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Investigating the Impact of Human Capital on Ecological Footprints: Insights from China and India

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Abstract

Existing literature primarily investigates the impact of human capital on economic growth, neglecting its impact on ecological footprints. This study addresses this gap by examining the impact of human capital on ecological footprints in China and India from 1980 to 2020. Using ARDL, VECM and diagnostic tests, findings reveal that a 1% increase in human capital reduces ecological footprints by −6.91% in China and −2.70% in India. Results validate the environmental Kuznets curve hypothesis and renewable energy's stronger influence in China (1.94%) than in India (0.25%). Causality tests revealed that human capital Granger-causes ecological footprints, economic growth and renewable energy in both countries. Bidirectional relationships are found between human capital, economic growth and renewable energy in China, while India exhibits unidirectional causality. Variance decomposition results further support these findings. The CUSUM and CUSUM-square stability tests confirm the structural stability of the estimated models, ensuring robustness. The analysis identifies three transmission mechanisms through which human capital mitigates ecological footprints: the scale effect via enhanced growth, the technique effect through improved renewable energy adoption and the awareness effect by fostering pro-environmental behaviour. In light of these findings, the study advocates for context-specific policy responses: China should deepen the integration of human capital development with renewable energy strategies, while India must intensify investments in education, health and skills to unlock environmental and economic co-benefits.

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The study highlights the imperative for coherent, nation-tailored policy frameworks aligning human capital advancement with environmental sustainability objectives in these economies.

Keywords

Ecological footprints, human capital, sustainable development, ARDL, VECM

I. Introduction

In the context of contemporary global development, aligning economic growth with environmental sustainability has become an urgent priority, particularly as climate change and ecological degradation threaten ecosystems and livelihoods. According to the OECD (2024), climate change could reduce global GDP by up to 10% by 2100, intensifying the effects of biodiversity loss, resource depletion and pollution (Wu et al., 2018). In response, the United Nation's 2030 Agenda for Sustainable Development emphasizes the importance of integrated development strategies that sustain economic advancement while protecting the environment.

One of the key indicators used to assess environmental sustainability is the ecological footprint (EFP), a comprehensive measure that accounts for human demand on natural ecosystems. Unlike carbon dioxide (CO_2) emissions, the EFP encompasses a broader range of human activities, including agriculture, industrial production and land use. When combined with bio-capacity data, EFP offers more holistic insights into environmental stress and ecosystem overload (Global Footprint Network, 2024). Human capital, which includes knowledge, education, health and skills, is well-established as a driver of economic growth. Growth models from neoclassical to endogenous theories highlight human capital as a key determinant of long-run productivity and innovation (Becker, 1964; Erich, 1996; Howitt, 2005; Lucas, 1988; Mankiw et al., 1992; Romer, 1990; Schultz, 1961). However, while the human capital and economic growth nexus has been widely studied, its environmental implications remain less examined, particularly regarding whether human capital fosters sustainable development or contributes to environmental degradation. In this context, this study addresses three key research gaps and makes distinct contributions to the existing literature.

First, this research investigates whether human capital possesses sustainability characteristics, that is, whether it can mitigate environmental degradation without impeding economic growth. By analysing the direct relationship between human capital and EFPs, this study contributes fresh empirical evidence relevant to sustainable development policy.

Second, while much of the empirical literature relies on CO_2 emissions as the proxy for environmental impact (Adikari et al., 2023; Dong et al., 2022; Yao et al., 2019, 2020, 2021), this study deliberately uses EFPs, which offer a more comprehensive environmental assessment. The shift in environmental indicators from CO_2 to EFPs fills an important methodological gap and enhances the study's relevance for broader sustainability evaluations.

Third, there is a notable lack of comparative research on the human capital and EFP link in large emerging economies such as China and India, despite their critical roles in global environmental trends. China, while leading in renewable energy investment and education reforms, faces growing ecological stress due to its rapid industrialization. India, the third-largest contributor to global ecological demand, continues to experience ecological imbalance and underinvestment in sustainability-linked education and health systems (World Population Review, 2024). Given their shared developmental challenges, substantial investments in human capital, and pivotal roles in advancing global sustainability, analysing these two countries enables us to derive context-specific insights with broad global relevance regarding the impact of human capital on environmental outcomes. The article is structured as follows. Section I introduces the study. Section II reviews the literature on human capital, EFPs and sustainability. Section III outlines data, methodology and variables. Section IV presents results and discussion. Section V concludes with a summary and policy recommendations.

II. Review of Literature

Human Capital and Environmental Quality

Investment in advanced human capital has been linked to reductions in CO_2 emissions, with postsecondary education and other forms of higher human capital potentially decreasing emissions by 50.1% and 65.8% (Yao et al., 2019, 2020, 2021). A 1% increase in human capital is associated with a 1.63% decline in carbon emissions, aiding the pursuit of Sustainable Development Goal 13 (Adikari et al., 2023). In Pakistan, educational improvements in human capital have led to a long-term decline in carbon emissions without hindering economic growth (Bano et al., 2018). In newly emerging market economies, human capital plays a vital role in lowering CO_2 emissions and improving environmental quality (Gnangoin et al., 2022). In China, a positive correlation between rising human capital levels and CO_2 emissions has been identified (Dong et al., 2022). However, these studies have used carbon emissions as the dependent variable, which does not provide a comprehensive or broader representation of environmental impact. Meanwhile, several studies emphasize the role of human capital in reducing EFPs, highlighting how education fosters sustainable consumption patterns and environmentally responsible behaviours (Danish et al., 2019; Zafar et al., 2019). Higher levels of educational attainment are also associated with lower EFPs (Ahmed & Wang, 2019; Ahmed et al., 2020). Chen et al. (2022) found that greater human capital substantially reduces EFPs, although this relationship initially shows an increasing trend. Using similar dynamic panel data techniques, Al-Mulali et al. (2022) confirmed the effectiveness of education in mitigating environmental impacts in upper-middle and high-income countries, though not yet in lower-income ones. Danish et al. (2019), using the ARDL approach, demonstrated that human capital influences both economic growth and EFPs in the short and long run. Similarly, Ahmed et al. (2020) concluded that human capital helps reduce environmental degradation. Conversely, Zhang et al. (2021), applying the ARDL model in the context of Pakistan, found a positive association between human capital and EFPs. However, in ASEAN countries, the effect varies depending on the sector and climate policies; while ICT reduces emissions, human capital formation has been observed to increase them (Hazwan, 2021). Grounded in the literature, the following hypotheses are set forth:

H_1: Human capital has a negative and statistically significant impact on EFPs in both China and India.

H_2: There exists a unidirectional causal relationship from human capital to EFPs in both the short run and long run in China and India, indicating that improvements in human capital contribute to reduced EFPs.

Human Capital and Economic Growth

The foundational contributions of Schultz (1961) and Becker (1964) established the significance of human capital in economic theory, emphasizing that education and training enhance labour productivity. Expanding on this, Lucas (1988) and Romer (1990) highlighted how human capital drives innovation and sustains long-term economic growth. These theoretical propositions are substantiated by empirical evidence demonstrating that human capital plays a pivotal role in promoting economic development (Ali et al., 2018; Barro, 1991; Becker, 2002; Khan et al., 2022; Krueger & Lindahl, 2001; Naik & Bairagyar, 2022; Qazi et al., 2014; Wirajing et al., 2023). Additionally, Mankiw et al. (1992) argue that by boosting labour productivity, human capital facilitates higher levels of output in the transition toward steady-state growth. In the field of environmental economics, researchers have explored the interaction between economic growth and environmental quality, leading to the development of the EKC hypothesis (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). Several studies confirm the existence of an 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), whereas others find no evidence supporting this pattern (Dietzenbacher & Mukhopadhyay, 2007; Jena et al., 2022). Based on the literature, the following hypotheses are proposed in this context.

