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Human capital, technological progress, and ecological sustainability in india: evidence from the load capacity factor approach

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Abstract
The study examines how human capital (HC) and technological progress (TFP) influence ecological sustainability in India within the load capacity factor (LCF) framework, while accounting for consumption of renewable energy (RE) and economic growth during the period 1990–2024. LCF is embraced as a holistic measure because it includes both ecological demand and biocapacity. ADF and Zivot-Andrews unit root tests were used in the analysis to account for structural breaks, while the Bayer–Hanck combined cointegration test and ARDL bounds tests were used to verify the long-run equilibrium relationship among the variables. Short and long-run dynamics were estimated by the ARDL model, and DOLS was used to test robustness and VECM Granger causality. The results indicate that human capital enhances ecological sustainability by increasing the load capacity factor, which may be due to scale, technique, composition effects, and improved environmental awareness. On the contrary, technological advancement enhances economic growth, but does not guarantee environmental sustainability; instead, productivity gains are being obtained at the expense of ecological imbalance, resulting in a deficit in the load capacity factor. Renewable energy has a positive influence on LCF in both the short and long-run. Moreover, there is a nonlinear relationship between economic growth and LCF, which upholds the Environmental Kuznets Curve (EKC) hypothesis. The implication of this research paper is valuable to policy makers as it incorporates LCF as an inclusive sustainability indicator and offers evidence on the contrasting roles of human capital and technological progress in India within a robust time-series framework.

Keywords Human capital · Technological progress · Load capacity factor · Renewable energy · Economic growth · India

Extended author information available on the last page of the article

1 Introduction

With climate change, environmental degradation and ecological fragility growing and intensifying, sustainability has become the primary pillar of global developmental discourse. The effects of environmental degradation, such as biodiversity loss and resource depletion, increase the risks in climate and underpin economic foundations (Wu et al. 2018). The OECD (2024) argues that unregulated climate change may cut the global GDP by as much as 10% by 2100. Over the years, a significant amount of evidence has pointed to climate change and global warming as one of the most urgent issues of humanity in the twenty-first century (Xu et al. 2022). The current development policy has been more emphasized on the necessity of the balance between the environment and economic growth. One of the Sustainable Development Goals (SDGs) is environmental protection (Ozturk and Acaravci 2016). The recent decades saw environmental degradation and the need to achieve sustainability becoming a significant economic and ecological issue of both developed and developing nations (Pata and Isik 2021). Sustainability, which is the preservation of the well-being of future generations (Burtland 1987). Sustainable Development calls on radical change towards inclusive, resilient, and greener growth models. Nonetheless, this balance requires a subtle insight into the role of different policy variables, such as economic, Technological, social and institutional setup, on the quality of the environment, especially in the context of developing economies that are going through rapid structural change.

India is the second most populous country in the world and one of the fastest-growing economies that has experienced a massive structural transformation due to the rapid industrialisation, urbanisation, and economic reforms. This has enhanced its macroeconomic indicators with the output, investment and employment continuing to rise. Consequently, economic growth has continued to be at the core of development policy in India, specifically on matters of alleviating major structural issues like poverty, unemployment, and regional imbalances, as well as the overall human development outcomes (United Nations Development Programme, 2021; Dinda, 2004). But the post-reform growth path has been mainly resource and energy consuming. Fossil fuels and traditional sources of energy have played a significant role in the growth of industrial activity, infrastructure, and urban systems, thus putting a strain on natural resources and the environment (Agarwal et al. 2021; Shahbaz et al. 2017). This trend has helped to increase carbon emissions and ecological pressure, which are the ecological costs of high-speed economic growth. As a result, India experiences serious environmental problems, such as rising CO2 emissions, deforestation, biodiversity loss, soil erosion, water shortage, and more common hazards associated with climate, such as floods, droughts, and heatwaves.

The Global Footprint Network (2022) reports that India experiences a persistent ecological deficit, highlighting that its ecological demand consistently exceeds its available biocapacity, as reflected by the low Load Capacity Factor (LCF) shown in Fig. 1. Specifically, India's ecological footprint is approximately 1.19 global hectares per capita, whereas its biocapacity is only about 0.43 global hectares per capita, indicating that the country's ecological footprint is nearly three times greater than its biocapacity and resulting in a substantial ecological deficit. This places India among the world's key ecological debtors (World Population Review 2024). The effects of these environmental pressures are evident across several dimensions. Environmental degradation has contributed to a higher prevalence of respiratory and waterborne diseases, while extreme climate events have increased vulner-

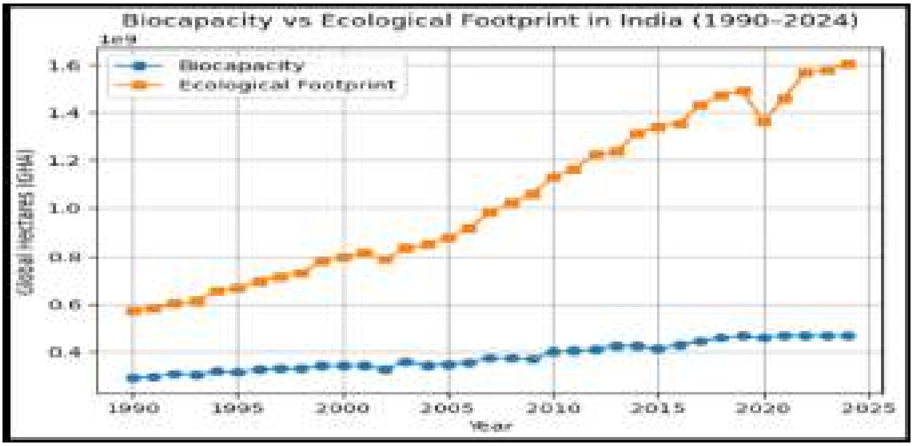

Fig. 1 Trends in biocapacity and ecological footprint in India (1990–2024).Source: Author's calculations based on Global Footprint Network (2025)

ability, and mortality risks (World Health Organization 2021; Intergovernmental Panel on Climate Change 2022). In rural areas, climate variability, soil erosion, and water scarcity have reduced agricultural productivity and farm incomes (Food and Agriculture Organization 2021; Ashok Gulati et al. 2019; Bhat et al. 2026). Likewise, urban areas, particularly informal settlements, remain highly vulnerable to environmental hazards due to inadequate infrastructure, further exacerbating existing inequalities (World Bank 2022; Anjali Revi et al. 2014). Overall, although economic growth is essential for addressing structural development challenges, its resource-intensive nature has intensified environmental degradation. This underscores the importance of aligning growth policies with sustainability goals through integrated policy frameworks that simultaneously promote economic development and environmental protection (Panayotou 2016; Stern 2015). Renewable energy accounts for 16% of India's final energy consumption, with investments totalling US$9.3 billion (Statista 2023). Furthermore, under its commitments to the Paris Climate Agreement, India has set targets of achieving net-zero emissions by 2070 and generating 50% of its electricity from renewable energy sources by 2030 (IEA 2022).

Human capital that includes education, health, knowledge and skills is commonly known to be one of the driving forces behind economic growth and technological advancements. The neoclassical and endogenous growth theories recognise human capital as a key origin of productivity growth over the long term (Schultz 1961; Becker 1964; Lucas 1988; Romer 1990). In India, on the other hand, the human capital is not yet developed, and the Human Capital Index is as low as 0.49, which indicates the continuous lack of nutrition, health, and educational achievements (World Bank 2020b). Although there have been some policy efforts, including the National Education Policy (2020), education and health results are still not evenly distributed, which highlights the necessity to implement integrated approaches that enhance human capital and alleviate environmental stress. In the neoclassical model, Total Factor Productivity (TFP) is used to measure growth in output that cannot be attributed to labour and capital (Solow 1956) whereas endogenous growth models focus on human capital, innovation and institutional quality as factors that drive growth in output (Romer 1990; Aghion and Howitt 1998). In the case of a densely populated economy like

India, technological efficiency plays a key role in balancing economic growth with ecological sustainability by reducing resource intensity and mitigating environmental degradation. In empirical terms, TFP growth in India ranged from −2.8 to 3.3% between 1991 and 2019, indicating progress while also revealing structural inefficiencies (KLEMS,2022). Human capital and technological advancement in this regard are key to the decoupling of economic growth and environmental degradation. With the ongoing dependence of India on resource and energy-intensive growth to enhance human development and living standards, there is a need to have a coherent policy framework to balance the growth of the economy, productivity, and green energy transition. This encourages empirical research on the factors of environmental sustainability, focusing especially on human capital and technological development, economic growth, and energy use (Fig. 2).

