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Artificial Intelligence and the Next-Gen Supply Chain: Energy-Economy Linkages in the United States

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Abstract

This study delves into the complex connections between AI advancements, energy usage, industrialization, population increase, GDP growth, and the cumulative effect on the ecological footprint (EF) in the United States from 1996 to 2022. The advanced econometric methods like unit root tests (ADF, P-P, and DF-GLS) were applied in the study to examine the non-stationary variables. Furthermore, the Autoregressive Distributed Lag (ARDL) was utilized for both short and long-term effects, and the paper delivers a comprehensive analysis of the dynamics of environmental sustainability. Additional validation of the ARDL findings comes from robustness checks done on FMOLS, DOLS, and CCR estimation. The findings indicate that there is a positive correlation between the growth of GDP, energy consumption, industrialization, and increase in population and EF, which implies that more economic activities, increased industrial expansion, and a rise in the population cause increased levels of pollution and depletion of resources. In contrast, AI innovation exhibits a negative correlation with the EF, indicating that AI advancements can mitigate environmental degradation by optimizing resource usage and promoting sustainable practices. These results demonstrate how AI innovation and renewable energy sources can improve environmental well-being while tackling the problems caused by industrialization and GDP growth. In order to achieve equilibrium between growth in the economy and environmental conservation, the investigation highlights the necessity of tailored regulations that encourage the use of alternative energy sources, environmentally friendly industrial processes, and AI-driven long-term viability systems. Policymakers can leverage these insights to foster sustainable innovation while reducing the environmental impact of population and industrial growth.

Keywords: Artificial intelligence innovation, Energy use, Economic growth, Ecological footprint, USA.

1 | Introduction

Over the past few years, the globe has faced enormous and critical difficulties related to global warming, rising temperatures and ecological constraints. Countries' pursuit of financial prosperity frequently results in

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elevated energy consumption, the primary contributor to environmental damage [1], [2]. The USA is recognized as the leading source of global CO_2 emissions, which have significant implications on the overall Greenhouse Gases (GHGs) in the environment [3]. The United States is the second-highest contributor of CO_2 since it consumes 16% of the world's energy while only making up 4.3% of the world's population [4]. Moreover, there has been a visible shift towards green power, with a strong 13% worldwide capability rise in 2022 [5]. The United States' consumption of energy in 2023 produced 4.8 billion metric tons of carbon dioxide ($GtCO_2$), which is 2.7% lower than the previous year. There has been an almost 20% reduction of U.S. CO_2 emissions from energy use since 2005 [6]. The United States has grown rapidly in recent years because of major technological progress [7]. Major expenditures in science and innovation have facilitated the expansion of the US economy, illustrating the nation's commitment to leveraging technology for long-term growth. The United States is already dominating in many countries for technology improvements, especially in the rapidly growing field of AI that highlights the country's interests in advanced technology [8]. The complex interaction of organizational, social, economic, and technical activity results in the destruction of the surroundings; thus, we posit that environmental shifts stem from multiple variables, including GDP growth, energy consumption, AI innovation, industrialization, and urbanization, among others in the USA.

The United States' economic expansion intrinsically correlates with the increasing trend of CO_2 emissions [9]. There exists a positive correlation between ecological degradation and the real output, which contributes to the rapid deterioration of the economy within the country. Considering the dominance of the USA as well as the dependence on fossil fuels by the USA in the international growth of GDP [10], it is shocking how the releases of carbon are still increasing [11]. Ecological gains of AI are more visible in honorific stages of its development, enhancing its ability to reduce EF and CO_2 outputs as well as facilitating shifts in energy [12]. The function of AI in saving the environment is diverse, involving the surveillance of natural systems, safeguarding species in danger, and managing natural assets [13]. AI can substantially aid in biodiversity conservation and the advancement of sustainable practices through novel tracking, security, and supervision technologies. However, fulfilling careful consideration of the legal, social, and technical aspects of AI development, with an emphasis on designing systems that are not only successful but also balanced and durable [14]. Moreover, the United States is prioritizing the proper advancement of AI technology to improve worldwide safety and wealth. It aims to solve pressing world problems such as the safety of food, ecological problems, and health dangers by partnering with foreign countries to create virtual communities, decrease risks, and ensure balanced artificial intelligence innovation [15].

