
**E-ISSN:** 2708-4523
**P-ISSN:** 2708-4515
Impact Factor (RJIF): 5.61
AJMC 2025; 6(2): 1146-1158

www.allcommercejournal.com
Received: 20-08-2025
Accepted: 25-09-2025
Published: 07-10-2025

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# What drives renewable energy in India? Examining the role of artificial intelligence, digitalization and green finance

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**DOI:** https://www.doi.org/10.22271/27084515.2025.v6.i2m.839

**Abstract**
**Purpose:** India is undergoing a twin transition that aims to align the goal of technological advancement with sustainability. Thus, the purpose of current investigation is to examine the intricate relationship between renewable energy, digitalization, artificial intelligence, and green finance.
**Design/Methodology/ Approach:** This study utilizes the time series data from 2000 to 2022 of India. The study employs ARDL test and Granger causality test to examine the nexus among variables under study.
**Findings:** The ARDL estimates show significantly positive connection between renewable energy consumption and digitalization in both long and short run. While, the outcome of artificial intelligence and green finance has shown insignificant impact on renewable energy consumption. The granger causality test reveals unidirectional causality between renewable energy consumption and green finance in India.
**Originality/ Value:** To the extent of authors' knowledge, earlier literature has focused on examining the relationship between renewable energy, emissions, and economic growth. Despite the growing importance of artificial intelligence, digitalization, emissions and renewable energy, authors find scarce literature in the context of India. Importantly, this study has given a thoughtful consideration to the green finance received by India for energy transition. Consequently, the present research advances understanding in an unexplored area and tries to bridge the scholarly gap.

**Keywords:** Renewable energy, Artificial intelligence, Digitalization, Green finance, India, ARDL

## 1. Introduction
The world is witnessing the global challenge of rising development and rapidly changing climate. Rapid rise in industrialization encourages technological advancements and innovation, and the world is thriving towards industrial revolution 4.0. Technology intensive industrialization requires more energy consumption (Sahoo and Sethi, 2020) [51], (Pan *et al.*, 2019) [43]. Despite these advancements, the world is still dependent on fossil-fuel based energy sources to meet the rising demand. Due to this, there is a tremendous rise in greenhouse gas emissions (World Meteorological Organization). Therefore, this becomes a vital necessity to address the issue of rising environmental degradation. The world leaders have heard this environmental call at global stage and initiated several initiatives such as Kyoto protocol, Paris agreement and continuous Conference of party meetings to overcome the issue of environmental degradation. Further, nations have committed to achieve sustainable development goals. It is noteworthy here that developed nations have reaped more economic dividend due to industrialization initially and developing nations have borne the burden of environmental deterioration. The rising environmental consciousness lead to Paris agreement in which developed nations committed to provide financial support to developing nations to mitigate environmental harm (United Nations Climate Change).
Reflecting worldwide patterns, India is also witnessing the wave of twin transition that is technological and sustainable transition simultaneously. Artificial intelligence and digital initiatives are rising as the major contributor and facilitator in the economy. At the same time, India is fostering towards achieving its sustainability targets of net zero by the year 2070 (PIB). On one side, the technology transition driven by artificial intelligence (AI) and digitalization is expected to increase the demand for energy. Here, the key concern is that Indian economy is majorly dependent on traditional sources of energy production. Due to this fact, nearly 75% of the emissions come from energy sector only in India (Climate

Watch). In this regard, renewable energy (RE) can play a vital role in decarbonizing the Indian economy and achieving sustainable development goal 7 which aims for sustainable energy (United Nations). Contrastingly, advancements in AI and digitalization can also foster energy efficiency, smart energy systems and accelerate the shift towards renewable energy (Awogbemi *et al.*, 2024) [5]. However, the positive impact of AI and digitalization can be extracted with the help of large scale investments to scale the transition towards sustainable energy. As a middle income country, the financial resource possessed by India may not be sufficient to move towards RE (Ember). This highlights the crucial role of green finance received from international sources in energy transition.

This paper explores the role of artificial intelligence, digitalization on RE consumption in India. Moreover, our research also focuses on the important role played by green finance on escalating renewable energy in India. By examining the nexus among artificial intelligence, digitalization and green finance, this study aims to illustrate how they can collectively drive the energy transition. The current study is important in number of ways. Firstly, this study contributes to the flourishing literature on twin transition. Secondly, this is the pioneer study that examines the crucial role of artificial intelligence, digitalization and green finance on energy transition in the context of India. Also, the study highlights the importance of aligning digital transformation with sustainability to achieve the targets of low carbon economy.

Despite being limited, prior studies are broadly confined to the developed and developing world or regional groupings. The literature highlights significant scarcity in the context of India. Beyond this, the literature highlights the critical role of AI, digitalization, and green finance in influencing energy transition. Hence, it becomes vital to explore the nexus among these variable to investigate the unexplored and propose a roadmap for the future. In this regard, this study intends to address following research questions in Indian context: First, does artificial intelligence promote renewable energy? Second, do rising digitalization influences renewable energy? Third, what role does green finance play in fostering renewable energy? By delving on these research questions, this study contributes to the existing literature on sustainability.

Subsequent to a detailed introduction (section1), this research is organized as follows. Section 2 summarizes the existing literature in this domain. Section 3 details about the data and methodology followed. Section 4 shows the econometric design of the study and section 5 discusses the empirical findings of the analysis. This is followed by section 6 conclusion, research limitations, and recommendations for future policy making.

## 2. Literature Review

This paper aims to delve upon the relationship between RE consumption and AI, digitalization, green finance. To get the theoretical and methodological understanding of the topic under study, it is important to delve upon the existing literature. The deep examination of the existing literature will help us understand the existing knowledge in the domain of RE, AI, digitalization, green finance and sustainability. The scholarly articles were collected from the Scopus database and related articles were identified for further review.