H_3: Human capital positively influences economic growth, and the relationship between economic growth and EFPs in China and India follows an inverted U-shaped pattern, consistent with the EKC hypothesis.

Human Capital and Energy Consumption

Human capital contributes significantly to environmental improvement by facilitating the adoption of efficient technologies and innovations. Researchers have shown that higher levels of education and skills foster innovation and technological advancement, which are crucial for the development and deployment of renewable energy technologies (OECD, 2020; Popp, 2019). Empirical studies by Hanushek and Woessmann (2008) and Grossman and Kreuger (1995) underscore the role of human capital in promoting energy efficiency. Additionally, Bloom et al. (2014) argue that education and training enhance environmental awareness, leading to increased public backing for renewable energy policies and initiatives. Further empirical evidence supports this linkage, demonstrating that human capital enhances energy efficiency (Badea et al., 2020; Marques & Fuinhas, 2011). According to Huang et al. (2020) and Apergis and Payne (2010), countries with strong educational frameworks and vocational training systems are more effective in integrating renewable energy into their energy mix. Other studies also highlight a strong association between human capital and green innovation, with regions exhibiting higher human capital levels also showing elevated rates of patent activity in renewable energy technologies (Acemoglu et al., 2012; Johnstone et al., 2010). Stern (2004) emphasizes that investments in human capital build a skilled workforce capable of supporting the renewable energy sector, thus reinforcing both sustainability and economic resilience. Moreover, the renewable energy sector's reliance on skilled labour suggests a bidirectional relationship between human capital and renewable energy (ILO, 2019; Renner et al., 2008). Danish et al. (2017) and Dong et al. (2018) demonstrate that renewable energy usage significantly reduces CO_2 emissions. In a similar vein, Yao et al. (2019) found that human capital expansion promotes the adoption of clean energy sources while simultaneously reducing the consumption of pollutant-intensive energy. In light of the literature, the following hypotheses have been formulated:

H_4: Human capital positively influences the adoption and consumption of renewable energy in China and India, indicating that improvements in human capital facilitate the transition toward sustainable energy sources.

III. Theoretical Foundation, Empirical Framework and Methodology

Theoretical Framework

The endogenous growth framework pioneered by Romer (1986, 1990) and Lucas (1988) places human capital at the core of innovation and long-run economic growth. Departing from exogenous models, this theory endogenizes technological progress attributing it to knowledge accumulation driven by human capital, thereby generating increasing returns (Aghion & Howitt, 1998). Lucas (1988) further highlights the role of knowledge spillovers in sustaining growth trajectories, while Arrow (1962) emphasizes the non-rival nature of knowledge, which ensures cumulative productivity enhancements over time.

The interplay between human capital and environmental sustainability has emerged as a pivotal theme in contemporary development discourse. Human capital is instrumental in enhancing environmental consciousness, encouraging the diffusion of green technologies, and fostering more efficient resource utilization (Dasgupta et al., 2002; UNESCO, 2015). Educated populations are more likely to support and advocate for robust environmental policies, thereby advancing sustainable development objectives. Moreover, human capital is a catalyst for eco-innovation, facilitating advancements in renewable energy, energy-efficient technologies and sustainable agricultural practices (Popp, 2002).

In addition, human capital contributes significantly to improving institutional capacity and environmental governance (Barbier, 2009). Literate and informed societies often demand transparency and accountability, which strengthens the enforcement of environmental regulations. It also plays a vital role in shaping sustainable consumption patterns, which are essential for reducing EFPs (Chen et al., 2022). As Nelson and Phelps (1966) assert, a more skilled labour force enhances the speed of technological adoption, thereby promoting economic growth while simultaneously mitigating adverse environmental impacts.

Empirical Framework and Methodology

Within the framework of human capital theory, this study seeks to examine the impact of human capital on EFPs. Employing EFP as the dependent variable and the human capital index (HCI) as the key explanatory variable, the analysis also controls for economic growth and renewable energy consumption. The empirical model is specified as follows:

$$\mathrm{EFP} = f\,(\mathrm{HC}, X), \tag{1}$$

where EFP represents the environmental pressure exerted by human activities, calculated as the biologically productive land and water area required to sustain a specific population or economy.

HC (human capital) denotes HCI representing the average human capital, typically assessed through years of schooling and the associated returns to education.

X (control variables): Comprises of Y (Economic Growth), Y^2 (Square of Economic Growth) and RE(Renewable Energy Consumption). Economic growth is measured as GDP per capita, this variable captures the scale of economic activities and their influence on environmental quality. Economic growth is included as it often leads to increased production and consumption, thereby potentially elevating ecological stress. At the same time, growth can finance cleaner technologies and infrastructure, suggesting an ambiguous effect on the environment.

Y^2 (Square of Economic Growth): This term is added to capture the potential non-linear relationship between income and environmental impact, in line with the EKC hypothesis. The EKC posits that environmental degradation initially increases with income but eventually decreases as income reaches a certain threshold due to greater environmental awareness, institutional capacity and adoption of green technologies. Its inclusion allows us to verify whether the income–environment relationship follows an inverted U-shape in the context of China and India.

RE (Renewable Energy Consumption): Represents the share of renewable energy consumption in total energy consumption. This variable is included to control for a country's transition towards sustainable energy sources. Since renewable energy use is typically associated with reduced carbon emissions and lower EFPs, it is crucial to isolate its effect when estimating the impact of human capital. Moreover, it helps capture the technique's effect on environmental degradation, complementing the influence of human capital in driving green energy adoption. Together, these control variables enable a more robust estimation of the independent impact of human capital on EFPs by accounting for economic scale, structural changes and energy composition. Detailed descriptions of these variables and their respective data sources are provided in Table 1.

The estimated empirical equation is represented as follows:

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

Following Shahbaz et al. (2012), the log-linear specification of our empirical equation is modelled as follows:

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

The expected sign of economic growth and square of economic growth is in EKC fashion. The expected sign of renewable energy is negative and a sign of human capital is to be determined.

Unit Root Test

In this study, we use the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests to evaluate the stationary properties of the data.

Table 1. Variable, Description and Data Sources.

Indicators (Variables)	Symbol	Measurements	Data Source	Expected Sign
Ecological footprints	EFP	Total ecological footprints per person	GFN	Dependent variable
Human capital index	HCI	Human capital index based on years of schooling and assumed rate to returns	Penn World Table 10	Negative (−)
Economic growth	Y	GDP per-capita constant 2015 US$	WDI	Positive (+)
Square of economic growth	Y^2	Square of GDP per capita	Authors' estimation	Negative (−) (EKC hypothesis)
Renewable energy	RE	Renewable energy consumption	WDI	Negative (−)

Source: GFN, WDI and Penn World Table 10.

The ADF test is based on the following equation:

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

where 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 less than the critical values. Accordingly, the PP is based on the following equation:

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

The PP unit root test also relies on the t-statistics that is linked with estimated coefficients of ρ^*.