In previous studies, environmental degradation has commonly been assessed using indicators such as CO_2, SO_2, and NO_x emissions, as well as the ecological footprint (Adebayo 2021; Yuping 2021; Kihombo et al. 2022). However, carbon emissions capture only one dimension of environmental degradation because they primarily reflect atmospheric pollution and climate change while overlooking broader ecological pressures arising from resource depletion and ecosystem degradation (Akinsola et al. 2022). Although the ecological footprint extends this assessment by measuring human demand on ecological resources, it does not account for the regenerative capacity of ecosystems, thereby limiting its ability to comprehensively evaluate environmental sustainability (Kihombo Kirikkaleli et al. 2021). To address this limitation, Siche et al. (2010) proposed the Load Capacity Factor (LCF), defined as the ratio of biocapacity to ecological footprint (Xu et al. 2022 a, b). The LCF simultaneously incorporates ecological demand and ecological supply, thereby providing a more comprehensive indicator of environmental sustainability than carbon emissions or the ecological footprint considered independently (Abdulmagid Basheer Agila et al. 2022; Kuldasheva and Salahodjaev 2023). Specifically, LCF values greater than one indicate that an ecosystem's biocapacity exceeds ecological demand, reflecting environmental sustainability, whereas values below one indicate that ecological demand surpasses the ecosys-

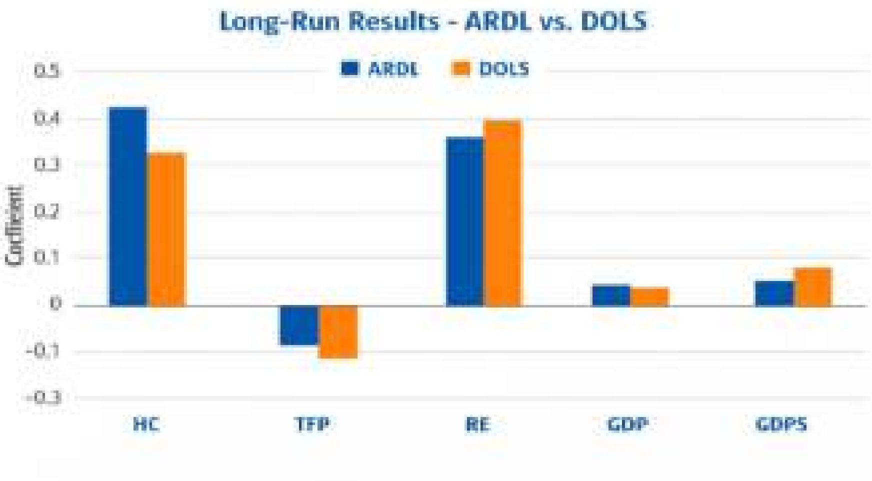

Fig. 2 Comparison of long-run coefficients (ARDL vs. DOLS). Note: The figure presents a comparison of long-run coefficients estimated using the ARDL (blue bars) and DOLS (orange bars) approaches

tem's regenerative capacity, signifying ecological stress (Siche et al. 2010). Nevertheless, while the LCF offers a more holistic measure by integrating both ecological consumption and regeneration, its interpretation depends on the quality and availability of biocapacity and ecological footprint estimates. Despite this limitation, it remains one of the most comprehensive indicators for evaluating long-term ecological sustainability.

The Indian context provides a particularly relevant application of the LCF framework. As one of the world's fastest-growing emerging economies, India faces persistent ecological deficits driven by rapid industrialization, urbanization, population growth, and increasing pressure on finite natural resources. In such a setting, indicators based solely on carbon emissions or ecological footprint may not adequately capture whether ecological demand remains within the country's regenerative capacity. By incorporating both ecological demand and ecological supply, the LCF provides a more policy-relevant framework for assessing whether India's economic development is ecologically sustainable. Accordingly, this study contributes to the sustainability and environmental economics literature by adopting the LCF as a comprehensive measure of environmental sustainability that extends beyond conventional carbon-based indicators and the ecological footprint. Furthermore, the study advances the LCF framework by incorporating human capital and total factor productivity (TFP) as key determinants, thereby linking ecological sustainability with the long-run growth mechanisms emphasized in both neoclassical and endogenous growth theories. While previous studies have primarily focused on economic growth, energy consumption, and urbanization as drivers of environmental sustainability, the roles of human capital accumulation and technological efficiency remain insufficiently explored within an LCF-based framework. By addressing this gap, the present study provides a more comprehensive understanding of the interactions between economic development, technological progress, and ecological sustainability in India.

This study, by empirically analyzing the impacts of human capital, TFP, economic growth, renewable energy, and energy consumption on LCF, provides a new nexus of growth-sustainability and measures whether productivity gains are able to decouple economic growth and ecological pressure. The introduction of renewable energy also transports the analysis to focus more on the sustainability of the ecosystem rather than on emission reduction. The relevance of the policy is to present the evidence on the short- and long-term effects of these factors on the ecological balance in India emphasizing education, innovation, and clean energy as supportive tools in the realisation of the productivity growth and environmental sustainability. Overall, anchored in the increasing ecological deficit and uneven human capital development in India, this study provides an integrated empirical framework, which reformulates the definition of environmental performance as the ecological balance instead of emissions per se, and the long-term sustainability and intergenerational well-being.

2 Review of literature

2.1 Theoretical framework

In line to investigate the issue of the effect of human capital and technological advances on the load capacity factor (LCF) as a measure of environmental quality, with economic growth and consumption of renewable energy held constant, this research is based on the endogenous growth theory, the Environmental Kuznets Curve (EKC) hypothesis, and the energy-growth nexus. The endogenous growth theory, especially the works of Romer (1990) and Lucas (1988), elucidates human capital and technological advancement as major factors contributing to the growth of the economy in the long-run. Human capital increases labour productivity, offers innovation, and helps to adopt cleaner technologies. In addition to its growth impacts, better and more education and skills can enhance environmental performance through heightened environmental awareness and institutional capacity. There are empirical studies indicating that human capital growth is linked to less ecological pressure and better environmental sustainability (Bano et al. 2018; Wang et al. 2020; Barro, 1999; Balk, 2001; Khan et al. 2025a, b). Total factor productivity (TFP) is a proxy for technological advancement that reflects improvements in innovation, production efficiency, and resource allocation. It captures output growth that cannot be explained by conventional inputs such as labour and capital (Solow 1957). Technological progress is generally expected to improve environmental sustainability by enabling cleaner technologies, enhancing energy efficiency, and reducing resource intensity (Huang et al. 2020). However, its environmental effects vary across countries. In developing economies such as India, productivity gains are often driven by industrial expansion and energy-intensive production processes, which can increase resource use and environmental pressure. In addition, efficiency gains may create rebound effects by encouraging higher production and energy consumption (Fig. 3).

More recently, research has examined the role of artificial intelligence (AI) in shaping sustainability and energy consumption dynamics. Evidence suggests that AI has a nonlinear but overall increasingly positive impact on environmental outcomes. In the early stages of adoption, AI tends to increase energy demand and emissions due to high computational requirements and digital infrastructure expansion. Over time, however, it improves environmental performance through efficiency gains, renewable energy integration, and stronger institutional support. AI also contributes to reducing energy poverty and enhancing equity, while financial development and human capital determine the extent of these benefits. At the macro level, AI improves carbon efficiency and reduces regional technological disparities, thereby supporting Sustainable Development Goal 7 (SDG 7) and Sustainable Development Goal 13 (SDG 13) (Wang et al. 2026; Wang et al. 2026a, b; Zhang et al. 2026a, b; Sun et al. 2026). Therefore, the effect of total factor productivity (TFP) on the Load Capacity Factor (LCF) remains an empirical question, depending on the nature of technological progress and prevailing economic conditions.

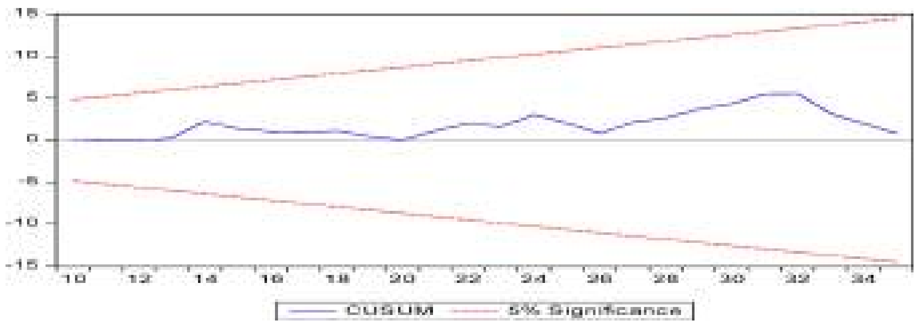

Fig. 3 CUSUM test for model stability. Notes: CUSUM plot shows model stability; line within 5% bounds indicates a stable model

This study is also based on the hypothesis of the Environmental Kuznets Curve (EKC), according to which the relationship between economic growth and environmental pressure is inverted U-shaped. Early in the development process, income growth tends to increase environmental degradation, but after a certain income level, further growth—driven by technological advancement and structural change—may improve environmental quality (Grossman and Krueger 1995). Since this study uses the load capacity factor (LCF), where higher values indicate better environmental performance, the traditional EKC interpretation implies a U-shaped relationship between economic growth and LCF. To capture this nonlinear relationship, both GDP and its squared term are included in the empirical model. Lastly, the energy-growth nexus also highlights the significance of energy structure to environmental sustainability. Consumption of renewable energy can assist in decoupling economic growth and ecological pressure by decreasing the share of fossil fuels and carbon intensity (Hasanov et al. 2021).In general, these theoretical approaches offer the conceptual framework of interconnection between human capital (HC), technological advancement in the form of total factor productivity (TFP), renewable energy usage (RE), economic growth (GDP), and environmental sustainability in the form of the load capacity factor (LCF) in the Indian context.

2.2 Empirical review

Environmental economics has extensively examined the relationship between economic growth and environmental sustainability, particularly through the Environmental Kuznets Curve (EKC) framework. The EKC hypothesis, originally proposed by Grossman and Krueger (1995) and later refined by Stern (2004), posits an inverted U-shaped relationship between economic growth and environmental degradation. According to this hypothesis, environmental degradation initially rises with economic growth but begins to decline once income exceeds a threshold. Although this framework has been widely tested across countries and environmental indicators, empirical evidence remains mixed. While several studies support the EKC hypothesis (Ahmed and Wang 2019; Ahmed et al. 2020; Al-Mulali et al. 2016; Danish et al. 2019; Ghoshal and Bhattacharyya 2008; Zafar et al. 2019), others find no evidence of a nonlinear relationship (Dietzenbacher and Mukhopadhyay 2007; Jena et al. 2022). These inconsistent findings suggest that the growth–environment relationship is context-specific and depends on structural factors such as energy composition, technological progress, and institutional quality.