Prior studies have found that renewable energy plays an important role in achieving environmental sustainability across several countries (Dong *et al.*, 2018) [13], (Deng *et al.*, 2024) [10], (Chen *et al.*, 2025) [8]. Globally, increased renewable energy consumption lowers CO2 emissions (Ranthilake *et al.*, 2024) [48], (Huang *et al.*, 2022) [24], (Ahmad *et al.*, 2023) [2]. Several factors such as economic growth, industrialization, trade, financial development, urbanization and natural resource rent etc. influence the relationship between renewable energy and sustainability. Economic growth increases emissions (Ahmad *et al.*, 2023) [2] but RE transition has a favorable influence on economic growth as well as environment sustainability (Hwang, 2023) [25]. Further, industrialization has a key role in promoting as well as hindering green growth (Murshed, 2024) [42]. It is worth mentioning here that green finance acts as a boost in scaling RE which ultimately leads to emission reduction (Yadav *et al.*, 2024) [71].

Artificial intelligence has a crucial role to play in the industrial transformation. Increased use of AI in all the spheres of life is going to raise the demand for energy. On the same time, AI can play crucial role in low carbon transformation of energy sector. Innovation in AI has a potential to achieve sustainability targets of a country (Tao *et al.*, 2024) [58]. Artificial intelligence has a potential to act as a facilitator of RE development (Zhang *et al.*, 2024) [74], (Zhao *et al.*, 2024) [75]. Despite that, the promoting effect is enhanced by increased environmental regulations by the government (Dong *et al.*, 2024) [14]. Table1 includes review of available literature on the nexus between AI and RE. Innovation and technological development is found to be the driving forces of RE (Awijen *et al.*, 2022) [4]. Information and communication technologies (ICT) can play a crucial role in developing energy efficient buildings (Rawte, 2017) [50]. Digital technologies such as internet of things can act as a facilitator in RE adoption (Mishra *et al.*, 2022) [41]. As evidenced worldwide, digitalization has harmful effects on environment by increasing harmful emissions (Gyamfi *et al.*, 2022) [19], (Awad *et al.*, 2023) [3], (Xie *et al.*, 2024) [70]. On the other hand, it has a positive impact on RE consumption of a country (Lee *et al.*, 2023) [32], (Wang *et al.*, 2024) [55], (Talan *et al.*, 2023) [25], (Gyamfi *et al.*, 2023) [20]. Further, ancillary effects of increased ICT include increased investment in RE (Evans, 2023) [35]. Rising investments in RE reduces ecological footprint in the country (Lin *et al.*, 2024) [35]. Table 2 shows the detailed literature review available in the context of digitalization and RE consumption. The literature survey shows that earlier studies have focused on the regional groupings as the basis of examining the influence of digitalization on RE consumption.

Green finance is the mobilization of finance towards environment friendly infrastructure and projects (Simionescu and Gavurová, 2023) [53]. Green finance has a key role in achieving sustainability especially in developing countries. Developing countries have potential to pursue environment friendly policies but they lack financial resources. In this situation, developed nations committed to provide financial aid to mitigate the impact of climate change. Green finance and RE can support in achieving the targets of environment sustainability (Tariq and Hassan, 2023) [59]. Further evidence shows that green finance helps in reducing carbon emissions. Table3 shows review of existing literature on the interconnection between green

finance and RE. However, there are two strands of literature on green finance. Studies such as (Tariq and Hassan, 2023) [59], (Wei *et al.*, 2023) [68], (Tiwari *et al.*, 2024) [61], (Quang and Thao, 2022) [47] means green finance as green financial instruments such as green credit, green bonds, and green securities etc. While other studies (Mahalik *et al.*, 2021) [40], (Ikegami and Wang, 2021) [26], (Yang *et al.*, 2024) [65], mean green finance as the international assistance received for RE development. Further, (Sinha *et al.*, 2023) [54] considers environment tax revenue as a proxy for green finance. However, the literature review exhibits that prior studies have not specifically focused on the effect of RE development in India.

In nutshell, exploration of existing literature reveals that the role of artificial intelligence, digitalization, and green finance on RE consumption is not explored in the context of India. Hence, present study aims to fill the gap in the literature by testing following hypothesis:

- **H1:** Artificial intelligence has a influencing effect on renewable energy consumption.
- **H2:** Digitalization has a significantly positive influence on renewable energy consumption.
- **H3:** Green finance has a promoting effect on renewable energy consumption.