ARDL Bound Testing Approach

The long-run and short-run dynamics between the variables are investigated through the ARDL bounds approach developed by Pesaran and Pesaran (1997), Pesaran and Shin (1999) and Pesaran et al. (2000, 2001) instead of other conventional techniques. Compared to previous cointegration techniques, the ARDL methodology offers numerous benefits. According to Pesaran and Shin (1999), ARDL may be applicable regardless of whether the underlying variables are mutually cointegrated, 1(0) or 1(1). Better small sample attributes have been computed using the ARDL technique (Huang, 2002). 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:

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

where Δ implies the first difference, β_0 indicates constant term, ε is the residual, β_1, β_2, β_3, β_4 and β_5 are the short-run coefficients, while λ_1 λ_2, λ_3, λ_4 and λ_5 denote the long-run coefficients. The study estimates the long-run relationship between the variables by conducting the null hypothesis testing of no cointegration $H_0 = \lambda_{1=} \lambda_{2=} \lambda_{3=} \lambda_{4=} \lambda_{5=}$ 0 against the alternative hypothesis. The values of F-statistic determine the cointegration. The critical values show whether to accept or reject the null hypothesis (Pesaran et al., 2001). 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 value means no cointegration. This study used the Akaike information criteria (AIC) for lag length selection.

When the long-run relation between the variables is found, the study used the following empirical equation for long-run coefficient estimation.

$$\Delta \text{EFP}_t = \delta_0 + \delta_1 \sum\nolimits_{i=1}^{0} \text{EFP}_{(t-\text{k})} + \delta_2 \sum\nolimits_{i=1}^{0} Y_{(t-\text{k})} + \delta_3 \sum\nolimits_{i=1}^{0} Y_{(i-\text{k})}^2 + \delta_4 \sum\nolimits_{i=1}^{0} HC_{(t-\text{k})} + \delta_5 \sum\nolimits_{i=1} \text{RE}_{(t-\text{k})} + \mu_t . \tag{7}$$

In the case of the existence of a long-run relationship, the study will then estimate the short-run coefficients by employing the following empirical equation:

$$\Delta \text{EFP}_t = \varphi_0 + \varphi_1 \sum\nolimits_{i=1}^{0} \Delta \text{EFP}_{(t-1)} + \varphi_2 \sum\nolimits_{i=1}^{0} \Delta Y_{(t-1)} + \varphi_3 \sum\nolimits_{i=1}^{0} \Delta Y_{(i-1)}^2 + \varphi_4 \sum\nolimits_{i=1}^{0} \Delta \text{HC}_{(t-1)} + \varphi_5 \sum\nolimits_{i=1}^{0} \Delta \text{RE}_{(t-1)} + \text{nEC}_{(t-1)} + \mu_t . \tag{8}$$

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

Vector Error Correction Model (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 vector error correction model (VECM) framework:

$$\begin{bmatrix} \Delta ln\,\text{EFP}_t \\ \Delta ln\ \ Y_t \\ \Delta ln\ \ Y^2{}_t \\ \Delta ln\ HC_t \\ \Delta ln\ \text{RE}_t \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \end{bmatrix} = \begin{bmatrix} \beta_{11,\,k}\beta_{12,\,k}\beta_{13,\,k}\beta_{14,\,k}\beta_{15,\,k} \\ \beta_{21,\,k}\beta_{22,\,k}\beta_{23,\,k}\beta_{24\,k}\beta_{25,\,k} \\ \beta_{31,\,k}\beta_{32,\,k}\beta_{33,\,k}\beta_{34,\,k}\beta_{35,\,k} \\ \beta_{41,\,k}\beta_{42,\,k}\beta_{43,\,k}\beta_{44,\,k}\beta_{45,\,k} \\ \beta_{51,\,k}\beta_{52,\,k}\beta_{53,\,k}\beta_{54,\,k}\beta_{55,\,k} \end{bmatrix} \times \begin{bmatrix} \Delta\text{lnEFP}_{t-1} \\ \Delta\text{ln}Y_{t-1} \\ \Delta\text{ln}Y^2{}_{t-1} \\ \Delta\text{lnHC}_{t-1} \\ \Delta\text{lnRE}_{t-1} \end{bmatrix} + \cdots +$$

$$\begin{bmatrix} \beta_{11,\,m}\beta_{12,\,m}\beta_{13,\,m}\beta_{14,\,m}\beta_{15,\,m} \\ \beta_{21,\,m}\beta_{22,\,m}\beta_{23,\,,}\beta_{24,\,m}\beta_{25,\,m} \\ \beta_{31,\,m}\beta_{32,\,m}\beta_{33,\,m}\beta_{34,\,m}\beta_{35,\,m} \\ \beta_{41,\,m}\beta_{42,\,m}\beta_{43,\,m}\beta_{44,\,m}\beta_{45,\,m} \\ \beta_{51,\,m}\beta_{52,\,m}\beta_{53,\,m}\beta_{54,\,m}\beta_{55,\,m} \end{bmatrix} \times \begin{bmatrix} \Delta\text{lnEFP}_{it} \\ \Delta\text{ln}Y_{it} \\ \Delta\text{ln}Y^2{}_{it} \\ \Delta\text{lnHC}_{it} \\ \Delta\text{lnRE}_{it} \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ n_3 \\ n_4 \\ n_5 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \end{bmatrix} \times \left(\text{ecm}_{t-1}\right) + \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \\ \mu_{3t} \\ \mu 4_t \\ \mu_{5t} \end{bmatrix},$$

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 lag 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

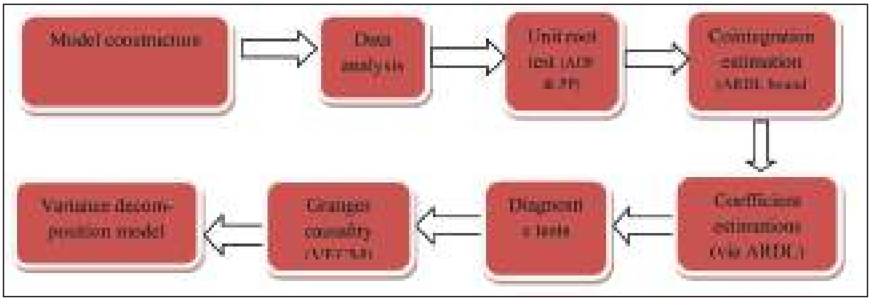

Figure 1. Flow Chart of Research Design and Methodological Framework.

independent variables, where t denotes the time period, $t - 1$ denotes the time period's lagged values, and ε denotes the residual term.

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 Figure 1.

IV. Empirical Results and Discussion

Preliminary Analysis

The descriptive statistics for China and India reveal significant differences in their environmental, economic and human capital development as presented in Table 2. China's EFP (lnEFP) has an average of 0.049, ranging from −0.73749 to 0.83397, with a standard deviation of 0.532082, indicating moderate variability and notable environmental shifts. In contrast, India's EFP (lnEFP) averages 0.7977, ranging from 0.5746 to 1.0822, with a smaller standard deviation of 0.1547, suggesting greater stability but significant environmental degradation. China's economic growth (ln$Y$) has a mean of 28.649, ranging from 26.770 to 30.313, reflecting sustained and robust growth. In comparison, India's economic growth has been more recent, with a minimum of 5.98, and reached the maximum of 7.5726, spurred by Liberalization, Privatization and Globalization (LPG) reforms. Human capital in China averages 0.797489 (lnHC), with values ranging from 0.55241 to 1.02629, highlighting substantial advancements in education. India, however, has seen steady improvement in human capital, from 0.2468% in 1980 to 0.7839% in 2020. Renewable energy use in China averages 3.114383 (lnRE), ranging from 2.4248 to 3.6283, indicating moderate growth in renewable energy, while India's

Table 2. Descriptive Statistics.