The energy requirements of numerous rising nations predominantly rely on nonrenewable power resources [16]. Fossil fuel-based energies are inexpensive yet destructive. In contrast, energy from green supplies is expensive yet resilient. An increase in fossil fuels for use and manufacturing operations would result in an increase in energy and CO_2 emissions [17]. In 2023, the total primary energy usage in the United States reached around 94 quadrillion Btu [18]. In 2022, CO2 emissions from fossil fuel burning, natural gas usage, and petroleum utilization increased by 8%, 5%, and 1%, respectively. However, CO2 emissions from burning coal dropped by 6% relative to 2021 [19]. While there is an increasing share of renewables in total energy consumption, the substantial increase in energy demand upon industrialization, urbanization, and globalization in the last few decades makes a just transition from non-renewable to renewable energy difficult [20]. The use of non-renewable sources of energy may require some forceful measures to ensure protection and conservation of fossil fuel reserves, which affect stability and geopolitical issues. However, regulation has the potential to stimulate the development of renewable energy infrastructure, but only if governments spend money on creating sustainable military facilities [21], [22]. Furthermore, swift industrialization significantly contributes to GHGs and can affect the dynamics of instability. The expansion of manufacturing can elevate fossil fuel use, thereby augmenting CO2 and other GHGs. In addition, industry leads to deforestation and urbanization.

This work significantly enhances the existing experience base by tackling important deficiencies in previous studies on environmental sustainability. This study applies the Ecological Footprint (EF), which is a known and wide measure of environmental condition, in contrast with previous studies that predominantly used CO_2 emissions as a proxy for ecological well-being. Therefore, this work quantifies EF, providing substantial and practical insights for fostering equal growth in the USA and worldwide. In addition, it examines the impacts of economic growth, AI innovation, and energy consumption on ecological quality in the USA, drawing from the recent statistics from 1990 to 2022. The present empirical study applies the novel Autoregressive Distributed Lag (ARDL) limits testing approach in the STIRPAT framework and confirms its results based on FMOLS, DOLS, and CCR. The results show that while AI innovation improves the quality of biodiversity, things like energy use, economic growth, industrialization, and urbanization have a destructive influence on the health of ecosystems in the USA. Therefore, with these contributions our work is to clarify the intricate link between the chosen factors and EF, hence directing future academic efforts towards greater knowledge and effective actions.

We structure the remaining portion of this investigation in a specific sequence. Section 2 scrutinizes relevant literature, Section 3 describes methodology and data, Subsection 4 analyzes the expected outcomes and discussion, and the latter section concludes the examination with the policy implications.

2 | Literature Review

At the outset, economies emphasized enhanced output as a foundation for societal improvement, establishing a robust connection between economic progress and ecological sustainability [23]. Researchers from all over the world have been looking at the correlation between GDP growth and environmental harm over the last few years, and their findings have been quite divergent [24]. For instance, Rahman et al. [25] study the causal effects of agriculture, GDP growth, and energy consumption on ecosystem damage in Bangladesh during 1971-2022. They employ the DOLS estimation and discover that ecological harm increases with rising GDP. Ahmad et al. [26] conducted an ARDL regression to discover how advances in the economy and technology shape eco-damage in China. The DOLS shows that if the GDP increases by 1%, CO_2 emissions rise by 0.51%. Raihan et al. [27] investigate the intertwined relationship between economic growth, energy usage, and CO_2 emission in Bangladesh from 1974 to 2022. Using the technique of the ARDL limit test, they established that an increase in GDP by 1% would lead to a 0.13% increase in CO_2 emissions. A similar conclusion was also recorded by Ahmed et al. [28] in China, and Saud et al. [29] in BRI countries. Conversely, Ridwan et al. [30] investigate the effect of urbanization, industrialization, and GDP in six South Asian countries from 1972 to 2021. They applied DKSE methodology and concluded that GDP significantly decreases CO_2 emissions. Mehmood et al. [31] assessed the GDP stimulus of the G-7 areas' initiatives to reduce GHGs from 1990 to 2020. This CS-ARDL model shows an inverse relationship between GDP and CO2 emissions. In addition, Raihan et al. [32] investigate the effect of GDP on the environment of China from the year 1993 to 2022. The ARDL technique was used in the study, and hence increased economic growth can bring down emission levels in the future.

