes
LHC/LY,LY^2,LEFP,LRE	9.58*	(1,2,1,2,2)	Yes
LRE/LY,LY^2,LHC,LEFP	16.29*	(1,2,2,1,2)	Yes

Note: *Indicates statistical significance at the 5% level. *F-statistic*: Tests for the presence of a long-run relationship. *Lag order*: Shows the selected lags for each variable in the ARDL model. *Co-integration*: 'Yes' indicates a long-run relationship exists.

the critical value for 1(1). This result indicates that the variables in the ecological footprint equation are co-integrated, signifying a long-run relationship among them. Similarly, when the independent variables in the ecological footprint equation are treated as dependent, the *F*-value surpasses the critical threshold, confirming co-integration and a long-run relationship. This co-integration is essential for evaluating Wald statistics through the VECM for the Granger causality test.

Model Estimation and Interpretation (ARDL Bound Testing Estimations)

After the confirmation of co-integration, Equations (7) and (8) are employed to estimate both long-run and short-run elasticities, as summarized in Table 6. The analysis reveals that human capital, economic growth, economic growth square, and renewable energy significantly affect the ecological footprint in India.

The variable of interest, human capital, demonstrates a notable and significant negative impact on the ecological footprint in India. In the long-run, a 1% rise in human capital results in a 2.70% reduction in the ecological footprint during the sample period. This finding highlights the importance of human capital as an important policy instrument for mitigating the ecological footprint and enhancing environmental quality in India. In the short-run, human capital also exerts a negative and significant impact on the ecological footprint, though to a lesser extent. An increase of 1% in human capital results in a 0.38% reduction in ecological footprint, indicating that even short-term improvements in human capital contribute to mitigating environmental impacts. This suggests that the benefits of human capital are both immediate and enduring. The role of human capital is multifaceted, encompassing technique, composition, and awareness effects. The technique effect is evident as increased human capital fosters the adoption of cleaner, more efficient technologies, thus reducing environmental impacts (Miller & Upadhyay, 2000; Zhang & Li, 2023; Zhang et al., 2022). The composition effect manifests in a shift from more polluting industrial sectors to less polluting service sectors, contributing to a reduction in overall

Table 6. Long-run, Short-run, and Diagnostic Test Results.

Variable/Test	Coefficients	*t*-statistic	Prob.
Long-run results			
LnY	7.018856	2.750257	0.0107**
LnY^2	–0.415858	–2.510959	0.0186**
LnHC	–2.702809	–3.085606	0.0048***
LnRE	–0.250226	–2.296460	0.0300**
Short-run results			
D(EFP-1)	–0.366428	–3.192427	0.0037***
LnY	7.281058	5.765467	0.0000***
LnY^2	–0.527722	–5.533903	0.0000***
LnHC	–0.387098	–2.535721	0.0176**
D(LnHC-1)	0.499507	2.482535	0.0198**
LnRE	0.005399	0.994810	0.3290
D(LnRE-1)	0.09046	7.172837	0.0000***
ECT	–0.410720	–6.322943	0.0000***
Diagnostic tests			
Breusch–Godfrey serial correlation	0.641523	–	0.5370
Normality test	23.18805	–	0.800
Ramsey RESET test	0.057586	–	0.8127
Heteroskedasticity (Breusch–Pagan–Godfrey)	1.358593	–	0.2524

Note: *D* (variable) represents the first difference of the variable. ECT represents the error correction term, indicating the speed of adjustment. ***Significant at 1% level, **significant at 5% level.

ecological footprint (Ahmed et al., 2020; Ozturk & Acaravci, 2013). Additionally, the awareness effect associated with higher education levels promotes sustainable consumption and production patterns, driving support for environmentally friendly practices (Singh & Sihmar, 2024). These findings are consistent with studies conducted in diverse contexts, including such studies (Ahmed & Wang, 2019; Huang et al., 2020; Marques & Fuinhas, 2011; Wetering et al., 2022) which highlight the critical role of human capital in advancing environmental sustainability.