	China					India				
Statistics	(lnEFP)	(lny)	(Lny^2)	(lnHC)	(lnRE)	(lnEFP)	(lny)	(Lny^2)	(lnHC)	(lnRE)
Mean	0.049	28.65	821.84	0.79748	3.1143	0.7977	6.69	45.003	0.5427	15.73
Median	0.05217	28.649	820.82	0.82300	3.39	0.7669	6.63	43.93	0.59	15.65
Maximum	0.83397	30.313	918.88	1.02629	3.6283	1.0822	7.5726	57.345	0.7839	18.246
Minimum	0.73749	26.770	716.63	0.55241	2.4248	0.5746	5.98	35.559	0.2468	15.321
Std Dev	0.53208	1.1110	63.564	0.13808	0.4444	0.1547	0.50	6.8057	0.1685	0.4407
Skewness	0.10548	0.0816	0.0390	0.27654	0.3850	0.4327	0.27	0.3518	0.2628	4.6876
Kurtosis	1.57113	1.7498	1.7377	1.84514	1.4042	1.9100	1.7948	1.8453	1.7014	27.689
Jarque–Bera	3.56389	2.7156	2.7321	2.80097	5.3630	3.3092	2.9880	3.1232	3.3514	1,191.5
Probability	.16831	.2572	.2551	.24647	.0684	.1911	.2244	.2097	.1871	.0000
Sum	2.02375	1,174.5	33,695.	32.6970	127.68	32.705	274.	1,845.0	22.254	644.54
SumSq. Dev.	11.3244	49.376	1,661.6	0.76273	7.9015	0.9572	10.1	1,852.7	1.1369	7.7715
Observations	41	41	41	41	41	41	41	41	41	41

renewable energy usage, with an average of 15.73 and a range between 15.321 and 18.246, highlights a stronger focus on renewable sources. Despite these differences, both countries demonstrate steady improvements in human capital and face environmental challenges, with India showing a more stable but concerning EFP.

Stationary Check

Before estimating the models, it is crucial to verify the stationarity of the variables to avoid spurious regression. This study employs the ADF and PP tests for this purpose and results are reported in Table 3. The unit root test results for both China and India indicate that all variables are stationary at $I(1)$. In China, the order of integration for all variables is $I(1)$. Similarly, in India, all variables also exhibit stationarity at $I(1)$. This finding meets the necessary condition for using the ARDL model for cointegration analysis, as it ensures that the order of integration does not exceed 1 (i.e., $p \leq 1$). Consequently, the study will proceed with the ARDL approach.

Model Estimation and Interpretation (ARDL Bound Testing Estimations)

In the ARDL estimation process, the initial step involves determining the lag order through the vector auto regression (VAR) model. Hence, this study is also identifying the optimal lag length for each model using the lag length criteria in the VAR model. For both China and India, the optimal lag length is 1, as reflected by the lowest AIC value and the likelihood ratio (LR) test. In both countries, lag 1 provides the best fit for the model, as supported by the significant final prediction error (FPE), AIC, Schwarz criterion (SC) and Hannan–Quinn (HQ) values as presented in Table 4.

The estimated equation (6) is employed to confirm the existence of cointegration and a long-run relationship among the variables for China and India for which results are summarised in Table 5. For China, the results derived from the F-statistic indicate the presence of cointegration, as the F-value of 4.72 in the EFP equation exceeds the 5% critical value for $I(1)$. Additionally, when the independent variables in the EFP equation are treated as dependent, the F-value again surpasses the critical threshold, reaffirming cointegration and a long-run relationship. Similarly, for India, the findings also confirm the existence of cointegration and a long-run association among the variables. The F-value of 5.58 in India's EFP equation exceeds the 5% critical value for $I(1)$. When the independent variables are alternatively treated as dependent, the F-value once more surpasses the critical level, validating cointegration. Overall, the bounds test results lead to the rejection of the null hypothesis for both countries, confirming long-run relationships across all equations in China and India. This evidence of cointegration is essential for applying Wald statistics in the VECM framework to conduct the Granger causality test.

Table 3. Stationarity Test Results.

	China				India			
Variables	ADF (C)	ADF(C&T)	PP (C)	PP (C&T)	ADF (C)	ADF(C&T)	PP (C)	PP (C&T)
lnEFP	4.602***	4.551***	4.478***	4.343***	4.759***	4.723***	4.680***	4.662***
	(0.001)	(0.003)	(0.001)	(0.005)	(0.000)	(0.003)	(0.001)	(0.003)
lnHC	7.892***	8.144***	8.015***	8.377***	8.345***	8.616***	8.360***	8.860***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln$Y$	2.919**	2.692	2.942**	2.857*	3.238**	2.984	3.240**	3.016
	(0.048)	(0.215)	(0.043)	(0.108)	(0.025)	(0.149)	(0.025)	(0.141)
lnY^2	3.409***	3.232**	3.454***	3.175**	3.724***	3.506**	3.747***	3.404*
	(0.011)	(0.032)	(0.011)	(0.046)	(0.007)	(0.053)	(0.007)	(0.066)
	7.621***	7.950***	37.821***	36.501***	8.084***	8.323***	38.278***	37.043***
lnRE	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: *** (p < .01), ** (p < .05) and * (p < 0.10) indicate significance at the 1%, 5% and 10% levels, respectively.
The ADF and PP tests confirm that lnEFP, lnHC and lnRE are stationary at the 1% level.
ln$Y$ shows weaker stationarity, with some cases only significant at 10% or not significant under trend specification.

Table 4. Lag Model of EFP.

	China						India					
Lag	LogL	LR	FPE	AIC	SC	HQ	LogL	LR	FPE	AIC	SC	HQ
0	21.34	NA	0.02	0.89	0.85	0.88	19.07	NA	0.02	0.93	0.88	0.91
1	95.62	132.79*	0.00*	4.39*	4.31*	4.37*	86.85	128.62*	0.00*	4.35*	4.27*	4.32*
2	96.14	0.29	0.00	4.33	4.20	4.29	87.03	0.33	0.00	4.31		

Notes: * Indicates the optimal lag order based on the lowest final prediction error (FPE), Akaike information criterion (AIC), Schwarz criterion (SC), Hannan–Quinn criterion (HQ) or highest likelihood ratio (LR) statistic.

LogL measures model fit, LR tests lag significance and FPE assesses prediction accuracy, while lower AIC, SC and HQ values indicate better model performance.

Table 5. Cointegration Results of the ARDL Bound Test,

	China			India		
Estimated Model	*F*-stat	Lag Order	Cointegration	*F*-stat	Lag Order	Cointegration
lnEFP/lnHC, ln$Y$, lnY^2, lnRE	4.72*	(2,1,2,1,2)	Yes	5.58*	(2,1,2,1,2)	Yes
lnHC/lnEFP, ln$Y$, lnY^2, lnRE	38.50*	(1,2,1,2,2)	Yes	46.62*	(1,2,1,2,2)	Yes
ln$Y$/lnEFP, lnHC, lnY^2, lnRE	50.24*	(2,1,2,2,1)	Yes	54.01*	(2,1,2,2,1)	Yes
lnY^2/lnEFP, lnHC, ln$Y$, lnRE	8.30*	(1,2,2,1,2)	Yes	9.58*	(1,2,2,1,2)	Yes
lnRE/lnEFP, lnHC, ln$Y$, lnY^2	14.87*	(2,1,1,2,2)	Yes	16.29*	(2,1,1,2,2)	Yes

Notes: * ($p < .10$) indicates significance at the 10% level.

All models confirm long-run cointegration in both China and India.

Lag orders are developed through the VAR of models.