Through the extent of AI use, it will be easier to ameliorate ecosystem damage, prioritize resources' execution, and unveil new disclosures. Few researchers have sharpened their awareness of the aggressive progress of AI and focused the investigations on its macroeconomic implications [33]. According to Chen et al. [34] AI can reorganize industrial segments, increase speedy development of budding areas, increase efficiency in consumption of energy as well as change company structures and further develop integrity of ecological realm. Ridwan et al. [35] discuss the impact of AI technology on developing the environment in the United States between 1990 and 2019. Upon using the ARDL approach, they found that AI technology had a positive correlation with LCF in the short and long terms. Bala et al. [36] explore how AI innovation impacts environmental sustainability in the G-7 region between the years 2010 and 2022. This work uses Panel ARDL and Quantile Regression analysis methods and found a significant positive relation between AI innovation and ecological health. In the same way, Hossain et al. [37] look at the impact of AI innovation on the environment in the Nordic region, where they use data from 1990 to 2020. They utilized the ARDL paradigm and found that the AI innovation significantly and positively affects the level of improved ecological health both in the short and long term. Moreover, several researchers also found same outcome such as Akther et al. [38] in USA, Atasoy et al. [39] in USA, and Dai [40] in Europe.

Nathaniel et al. [41] analyze the effects of conservation measures on EF in the Next-11 nations from 1990 to 2016. Their socioeconomic analysis shows that EF is amplified by rising energy consumption. Between 1990 and 2020, Raihan et al. [42] studied the connections between Vietnam's the expansion of GDP, energy use, and the health of ecosystem. The DOLS method proves that energy consumption degrades ecological integrity. In their analysis of the EF in the UK from 1970 to 2015, Eweade et al. [43] consider the effects of energy consumption and globalization. The ARDL limit test indicates that energy use positively influences the EF. Also, from 1972 to 2021, Pattak et al. [44] use the STIRPAT paradigm to explain how nuclear, clean, and non-green energies affected the release of CO_2 in Italy. The results show that CO_2 emissions can grow by 1.505 % for every 1% increase in the use of fossil fuels over a long period of time. On the other hand, Sun et al.[45] look at how BRICS nations' energy consumption affects them. Using the quantile-on-quantile technique, they find that for most quantiles in South Africa, energy consumption has a detrimental impact on EF, whereas for most quantiles in China and India, it has a positive effect. Conversely, Rahman et al. [46] analyze the implication of industrialization and green power on the EF of the ten most populous countries from 1990 to 2020. It utilizes ARDL, PMG, and MMQR regression methods and demonstrates that renewable energy usage significantly negatively impacts the EF. The encouraging connection between energy consumption and EF were illustrated by Raihan et al. [47] in India, and Khan et al. [48] within India.

According to Yang et al. [49], industrialization has increased the release of CO_2 and established a large environmental impact. Voumik and Ridwan [50] adopted the STIRPAT model to determine the implication of industrialization on the environment in Argentina from 1972 to 2021. The data demonstrate that INDUS adversely affects the ecology in Argentina over the long term. Aslam et al. [51] investigates the effect of INDUS on the EF of 11 East Asian and Pacific nations from 2000 to 2023. The FMOLS method and panel quantile regression indicated that industrialization amplifies the EF. Nevertheless, Munir and Ameer [52] used the non-linear ARDL method to show how INDUS caused ecological destruction in Pakistan between 1975 and 2016. They observed that heightened INDUS exacerbates the loss of ecosystems, whereas diminished industrialization had no impact on the ecosystem. In contrast, Ridwan et al. [53] analyze the ecological consequences of financial growth and INDUS in the United States from 1990 to 2022. The ARDL bounds test established an upward trend between industrialization and LCF. Yang and Usman [54] examined the effects of industrialization on EF from 1995 to 2018 across ten nations. The author employed the STIRPAT model and determined that INDUS increases the EF. Furthermore, Patel and Mehta [55] evaluated the disparate effects of INDUS on the environment in India employing the NARDL model. The research indicated that INDUS markedly decreases CO_2 emissions in the long term.