**Table1:** Review of Literature on RE and artificial intelligence**:**

| Sample | Variables | Methodology | Result | Reference |
|---|---|---|---|---|
| China 2015-2023 | Role of AI in promoting energy transition | Wavelet-based QQ approach | Negative influence of AI on RE generation and investment in short run. AI has a promoting effect in long run. | (Zhao *et al.*, 2024) [75] |
| | Integration of AI with RE on large scale | Conceptual | | (Liu *et al.*, 2022) |
| China 2014-2016 | AI impacts RE development Positive impacts of AI in long run | Wavelet analysis | Initially, the role of AI is low but as AI technology advances it reduces the tech challenges and cost reduction of AI. Also, AI investors start considering investments in RE. | (Zhang *et al.*, 2024) [74] |
| 61 countries 2000-2019 | Examines the role of AI on RE supply chain and spillover effects of AI on neighboring countries | Mixed-methods | AI has a promoting effect By reducing RE supply chain vulnerability in host and neighboring countries through tech innovation, improving governance system and trade network promotion. | (Song *et al.*, 2024) [55] |
| | Application, challenges and approach to overcome these challenges. | Review | | (Bennagi *et al.*, 2024) [6] |
| China 2013-2023 | Role of AI and climate policies on RE development. | NARDL | Strong positive influence of AI on RE development and decline in AI has a strong influence than increase. | (Tian *et al.*, 2024) [60] |
| China 2006-2021 | Role of AI in driving low carbon energy | Mixed method | AI stimulates clean energy transformation. Innovation driven AI has more encouraging impacts on transition towards low carbon energy. | (Tao *et al.*, 2024) [28] |
| Panel data of 50 countries 2002-2019 | Impact of AI on energy transition with threshold effect of regulatory quality | Regression Analysis | AI has a significant positive impact on energy transition. The impact of AI on energy transition depends on regulatory quality of the government. Moderate level of regulations influence the positive impact of AI on energy transition. | (Dong *et al.*, 2024) [14] |
| Panel of 63 countries 2000-2019 | Role of AI in promoting RE development | GMM model | AI exerts significantly positive influence on RE. Also, technology and innovation enhances this effect. | (Zhao *et al.*, 2024) [75] |
| Panel of 69 countries 1993-2019 | Role of AI in promoting energy transition and carbon emission reduction | STRIPAT and Panel threshold | Several factors such as trade openness, income level of countries, and technological level influences the impact of AI on RE development | (Wang *et al.*, 2024) [55] |

Source: Authors' own work

**Table 2:** Review of literature on RE and digitalization

| Sample | Theme | Methodology | Result | Reference |
|---|---|---|---|---|
| ASEAN countries 1995-2023 | Effect of digitalization, and supply chain globalization on RE consumption | MMQR and PCSE | Digitalization of ICT has negative impact on RE consumption. | (Chen *et al.*, 2025) [8] |
| China | Analyzed the effect of digital economy in RE development | PCSE | Digital economy accelerates RE and physical capital acts as a positive mediator. | (Ma *et al.*, 2024) |
| 1990-2022 | Role of green supply chains and digitalization on renewable energy innovations and the influence of inflation and financial development | Wavelet quantile regression | Strong influencing effect in long run. | (Huang and Tan, 2025) [23] |
| G7 countries 1990-2020 | Explores the effect of supply chain disruptions, digitalization, economic growth, democracy, and globalization on RE innovations. | Moment quantile regression | Economic growth and digitalization have a promoting effect. | (Wang *et al.*, 2024) [55] |
| G7 countries 1990-2018 | Role of ICT, fossil fuel use, democracy and financial inclusion on RE use. | MMQR and Granger causality test | ICT has a significant positive impact and bi-directional causality with RE use. | (Talan *et al.*, 2023) [57] |
| Highly | Nexus between ICT development and RE | CS-ARDL | Positive inter-connection between ICT | (Luo, 2023) |

| | | | | |
|---|---|---|---|---|
| polluted economies 1998-2021 | investments | | and RE investments in long run but insignificant in short-run. | |
| 22 leading AI countries 1991-2020 | Effect of AI, ICT and natural resources, economic growth on RE production | Panel NARDL | AI and ICT exhibits promoting effect on RE production. | (Rasheed *et al.*, 2024) [49] |
| BRICS 2000-2020 | Role of ICT on RE generation | Dumistrec Hurlin Panel Causality test | RE generation causes ICT. Integration of good governance with ICT has a supporting effect on RE. | (Jiang *et al.*, 2023) [29] |
| Six African countries 1995-2020 | Effect of oil prices, ICT, and economic growth on RE investments | NARDL | Positive relation between ICT and RE investments. | (Evans, 2023) [35] |
| 35 countries | Effect of ICT and financial development on RE consumption | Threshold effect model | ICT has a promoting effect on RE consumption. | (Yu *et al.*, 2023) |

Source: Authors' own work

**Table 3:** Review of existing literature on RE and green finance:

| Sample | Theme | Methodology | Result | Reference |
|---|---|---|---|---|
| Panel of 70 countries | Green finance, carbon finance, RE, economic activity and environment regulations | GMM | RE reduces CO2<br>Green finance reduces CO2<br>Carbon finance has no impact | (Tariq and Hassan, 2023) [59] |
| China 2011-2020 | Impact of digital financial inclusion on RE | Feasible Generalized Least Squares (FGLS) | Positive impact on RE production and consumption | (Wei *et al.*, 2023) [68] |
| Select asian countries | Impact of Green finance, RE on carbon emission | Panel quantile autoregressive distributed lag (QARDL) model | Negative impact of GF on carbon intensity across all quantiles in short and long run<br>REC reduces emissions in long run | (Du, 2023) |
| USA 1985-2020 | Effect of Green finance on RE | Multivariate Quantile-on-Quantile Regression" (m-QQR) | Economic policy ucertainity, unemployment rate and business confidence moderates the impacts the association of green finance and RE. | (Sinha *et al.*, 2023) [54] |
| USA 2008-2022 | Role of RE, energy innovations and green finance in energy transition | Dynamic Autoregressive Distributed Lag simulations (DARDLS) | Strong influence of green finance on energy transition in long run as compared to short run. | (Tiwari *et al.*, 2024) [61] |
| G7 economies | Effect of green finance and RE on carbon emissions | Regression modelling | Green finance and RE reduces CO2 emissions. | (El Khoury *et al.*, 2024) [16] |
| Chinese provinces | Impact of GF on RE development efficiency | System GMM | Positive effect of Green finance on RE development. | (Zhou *et al.*, 2024) [65] |
| China | Role of green finance on investments potential of RE companies | Dynamic panel threshold model | Green finance initiatives increases investment in RE | (Wang and Fan, 2023) [25] |
| Singapore 2000-2020 | Influence of green finance on RE development | Dynamic ordinary least squares (DOLS) regression | Green finance facilitates adoption of RE projects<br>Reduces financial risk of RE investments | (Subramaniam and Loganathan, 2024) [56] |
| ASEAN 2000-2018 | Role of natural resources and green finance on RE development and abating climate degradation | MMQR method | Green finance and ecological conservation are critical drivers of RE adoption | (Yang *et al.*, 2024) [65] |
| ASEAN 2017-2020 | Effect of green bonds on energy efficiency | Two-stage GMM model | Green bonds have negative effect on energy intensity in short run. | (Quang and Thao, 2022) [47] |
| 64 energy aid recipient countries 1995-2014 | Role of energy aid received on countries' CO2 emissions | System GMM | Energy aid reduces CO2 emissions.<br>The effect of energy aid is not strong in fossil fuel rich countries. | (Ikegami and Wang, 2021) [26] |
| India 1978-2014 | Role of foreign aid and energy aid inflow on CO2 emissions | ARDL | Foreign energy aid exacerbate emissions, whereas as foreign aid reduces it. | (Mahalik *et al.*, 2021) [40] |