Equations (7) and (8) are employed to estimate both long-run and short-run elasticities, with results summarized in Table 6. The analysis for China highlights the significant role of human capital in mitigating EFPs. The findings revealed that in the long run, human capital exerts a significant negative impact on EFPs in China. Results demonstrated that a 1% increase in human capital in China leads to a −6.91% reduction in EFPs, emphasizing its transformative potential for enhancing environmental quality over time. In the short run, although the direct coefficient of human capital is statistically insignificant, lagged changes in human capital show a positive but insignificant impact on EFPs in China. These findings highlight the importance of prior human capital improvements in shaping present environmental outcomes and highlight its multifaceted effects on EFPs in China. For India, human capital has a statistically significant and negative impact on EFPs. Results revealed that a 1% increase in human capital reduces EFPs by −2.70% in the long run, reinforcing its role as a vital policy instrument for reducing EFPs and improving environmental quality in India. In the short run, a 1% increase in human capital leads −0.38% reduction in EFPs in India, as shown in Table 6. The relatively greater significance of human capital in the long run in China can be attributed to its early emphasis on human development compared to India. The higher education levels of the Chinese population indicate that improvements in human capital have fostered greater awareness. Another contributing factor is the adoption of energy-efficient technologies, which tends to rise alongside advancements in human capital, leading to a more significant impact on EFPs. Additionally, human capital has been one of the important factors that added to the pronounced transformation in China's industrial structure compared to India. The findings support the conclusion that the role of human capital is multifaceted, encompassing technique, composition and awareness effects. The difference in these dimensions adds to different effect of human capital on EFPs in China and India. The technique effect involves adopting cleaner, more efficient technologies through higher human capital levels (Miller & Upadhyay, 2000; Zhang et al., 2022). The composition effect reflects a shift from more polluting industries to less polluting service sectors, aiding reductions in EFP (Ahmed et al., 2020; Ozturk & Acaravci, 2013). The awareness effect, fostered by higher education, promotes sustainable consumption and production patterns, encouraging environmentally conscious behaviours (Al-Nuaimi& Al-Ghamdi, 2022; Novo-Corti, et al., 2018; Singh et al., 2022). These findings align with studies across various contexts, such as Marques and Fuinhas (2011) in Europe, Huang et al. (2020) in China and Ahmed and Wang, (2019) in India, further illustrating the critical role of human capital in fostering environmental sustainability.

The results of the controlled variables are also important to analyse their expected relation with the dependent variable and the existence of any vital findings. Regarding the economic growth and EFPs the findings indicate that in China, economic growth positively impacts EFPs in the long term, with a 1% increase in economic growth resulting in an 11.68% increase in EFPs. However, the square of economic growth exhibits a negative effect, with a 1% increase leading to a −0.59% reduction in EFPs in China. In the short term, economic growth positively influences EFPs, with a 1% increase causing a 0.65% rise.

Table 6. Long-run, short-run and Diagnostic Test Results for China and India.

	China			India		
Variable/Test	Coefficient	*t* Statistic	Probability	Coefficient	*t* Statistic	Probability
Long-run Results						
lnHC	−6.910790**	−2.521249	.0172	−2.702809***	−3.085606	.0048
ln*Y*	11.677876*	−1.291300	.0650	7.018856**	2.750257	.0107
lnY^2	−0.590635**	2.108073	.0435	−0.415858**	−2.510959	.0186
lnRE	−1.94e−05**	0.073822	.0416	−0.250226**	−2.296460	.0300
Short-run Results						
D(lnEFP(−1))	0.429045***	3.937000	.0007	−0.366428***	−3.192427	.0037
lnHC	1.616501	1.587647	.1260	−0.387098**	−2.535721	.0176
D(lnHC(−1))	4.298938**	2.656595	.0141	0.499507**	2.482535	.0198
ln*Y*	0.649051***	7.338903	.0000	7.281058***	5.765467	.0000
lnY^2	−0.240272***	−3.313755	.0030	−0.527722***	−5.533903	.0000
lnRE	0.000209**	2.466105	.0215	0.005399	0.994810	.3290
D(lnRE(−1))	0.000201*	1.819941	.0818	0.090460***	7.172837	.0000
ECT	−0.631404***	−7.032483	.0000	−0.410720***	−6.322943	.0000
Diagnostic Tests						
Breusch−Godfrey serial correlation	3.242182	–	.0593	0.641523	–	.5370
Normality test	23.18805	–	.000008	23.18805	–	.000008
Ramsey reset	0.057586	–	.8127	0.057586	–	.8127
Breusch–Pagan−Godfrey	1.579770	–	.1602	1.358593	–	.2524

Notes: ***Significant at the 1% level ($p < 0.01$).
**Significant at the 5% level ($p < .05$).
*Significant at the 10% level ($p < 0.10$).
ECT represents the error correction term, confirming the speed of adjustment towards long-run equilibrium.

However, the square of economic growth mitigates this impact, as a 1% increase reduces EFPs by −0.24%. The positive coefficient of economic growth ($\beta_2 > 0$) and the negative coefficient of its square ($\beta_3 < 0$) suggest the existence of an inverted U-shaped EKC in China. The findings also indicate that economic growth positively impacts EFPs in both the short and long term in India, while the square of economic growth has a mitigating effect. Specifically, a 1% increase in economic growth is associated with a 7.02% rise in EFPs over the long term and a 7.28% increase in the short term. However, the square of economic growth is negatively impacting the EFPs in India, indicating that a 1% change in this square leads to a −0.41% decrease in EFPs in the long term and a −0.52% decrease in the short term (Table 6). The positive coefficient of economic growth ($\beta_2 > 0$) and the negative coefficient of its square ($\beta_3 < 0$) suggest the existence of an inverted U-shaped EKC in India. The positive relationship between economic growth and EFPs can be attributed to rapid growth focused primarily on improving living standards, often at the expense of environmental considerations in both countries. The variations demonstrate the differences in development stages, policy effectiveness and economic transformations between the two countries. This implies that in a country facing challenges such as poverty and unemployment, environmental priorities may be side-lined in favour of economic growth. Increased growth pressures frequently lead to the unsustainable exploitation of resources. Nevertheless, higher income levels, indicated by the negative impact of the square of economic growth, may help mitigate EFPs. The study's confirmation of an inverted U-shaped EKC for both countries aligns with previous research, including studies by Ahmed and Wang (2019) in India, Rafindadi (2016) in Nigeria, Danish et al. (2019) in Pakistan, Zafar et al. (2019) in the USA and Ahmed et al. (2020) in China. Additional studies by Dasgupta (2002), Odugbesan and Adebayo (2020), Sinha et al. (2017) and Ozgur et al. (2022) also evidenced the inverted U-shaped EKC in their respective studies. However, this study does not support the conclusions of Ghosh (2010) and Jena (2022), which suggested no long-run causal relationship between carbon emissions and economic growth.

In the long run, renewable energy represented in Table 6 has a coefficient of −1.95 for China and −0.25 for India. This reduction reflects both the inherent environmental benefits of renewable energy and the gradual shift from non-renewable to renewable energy sources. However, the short-run impact of renewable energy on EFPs is not statistically significant, suggesting that the benefits of renewable energy on environmental quality may take time to fully materialize (Apergis & Payne, 2010; Badea et al., 2020). This finding is consistent with international research but diverges from studies like Mai et al. (2024), which report more immediate impacts of renewable energy on environmental outcomes. The stronger long-run effect in China compared to India may be attributed to China's more aggressive renewable energy policies, greater investment in clean energy infrastructure and faster technological adoption, supported by large-scale government initiatives and industrial capacity. This gradual adjustment process highlights the importance of strategic policy interventions in aligning short-term practices with long-term sustainability goals (Rahman & Velayutham, 2020).