The impact of human population on the natural world can have positive and negative outcomes. Population growth has negative effects on the ecosystem since it causes energy consumption to increase [56]. By analyzing data from 50 large, complex economies between 1990 and 2018, Abbas et al. [57] determine the impact of several variables on EF. According to the results obtained using an expanded STIRPAT equation, the EF is negatively affected by the larger population. Using data from 1990–2017, Javeed et al. [58] analyze the EF in Asian countries by looking at the correlation between GDP growth, population increase, and renewable energy. The FM-OLS data shows that the EF increases by 0.03% for every 1% increase in population size. Raihan et al. [59] analyze the effects on China's environment of renewable energy, urbanization, and GDP. The study found that urbanization had a favorable and significant impact on CO_2 emissions, using the ARDL technique. Xie et al. [60] found similar results for China's ecological situation, suggesting that the country's population explosion worsens the loss of biodiversity. Similar outcome was also observed by Ridwan et al. [61] across G-7 region, Raihan et al. [62] within USA, Raihan et al. [63] in G-7 region. Consequently, it is essential to implement green technologies in regions to establish sustainable cities and surroundings. However, using the ARDL bounds test method, Begum et al. [64] showed that there is no conclusive connection between the rate of growing population and environmental harm in Malaysia.

As far as we are aware, no individual has looked at the consequences of the United States' energy consumption, AI innovation, GDP growth, and EF all at once. Several investigations have been conducted by individuals in these domains, particularly utilizing CO_2 emissions as a substitute for environmental health; nevertheless, there hasn't been a collective effort to unify data in these areas. Moreover, the significance of innovation in artificial intelligence and its consequences for the consumption of energy have not received adequate attention, particularly in the United States. From the USA viewpoint, these qualities make AI innovation a whole fresh subject for study. Furthermore, our research employs the ARDL, which facilitates the effective estimation of panel data models and thus augments methodological comprehension in the discipline. Consequently, this research intends to fill a knowledge vacuum and provide national and international governance structures concerning the preservation of the planet.

3 | Methodology

To evaluate the connection between the selected factors and EF, the investigation used sophisticated econometric methodologies with the EF as the endogenous factor. Data on population, energy usage, and GDP were sourced from the World Development Indicators (2022), while reputable resources like our world in data offered details on breakthroughs in AI. All of the characteristics that were analyzed, together with their descriptions, avenues, and units of measure, are summarized in *Table 1*.

Table 1. Variables description.

Variables	Description	Logarithmic Form	Unit of Measurement	Source
EF	EF	LEF	Gha per person	GFN
GDP	Gross Domestic Product	LGDP	GDP per capita (current US$)	WDI
AI	AI innovation	LPAI	Estimated investment in AI (US$)	Our world in data
ENU	Energy use	LENU	Energy use (kg of oil equivalent per capita)	WDI
INDUS	Industrialization	LINDUS	Industry value added (% of GDP)	
POP	Population	LPOP	Population, total	WDI

The STIRPAT model is a traditional framework for identifying factors contributing to environmental damage [65]. We used IPAT framework [66] to examine the influence of relevant factors. Their main focus was on the three important factors that impact the environment. One problem with this approach is that it doesn't pay enough attention to the things that cause alterations that aren't proportionate or traditional [67]. Furthermore, the IPAT model lacks the capacity to assess the specific importance of influencing factors in relation to one another [68]. Hence, the modified STIRPAT model (*Eq. (4)*) has been used in numerous research studies to investigate the implications for the natural world [69], [70]. We can find the IPAT pattern in *Eq. (1)*:

$$\mathrm{I} \equiv \mathrm{P.A.T.} \tag{1}$$

Dietz and Rosa [71] devised the STIRPAT model, which uses stochastic effects through regression in assessing the ecological impacts of population, affluence, and technological advancement by reformulating the IPAT model. The new form of the model is the following:

$$\mathrm{I}_{\mathrm{it}} = \mathrm{C}\mathrm{P}_{\mathrm{it}}^{\varphi_1}\mathrm{A}_{\mathrm{it}}^{\varphi_2}\,\mathrm{T}_{\mathrm{it}}^{\varphi_3}\,\varepsilon_{\mathrm{it}} \tag{2}$$