Source: Authors' own work

## 3. Data and Methodology

In this research, accessible time-series data was sourced ranging from 2000 to 2022. The availability of data on AI, digitalization, and green finance decided the timeframe of this study. This study evaluates several important factors comprehensively as shown in Table4. The data for RE consumption, Internet, Broadband, Carbon emissions (per capita), GDP (per capita), Trade, Industrial value added is retrieved from World Bank's World development indicators (WDI) database. The data for artificial intelligence is taken from International federation of robotics (IFR) and green finance data is sourced from our world in data. The proxies used for variable description is based on the commonly accepted norm in existing literature. Also, all the data series are converted into natural logarithms to ensure normality of the data. The research methodology employed for statistical examination is as follows. Firstly, summary statistics are diagnosed to ensure the normality of data. Then, correlation analysis is performed to check the existence of relation among the variables. Using augmented dickey fuller

(Dickey and Fuller, 1979) [11] and phillips-perron (Phillips and Perron, 1988) [45] unit root test is performed to check the level of stationarity of the data. The long run cointegration among variables is checked using bounds test. Using ARDL, short run and long run estimation are formed. Further, to check the presence of causal relation among the variables granger causality test is performed. Lastly, to validate the robustness of the statistical outcomes Breusch Godfrey serial correlation LM test and Ramsay test are performed.

**Table 4:** Variable definition:

| Variable | Variable Measurement | Abbreviation | Source | Reference |
|---|---|---|---|---|
| RE consumption | RE consumption as a % of total final energy consumption | LN_REC | WDI | (Zhu *et al.*, 2024) [79] |
| Artificial intelligence | Industrial robot inventory | LN_AI | IFR, Robotics | (Dong *et al.*, 2018), (Song *et al.*, 2024) [14, 55] |
| Digitalization | Internet usage among individuals as a percent of total population | LN_INT | WDI | (Haldar *et al.*, 2023) [21] |
| Digitalization | Fixed broadband subscriptions | LN_BR | WDI | (Hwang, 2023) [25] |
| Green finance | International finance received for clean energy | LN_GR | Our world in Data | (Ikegami and Wang, 2021) [26] (Yang *et al.*, 2024) [65], |
| Environment quality | CO2 emissions per capita (tCO2e/capita) | LN_CO2 | WDI | (Tariq and Hassan, 2023) [59] |
| Economic growth | Gross Domestic Product per capita | LN_GDP | WDI | (Wang *et al.*, 2024) [55] |
| Trade | Trade (% of GDP) | LN_TR | WDI | (Wang *et al.*, 2024) [55] |
| Industrialization | Industrial value added (% of GDP) | LN_IVA | WDI | (Lee *et al.*, 2022) [33] |

Source: Authors' creati

## 4. Econometric modeling:

The Auto-regressive distributed lag model (ARDL) is employed in this research was suggested by (Pesaran *et al.*, 2001) [44]. According to (Haug, 2002) [22], this method is found suitable for current study as it provides credible results for small number of observations. Also, it is suitable for the series integrated of mix order, I(0) and (I1).

The ARDL model for long run and short run estimates is as follows:

**H1:** Artificial intelligence has a influencing effect on RE consumption.

$$LN(REC)_t = \alpha_1 \text{LN\_AI}_{t-1} + \alpha_2 \text{LN\_GR}_{t-1} + \alpha_3 \text{LN\_CO2}_{t-1} + \alpha_4 \text{LN\_TR}_{t-1} + \alpha_5 \text{LN\_IVA}_{t-1} + \sum_{i=1}^{\alpha_1-1} \beta_1 \Delta \text{LN\_AI}_{t-i} + \sum_{i=1}^{\alpha_2-1} \beta_2 \Delta \text{LN\_GR}_{t-i} + \sum_{i=1}^{\alpha_3-1} \beta_3 \Delta \text{LN\_CO2}_{t-i} + \sum_{i=1}^{\alpha_4-1} \beta_4 \Delta \text{LN\_TR}_{t-i} + \sum_{i=1}^{\alpha_5-1} \beta_5 \Delta \text{LN\_IVA}_{t-i} + \epsilon_t \quad \text{(Eq. 1)}$$