For China, the ECT is −0.631404 and significant, indicating that 63% of the deviation from the long-run equilibrium is corrected within one year, with a complete adjustment taking approximately one year and eight months. The ECT is −0.410720 for India, indicating that 41% of the deviation from the long-run equilibrium is corrected within one year, with a complete adjustment taking approximately two years and four months.

VECM (Granger Causality)

Upon establishing long-run and short-run elasticities, it is essential to examine the causality, which may be unidirectional or bidirectional, using the VECM. Such analyses are vital for informing policy and optimizing resource allocation. The results are summarized in Tables 7 and 8 for China and India, respectively, which present short-run, long-run and joint causality among the cointegrated variables.

In the short run, the analysis reveals that human capital, economic growth, square of growth and renewable energy all exhibited unidirectional Granger causality towards EFPs for both China and India as presented in Tables 7 and 8. These variables are statistically significant at the 5% level in the EFP equation. Further, the unidirectional causality from economic growth and its square supports the inverted U-shaped Kuznets curve in both China and India in the long run and short run. A significant difference emerges in the relationship between economic growth and human capital. In China, human capital and economic growth indicated bidirectional causality and support for the feedback hypothesis. This suggests that economic growth enhances human capital, which in turn fuels further economic growth. Conversely, in India, economic growth does not Granger-cause human capital, and the causality runs unidirectional from human capital to economic growth. Another distinction lies in the causality of renewable energy adoption. In China, both economic growth and human capital Granger-cause renewable energy adoption, emphasizing their role in promoting clean energy. In contrast, in India, no evidence supports the causality from economic growth to renewable energy adoption but supports the unidirectional causality from human capital to renewable energy. In the long run, the ECT is significant in the EFP and renewable energy equations for China, while it is only significant in the EFP equation for India. This indicates that while both countries exhibit long-run relationships among economic growth, human capital, renewable energy and EFPs, the adjustment processes differ. In China, economic growth and human capital interact to foster long-term sustainability, while in India the primary focus is on managing EFPs. These results underscore the importance of integrated policy approaches that balance economic development with environmental preservation.

Variance Decomposition Approach

The generalized forecast error variance decomposition technique under the vector autoregressive (VAR) framework has been applied to examine the relative contributions of each variable to fluctuations in EFPs over time. Table 9 presents the results for both China and India across a 10-period horizon.

Table 7. VECM Granger Causality (China).

	Direction of Causality Short Run						Joint Long-run and Short-run Causality				
	Δeft − 1	Δ*yt*_1	Δ*y2t*_1	Δ*hct*_1	Δ*ret*_1	Long Run	Δeft − 1 ETCt_1	Δ*hct*_1 ETCt_1	Δ*yt*1 ETCt_1	Δ*y2t*_1 ETCt_1	Δ*ret*1 ETCt_1
Δeft		2.45 (0.09)	4.21 (0.04)	2.98 (0.06)	6.12 (0.04)	−0.13 (0.05)	–	12.33 (0.000)	9.11 (0.000)	12.25 (0.000)	18.22 (0.000)
Δ*hct*	0.84 (0.43)	3.23 (0.02)	6.56 (0.01)		0.87 (0.42)						
Δ*yt*	15.24 (0.18)		5.87 (0.16)	1.23 (0.02)	7.22 (0.000)		–	–		–	–
Δ*y2t*	7.34 (0.91)	9.12 0.63)		1.56 (0.01)	48 (0.000)		–	–		–	–
Δ*ret*	4.78 (0.03)	6.87 (0.019)	8.32 (0.010)	2.11 (0.10)		−0.68 (−0.07)	–	−13.90 (0.02)	−4.49 (0.09)	−3.56 (0.06)	−9.1 (0.04)

Notes: The results show significant short-run and long-run causality between human capital and ecological footprints. Renewable energy and income also exhibit joint causality, highlighting their environmental impact.

Table 8. VECM Granger Causality (India).

	Direction of Causality Short Run						Joint Long-run and Short-run Causality				
	Δeft – 1	Δyt_1	$\Delta y2t$_1	Δhct_1	Δret_1	Long Run	Δeft – 1 ETCt_1	Δhct_1 ETCt_1	Δyt1 ETCt_1	$\Delta y2t$_1 ETCt_1	Δret1 ETCt_1
Δeft		18.32 (0.002)	10.33 (0.001)	1.35 (0.024)	42.1 (0.013)	−0.13 (5.58)	—	15.63	16.41 (0.000)	16.18 (0.000)	21.42 (0.000)
Δhct	0.26 (0.60)	1.45 (0.23)	1.45 (0.23)		0.02 (0.98)						
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)		—	—		—	—
Δret	1.33 (0.25)	6.54 (0.15)	8.31 (0.049)	0.51 (0.047)			—	—	—	—	—

Notes: The results indicate strong long-run causality from human capital, income and renewable energy to ecological footprints in India.
Short-run dynamics also highlight significant interactions between these variables.

Table 9. Variance Decomposition of Ecological Footprints (China and India).

	China					India				
Period	lnEF	lnY	lnY^2	lnHC	lnRE	EF	lnY	lnY^2	lnHC	lnRE
1	100.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00
2	86.50	7.00	5.80	0.00	0.70	84.90	6.28	0.69	3.05	5.07
3	45.00	15.00	17.50	10.00	12.50	39.01	8.74	0.32	14.89	37.04
4	34.00	22.50	20.00	17.00	6.50	33.70	18.70	0.56	16.26	30.78
5	35.00	18.50	16.00	20.00	10.50	30.86	20.37	0.47	17.11	31.19
6	30.00	19.50	15.00	25.00	10.50	23.53	20.37	0.40	17.77	37.92
7	25.00	22.00	18.00	25.00	10.00	21.91	24.64	0.49	17.87	35.08
8	20.00	30.00	15.00	25.00	10.00	21.66	25.61	0.48	17.64	34.61
9	18.00	35.00	20.00	15.00	12.00	19.58	25.18	0.43	17.42	37.40
10	19.00	30.00	25.00	15.00	11.00	19.11	27.18	0.42	17.20	36.09

Notes: Income (lnY) and human capital (lnHC) significantly influence EFPs (lnEF) over time.
The role of renewable energy (lnRE) grows in later periods, indicating its increasing impact on sustainability.

In China, the initial period shows that 100% of the variation in EFPs stems from its own shocks. By the second period, economic growth (7.00%) and its squared term (5.80%) begin to exert influence, with minimal contributions from renewable energy and no immediate role for human capital. By the fifth period, economic growth (18.50%) and human capital (20%) emerge as significant contributors, while renewable energy accounts for 10.50%. Over the ten periods, economic growth remains a dominant force (30%), with renewable energy stabilizing at 11% and human capital contributing 15%. The squared term of income continues to show a moderate and stable effect. These results highlight the growing role of human capital and renewable energy in shaping China's ecological sustainability, alongside economic development.

In India, EFPs in the first period are also entirely explained by their own shocks. From the second period onwards, economic growth (6.28%), human capital (3.05%) and renewable energy (5.07%) started influencing EFP dynamics. By the fifth period, renewable energy (31.19%) and economic growth (20.37%) become the key drivers, while human capital also contributes meaningfully (17.11%). In the tenth period, renewable energy retains its dominant influence (36.09%), followed by economic growth (27.18%).