Here, P represents the population of the country; A signifies its wealth, and T indicates its technology at time t. In the STIRPAT model, the constant term is denoted as C, while the random error component is represented by ε. Conversely, φ_1 , φ_2 and φ_3 denote the coefficients of P, A, and T, respectively. We can articulate the model's logarithmic transformation as follows:

$$\mathrm{lnI_{it}} = \mathrm{C} + \varphi_1\mathrm{lnP_{it}} + \varphi_2\mathrm{lnA_{it}} + \varphi_3\mathrm{lnT_{it}} + \varepsilon_{it} \quad (3)$$

In addition, using the necessary material that exists right now, we created an experimental variant of the conceptual structure in *Eq. (4)*:

$$\mathrm{EF} = \mathrm{f(GDP_{it}, AI_{it}, ENU_{it}, INDUS_{it}, POP_{it})}. \quad (4)$$

In this context, EF represents the EF, AI signifies artificial intelligence innovation, ENU implies energy use, GDP stands for per capita gross domestic product, INDUS denotes industrialization, and POP reflects total population size. We use the natural logarithm in *Eq. (5)*, which can be expressed in this manner:

$$\mathrm{lnEF_{it}} = \beta_0 + \beta_1\mathrm{lnGDP_{it}} + \beta_2\mathrm{lnAI_{it}} + \beta_3\mathrm{lnENU_{it}} + \beta_4\mathrm{lnINDUS_{it}} + \beta_5\mathrm{lnPOP_{it}} + \varepsilon_{it} \quad (5)$$

The parameters β_0 symbolize the particular intercept terms and β_1, β_2 β_3, β_4,and β_5 the exogenous factors' elasticities. The natural logarithmic modifications of EF, GDP, AI innovation, energy utilization, industrialization, and lnPOP, respectively, and the stochastic error term, denoted as ε_{it}.

We utilized the ADF, the Phillips-Perron (PP), and the ADF-GLS method to establish whether the time series data series are stationary or not. Fuller [72] notes that the ADF process is better suited to more complicated procedures and are more durable than the Dickey-Fuller (DF) procedure. On the other hand, the PP test was used to find the lag part of a regression model while unit root tests were done on time series with autocorrelated and heteroscedastic non-systematic features [73]. In order to prepare statistics for the DF-GLS test, they are transformed using GLS regression. The test is divided into two parts. Before determining whether a unit root exists, the test de-trends (de-means) the data using the GLS technique [74].

This research utilized the ARDL bound test for cointegration. In contrast to other methods that necessitate bigger datasets for relevance, this one works irrespective of the regressor insertion order (I(1) or I(0)), and it's statistically more reliable to assess connection in situations with less information [75]. It also permits the parameters to possess distinct optimal delays, a feature not relevant to other methodologies. Lastly, the approach determines the long- and short-term interactions among components using a single reduced-form model [76]. After describing the advantages of the ARDL method, we use the bound test to check if the variables in this study are cointegrated. We set up the ARDL construction like *Eq. (1)*:

$$\begin{aligned}\Delta\mathrm{LEF_t} = {} & \delta_0 + \delta_1\mathrm{LEF_{t-1}} + \delta_2\mathrm{LGDP_{t-1}} + \delta_3\mathrm{LAI_{t-1}} + \delta_4\mathrm{LENU_{t-1}} + \delta_5\mathrm{LINDUS_{t-1}} + \delta_6\mathrm{LPOP_{t-1}} \\ & + \sum_{i=1}^{m}\gamma_1\,\Delta\mathrm{LEF_{t-i}} + \sum_{i=1}^{m}\gamma_2\,\Delta\mathrm{LGDP_{t-i}} + \sum_{i=1}^{m}\gamma_3\,\Delta\mathrm{LAI_{t-i}} + \sum_{i=1}^{m}\gamma_4\,\Delta\mathrm{LENU_{t-i}} \\ & + \sum_{i=1}^{m}\gamma_5\,\Delta\mathrm{LINDUS_{t-i}} + \sum_{i=1}^{m}\gamma_6\,\Delta\mathrm{LPOP_{t-i}} + \varepsilon_t\end{aligned} \quad (6)$$