**H2:** Digitalization has a significantly positive influence on RE consumption.

$$LN(REC)_t = \alpha_1 \text{LN\_INT}_{t-1} + \alpha_2 \text{LN\_BR}_{t-1} + \alpha_3 \text{LN\_GR}_{t-1} + \alpha_4 \text{LN\_CO2}_{t-1} + \alpha_5 \text{LN\_GDP}_{t-1} + \sum_{i=1}^{\alpha_1-1} \beta_1 \Delta \text{LN\_INT}_{t-i} + \sum_{i=1}^{\alpha_2-1} \beta_2 \Delta \text{LN\_BR}_{t-i} + \sum_{i=1}^{\alpha_3-1} \beta_3 \Delta \text{LN\_GR}_{t-i} + \sum_{i=1}^{\alpha_4-1} \beta_4 \Delta \text{LN\_CO2}_{t-i} + \sum_{i=1}^{\alpha_5-1} \beta_5 \Delta \text{LN\_GDP}_{t-i} + \epsilon_t \quad \text{(Eq. 2)}$$

Where, $\alpha_1$, $\alpha_2$, $\alpha_3$, $\alpha_4$, and $\alpha_5$ is long run relation and $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$, $\beta_5$ is short run relation. $\varepsilon_t$ is the error correction term.

### Granger Causality test:

Furthermore, we test granger causality test is a statistical measure to check the causal relation among the variables under study. In accordance with granger causality test, if a Y variable can help in forecasting variable X, then it is said that Y granger causes X. The direction of causal relation among variables holds significance in better understanding of empirical findings.

$$X_t = \sum_{w=1}^{p} \left( a_{11,w} X_{t-1} + a_{12,w} Y_{t-w} \right) + \epsilon_t$$

$$Y_t = \sum_{w=1}^{p} \left( a_{21,w} X_{t-w} + a_{22,w} Y_{t-1} \right) + \exists_t$$

Where p represents the model order and $a_{1,2,w}$ are the coefficients, and the residuals are $\epsilon_t$ and $\exists_t$.

## 5. Empirical evidence and Analysis:

### 5.1 Descriptive Statistics

Table5 summarizes the key features of the data set which includes mean, median, skewness, kurtosis, and jarque bera. These statistics are crucial in testing the normality of the data (Jarque, 2011) [28]. The data spans from 2000 to 2022 for India. The data follows normal distribution because the values of mean and median for all the variables are near to each other. Also, the skewness values are close to zero indicating normality of the distribution (Kim, 2013) [31]. Except RE consumption and industrial value added, all the variables under study are negatively skewed. Kurtosis value signifies leptokurtic distribution of broadband, green finance, and gdp whereas the remaining variables are platykurtic. The probability values shows normal distribution for all the variables except green finance and gdp. Also, the jarque bera values are low indicating normal distribution. Table6 depicts the results of correlation analysis. The results highlight highly negative association of RE with AI, digitalization, green finance, environment quality, economic growth and trade. The strong negative relation with environment quality suggests that RE consumption can have a positive influence in driving sustainability.

**Table 5:** Summary of Descriptive Statistics

| | LN_REC | LN_AI | LN_INT | LN_BR | LN_GR | LN_CO2 | LN_GDP | LN_TR | LN_IVA |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 3.64 | 3.98 | 1.95 | 15.39 | 19.97 | 0.32 | 2.99 | 3.73 | 3.33 |
| Median | 3.58 | 7.70 | 2.30 | 16.46 | 20.23 | 0.38 | 3.00 | 3.77 | 3.31 |
| Maximum | 3.85 | 10.57 | 3.87 | 17.32 | 21.59 | 0.64 | 3.07 | 4.02 | 3.43 |
| Minimum | 3.48 | -9.21 | -0.63 | 10.81 | 16.24 | -0.06 | 2.78 | 3.25 | 3.20 |
| Std. deviation | 0.13 | 8.09 | 1.31 | 2.01 | 1.33 | 0.25 | 0.07 | 0.22 | 0.07 |
| Skewness | 0.39 | -1.01 | -0.33 | -1.21 | -1.45 | -0.33 | -1.63 | -0.79 | 0.00 |
| Kurtosis | 1.52 | 2.13 | 2.17 | 3.04 | 4.94 | 1.55 | 5.45 | 2.79 | 1.84 |
| Jarque Bera | 2.55 | 4.68 | 1.07 | 5.38 | 11.71 | 2.43 | 16.08 | 2.47 | 1.28 |
| Probability | 0.27 | 0.09 | 0.58 | 0.06 | 0.00 | 0.29 | 0.00 | 0.28 | 0.52 |
| Sum | 80.12 | 91.57 | 45.06 | 338.64 | 459.39 | 7.51 | 68.81 | 85.94 | 76.67 |
| SumSq. Deviation | 0.37 | 1443.36 | 37.89 | 85.41 | 39.08 | 1.44 | 0.10 | 1.07 | 0.11 |
| Observation | 22 | 23 | 23 | 22 | 23 | 23 | 23 | 23 | 23 |

**Source:** Authors' own computations

**Table 6:** Correlation Analysis

| 2 | LN_REC | LN_AI | LN_INT | LN_BR | LN_GR | LN_CO2 | LN_GDP | LN_TR | LN_IVA |
|---|---|---|---|---|---|---|---|---|---|
| LN_REC | 1.00 | | | | | | | | |
| LN_AI | -0.87 | 1.00 | | | | | | | |
| LN_INT | -0.90 | 0.84 | 1.00 | | | | | | |
| LN_BR | -0.92 | 0.94 | 0.91 | 1.00 | | | | | |
| LN_GR | -0.79 | 0.75 | 0.75 | 0.81 | 1.00 | | | | |
| LN_CO2 | -0.98 | 0.87 | 0.95 | 0.92 | 0.80 | 1.00 | | | |
| LN_GDP | -0.77 | 0.74 | 0.74 | 0.80 | 0.99 | 0.79 | 1.00 | | |
| LN_TR | -0.56 | 0.68 | 0.48 | 0.74 | 0.56 | 0.51 | 0.57 | 1.00 | |
| LN_IVA | 0.32 | -0.09 | -0.45 | -0.11 | -0.19 | -0.43 | -0.17 | 0.49 | 1.00 |

**Source:** Authors' own Computations

### 5.2 Unit root test results

To check the stationarity of data, we have employed augmented dickey Fuller test and phillips-perron test. The results of unit root test as shown in Table7 suggest that some variables are stationary at level (I0) while others are integrated of order one, (I1). As no variable is found stationary at 2nd difference, ARDL test was found suitable for further analysis.