Energy consumption plays a central role in the growth–environment nexus. Economic expansion increases energy demand, which in turn places pressure on environmental quality depending on the energy mix (Jahanger et al. 2022a; Balsalobre-Lorente et al. 2022; Jahanger et al. 2022b; Jiang et al. 2022; Sinha et al. 2022; Usman and B). In particular, fossil fuel consumption remains strongly associated with environmental degradation due to higher emissions and resource depletion (Feng 2022; Shafiei and Salim, 2014; Menyah and Wolde-Rufael, 2010; Rahman and Kashem 2017). Therefore, the environmental impact of economic growth is strongly mediated by the structure of energy consumption and the transition toward cleaner energy sources (Fig. 4).

Beyond energy consumption, human capital has emerged as an important determinant of both economic growth and environmental sustainability (Khan et al. 2022, 2025a, b). However, its environmental effects remain empirically ambiguous. One strand of literature argues

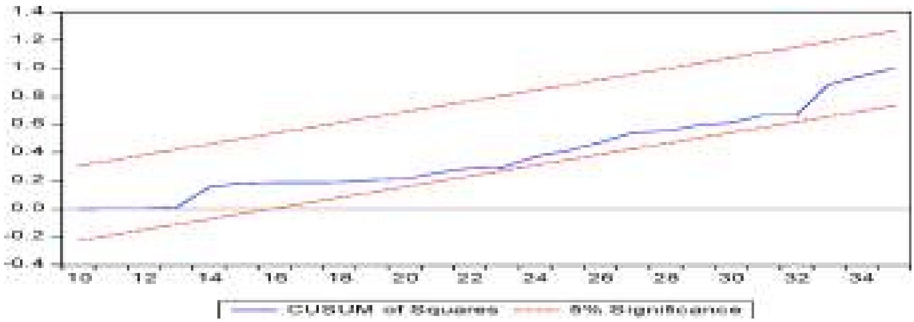

Fig. 4 CUSUMSQ test for model stability. Notes: CUSUMSQ plot checks stability of variance; line within 5% bounds indicates stable model

that human capital—through education, skills, and environmental awareness—facilitates the adoption of cleaner technologies and environmentally friendly production processes, thereby reducing emissions and environmental degradation (Yao et al. 2019, 2020, 2021; Bano et al. 2018). Conversely, other studies suggest that human capital may also contribute to environmental deterioration, particularly in developing economies where economic expansion is prioritized over environmental efficiency (Hazwan, 2021; Dong et al. 2022; Zhang et al. 2021). Recent empirical studies increasingly employ the Load Capacity Factor (LCF), defined as the ratio of biocapacity to ecological footprint, as a more comprehensive indicator of environmental sustainability. Evidence suggests that human capital improves LCF in the United States (Pata et al. 2023), India (Pata and Ertugrul 2023), OECD countries (Guloglu et al. 2023), ASEAN economies (Dai et al. 2024), and G20 countries (Ali et al. 2024), whereas opposing evidence from MENA countries indicates a negative relationship (Ben-Salha and Zmami 2024), highlighting substantial regional heterogeneity. Similarly, technological advancement, particularly measured through total factor productivity (TFP), plays a crucial role in improving production efficiency and environmental performance. A substantial body of literature suggests that technological innovation can reduce emissions and improve environmental efficiency (Goulder and Schneider 1999; Buonanno et al. 2003; Popp et al. 2011; Gerlagh, 2007; Khalil and Abas, 2014; Khan et al. 2019; Kahouli; Khan et al. 2026a, b). Evidence from East Asian economies also highlights the role of productivity improvements and ICT-based development in achieving lower emissions and improved environmental outcomes (Ahmed 2012, 2017; Ahmed and Kialashaki 2023). However, the environmental impact of technological progress remains uncertain due to sectoral heterogeneity (Li and Cheng, 2020), efficiency gaps (Xie et al. 2021), rebound effects (Acemoglu et al. 2009, 2012; Jaffe et al. 2002), and renewable energy spillovers (Chen).Although Ahmed and Kialashaki (2021) provide evidence supporting the Technological Kuznets Curve, overall empirical evidence remains limited, particularly when technological progress is examined within a comprehensive sustainability framework such as the Load Capacity Factor (LCF). The LCF, defined as the ratio of biocapacity to ecological footprint, has increasingly been used as a holistic measure of environmental sustainability. Recent studies show that human capital enhances LCF in the United States (Pata et al. 2023), India (Pata and Ertugrul 2023), OECD countries (Guloglu et al. 2023), ASEAN economies (Dai et al. 2024), and G20 countries (Ali et al. 2024), while contrasting evidence from MENA countries reports a negative relationship (Ben-Salha and Zmami 2024). Despite this growing literature, limited studies have jointly examined human capital and technological advancement within an LCF-based framework, particularly in the context of India, where structural transformation and energy transition dynamics remain highly relevant (Fig. 5).

2.3 Research gap

There are several gaps in the increasing literature. To begin with, the vast majority of research is based on partial measures like CO2 emissions and ecological footprint, which fail to reflect the equilibrium between the ecological demand and biocapacity. Second, the Load Capacity Factor (LCF) is a more detailed measure, but its use is still restricted, especially in developing economies like India. Third, available data on the environmental impact of human capital and technological developments is sporadic and scattered in nature, which does not allow for making general conclusions. In a bid to fill these gaps, this paper re-examines environmental sustainability in India by looking at the contribution of human capital and technological advancement in the LCF model, and keeping renewable energy usage and economic growth constant. This methodology offers a more context-related and consistent comprehension of sustainability dynamics.

Hypotheses

H1 (Human Capital Hypothesis) There is a positive impact of human capital on the load capacity factor.

H2 (Technological Progress Hypothesis) Total factor productivity (TFP) significantly affects the Load Capacity Factor (LCF).

H3 (Renewable Energy Control Hypothesis) The consumption of renewable energy increases the load capacity factor.

H4 (Economic Growth–Environment Hypothesis based on EKC) Economic growth has a nonlinear (U-shaped) relationship with the load capacity factor.

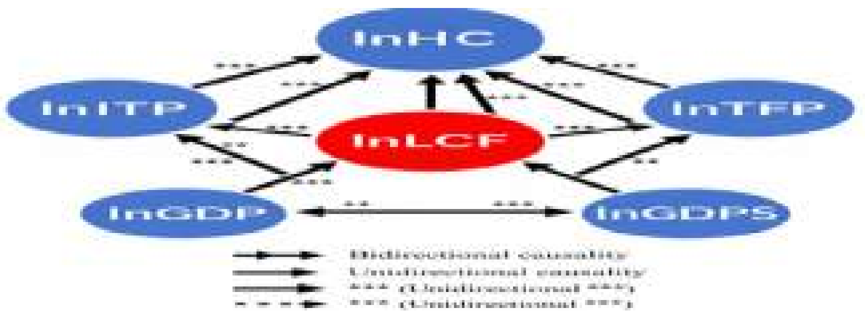

Fig. 5 Short-run and long-run causality network among key variables.Source: *Authors' estimates based on VECM Granger causality results. Arrows indicate direction and significance of causality: ***, *, * denote 1%, 5%, and 10% significance, respectively

3 Data and model

This study uses annual time-series data for India over the period 1990–2024 to examine environmental sustainability within the Load Capacity Factor (LCF) framework, focusing on the roles of human capital and technological advancement. LCF is a comprehensive sustainability indicator that reflects the balance between ecological demand and biocapacity (Guloglu et al. 2023; Dai et al. 2024; Pata and Ertugrul 2023), and the data are obtained from the Global Footprint Network (GFN). Human capital is proxied by the Human Capital Index (HC) from the Penn World Table 1, while technological progress is measured using Total Factor Productivity (TFP), based on the Solow residual approach (Hall and Jones, 1999; Carlaw and Lipsey 2003; Hasanov et al. 2021; Ahmed and Elfaki, 2024). Renewable energy consumption and GDP per capita (constant 2015 US$), obtained from the World Development Indicators (WDI), are included to capture the role of clean energy and to test the Environmental Kuznets Curve (EKC) hypothesis (Sadorsky, 2009; Pata, 2018; Grossman and Krueger 1995). To capture potential nonlinear effects, the squared term of GDP (GDP^2) is included in the model specification. All variables are transformed into natural logarithms and are denoted as lnLCF, lnHC, lnTFP, lnRE, lnGDP, and $lnGDP^2$ in the empirical analysis to ensure consistency and elasticity interpretation. Table 1 provides a detailed description of variables and data sources.

The empirical model is developed based on the existing literature to examine the effects of human capital, technological advancement, renewable energy consumption, and economic growth on environmental sustainability, proxied by the load capacity factor (LCF). The baseline functional relationship is specified as:

$$LCF_t = f(HC_t, TFP_t, RE_t, GDP_t, GDP_t^2) \tag{1}$$

where LCF_t represents the load capacity factor, HC_t denotes the human capital index; TFP_t represents the total factor productivity, *RE* signifies the renewable energy consumption; GDPt measures economic growth; and $GDPS_t$ is the square of economic growth to capture potential non-linear effects.