Eq. (6) constitutes the initial phase of the estimation procedure. Although ongoing associations with F-statistics under the threshold are acceptable, Pesaran et al. [77] state that they are implausible when the F-statistics are between the test values. Hence, we computed the Error Correction Model (ECM) to verify the existence of factor-level cointegration. The ARDL methodology uses the following ECM formulation:

$$\begin{aligned}\Delta LEF_t = {} & \delta_0 + \delta_1 LEF_{t-1} + \delta_2 LGDP_{t-1} + \delta_3 LAI_{t-1} + \delta_4 LENU_{t-1} + \delta_5 LINDUS_{t-1} + \delta_6 LPOP_{t-1} \\ & + \sum_{i=1}^{m} \gamma_1 \Delta LEF_{t-i} + \sum_{i=1}^{m} \gamma_2 \Delta LGDP_{t-i} + \sum_{i=1}^{m} \gamma_3 \Delta LAI_{t-i} + \sum_{i=1}^{m} \gamma_4 \Delta LENU_{t-i} \\ & + \sum_{i=1}^{m} \gamma_5 \Delta LINDUS_{t-i} + \sum_{i=1}^{m} \gamma_6 \Delta LPOP_{t-i} + ¥ECM_{t-1} + \varepsilon_t\end{aligned} \tag{7}$$

We utilized the FMOLS, CCR and the DOLS test to evaluate the stability of the ARDL conclusions. Narayan and Narayan [78] assert that FMOLS is capable of addressing endogeneity, autoregression issues, and mistakes resulting from sample bias. To account for variations in the stochastic regression, the DOLS permits the error component to be included in the symmetric cointegration formulation. According to Fatima et al. [79], this method is useful for incorporating cointegrated architectures wherein elements are combined in different orders. A goal of the CCR modification is to eliminate the inevitable internality that arises from extended association [80]. It is analogous to FMOLS in numerous aspects, particularly in theory [81].

The Lagrange Multiplier (LM), Jarque-Bera, and Breusch-Pagan-Godfrey tests are vital for testing the assumption of the model and ensuring that the findings are credible when examining time series. In order to ensure that the residuals are normal, a Jarque-Bera test is a process that can help in this regard. By tracking serial correlation in residuals, the LM test ensures that errors are not made simultaneously, meaning that estimates would not be tilted and erroneous [82]. Additionally, we use the Breusch-Pagan-Godfrey test in confirming the heteroscedasticity, or non-constant variance, of the residuals.

Table 1 presents the statistical results for various normality metrics, including mean, standard deviation, minimum, and maximum values, derived from a dataset covering the USA from 1996 to 2022. Every factor has 32 observations, indicating that all variables exhibit positive means, with LINDUS possessing the greatest mean and LENU the lowest. Furthermore, we attribute the smallest value to LINDUS and the maximum to LPOP. Furthermore, almost all measurements have low standard deviation, which means that the data points move about the mean rather than suddenly expanding across the area.

Table 2. Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
T	32	2005.5	3.091	1990	2021
LEF	32	4.8797	4.891	15.279	15.569
LGDP	32	8.0987	2.576	10.081	11.159
LAI	32	9.7865	1.82	6.321	9.724
LENU	32	4.779	0.728	3.949	5.272
LINDUS	32	10.625	2.133	2.268	2.871
LPOP	32	6.7829	3.0871	19.335	19.621

Table 3 shows the results of the stationarity tests (ADF, DF-GLS, and P-P) both at the level (I(0)) and first difference (I(1)) for the components that have been log-transformed. With no exception whatsoever, the data points to a stable state at the I(0) level for both advancements in AI and population. There is a 5% level of significance for the LAI but a 1% level of significance for the LOP. Conversely, LEF, LGDP, LENU, as well as LINDUS exhibited non-stationarity at the level but attained stationarity following initial difference adjustment. In addition, at the 1% level of significance, all of these features stand out. We can proceed with our analysis in the subsequent part utilizing the ARDL strategy, considering the diversified sequence of insertion.

Table 3. Results of unit root test.