**Table 7:** Outcomes of unit root test

| | Augmented Dickey Fuller Test | | Phillips-Perron Test | |
|---|---|---|---|---|
| | Log level | 1st Difference (Intercept) | Log level | 1st Difference (Intercept) |
| REC | -2.378** | -3.005*** | -1.469*** | -2.410* |
| AI | -1.520*** | -4.561* | -1.515*** | -4.561* |
| INT | -4.424* | -5.586* | -2.474 | -4.186* |
| BR | -4.000* | -1.266*** | -4.058* | -2.628 |
| GR | -1.774 | -6.347* | -2.058 | -7.168* |
| CO2 | -0.940*** | -3.977* | -0.944*** | -3.955* |
| GDP | -1.815 | -6.511* | -2.097 | -6.854* |
| TR | -2.025 | -3.745* | -2.025 | -3.754* |
| IVA | -3.990** | -4.318*** | -0.685*** | -4.372* |

**Source:** Authors' own computations

### 5.3 Lag Selection Criteria

To proceed further, lags were selected using VAR estimates. The lags for both the models were selected based on LR, FPE, AIC, SC, and HQ. Table8 shows that optimum lags for model 1 is one and for model 2 the optimal lag length is two.

**Table 8:** Lag length selection results

| | Model 1 | Model 2 | |
|---|---|---|---|
| Lag | 1 | 1 | 2 |
| LR | 116.76* | 159.37 | 56.34* |
| FPE | 2.18* | 1.91 | 3.55* |
| AIC | -7.68* | -19.38 | -24.98* |
| SC | -5.59* | -17.29 | -21.10* |
| HQ | -7.22* | -19.03 | -24.32* |

**Source:** Authors' own computations

### 5.4 Bounds Test

Table 9 reveal the outcomes of bound test. In the model 1, F-statistic value of 13.41 is greater than the upper and lower bound value of 2.39 and 3.38 respectively at 5% level of significance. Likewise, bound test results of model 2 shows greater value of F-statistics 3.944 than upper 3.38 and lower bound 2.39 values at 5% significance level. This illustrates that long run cointegration exists between RE consumption and all the variables under consideration in both the models.

**Table 9:** Results of Bounds test

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| **Significance Level** | I(0) | I(1) | I(0) | I(1) |
| 1% | 3.06 | 4.15 | 3.06 | 4.15 |
| 5% | 2.39 | 3.38 | 2.39 | 3.38 |
| 10% | 2.08 | 3 | 2.08 | 3 |
| F Statistics | 13.41 | | 3.944 | |
| k | 5 | | 5 | |

**Source:** Authors' own computations

### 5.5 ARDL estimates

ARDL estimates for long run and short run are derived for both the models. In Eq.1, the impact of AI on RE consumption is assessed. The outcome shown in Table10 reveals that the impact of artificial intelligence is positive in long run but it is insignificant in both long run and short run in India. Prior studies (Zhao *et al.*, 2024) [75] find negative impact of AI on RE consumption in short and medium term. Also, (Zhang *et al.*, 2024) [74] finds that AI has minimal impact on RE development in case of China. The findings are inconsistent with earlier studies (Tian *et al.*, 2024) [60]. But (Chawla *et al.*, 2022) [7] also finds that energy sector has not fully utilized the potential of AI in India. Similarly, green finance exhibit insignificant positive relation with RE consumption. However, industrialization in short and long run exhibit significant negative impact on RE consumption in India. This suggests that a 1% increase in industrialization will decrease RE consumption by 1.25% and 0.32% in short run. On the other hand, trade has significant positive influence on RE consumption which means 1% increase in trade increases RE consumption by 0.29% in long run and 0.08% in short run.

**Table 10:** ARDL estimates for Eq.1

| **Long run estimates** | | | |
|---|---|---|---|
| **Variables** | **Coefficient** | **t-statistics** | **p-value** |
| LN_AI | 0.002 | 1.208 | 0.250 |
| LN_GR | 0.008 | 1.254 | 0.233 |
| LN_CO2 | -0.877 | 0.118 | 0.000 |
| LN_TR | 0.292 | 0.106 | 0.017 |
| LN_IVA | -1.251 | 0.357 | 0.004 |
| C | 6.819 | 8.133 | 0.000 |
| **Short run estimates** | | | |
| LN_TR | 0.080 | -3.345 | 0.029 |
| LN_IVA | -0.329 | -3.345 | 0.005 |
| ECM(-1) | -0.580 | -11.870 | 0.000 |
| $R^2$ | 0.87 | | |
| Adjusted $R^2$ | 0.86 | | |

**Source:** Authors' own computations

In Eq.2, the evolving linkage between RE consumption and digitalization is examined. Table 11 shows the results of long run and short run estimations. The result indicates that 1% increase in internet can cause 0.1% increase in RE consumption in the long run. Similarly, broadband exhibits a significantly negative influence on RE consumption in the long run. Further, green finance and economic growth shows insignificant and negative association with RE consumption. Moreover, CO2 shows significantly negative relation with RE consumption in long run. The result conveys that 1% rise in emissions leads to 0.72% decrease in RE consumption.