The econometric specification of the baseline model is expressed as:

$$LCF_t = \beta_0 + \beta_1 HC_t + \beta_2 TFP_t + \beta_3 RE_t + \beta_4 GDP_t + \beta_5 GDP_t^2 + \epsilon_t \tag{2}$$

whereβ_0 is the intercept, $\beta_1, \beta_2, \beta_3, \beta_4,$ *and* β_5 are coefficients, and ε_t is the error term. Following Shahbaz et al. (2012), a log-linear specification is also employed to ensure robustness

Table 1 Data and variable description.*Source*: Authors' calculation.Note: HC and TFP data for 2020–2024 are extended using interpolation/extrapolation based on recent observed trends due to data unavailability in Penn World Table 10.0 beyond 2019

Variable	Symbol	Measurement/Proxy	Source
Load Capacity Factor	LCF	Ratio (Biocapacity / Ecological Footprint)	GFN
Human Capital	HC	Human Capital Index	PWT 10.0
Technological Progress	TFP	Total Factor Productivity Index	PWT 10.0
Renewable Energy Consumption	RE	% of total final energy consumption	WDI
Economic Growth	GDP	Aggregate real GDP (constant 2015 US$)	WDI

and comparability with existing empirical studies. The log-transformed model is specified as

$$\ln LCF_t = \beta_0 + \beta_1 \ln HC_t + \beta_2 \ln TFP_t + \beta_3 \ln RE_t + \beta_4 \ln GDP_t + \beta_5 (\ln GDP_t)^2 + \epsilon_t \tag{3}$$

This specification ensures a correct and non-redundant treatment of the nonlinear income effect by incorporating the squared term of the logarithm of GDP rather than the logarithm of GDP squared, thereby avoiding multicollinearity. The proposed framework enables a robust and transparent analysis of the determinants of environmental sustainability, consistent with established theoretical and empirical approaches in the literature.

4 Econometric techniques

4.1 Unit root test

The Augmented Dickey–Fuller Test (ADF) and Phillips–Perron Test (PP) unit root tests are employed to examine the stationarity properties of the time series variables in determining long-run relationships. However, a key limitation of these conventional tests is that they do not account for possible structural breaks in the data, which may lead to biased and unreliable results. To address this limitation, the Zivot–Andrews Unit Root Test with a structural break is also applied. This test endogenously determines the break point in the series and allows one structural break in each variable. The Zivot–Andrew's test considers three models.

Model A (break in intercept):

$$\text{Model A} : \Delta y_t = \mu + \alpha y_{t-1} + \gamma DUt + \sum_{j=1}^{k} \delta_j \Delta y_{t-1} + \varepsilon_t \tag{4}$$

Model B (break in trend):

$$\text{Model B} : \Delta y_t = \mu + \alpha y_{t-1} + \theta DTt + \sum_{j=1}^{k} \delta_j \Delta y_{t-1} + \varepsilon_t \tag{5}$$

Model C (break in both intercept and trend):

$$\text{Model } C : \Delta y_t = \mu + \alpha y_{t-1} + \gamma DUt + \theta DTt + \sum_{j=1}^{k} \delta_j \Delta y_{t-1} + \varepsilon_t \tag{6}$$

where

$$DU_t = \begin{cases} 1 & if\ t > TB \\ 0, & otherwise. \end{cases}$$

DUt captures a *one-time structural break in the intercept (level shift).*

$$DT_t = \begin{cases} t - TB & if\ t > TB \\ 0, & otherwise. \end{cases}$$

DTt captures a *one-time structural break in the deterministic trend (slope change).*

TB is the break year determined endogenously by the model, ϵ_t is a white-noise error term.

4.2 Co-integration analysis

There are several co-integration methodologies that have been constructed to analyze the long-run equilibrium relationship among variables. Engle and Granger (1987), Johansen (1988) and Johansen and Juselius (1990) are some of the co-integration tests proposed in the literature. Nonetheless, such traditional approaches can deliver incongruent and conflicting outcomes based on their inherent limitations that result in uncertainty in empirical inference (Ahmed and Wang 2019). In order to address this problem, Bayer and Hanck (2013) present an integrated cointegration model, which involves a combination of four common tests such as Engle and Granger (EG), Johansen (JOH), Boswijk (1994) and Banerjee et al. (1998) into a single statistic, which is of a Fisher type, and, therefore, makes cointegration The combined statistics is calculated using the Fisher (1932) technique as follows:

$$EG - JOH = -2[\ln(P_{EG}) + \ln(P_{JOH})] \tag{7}$$

$$EG - JOH - BO - BDM = -2[\ln(P_{EG}) + \ln(P_{JOH}) + \ln(P_{BO}) + \ln(P_{BDM})] \tag{8}$$

where P_{EG}, P_{JOH}, P_{BO}, and P_{BDM} denote the p-values of the Engle and Granger (1987), Johansen (1995), Boswijk (1994), and Banerjee et al. (1998) cointegration tests, respectively.

Rejection of the null hypothesis of no cointegration occurs when the calculated Fisher statistic is above the critical values that Bayer and Hanck (2013) present, and the variables have a stable relationship at a long-run equilibrium. In addition, the ARDL bounds testing method is also employed in order to determine the strength of the cointegration results.

4.3 ARDL bound testing approach

To examine both the short-run and long-run relationships among the variables, this study employs the Autoregressive Distributed Lag (ARDL) bounds testing approach to cointegration developed by Pesaran and Shin (1999) and Pesaran et al. (2001). Given the relatively small sample size (1990–2024), the study acknowledges the potential limitations associated with finite-sample bias in ARDL, bounds testing, and VECM estimations. However, the ARDL bounds testing approach is particularly suitable for small samples and mixed integration orders, as it provides robust long-run relationship estimates even in limited data settings (Ganai and Khan 2025 a; Ganai et al. 2025 b). The critical values employed follow appropriate small-sample adjustments, thereby improving the reliability of inference.

The ARDL model for the load capacity factor (LCF) is specified as:

$$\begin{aligned}\Delta LnLCF_t =&\alpha_0 + \sum_{k=1}^{p}\alpha_{1k}\Delta LnLCF_{t-k} + \sum_{k=1}^{p}\alpha_{2k}\Delta LnHC_{t-k}\\ &+ \sum_{k=1}^{p}\alpha_{3k}\Delta LnTFP_{t-k} + \sum_{k=1}^{p}\alpha_{4k}\Delta LnRE_{t-k}\\ &+ \sum_{k=1}^{p}\alpha_{5k}\Delta LnGDP_{t-k} + \sum_{k=1}^{p}\alpha_{6k}\Delta LnGDP^2_{t-k}\\ &+ \lambda_1 LnLCF_{t-1} + \lambda_2 LnHC_{t-1} + \lambda_3 LnTFP_{t-1}\\ &+ \lambda_4 LnRE_{t-1} + \lambda_5 LnGDP_{t-1} + \lambda_6 LnGDP^2_{t-1} + \in_t\end{aligned} \tag{9}$$

where Δ denotes the first-difference operator, p is the optimal lag length selected using Akaike Information Criterion (AIC), α_{ik}represent short-run dynamics, $\lambda_i$represent long-run relationship parameters, and $\epsilon_t$is the white-noise error term. The existence of a long-run relationship is tested using the following hypotheses:

Null hypothesis (no cointegration):

$$H_0 : \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = 0$$

Alternative hypothesis (cointegration exists):

$$H_1 : \text{at least one}\lambda_i \neq 0$$

The computed F-statistic is compared with the critical bounds provided by Pesaran et al. (2001). If $\boldsymbol{F}$ >upper bound → *cointegration exists*, If $\boldsymbol{F}$ <lower bound → *no cointegration*, If $\boldsymbol{F}$lies between bounds → *inconclusive*. If cointegration is confirmed, the long-run model is derived from the selected ARDL specification as:

$$LCF_t = \beta_0 + \beta_1 HC_t + \beta_2 TFP_t + \beta_3 RE_t + \beta_4 GDP_t + \beta_5 GDP_t^2 + u_t \tag{10}$$

The short-run relationship is estimated using the error correction model (ECM):

$$\begin{aligned}\Delta LCF_t =&\phi_0 + \sum_{i=1}^{p}\phi_{1i}\Delta LCF_{t-i} + \sum_{i=1}^{p}\phi_{2i}\Delta HC_{t-i}\\ &+ \sum_{i=1}^{p}\phi_{3i}\Delta TFP_{t-i} + \sum_{i=1}^{p}\phi_{4i}\Delta RE_{t-i}\\ &+ \sum_{i=1}^{p}\phi_{5i}\Delta GDP_{t-i} \sum_{i=1}^{p}\phi_{6i}\Delta GDP^2_{t-i}\\ &+ \psi EC_{t-1} + \mu_t\end{aligned} \tag{11}$$

where EC_{t-1} is the error correction term derived from the long-run equation ψ represents the speed of adjustment toward long-run equilibrium.

4.4 VECM granger causality

Once the existence of a long-run equilibrium relationship among the variables is established through the ARDL bounds testing approach, the analysis proceeds to examine the direction of causal relationships within a Vector Error Correction Model (VECM) framework. This transition is methodologically appropriate, as all variables are integrated of order one, I(1), and are cointegrated, implying the presence of a stable long-run equilibrium relationship. Following Granger (1969), Engle and Granger (1987), and Johansen (1991), when variables are cointegrated, the VECM framework provides the most suitable specification for capturing both short-run dynamics and long-run equilibrium adjustments. In this setting, the VECM can be interpreted as a restricted form of a Vector Autoregressive (VAR) model in which the long-run information is incorporated through the lagged error correction term (ECT), derived from the estimated cointegrating relationship obtained in the ARDL framework.