In Table 9, human capital's role in ecological sustainability shows a sharper and earlier impact in India than in China. In India, its contribution rises to 14.89% by period 3 and remains steady at around 17% through period 10, indicating a strong and sustained influence. In China, human capital starts contributing from period 3 (10%), peaks at 20% by period 5 but declines to 15% by period 10, showing a slower and less consistent effect. Thus, India exhibits a more immediate and persistent role of human capital, while China shows gradual but growing importance.

Overall, the decomposition reveals that in both countries, human capital and renewable energy increasingly drive EFP dynamics, with economic growth also playing a strong but diminishing role over time. The findings underline the critical importance of long-term investment in human capital and clean energy transitions to ensure environmental sustainability in both China and India.

Stability Test

The CUSUM and CUSUMSQ statistics indicate that the values remain within critical bounds, validating the robustness of the model. The graphical presentation of CUSUM and CUSUMSQ for China and India is provided in Figures 2–5.

The graphical representations of the results and the variance decomposition of variables for China and India are presented in Figures 6 and 7.

Additionally, Figures 8 and 9 for both countries highlight the variables with more pronounced fluctuations (larger peaks and troughs) that suggest a higher degree of sensitivity, indicating that these variables are crucial in determining the outcome of the model. The flatter or smoother gradients indicate a more stable influence, where changes in those variables lead to relatively smaller impacts on the objective function. The range of the Y-axis indicates the magnitude of the gradient, with steeper gradients indicating a stronger influence on the model's objective function.

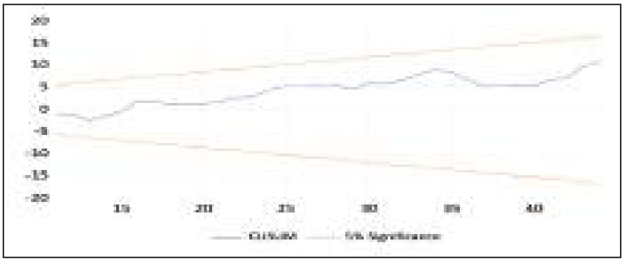

Figure 2. China: Plot of Cumulative Sum of Recursive Residuals.

Note: The straight lines represent critical bounds at a 5% significance level.

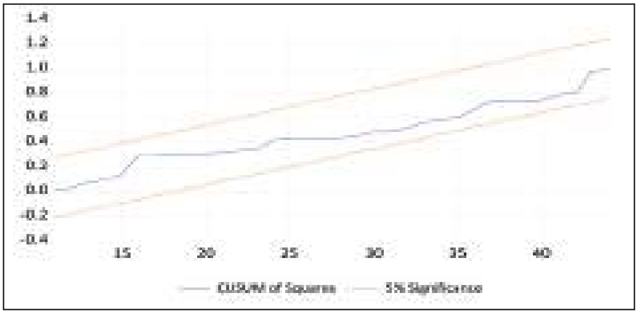

Figure 3. China: Plot of Cumulative Sum of Square of Recursive Residuals.

Note: The straight lines represent critical bounds at a 5% significance level.

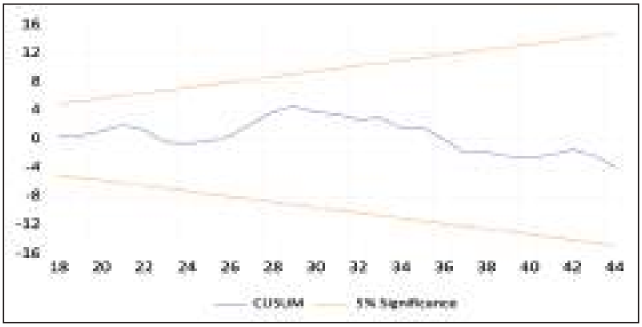

Figure 4. India: Plot of Cumulative Sum of Recursive Residuals.

Note: The straight lines represent critical bounds at a 5% significance level.

V. Summary and Policy Implications

The primary objective of the study was to empirically investigate the impact of human capital on EFPs in China and India, controlling for economic growth and renewable energy adoption. Using the ARDL model and VECM, the study ensures data stationarity and cointegration. Long-run results show that a 1% increase in

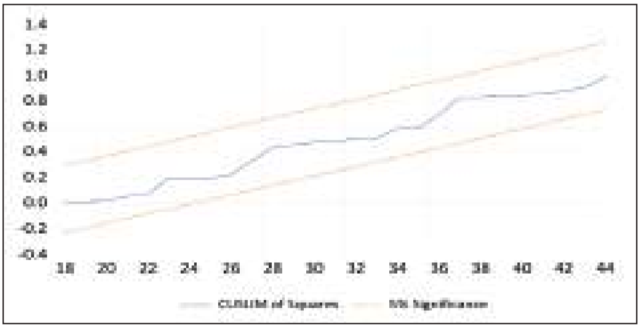

Figure 5. India: Plot of Cumulative Sum of Square of Recursive Residuals.

Note: The straight lines represent critical bounds at a 5% significance level.

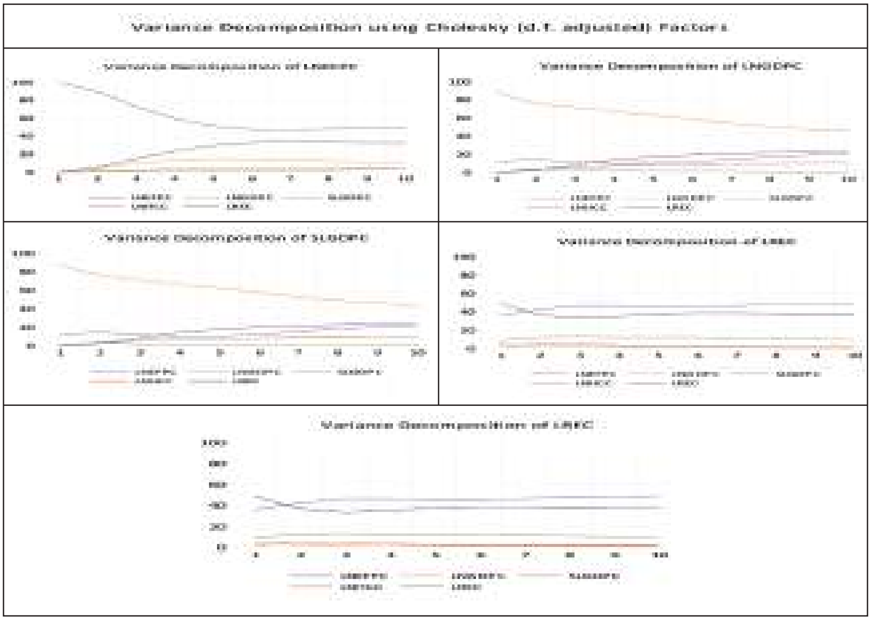

Figure 6. China: Variance Decomposition.

human capital leads to a reduction in EFPs by −6.91% in China and −2.70% in India. The study's findings support the EKC hypothesis in both countries, where economic growth initially increases EFPs, but the squared term of economic growth mitigates the effect. Renewable energy adoption significantly impacts EFPs, with a stronger impact on China (1.94%) than on India (0.25%). Causality tests reveal that human capital drives economic growth, renewable energy adoption and EFP reduction in both countries. Causality findings also revealed a bidirectional relationship from human capital to growth and renewable energy to growth in China, while India shows unidirectional causality. Variance