The findings also demonstrate the positive impact of economic growth on ecological footprint in the short-run as well as in the long-run. It reveals that increasing income can mitigate the ecological footprint in India. The coefficient of growth indicates that a 1% increase contributes to a 7.018856% increase in ecological footprint in the long-run and a 7.28% increase in the short-run. However, the square of economic growth is associated negatively with ecological footprint in India, indicating that a 1% change leads to a 0.41% decrease in the long-run and a 0.52% decrease in the short-run. The positive coefficient of growth, that is, $\beta_1 > 0$, and the negative coefficient of growth square, that is, $\beta_2 < 0$, mean an inverted U-shaped EKC, indicating the existence of the EKC in India during the sample period 1980–2020. The positive impact of economic growth on ecological footprint can be attributed to the rapid pace of growth, with a primary focus on improving living standards, often at the expense of environmental considerations. The positive nexus between economic growth and ecological footprint during the sample period implies that this growth has come at the cost of environmental degradation in India. In a country grappling with poverty, unemployment, and low living standards, environmental priorities often take a backseat to economic development. The increased pressure for growth is frequently met by exploiting resources that are not environmentally sustainable. However, higher income levels, as indicated by the negative impact of the square of economic growth, could play a favorable role in mitigating the ecological footprint. The confirmation of an inverted U-shaped EKC for India exhibited in this study aligns with previous research (Ahmed & Wang, 2019; Danish et al., 2019; Dasgupta, 2002; Farhani & Shahbaz, 2014; Shiraz et al., 2021; Sinha & Bhattacharya, 2017; Sulaiman et al., 2013; Zafar et al., 2019).

Another finding revealed that renewable energy significantly reduces the ecological footprint in India during the sample period. This reduction reflects both the inherent environmental benefits of renewable energy and the gradual shift from non-renewable sources of energy to renewable ones. However, the short-run effect is not statistically significant, suggesting that the benefits of renewable energy on environmental quality may take time to fully materialize. This finding is consistent with international research of Apergis and Payne (2010) and Edziah et al. (2021), but diverges from Mai et al. (2024), which report more immediate impacts of renewable energy on environmental outcomes.

The ECT was –0.410720 and significant, indicating that 41% long-run equilibrium deviation is corrected within 1 year, with a complete adjustment taking approximately 2 years and 4 months, as represented in Table 6. This gradual adjustment process highlights the importance of strategic policy interventions in aligning short-term practices with long-term sustainability goals (Rahman & Velayutham, 2020). As represented in Table 6, the model passes all diagnostic tests, including serial correlation, normality, specification error, and heteroskedasticity, indicating it is well-specified and statistically robust.

VECM (Granger Causality)

When co-integration among variables is confirmed, it necessitates an examination of causality, which may be either unidirectional or bidirectional. The results of the direction of causality, using the VECM, are presented in Tables 7 and 8, with the former showing the coefficients of the variables and the latter presenting the direction of causality. Such analyses are vital for guiding policy decisions and optimizing resource allocation in India. In the short-run, the analysis shows economic growth, its square, human capital, and renewable energy all exhibit unidirectional Granger causality toward ecological footprint and are statistically significant. Human capital demonstrates robust short-run effects. It is statistically significant in ecological footprint, economic growth, and renewable energy equations, indicating that human capital Granger-causes ecological footprint, economic growth, and renewable energy. This causality is unidirectional, as it does not indicate evidence of a feedback effect. In particular, human capital plays a crucial role in driving economic growth and enhancing renewable energy capacity, thus contributing to reductions in ecological footprint. The evidence suggests that investment in human capital leads to increased economic growth, a greater adoption of renewable energy, and a decrease in ecological footprint in India, highlighting the essential role of human capital in fostering sustainable development. Human capital continues to play a vital role, as it is found to have a unidirectional Granger-cause ecological footprint, affirming its influence on long-term environmental outcomes.

The control variables, economic growth, and its square represent unidirectional causality to ecological footprint, hence supporting the Kuznets curve (inverted U-shaped) in the short and long-run in India during the sample period. Significantly, the joint short- and long-run causality results with the ECT provide a comprehensive understanding of how human capital, economic growth, and renewable energy

Table 7. Granger Causality: Vector Error Correction Model (VECM).

	Short-run Causality					Long-run Causality	Joint Causality (Long-run and Short-run)				
	Δeft_1	Δyt_1	$\Delta y2t\_1$	Δhct_1	Δret_1		Δeft_1 ETCt_1	Δyt_1 ETCt_1	$\Delta y2t\_1$ ETCt_1	Δhct_1 ETCt_1	Δret_1 ETCt_1
Δeft		18.32 (0.002)	10.33 (0.001)	1.35 (0.024)	42.1 (0.013)	–0.13 (–5.58)	–	16.41 (0.000)	16.18 (0.000)	15.63	21.42 (0.000)
Δyt	1.72 (0.19)		5.87 (0.16)	3.23 (0.038)	37.2 (0.000)		–	–	–	–	–
$\Delta y2t$	2.04 (0.16)	5.12 0.030)		3.72 (0.06)	48 (0.000)		–	–		–	–
Δhct	0.26 (0.60)	1.45 (0.23)	1.45 (0.23)		0.02 (0.98)						
Δret	1.33 (0.25)	6.54 (0.15)	8.31 (0.049)	0.51 (0.047)			–	–	–	–	–

Table 8. Granger Causality Results.