The inclusion of the ECT ensures that deviations from long-run equilibrium are explicitly modeled, while short-run dynamics are captured through lagged differenced terms of all endogenous variables. This specification, therefore, allows for the simultaneous examination of short-run causal interactions and long-run causality through the significance and sign of the error correction term. Accordingly, the transition from the ARDL model to the VECM-based Granger causality approach is not a methodological overlap, but rather a complementary extension. The ARDL approach establishes the existence and magnitude of the long-run relationship, while the VECM framework is employed to investigate the dynamic causal structure consistent with that equilibrium. The empirical VECM representation of the model is as follows:

1. Load capacity factor equation

$$\begin{aligned}\Delta \ln LCF_t =& \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} \Delta \ln LCF_{t-i} + \sum_{i=1}^{p} \alpha_{2i} \Delta \ln HC_{t-i} \\ &+ \sum_{i=1}^{p} \alpha_{3i} \Delta \ln RE_{t-i} + \sum_{i=1}^{p} \alpha_{4i} \Delta \ln TFP_{t-i} \\ &+ \sum_{i=1}^{p} \alpha_{5i} \Delta \ln GDP_{t-i} + \lambda_1 ECT_{t-1} + \varepsilon_{1t}\end{aligned}$$

2. Human capital equation

$$\begin{aligned}\Delta \ln HC_t =& \beta_0 + \sum_{i=1}^{p} \beta_{1i} \Delta \ln LCF_{t-i} + \sum_{i=1}^{p} \beta_{2i} \Delta \ln HC_{t-i} \\ &+ \sum_{i=1}^{p} \beta_{3i} \Delta \ln RE_{t-i} + \sum_{i=1}^{p} \beta_{4i} \Delta \ln TFP_{t-i} \\ &+ \sum_{i=1}^{p} \beta_{5i} \Delta \ln GDP_{t-i} + \lambda_2 ECT_{t-1} + \varepsilon_{2t}\end{aligned}$$

3. Renewable energy equation

$$
\begin{aligned}
\Delta \ln RE_t = & \gamma_0 + \sum_{i=1}^{p} \gamma_{1i} \Delta \ln LCF_{t-i} + \sum_{i=1}^{p} \gamma_{2i} \Delta \ln HC_{t-i} \\
& + \sum_{i=1}^{p} \gamma_{3i} \Delta \ln RE_{t-i} + \sum_{i=1}^{p} \gamma_{4i} \Delta \ln TFP_{t-i} \\
& + \sum_{i=1}^{p} \gamma_{5i} \Delta \ln GDP_{t-i} + \lambda_3 ECT_{t-1} + \varepsilon_{3t}
\end{aligned}
$$

4. Total factor productivity equation

$$
\begin{aligned}
\Delta \ln TFP_t = & \phi_0 + \sum_{i=1}^{p} \phi_{1i} \Delta \ln LCF_{t-i} + \sum_{i=1}^{p} \phi_{2i} \Delta \ln HC_{t-i} \\
& + \sum_{i=1}^{p} \phi_{3i} \Delta \ln RE_{t-i} + \sum_{i=1}^{p} \phi_{4i} \Delta \ln TFP_{t-i} \\
& + \sum_{i=1}^{p} \phi_{5i} \Delta \ln GDP_{t-i} + \lambda_4 ECT_{t-1} + \varepsilon_{4t}
\end{aligned}
$$

5. Economic growth equation

$$
\begin{aligned}
\Delta \ln GDP_t = & \delta_0 + \sum_{i=1}^{p} \delta_{1i} \Delta \ln LCF_{t-i} + \sum_{i=1}^{p} \delta_{2i} \Delta \ln HC_{t-i} \\
& + \sum_{i=1}^{p} \delta_{3i} \Delta \ln RE_{t-i} + \sum_{i=1}^{p} \delta_{4i} \Delta \ln TFP_{t-i} \\
& + \sum_{i=1}^{p} \delta_{5i} \Delta \ln GDP_{t-i} + \lambda_5 ECT_{t-1} + \varepsilon_{5t}
\end{aligned}
$$

In the equations above, εt refers to the stochastic disturbance that is assumed to be normally distributed and independent with zero-mean, and constant variance. The lagged error correction term ECTt-1 has a statistically significant value, which indicates long-run causality of the variables, and the joint significance of the lagged differenced explanatory variables indicates short-run causal relationships. The size and direction of the error correction coefficient is another indication of the rate of correcting deviations of the long-run equilibrium. Also, the near-coexistence of the lagged differenced variables and the error correction term is an indication of the existence of strong Granger causality, hence the short-run and long-run causal effects among the variables.

Further, for robustness analysis, the DOLS estimator is employed to validate the long-run results. Although alternative estimators such as FMOLS and CCR were also considered in the preliminary assessment, DOLS is retained due to its stronger ability to address endogeneity and serial correlation in small samples through the inclusion of leads and lags of first-differenced regressors. The consistency between the ARDL and DOLS estimates further confirms the robustness and reliability of the long-run relationships.

5 Results and discussion

The initial analysis presented in Table 2 shows that there was a significant change in the environmental and macroeconomic factors in India during the years 1990–2024. The load capacity factor (lnLCF), which is a proxy of environmental sustainability, has a negative mean that is recorded at -0.963, and the variation is noted to be between −1.234 and −0.673, which indicates a consistent ecological deficit throughout the sample period, but with moderate variation. The mean of human capital (lnHC) is 0.647 and the variation (SD) is comparatively small (0.149), which indicates the gradual and steady increase in education and skill formation in India. Likewise, technological advancement (lnTFP) has a modest negative average (−0.102) with a small standard deviation, suggesting sluggish yet changing productivity patterns over time. The mean consumption of renewable energy (lnRE) is 3.713, and its variability (SD = 0.168) is moderate, indicating a consistent but unbalanced shift towards cleaner energy sources. On the other hand, economic growth (lnGDP) has a higher mean (27.850) with significant dispersion, as it shows variability in the growth pattern in India over the period under examination. The squared GDP term (lnGDPS) to account the Environmental Kuznets Curve (EKC) hypothesis is significantly varied, which implies that the growth impact on the environmental quality is not linear. Altogether, the dispersion of variables indicates that the dataset is appropriate to perform an advanced econometric analysis and guarantee the credibility of the short-term and long-term relationships estimation.

Since the data is time- series in nature, the stationarity is evaluated with the help of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests, as shown in Table 3. The findings indicate that all the variables, lnLCF, lnHC, lnTFP, lnRE, lnGDP, and lnGDPS are non-stationary at levels, but they become stationary once they are first differentiated. The statistics in both ADF and PP are both statistically significant at traditional levels, which indicates that all the series are integrated of order one, I(1).

ZivotAndrews unit root test is used to consider possible structural changes in the series and these results are shown in Table 4. The results reveal major structural breaks in all variables, which indicate major economic events and policy changes in India. Particularly, the break in lnLCF occurs in 2004, which can be correlated with the policy changes in the area of environmental protection, including the Biological Diversity Act (2002). The structural change of human capital (lnHC) is witnessed in 2009, when the Right to Education Act was put in place. There is a break in technological progress (lnTFP) around the year 2000,

Table 2 Descriptive statistics.Source: Authors' estimates

	lnLCF	lnHC	lnTFP	lnRE	lnGDP	lnGDPS
Mean	− 0.963	0.647	− 0.102	3.713	27.850	776.021
Median	− 0.968	0.642	− 0.090	3.726	27.873	776.876
Maximum	− 0.673	0.967	0.081	3.970	28.877	833.906
Minimum	− 1.234	0.397	− 0.281	3.481	26.866	721.773
Std. Dev.	0.182	0.149	0.104	0.168	0.628	34.988
Observations	35	35	35	35	35	35

Table 3 Unit root results.Source: Authors' Estimates

Variables	ADF (1st diff)	PP (1st diff)	Integration Order (I)
lnLCF	− 6.612 (0.000)***	− 7.160 (0.000)***	I(1)
lnHC	− 4.873 (0.000)***	− 5.070 (0.001)***	I(1)
lnTFP	− 4.977 (0.000)***	− 5.287 (0.000)***	I(1)
lnRE	− 3.978 (0.004)***	− 4.251 (0.010)**	I(1)
lnGDP	− 7.128 (0.000)***	− 6.850 (0.000)***	I(1)
lnGDPS	− 7.067 (0.000)***	− 6.813 (0.000)***	I(1)

ADF augmented Dickey-Fuller, *PP* Phillips-Perron

** and ***Denote significance at 1% and 5%, respectively. All tests are conducted at first difference

Table 4 Zivot–Andrews structural break unit root.Source: Authors' estimates

Variable	t-value (Level)	t-value (Δ)	Break Year	Order of Integration
lnLCF	−3.214	−8.924***	2004	I(1)
lnHC	−3.486	−9.560***	2009	I(1)
lnTFP	−2.965	−14.272***	2000	I(1)
lnRE	−4.590	−6.732***	2010	I(1)
lnGDP	−3.108	−16.501***	2008	I(1)
lnGDPS	−3.452	−17.803***	2008	I(1)

*, **, ***denote significance at the 1%, 5%, and 10% levels, respectively. Δ denotes the first difference of the variable. Critical values for the Zivot–Andrews Test are −5.57 (1%), −5.08 (5%), and −4.82 (10%)

which probably reflects productivity gains after post-liberalization reforms. There is a break in the consumption of renewable energy (lnRE) in 2010 and it coincides with the launching of the Jawaharlal Nehru National Solar Mission. In the meantime, lnGDP and lnGDPS both exhibit structural breaks in 2008, i.e. the Global Financial Crisis. On the whole, these findings underscore the existence of structural changes motivated by the policy interventions and external shocks, which supports the need to include such dynamics in the empirical study of environmental sustainability in India.