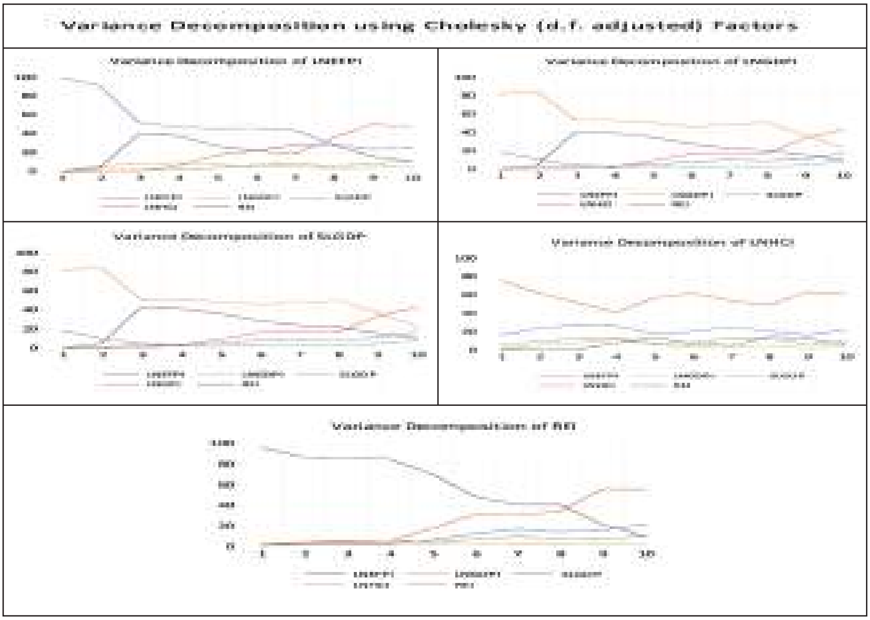

Figure 7. India: Variance Decomposition.

decomposition results further support these findings, indicating that China's EFPs are more influenced by renewable energy and human capital, whereas in India, the reduction in EFPs is primarily driven by human capital**,** India exhibits a more immediate and persistent role of human capital**,** while China shows gradual but growing importance**.** The CUSUM and CUSUM-square stability tests confirm the structural stability of the estimated models, ensuring robustness.

The analysis identifies three key ways in which human capital contributes to reducing EFPs in China and India. First, it stimulates economic growth through increased productivity, leading to more efficient resource utilization (scale effect). Second, it fosters the adoption of renewable energy by improving technical skills and institutional capacity, promoting cleaner and more sustainable production methods (technique effect). Third, human capital enhances environmental consciousness, encouraging sustainable behaviours and lifestyle choices, which lower ecological pressure (awareness effect). Together, these channels—economic growth, technological adoption and behavioural adaptation—enable human capital to play a pivotal role in reducing EFPs and promoting sustainability. The policy implications emphasize the importance of human capital investments such as education, health and skill development in reducing EFPs. The bidirectional causality in China suggests integrated policies promoting both human capital and renewable energy adoption. On the other hand, India's unidirectional causality emphasizes the need to focus on human capital development as a primary strategy for sustainable growth. Ultimately, tailored, country-specific policies are needed: China should focus on accelerating renewable energy infrastructure, while India

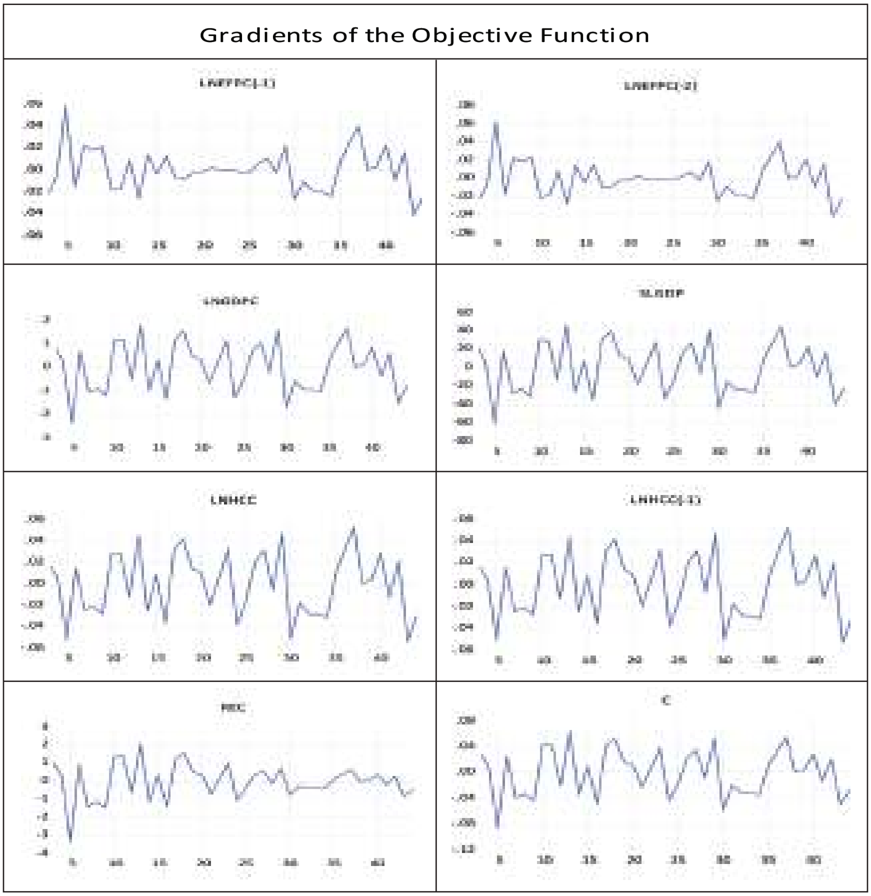

Figure 8. China: Gradient.

must prioritize enhancing human capital to address its unique developmental challenges.

Limitations and Future Research

This study, while insightful, is limited to China and India, which may not represent the full diversity of emerging economies. Its quantitative focus may overlook contextual and qualitative factors. Future research could expand to more countries, include regional analyses and adopt mixed-method approaches. Despite these limits, the study offers a strong foundation for examining how human capital affects environmental outcomes. It highlights an emerging research theme critical for sustainable development, paving the way for deeper exploration into policy roles, industrial practices and the broader impact of human capital on sustainability.

(Figure 9 continued)

(Figure 9 continued)

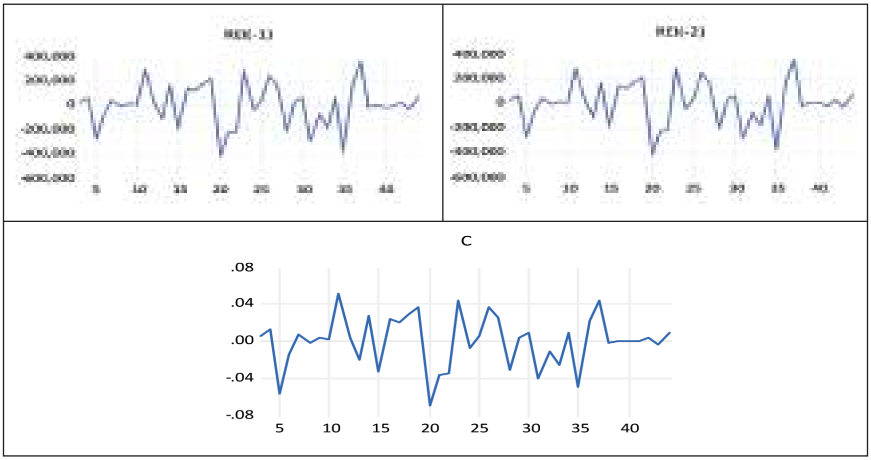

Figure 9. India: Gradient.

Declaration of Conflicting Interests

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