The value of ECM (-1) indicates the speed of adjustment towards long run equilibrium. The negative value -0.57 means that the model comes back to equilibrium after a shock. The R2 value of 95% is consistent with earlier studies (Wang *et al.*, 2024) [55]. Further, the finding signifies that a 1% increase in internet increases RE consumption by 0.02%. However, the effect of internet is statistically not strong. Interestingly, the broadband has a significant positive effect on RE development in short run. Also, economic growth has significant positive effect on RE. The result signifies that 1% increase in economic growth lead to 4% increase in RE. The effect of green finance on RE is negative. A 1% growth in green finance decreases RE consumption by 0.19%. However, the lagged value of green finance is significant and positive which suggests a delayed positive effect of green finance on RE consumption. CO2 emissions have a negative impact on RE consumption. However, the lagged value of CO2 shows that previous

years' emission have significant positive effect on RE consumption.

The outcomes of negative relation between CO2 emission and RE consumption are consistent with earlier studies (Dilanchiev *et al.*, 2023) [12] in Bulgaria, and (Achuo and Ojong, 2023) [1] in Africa and (Işık *et al.*, 2024) [27] in OECD countries. Further, (Ikegami and Wang, 2021) [26] and (Kablan and Chouard, 2022) [30] also finds that the aid received by the fossil fuel dominant developing countries for energy sector shows insignificant impact on emissions. Also, (Mahalik *et al.*, 2021) [40] concludes that energy aid received has exacerbated emissions in India. This justifies our finding that green finance has insignificant impact on RE consumption.

**Table 11:** ARDL estimates for Eq.2

| **Long run estimates** | | | |
|---|---|---|---|
| **Variables** | **Coefficient** | **t-statistics** | **p-value** |
| LN_INT | 0.118 | 2.627 | 0.046 |
| LN_BR | -0.081 | -2.599 | 0.048 |
| LN_GR | -0.279 | -0.502 | 0.636 |
| LN_CO2 | -0.719 | -3.651 | 0.014 |
| LN_GDP | 7.677 | 0.782 | 0.469 |
| C | -12.576 | -0.690 | 0.520 |
| **Short-run estimates** | | | |
| D(LN_INT) | 0.020 | 2.282 | 0.071 |
| D(LN_BR) | 0.085 | 6.627 | 0.001 |
| D(LN_GR) | -0.189 | -6.317 | 0.001 |
| D(LN_GR (-1)) | 0.178 | 4.658 | 0.005 |
| D(LN_CO2) | -0.431 | -10.135 | 0.000 |
| D(LN_CO2(-1)) | 0.288 | 4.806 | 0.004 |
| D(LN_GDP) | 4.237 | 7.010 | 0.000 |
| D(LN_GDP(-1)) | -4.223 | -5.291 | 0.003 |
| C | -0.574 | -7.793 | 0.000 |
| $R^2$ | 0.95 | | |
| Adjusted $R^2$ | 0.92 | | |

**Source:** Authors' own computations

### 5.6 Granger Causality Test

The outcomes of Granger causality test are shown in the table12, depicts the relationship between the variables. Granger causality test shows the direction of causality between variables, such as towards right (→) and bi-directional causal relation (↔) when both the variables cause each other. This test shows presence of causal relation when the null hypothesis is rejected at significance level. To simplify the findings, the table shows only those outcomes which shows causal relation among the variables.

The result demonstrates that RE consumption has a bi-directional causality with industrialization. Further, industrialization has a bi-directional causality with CO2 emissions. This implies that they both accelerate each other. It is crucial to emphasize here that RE consumption, artificial intelligence, digitalization, trade and CO2 emissions granger causes green finance. Therefore, all these variables become important for receiving international aid for the development of clean energy in India. Furthermore, broadband outreach exhibits bi-directional causality with green finance and economic growth. Additionally, artificial intelligence does not exhibit causality with CO2 emissions, trade, broadband, and internet. Further, trade does not granger causes CO2 emissions, broadband, internet, and RE consumption. Also, RE consumption does not cause CO2 emissions which are consistent with earlier study (Saidi and Omri, 2020) [52] in long run.

**Table 12:** Results of Granger Causality Test

| **Null hypothesis** | **F- Statistics** | **Decision** | **Direction** |
|---|---|---|---|
| LN_REC does not Granger-cause LN_IVA | 8.823 | Reject | REC↔IVA |
| LN_IVA does Granger-cause not LN_REC | 4.462 | Reject | |
| LN_REC does Granger-cause not LN_GR | 11.969 | Reject | REC→GR |
| LN_BR does Granger-cause not LN_REC | 4.540 | Reject | BR→REC |
| LN_REC does Granger-cause not LN_GDP | 11.266 | Reject | REC→GDP |
| LN_AI does Granger-cause not LN_IVA | 5.481 | Reject | AI→IVA |
| LN_AI does Granger-cause not LN_GR | 8.398 | Reject | AI→GR |
| LN_AI does Granger-cause not LN_GDP | 9.238 | Reject | AI→GDP |
| LN_IVA does Granger-cause not LN_CO2 | 6.149 | Reject | IVA↔CO2 |
| LN_CO2 does Granger-cause not LN_IVA | 16.904 | Reject | |
| LN_CO2 does Granger-cause not LN_GR | 10.318 | Reject | CO2→GR |
| LN_BR does Granger-cause not LN_CO2 | 3.881 | Reject | BR→CO2 |
| LN_CO2 does Granger-cause not LN_GDP | 9.916 | Reject | CO2→GDP |
| LN_TR does Granger-cause not LN_IVA | 5.157 | Reject | TR→IVA |
| LN_GR does Granger-cause not LN_IVA | 4.790 | Reject | GR→IVA |
| LN_BR does Granger-cause not LN_IVA | 6.486 | Reject | BR→IVA |
| LN_GDP does Granger-cause not LN_IVA | 4.537 | Reject | GDP→IVA |