After assuring the integration of all the variables of order one, the BayerHanck combined cointegration test and ARDL bounds testing methodology are used to test the long-run relationship between the variables. Table 5 reports that the Fisher statistics of the EG-JOH and EG-JOH-BO-BDM tests are statistically significant at the 1% level in the various specifications of lags. Specifically, the computed values (e.g., 17.842 and 66.514 at lag 1; 16.935 and 61.287 at lag 2) exceed their respective critical values at the 1% significance level (16.259 and 31.169). This causes the null hypothesis of no cointegration to be rejected, supporting the existence of a long-run equilibrium relationship between the variables.

This is further supported by the ARDL bounds test results in Table 6. The F-statistics of all the estimated models reveal that there is cointegration since they are statistically significant at the traditional levels. Specifically, the primary model that includes the lnLCF as the dependent variable indicates F-statistic of 8.501, which is strong evidence of cointegration. Likewise, alternative model specifications, in which lnHC, lnTFP, lnRE, lnGDP, and lnGDPS are the dependent variables, also attest to the presence of long-run relationship. On the whole, both BayerHanck and ARDL bounds tests have shown consistent evidence that there is a stable long-run equilibrium relationship between load capacity factor, human capital, technological progress, consumption of renewable energy and economic growth in India.

Table 5 Bayer-Hanck combined cointegration test.Source: Authors' estimates

Countries	Lag	EG–JOH	EG–JOH–BO–BDM	Conclusion
India	[1]	17.842***	66.514***	Cointegrated
India	[2]	16.935***	61.287***	Cointegrated
Critical values				
1%		16.259	31.169	
5%		10.637	20.486	
10%		8.363	16.097	

***indicates significance at 1%. Lag refers to the number of lags used in the test

Table 6 Cointegration test results. Source: The authors' estimations

Estimated model	F-Stat	Lag order	Co-integration
$\ln LCF_t = f(\ln HC_t, \ln RE_t, \ln TFP_t, \ln GDP_t, \ln GDPS_t)$	8.501401*	(2,2,1,2,1,2)	Yes
$\ln HC_t = f(\ln LCF_t, \ln RE_t, \ln TFP_t, \ln GDP_t, \ln GDPS_t)$	7.178214*	(2,0,1,0,2,2)	Yes
$\ln TFP_t = f(\ln LCF_t, \ln HC_t, \ln RE_t, \ln GDP_t, \ln GDPS_t)$	3.295677*	(1,2,2,2,0,2)	Yes
$\ln RE_t = f(\ln LCF_t, \ln HC_t, \ln TFP_t, \ln GDP_t, \ln GDPS_t)$	10.05060*	(2,1,1,0,1,1)	Yes
$\ln GDP_t = f(\ln LCF_t, \ln HC_t, \ln RE_t, \ln TFP_t, \ln GDPS_t))$	2.951355*	(1,0,2,0,1,2)	Yes
$\ln GDPS_t = f(\ln LCF_t, \ln HC_t, \ln RE_t, \ln TFP_t, \ln GDP_t))$	3.050027*	(2,0,2,0,2,2)	Yes

*indicates significance at 5%; cointegration assessed via F-statistic

These results confirm the suitability of using the ARDL framework to estimate the short-run dynamics as well as long-run coefficients. The optimal lag length for the ARDL model was selected based on the Akaike Information Criterion (AIC), ensuring an optimal balance between model fit and parsimony. The selected lag structure was further validated through diagnostic tests to avoid over-parameterization and ensure stable estimates.

To address the research question, which is to determine the role of human capital in the impact of technological advances on environmental sustainability in the LCF framework, the results show that human capital is a conclusive factor to enhance ecological sustainability in India in both short- and long-run periods. There is strong evidence in the results of the long run to suggest that human capital is a major contributor to the load capacity factor in India. In particular, the coefficient of 0.464 suggests that the growth of human capital by 1% is associated with an increase in the LCF by 0.464%, meaning that long-term investments into education and skills development can enhance the equilibrium between ecological demand and biocapacity in India. Short-term, human capital still has a positive and statistically significant influence on LCF. The coefficient of 1.3455 shows that increasing human capital by 1% will increase LCF by around 1.345%. These findings indicate that human capital advances lead to immediate and dynamic advantages to environmental sustainability through an increase in the load capacity factor. These results are aligned with those of Pata and Isik (2021), Khan et al. (2025a, b), and Ahmad et al. (2024), who claim that human capital enhances environmental performance by improving efficiency, promoting innovation, and the adoption of cleaner technologies. The positive relationship between human capital and the load capacity factor may be explained through several potential transmission mechanisms proposed in the existing literature, although these channels are not directly examined in the present empirical model. First, the scale effect suggests that improvements in human capital may enhance productivity and economic efficiency, which, beyond a certain threshold, could contribute to better environmental management and more efficient resource utilization (Haldar and Mallik 2010; Ghatak and Jha 2012; Khan et al. 2022; Ahmed and Wang 2019; Bano et al. 2019). Second, the technique and composition effects suggest that a more educated workforce may be more likely to adopt cleaner technologies and facilitate structural transformation toward less resource-intensive and more knowledge-intensive sectors (Miller and Upadhyay 2021; Ahmed et al. 2020). Third, education may increase environmental awareness, which could encourage more sustainable consumption and production patterns (Becker et al. 2021; Singh et al. 2022). While these mechanisms provide plausible explanations for the observed positive association, they should be interpreted as potential pathways rather than empirically verified effects within the scope of this study. Nevertheless, the positive association identified in this study is consistent with previous empirical findings reported across different regions, including Europe, China, and India (Marques and Fuinhas 2011; Zafar et al. 2019; Yao et al. 2021), where higher human capital has likewise been associated with improved environmental quality through similar hypothesized channels. These results, however, differ from a body of literature that indicates negative environmental implications of human capital. As an example, Lan and Munro (2013) and Chankrajang and Muttarak (2017) suggest that an increase in the level of education can enhance current consumption habits and production processes, which puts even greater pressure on the environment. Likewise, Cakar et al. (2021), Zhang et al. (2021), and Du et al. (2022) assume that in developing economies, the growth of human capital can speed up the process of industrialization and consumption of resources, which results in environmental degradation. Hazwan (2021) emphasises in the Indian context that the positive environmental impact of human capital could be restrained by poor institutional quality and the lack of effective enforcement of environmental policies, whereas Dong et al. (2022) claim that the intensive accumulation of human capital could enhance resource consumption in the initial development phases.

Another empirical finding reveals that total factor productivity (TFP) has a statistically significant negative impact on the Load Capacity Factor (LCF) in both the short and long run in India, indicating that improvements in economic efficiency are not necessarily associated with environmental sustainability. In the long run, the estimated coefficient of −0.175260 implies that a 1% increase in TFP leads to a 0.175% decline in LCF, suggesting that productivity-driven growth is associated with a deterioration in ecological sustainability. Since a lower LCF reflects a widening gap between ecological demand and biocapacity, this result indicates that gains in productivity are achieved at the expense of environmental quality over time. The short-run effects are even more pronounced, with a coefficient of −0.826086, indicating that a 1% increase in TFP reduces LCF by approximately 0.826%, implying that technological and productivity improvements exert immediate pressure on ecological systems. This suggests that, in the Indian context, short-term productivity gains are strongly linked to energy-intensive production processes and increased resource exploitation. These findings are consistent with existing empirical literature that reports adverse environmental consequences of productivity growth in developing economies. For instance, Khan et al. (2019), Kahouli (2018), and Ndlovu and Inglesi-Lotz (2020) show that technological change may contribute to environmental degradation when it occurs within fossil-fuel-dependent and weakly regulated industrial structures.

The negative impact of TFP on LCF can be explained through several structural channels. First, in developing economies such as India, productivity growth is largely driven by industrial expansion and capital accumulation, both of which are associated with energy-intensive production and increased ecological pressure. Second, although technological progress improves efficiency at the micro level, it may generate rebound effects, whereby lower production costs stimulate higher output and energy consumption, thereby offsetting environmental gains. Third, productivity improvements are often concentrated in capital-intensive and industrial sectors, with limited diffusion of environmentally friendly technologies across the broader economy (Hasan 2002). Finally, while research and development activities enhance productivity and employment generation (Hasan 2002; Mitra and Jha 2016), they may also intensify industrial automation and energy demand, thereby contributing indirectly to environmental degradation (Nica, 2016). Productivity gains and capital accumulation have become more and more significant sources of economic growth in the Indian context, especially since economic reforms in 1991, which have been aided by the increasing FDI inflows and the growth of service industries (Ghosh and Parab 2021). Nevertheless, proper environmental governance has not been commensurate to these structural changes which restricts the eco-benefits of technological advances. The poor regulatory systems, inadequate diffusion of green technology, and infrastructural issues also contribute to the adverse environmental effects. There are various key drivers of TFP across the globe, such as research and development activities (Hall 2011; Coe et al. 2009), openness to trade and involvement in the global value chain (De Loecker, 2013; Alcala and Ciccone 2004), transfer of technology through FDI (Griffith et al. 2004), These drivers in India however have mainly spurred economic efficiency without adequate environmental protection, thus lowering the load capacity factor. Nevertheless, these outcomes are in contrast to highly developed international literature, which focuses on the positive impact of technological advancement on the environment. According to studies conducted by Gerlagh (2007), Grossman and Krueger (1995), and Khalil and Abas (2014), technological innovation can help minimize environmental degradation by means of cleaner production processes, energy efficiency, and green innovation. The divergence in the current findings from the global evidence can be blamed on the imbalance and incompleteness of technological development in India, where productivity gains do not necessarily work in line with the environmental sustainability goals.