Causality Direction	Short-run Causality	Long-run Causality
HC $\rightarrow$ EF	Yes (unidirectional)	Yes (unidirectional)
Y $\rightarrow$ EF	Yes (unidirectional)	Yes (unidirectional)
Y^2 $\rightarrow$ EF	Yes (unidirectional)	Yes (unidirectional)
RE $\rightarrow$ EF	Yes (unidirectional)	Yes (unidirectional)
HC $\rightarrow$ *Y*	Yes (unidirectional)	No
Y $\rightarrow$ HC	No	No
Y^2 $\rightarrow$ HC	No	No
HC $\rightarrow$ RE	Yes (unidirectional)	No
RE $\rightarrow$ HC	No	No
RE $\rightarrow$ *Y*	Yes (unidirectional)	No
Y $\rightarrow$ RE	No	No
Y^2 $\rightarrow$ RE	No	No

interact with the ecological footprint. The significant ECT across these variables confirms their crucial role in achieving long-term environmental sustainability and highlights the importance of integrated policy approaches to balance economic growth with environmental sustainability. These findings illustrate the importance of focusing on human capital development in India. The study highlights that while economic growth comes at environmental costs, leveraging human capital effectively can mitigate these impacts and support long-term environmental sustainability.

Table 9. Variance Decomposition of Ecological Footprint.

Period	S.E.	EFP (%)	Y (%)	Y^2 (%)	HC (%)	RE (%)
1	0.017317	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.021731	84.90253	6.283944	0.693080	3.053161	5.067284
3	0.035060	39.01285	8.744066	0.315675	14.88713	37.04029
4	0.038520	33.70127	18.70480	0.560688	16.25800	30.77524
5	0.042228	30.86454	20.36615	0.470386	17.10871	31.19022
6	0.048964	23.52767	20.37431	0.403332	17.77069	37.92400
7	0.051037	21.91385	24.64282	0.491583	17.86852	35.08323
8	0.052614	21.65667	25.61480	0.482253	17.63724	34.60904
9	0.055908	19.57818	25.17694	0.427355	17.41899	37.39853
10	0.056910	19.10755	27.18474	0.417800	17.19634	36.09358

Variance Decomposition Approach

The variance decomposition values in Table 9, during the first period, show that 100% of the change in ecological footprint is due to its shocks. By the second period, the contribution distribution shifts: 84% is still explained by own innovations, while 6% is attributed to economic growth, 0.69% to the square of growth, 3% to human capital, and 5% to renewable energy.

As the periodical progress takes place, the percentage contributions of controlled variables increase. By the fifth period, 30.86% of the change in EFP is due to its shocks, while 20.36% is explained by economic growth, 0.47% by the square of growth, 17% by human capital, and 31% by renewable energy. By the 10th period, the distribution further evolves, with 19% explained by own innovations, 27% by economic growth, 0.41% by the square of growth, 17% by human capital, and 36% by renewable energy.

These variance decomposition results demonstrate that while innovations in ecological footprint initially dominate, renewable energy and human capital become increasingly important drivers of ecological footprint changes over time. Although economic growth plays a significant role, its squared term has a relatively minimal impact. This suggests that long-term management of the ecological footprint will heavily rely on investments in renewable energy and human capital.

Stability Test

The CUSUM and CUSUM of squares test results are shown in Figures 2 and 3, respectively. The findings imply that the residuals of the ecological footprint equation do not exhibit structural instability.