| | | | |
|---|---|---|---|
| LN_INT does Granger-cause not LN_IVA | 4.296 | Reject | INT→IVA |
| LN_TR does Granger-cause not LN_GR | 3.772 | Reject | TR→GR |
| LN_TR does Granger-cause not LN_GDP | 4.063 | Reject | TR→GDP |
| LN_BR does Granger-cause not LN_GR | 13.517 | Reject | BR↔GR |
| LN_GR does Granger-cause not LN_BR | 10.314 | Reject | |
| LN_INT does Granger-cause not LN_GR | 9.931 | Reject | INT→GR |
| LN_GDP does Granger-cause not LN_BR | 12.848 | Reject | GDP↔BR |
| LN_BR does Granger-cause not LN_GDP | 16.285 | Reject | |
| LN_INT does Granger-cause not LN_GDP | 10.630 | Reject | INT→GDP |

**Source:** Authors' own computations

### 5.7 Diagnostic test

To diagnose the credibility of ARDL test, Breusch Godfrey Serial correlation LM test is carried out to test the presence of serial correlation. The p-values of this test for both the models are greater than 5% level of significance. This means that the null hypothesis cannot be accepted and the model does not demonstrate serial correlation. Further, Breusch Pagan Godfrey test was conducted to check heteroskedasticity. As the p-values are greater than 0.05, both the model are found to be homoscedastic. As there is no presence of serial correlation and heteroskedasticity, the results of ARDL are found to be validated.

**Table 13:** Results of serial correlation and heteroskedasticity

| | P-value | | Decision |
|---|---|---|---|
| | Eq.1 | Eq. 2 | |
| Breusch Godfrey Serial correlation LM test | 0.4923 | 0.29 | No Serial Correlation |
| Breusch Pagan Godfrey test | 0.9669 | 1.00 | No heteroskedasticity |

**Source:** Authors' own computations

## 6. Conclusion

Environment issues are a growing concern and cleaner sources of energy sparks hope in overcoming such issues. The present study examined the interconnection between RE consumption and the emerging aspects of technology such as artificial intelligence, and digitalization in India. Also, researchers assessed the role of international aid received for energy development. The study was conducted using time series data from 2000 to 2022. The short run and long run estimates were made using ARDL and the causal relation is checked using Granger causality test. The research outcomes provide some crucial insights and add to the existing literature.

In nutshell, the outcomes suggest that artificial intelligence has insignificantly positive impact on RE consumption. Industrialization negatively impacts RE consumption in both long and short run. Further, trade has influencing effect on RE consumption. Also, the result reveals that increase in internet usage significantly increases RE consumption in long run but it is insignificant in short run. Whereas, broadband significantly decreases RE consumption in long run and increases in short run. Economic growth has insignificant impact in long run but a significantly positive effect in short run. Green finance has insignificant impact on RE consumption. Further, estimates show a negative relation between CO2 emission and RE consumption.

This study has a limitation. The data availability for the variables under study was limited for a condensed timeframe. This may have restricted the elaborate statistical analysis. However, the present study is pioneer to statistically examine this phenomenon.

### 6.1 Policy implications

Based on the evidence, the present research provides policy insights for future decision making.

Firstly, the effect of artificial intelligence has a positive but insignificant impact on RE consumption. This result can be attributed to the fact that the usage of AI is at nascent stage in India. In this scenario, government should serve as a guiding force through resources as well as policies. The government should provide flexible regulatory environment to promote the integration of AI in energy sector. Government can provide subsidies to enhance private sector participation. Also, research and development expenditure should be channelized in the direction of convergence of AI and energy sector. Artificial intelligence can provide significant advantages in terms of smooth energy transition, reduction in costs, energy efficiency, and smart monitoring (Ukoba *et al.*, 2024) [62].

Secondly, digitalization and energy consumption has a strong positive relation as increase in digitalization in the economy increases energy consumption and carbon footprints. Our findings also suggest the significant and positive relation between digitalization and RE consumption in long run and short run. However, the positive impact of digitalization can be enhanced by leveraging cost effective renewable technology in achieving sustainability target. Digital technologies can be beneficial in greening the conventional energy system as well as RE adoption. However, high cost and lack of technical know-how are the main constraints (Luthra *et al.*, 2015) [38]. The policymakers should frame a strategy to encourage investments in ICT enabled energy systems and provide incentives for energy transition.

Importantly, the result unveiled the insignificant role of green finance in promoting RE consumption in India. This is due to the fact that green finance received for clean energy technologies is utilized for the development purposes instead of building sustainable energy (Kablan and Chouard, 2022) [30], (Mahalik *et al.*, 2021) [40]. Given these conditions, the policymakers need to consider climate policies that focus on energy aid being utilized for the intended purpose. Firstly, this will be helpful in efficient and sustainable use of energy aid. Secondly, the positive outcomes of this efficient utilization will result in more aid disbursements by the developed countries. This phenomenon is confirmed by the results of granger causality test stating RE consumption causes green finance.

Further, the negative relation between RE consumption and CO2 emission suggest that policymakers should incentivize the large scale adoption of RE in India. Ultimately, all these policy measures will help in achieving SDG7 and sustainability targets in India.

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