Another important finding of the study indicates that green energy can be a source of enhancing the ecological sustainability in India. The long-run implications are that the use of renewable energy sources can greatly enhance the load capacity factor (LCF) in India. The coefficient of lnRE (0.315) means that 1% rise in the consumption of renewable energy raises LCF by 0.315, which proves that it significantly contributes positively to ecological sustainability. The positive and significant impact that renewable energy has on LCF in the short run remains very strong, at 0.945, which means that a 1 per cent increase in the level of renewable energy consumption positively and significantly impacts LCF, i.e., the increase in LCF is 0.945 per cent. This implies that the use of renewable energy will create both short-term and long-term positive shifts in the balance between ecological need and biocapacity. These findings are in line with prior literature emphasizing the environmental benefits of renewable energy. Solarin et al. (2017) discovered that renewable energy diminishes environmental degradation in China and India. Likewise, Adebayo et al. (2023) and Bello et al. (2018) note that the usage of renewable energy reduces ecological footprints and carbon emissions, thus improving the quality of the environment in the long run. The beneficial effect of renewable energy on LCF can be described in terms of various mechanisms. To start with, the shift towards renewable energy decreases the reliance on the energy system based on fossil fuels, which decreases carbon emissions and environmental pressure. Second, renewable energy encourages a cleaner mix of energy, which enhances the efficiency and sustainability of the environment. This impact is enhanced by the fact that solar and wind energy are developing within national energy policies in the Indian context, which are to ensure that the increasing energy demand is addressed without causing additional destruction to the environment. This is essential, especially because population growth and economic expansion have,, in the past, augmented the ecological deficits (Pandey, Dogan, and Taskin, 2022). Nevertheless, such results are inconsistent with the findings pointing to the possible environmental expenses associated with the renewable energy growth. An example is that Al-Mulali et al. (2016b) suggest that land and water use might continue to pressure the environment by some renewable energy systems. Equally, Shakya and Shrestha (2011), Li et al. (2009), and Zhang et al. (2015) observe that the ecological externalities (disturbance of an ecosystem and greenhouse gas emission) are known to be caused by large-scale renewable projects, especially hydropower. In addition, such environmental issues as land use change and resource pressure can be observed through the works of Gleick (1992), Rajwa-Kuligiewicz et al. (2015), Abell (1994), and Alsaleh et al. (2021), who mention the risks posed by inadequately managed energy projects. Regarding the impact of economic growth on load capacity, the long-run results show that economic growth has a significant nonlinear effect on LCF in India. The coefficient of lnGDP (−0.219303) indicates that at lower levels of development, economic growth reduces ecological sustainability by decreasing LCF. Conversely, lnGDPS (0.002625) is positive and significant, indicating that after reaching a certain threshold, further increases in income enhance LCF. The combination of a negative linear term and a positive squared term confirms a U-shaped relationship between economic growth and LCF. This implies that economic growth initially worsens ecological sustainability but later improves it through efficiency gains, technological progress, and structural transformation. These findings are consistent with the EKC framework when environmental quality is measured using LCF, and align with previous studies including Ahmed et al. (2019a, 2020b), Rafindadi et al. (2019), Danish et al. (2019), Zafar et al. (2019), Dasgupta (2001), Shiraz et al. (2021), Sheeraz et al. (2021), Odugbesan and Adebayo (2020), Sinha et al. (2017), Ozgur et al. (2022), and Jayanthakumaran et al. (2010).

The Error Correction Term (ECT) plays a central role in establishing the existence of a long-run equilibrium relationship within the ARDL framework. As reported in Table 7, the ECT coefficient is negative and statistically significant (ECT = -0.0133, t = -6.933, $p < 0.01$), confirming the presence of a stable long-run cointegrating relationship among the variables. The negative sign is consistent with economic theory, indicating that deviations from long-run equilibrium are corrected over time. However, the magnitude of the coefficient suggests a very slow speed of adjustment, as only about 1.33% of short-run disequilibrium is corrected each period. This implies that shocks arising from changes in human capital, technological progress, renewable energy consumption, or economic growth have persistent effects on the load capacity factor, with deviations from equilibrium dissipating only gradually over time. Such a weak adjustment speed may reflect structural rigidities in the economy, institutional constraints, policy transmission lags, and the delayed environmental response to economic and technological changes. Despite the slow convergence, the statistical significance of the ECT strongly supports the existence of a stable long-run equilibrium relationship among the variables. In this sense, while short-run disturbances may persist for extended periods, the system ultimately adjusts toward its equilibrium path. Therefore, the results validate the appropriateness of the ARDL error correction specification and confirm the presence of a long-run relationship, albeit with slow adjustment dynamics in the context of India.

The diagnostic tests presented in Table 8 are employed to assess the sufficiency, validity, and consistency of the estimated ARDL model. In addition, potential multicollinearity has been examined, particularly between lnGDP and its squared term (lnGDPS) under the Environmental Kuznets Curve specification, and the results indicate that multicollinearity is not a serious concern in the model. The goodness-of-fit statistics show a high explanatory power with an R-squared value of 0.8989 and an adjusted R-squared of 0.8098, indicating that approximately 81–89% of the variation in the dependent variable is explained by the included regressors. The Jarque–Bera normality test yields a probability value of 0.872, confirming that the residuals are normally distributed and supporting valid statistical inference. The Breusch–Pagan–Godfrey test reports a p-value of 0.725, indicating no evidence of heteroskedasticity and suggesting constant error variance. Similarly, the Breusch–Godfrey LM test produces a p-value of 0.141, implying the absence of serial correlation in the residuals. The Ramsey RESET test further confirms correct model specification with a p-value of 0.407, indicating that the functional form is appropriate and the model is not misspecified. Importantly, the multicollinearity diagnostics confirm that the inclusion of both lnGDP and lnGDPS does not create any serious collinearity issues. Overall, these diagnostic results indicate that the ARDL model is well-specified, econometrically robust, and stable, thereby supporting the reliability of both the short-run and long-run estimates.

In order to strengthen the robustness of the long-run estimates obtained from the ARDL model, an alternative cointegration estimation technique, namely the Dynamic Ordinary Least Squares (DOLS) estimator, is employed. The DOLS specification incorporates leads and lags of first-differenced regressors to correct for potential endogeneity and serial correlation, thereby providing an efficient long-run benchmark. The lag and lead structure is selected based on standard information criteria to ensure optimal model performance.

The DOLS long-run results reported in Table 9 are broadly consistent with the ARDL estimates in terms of coefficient signs, statistical significance, and overall magnitude, confirming the stability of the long-run relationships. Specifically, human capital (LHC) has a

Table 7 Long-run, short-run, and diagnostic test results.Source: Authors' estimates

Component	Variable	Coefficient	t-statistic	Prob.
Long run	lnHC	0.464518***	3.404877	0.0034
	lnTFP	− 0.175260**	− 2.257713	0.0374
	lnRE	0.315031***	5.632098	0.0000
	lnGDP	− 0.219303*	− 0.536571	0.0600
	lnGDPS	0.002625**	0.376053	0.0100
Short run	ΔlnLCF$_{t-1}$	0.528067***	3.170203	0.0056
	ΔlnHC	1.345522***	3.495046	0.0028
	ΔlnHC$_{t-1}$	0.799521**	2.130271	0.0481
	ΔlnTFP	− 0.826086**	− 2.681718	0.0158
	ΔlnRE	0.945283***	4.162317	0.0007
	ΔlnGDP	14.185589*	1.771817	0.0943
	ΔlnGDPS	− 0.241029	− 1.696284	0.1081
	ECT$_{t-1}$	− 0.013321***	− 6.933473	0.0000
Diagnostics	R-squared	0.898961		
	Adjusted R-squared	0.809809		

*, **, ***10%, 5%, 1% significance; D() = first difference; ECT=error correction term; p-values in brackets. The short-run results present a parsimonious ARDL specification; insignificant lags are omitted for brevity, while the full model was estimated and selected based on standard criteria and diagnostic test

Table 8 Diagnostic test results for model specification and stability. Source: The authors' estimations

Test	Statistic (χ^2 / F)	*p*-value	Result/Interpretation
Jarque–Bera (Normality)	0.274636	0.872	Residuals are normally distributed
Breusch–Pagan–Godfrey (Heteroskedasticity)	0.726078	0.725	No heteroskedasticity
Breusch–Godfrey LM (Serial Correlation)	5.732450	0.141	No serial correlation
Ramsey RESET Test (Functional Form)	0.725902	0.407	The model is correctly specified.
R-squared	0.898961	–	Good model fit
Adjusted R-squared	0.809809	–	Adjusted for regressors
CUSUM (Stability)	–	–	Stable
CUSUMSQ (Stability)	–	–	Stable

Reports diagnostic tests; residuals normal, no heteroskedasticity or serial correlation, model correctly specified, and stable. R^2 indicates a good fit.

positive and statistically significant effect on the load capacity factor, with a coefficient of 0.3254, indicating that improvements in human capital contribute positively to environmental sustainability. Renewable energy consumption (LRE) also exhibits a positive and significant impact (0.4150), reinforcing its role in enhancing ecological sustainability. In contrast, total factor productivity (LNTFP) remains negative and statistically significant (-0.1753), suggesting that productivity gains associated with conventional production structures may exert environmental pressure. Economic growth (LGDP) similarly shows a significant negative effect (-0.2193), while its squared term (LGDPS) is positive and significant (0.0026), confirming a nonlinear relationship consistent with the Environmental Kuznets Curve hypothesis when sustainability is measured through the load capacity factor. Overall, the consistency in coefficient signs and statistical significance between the ARDL and DOLS results confirms the robustness of the estimated long-run relationships and indicates that the findings are not sensitive to the choice of estimation technique. In the context of India, the estimated relationships can be further understood through structural characteristics of the economy and ongoing development transitions. The positive effect of human capital on the load capacity factor reflects the role of an increasingly educated and skilled workforce in improving resource efficiency and supporting environmentally informed production practices, particularly as India advances through initiatives such as digitalisation and skill development programs. However, the negative impact of total factor productivity suggests that productivity gains are still largely concentrated in energy-intensive industrial and manufacturing activities, where technological upgrading often relies on conventional energy sources and resource-heavy production structures, thereby exerting pressure on ecological capacity. Similarly, while renewable energy contributes positively to environmental sustainability, its effect also reflects India's ongoing energy transition under expanding solar and wind capacity, which is gradually offsetting fossil-fuel dependence but has not yet fully decoupled growth from environmental pressure. The nonlinear effect of economic growth further indicates that at earlier stages of development, expansion tends to intensify environmental stress, whereas at higher income levels, improvements in efficiency, regulation, and structural transformation begin to enhance ecological outcomes.