Conclusion and Policy Implications

This study examined the impact of human capital on ecological footprint in India, while controlling for growth and renewable energy from 1980–1981 to 2020–2021. Utilizing ARDL, VECM Granger causality, stability tests, and decomposition analysis, the findings revealed that a 1% rise in human capital causes a 2.70% reduction in ecological footprint in the long-run and 0.38% in the short-run, highlighting the sustainable benefits reaped by the investments in human capital. The result of this study also supports

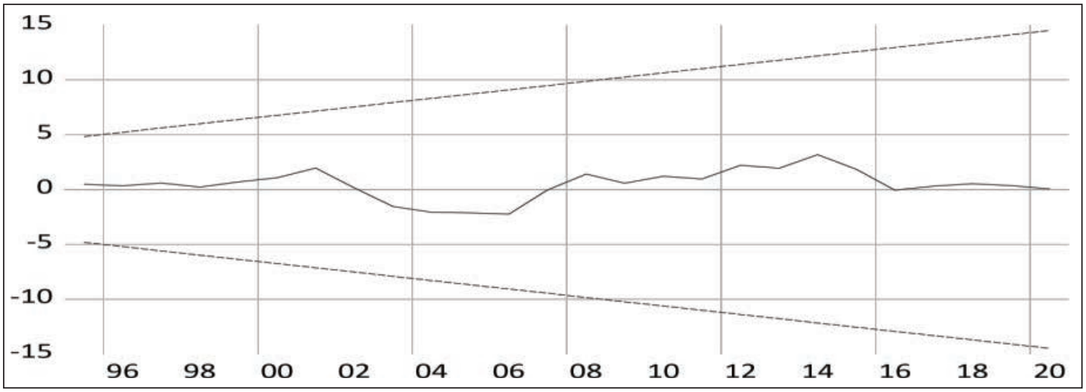

Figure 2. Plot of Cumulative Sum (CUSUM) of Recursive Residuals.

Source: Plots based on Table 6.

Note: The stability of the model is shown by the CUSUM within straight lines being in the 5% significance lines.

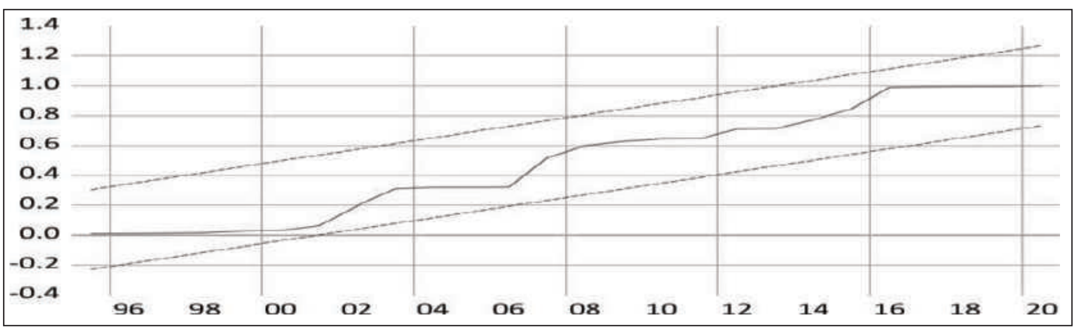

Figure 3. Plot of the Cumulative Sum (CUSUM) of Square of Recursive Residuals.

Source: Plots based on Table 6.

Note: The CUSUM square line being within the 5% significance boundaries shows the stability of the model.

the EKC hypothesis in India. Additionally, the study revealed that a 1% rise in renewable energy use is also linked to a 0.25% reduction in ecological footprint, emphasizing the importance of advancing sustainable energy practices. The study further found that human capital Granger-causes ecological footprint, economic growth, and renewable energy, with no feedback effect in the long-run, emphasizing its critical role in driving economic growth and enhancing renewable energy capacity. The analysis identifies three key channels through which human capital contributes to reducing the ecological footprint. First, human capital fosters economic growth, representing the scale effect. Second, it influences the adoption of renewable energy, signifying a shift in production methods as skills improve, which leads to changes in production techniques. Third, advancements in human capital drive societal behavioral changes through an awareness effect. The study advocates for prioritizing human capital development in India through education, health, and skill development. This approach will not only reduce the ecological footprint but also contribute to securing a sustainable future for the country. These crucial findings suggest that several initiatives, such as the National Education Policy (NEP) 2020, the Green India

Mission, the Swachh Bharat Abhiyan (Clean India Mission), the Skill India Mission, the National Solar Mission, and the Pradhan Mantri Kisan Urja Suraksha evam Utthaan Mahabhiyan (PM-KUSUM) scheme, should be expanded to incorporate sustainability objectives. These initiatives can significantly mitigate ecological degradation while promoting economic growth.

Data Availability Statement

Upon a reasonable request, the relevant author shall provide the data supporting the study's conclusions.

Declaration of Conflicting Interests

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