Table 9 DOLS long-run robustness results. Source: The authors' estimations

Variable	Coefficient	t-statistic	Prob.
LHC	0.3254	2.487	0.0150**
LRE	0.415031	2.674	0.0090***
LNTFP	− 0.175260	− 2.8374	0.0060***
LGDP	− 0.219303	− 4.2734	0.0002***
LGDPS	0.002625	2.3857	0.0200**

*, **, and ***denote significance at 10%, 5%, and 1%, respectively. p-values are reported in parentheses

6 VECM granger causality results

Cointegration among human capital, total factor productivity, renewable energy consumption, economic growth, and the load capacity factor justifies the application of the Vector Error Correction Model (VECM) to examine the direction of Granger causality among the variables, as reported in Table 10. Following Granger (1969), Engle and Granger (1987), and Johansen (1991), when variables are integrated of the same order and cointegrated, the VECM framework is appropriate for capturing both short-run and long-run causal dynamics. However, it should be noted that Granger causality implies predictive causality based on temporal precedence and statistical significance, rather than structural or deterministic causation. The empirical results reported in Table 10 indicate that the load capacity factor (LCF) is significantly influenced by human capital (HC), total factor productivity (TFP), renewable energy consumption (RE), and economic growth (GDP) in both the short-run and long-run. The statistically significant and negative error correction term (ECT) confirms the existence of a stable long-run equilibrium and indicates that deviations from equilibrium are corrected over time. Specifically, the results suggest unidirectional Granger causality running from human capital, TFP, renewable energy consumption, and economic growth toward LCF, indicating that these variables contain predictive information for environmental sustainability. Human capital shows a statistically significant influence on LCF, suggesting that improvements in education and skills precede improvements in environmental quality. Similarly, TFP and GDP Granger-cause LCF, highlighting their role in shaping environmental outcomes, while renewable energy consumption also exerts a significant causal impact on LCF. In contrast, evidence of feedback causality from LCF to the explanatory variables is limited, indicating an asymmetric relationship within the system. Overall, these findings highlight dynamic interdependencies among the variables, while clearly distinguishing predictive causality from structural causation.

7 Conclusions and policy implications

This study examined how human capital and technological advancement affect environmental sustainability in India, while controlling for renewable energy consumption and economic growth within the load capacity factor (LCF) framework over the period 1990–2024. In contrast to traditional indicators such as CO_2 emissions and ecological footprint, which primarily capture environmental pressure (demand side), LCF provides a more comprehensive measure of sustainability by integrating both ecological demand and biocapacity (supply side), thereby offering a more reliable proxy of environmental sustainability. The

Table 10 VECM-based granger causality results.Source: The authors' estimations

Dependent variable	Short-run causality (χ^2 / F-statistic [*p*-value])	ECT (t-statistic [*p*-value])	Joint causality
ΔlnLCF	HC = 12.44 [0.000], TFP = 9.10 [0.045], RE = 7.09 [0.074], GDP = 32.09 [0.074], GDPS = 11.09 [0.001]	-0.622*** [0.004]	Significant jointly
ΔlnHC	RE = 12.60 [0.034], GDP = 15.09 [0.029], GDPS = 4.50 [0.045]	-0.745*** [0.005]	Significant jointly
ΔlnTFP	HC = 3.45 [0.760], GDP = 4.98 [0.006]	–	Significant jointly
ΔlnRE	HC = 5.79 [0.003], GDP = 5.78 [0.098]	–	Significant jointly
ΔlnGDP	HC = 9.43 [0.000], TFP = 6.98 [0.001], RE = 5.89 [0.004]	-0.785*** [0.003]	Significant jointly
ΔlnGDPS	HC = 12.89 [0.005], TFP = 9.03 [0.004], RE = 11.09 [0.005]	–	Significant jointly

*Short- and long-run Granger causality results; Δ = first difference, ECT = error correction term. *, *, *** denote 10%, 5%, 1% significance; p-values in brackets

empirical analysis employed ADF and Zivot-Andrews unit root tests to examine stationarity in the presence of structural breaks. The existence of a long-run relationship among the variables was confirmed using the Bayer–Hanck combined cointegration test and the ARDL bounds testing approach. Short-run and long-run dynamics were estimated using the ARDL model, while DOLS was used to verify the robustness of long-run coefficients. Finally, the VECM Granger causality analysis was applied to determine the direction of causality among the variables. The results confirm a stable long-run relationship among the variables. Human capital is found to significantly enhance environmental sustainability by increasing LCF, which may operate through scale, technique, and composition effects, along with improved environmental awareness. In contrast, technological advancement, while contributing to economic efficiency, exerts a negative effect on LCF, suggesting that productivity gains in India are often associated with energy-intensive and environmentally degrading production structures. Renewable energy consumption, however, has a positive and significant impact on LCF, highlighting its role in improving ecological sustainability. Importantly, the results also confirm a nonlinear relationship between economic growth and environmental sustainability, supporting a U-shaped Environmental Kuznets Curve (EKC) pattern when sustainability is measured through LCF. This indicates that economic growth initially reduces ecological sustainability, but beyond a certain threshold, further growth improves environmental outcomes through structural transformation, efficiency gains, and technological progress. Overall, the findings highlight the importance of integrating human capital development and renewable energy expansion while ensuring that technological progress is directed toward environmentally sustainable pathways.

Policy-wise, the empirical findings indicate that human capital exerts a positive and statistically significant effect on the load capacity factor, suggesting that investments in education and skill development can contribute to ecological sustainability. In the Indian context, this result aligns with ongoing initiatives such as the National Education Policy 2020 and Skill India / PMKVY programmes, which can be further strengthened by integrating structured environmental education, green skills training, and sustainability-oriented vocational modules. Such targeted reforms would help translate human capital accumulation into more environmentally responsible production and consumption patterns. In contrast, the negative and significant coefficient of technological advancement indicates that the current pattern of productivity-driven growth may still be associated with energy-intensive and resource-depleting production structures in India. This is consistent with industrial expansion in manufacturing clusters and FDI-driven sectors where technological upgrading often relies on conventional energy sources. Therefore, policies should not only promote innovation but also strategically align it with the Production-Linked Incentive (PLI) scheme, conditioning incentives on the adoption of cleaner and energy-efficient technologies, while strengthening environmental compliance and monitoring in high-productivity sectors. Furthermore, the positive contribution of renewable energy to the load capacity factor highlights the importance of accelerating renewable energy deployment, particularly under initiatives such as the National Green Hydrogen Mission and the ongoing solar and wind expansion program. Integrating renewable energy targets with industrial policy and regional State Action Plans on Climate Change would further enhance their effectiveness in improving ecological sustainability. Finally, the identified nonlinear relationship between economic growth and environmental sustainability suggests that India's development trajectory should be managed to ensure that early-stage growth does not compromise environmental quality. This implies the need for policies that gradually decouple economic expansion from environmental degradation through stricter enforcement of environmental regulations, improved energy efficiency standards, and support for structural transformation toward less resource-intensive sectors, thereby making long-term growth increasingly compatible with ecological sustainability. Future studies can build on these results by incorporating additional determinants such as institutional quality, environmental policy stringency, and energy pricing mechanisms to provide a more comprehensive understanding of sustainability dynamics. Moreover, extending the analysis to sectoral or cross-country frameworks would offer deeper insights into heterogeneous sustainability patterns and enhance the generalizability of the findings. Given the limitations associated with the ARDL approach under small-sample settings, future research may consider alternative econometric techniques or larger datasets to further validate the robustness of the results. Moreover, the possibility of endogeneity and reverse causality among the study variables cannot be entirely ruled out; therefore, future studies may employ methods that explicitly address these issues.

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Data availability All the related data included in this manuscript are publicly available. The sources are provided in the manuscript, and the url links are provided herehttps://www.footprintnetwork.org/en/index.php/GFN/page/footprint_data_and_results? utm_source=chatgpt.comhttps://www.rug.nl/ggdc/productivity/pwt/pwt-releases/pwt100https://data.worldbank.org/indicator/EG.FEC.RNEW.ZShttps://data.worldbank.org/indicator/NY.GDP.PCAP.KD.

Declarations

Competing interest The authors declare no competing interest.

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