Variables	ADF		P-P		DF-GLS		Decision
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
LEF	-0.768	-5.234***	-0.564	-5.087***	-0.679	-5.981***	I(1)
LGDP	-0.872	-4.214***	-0.871	-4.451***	-0.451	-3.245***	I(1)
LAI	-2.981**	-6.241***	-2.871**	-5.781***	-2.781**	-6.781***	I(0)
LENU	-0.361	-6.231***	-0.562	-4.451***	-0.782	-5.873***	I(1)
LINDUS	-0.381	-4.501***	-0.231	-4.231***	-0.451	-4.778***	I(1)
LPOP	-4.561***	-5.781***	-4.990***	-6.071***	-4.981***	-5.081***	I(0)

To find out if the factors chosen were co-integrated, the current study used an ARDL bounds assessment. The findings of the ARDL bound test indicate that there is co-integration, rejecting the null hypothesis at the 1% significance threshold. According to *Table 5*, the F-test statistic reached the specified value with a value of 6.997. Therefore, it's reasonable to say that there are clear co-integrating interactions among the settings of the model. Such features make it easy for the simulation to quickly adjust to a common, unpredictable disruption. This leads us to the conclusion that changes in US sustainability are affected by variations in all factors mentioned.

Table 4. Results of ARDL bound test.

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	6.997	10%	2.08	3.01
K=5		6%	2.39	3.38
		2.50%	2.7	3.73
		1%	3.06	4.15

Table 5 displays the findings of the Panel ARDL framework, which show the complex patterns that affect the environmental impact of the USA region. When it comes to LGDP, the traditional scales of significance are maintained for the immediate coefficient (0.234) and the subsequent coefficient (-0.361). In this particular context, it appears that growth in the economy is the sole factor leading to ecological damage. This outcome is supported by Raihan et al. [83], Addai et al. [84], Sahoo and Sethi [85], and Syed et al. [86]. Conversely, Georgescu and Kinnunen [87] asserted that separating GDP expansion from EF enables economic development while concurrently diminishing adverse environmental effects.

Conversely, the LAI coefficient and LEF are positively related, and this is indicated by a 1% level of significance (both instances have p-values lower than the typical standard). Statistics show that a 1% increase in LAI leads to a long-term decrease of 0.542% in LEF and an immediate reduction of 0.781%. With a long-term significance level of 1% and a short-term significance level of 5%, the findings suggest that using advanced AI technology could improve the ecosystem in both time frames. Utilizing AI enables humanity to more effectively address global warming and attain ecological sustainability while leveraging natural resources [88]. Several researchers across different regions, including Rayhan [89], and Rahman et al. [90] corroborate the findings of our study. Conversely, the destructive relationship between LENU and LAEF over both short and long periods demonstrates the unfavorable link within electricity use and EF. A 1% rise to LENU will have a short-term impact of 0.146% on LEF and a long-term impact of 0.346%. This outcome is statistically significant in both instances at the 1% threshold. Similar findings were found by Asif et al. [91] in South Asia, Ali et al. [92] in China, and Deka et al. [93] in the EU-27 countries. Therefore, countries that use an excessive amount of contaminated energy will have a tremendous adverse effect on the ecosystem in the US compared to those who use a lot of green energy.

Similarly, the LINDUS shows an unfavorable association with LEF, and the coefficient is significant at the 1% level. In particular, industrialization is beneficial for the US ecosystem since a 1% rise in LINDUS generates a 0.450% increase in the long run and a 0.561% increase in the short run. However, Adejumo et al.[94] see industrialization as the primary catalyst for sustainable monetary expansion. Researchers such as Nasrollahi et al. [95] for the OECD and MENA region, and Li et al. [96] from China concur with our findings, concluding that industrialization exacerbates ecosystem damage. According to the data in the table, there is a positive correlation between LPOP and LEF over both the near and long term. The p-value is lower than the typical limit, indicating statistically significant consequences in both time periods' findings. In the long run, LEF will go up by 0.0761%, whereas for each 1% increment in LPOP, there will be a 0.731% decrease in the near term. Our results in various locations are consistent with the ones of Rahman [97] and Jie et al. [98]. On the flip side, industrial development might result from higher public transit and facility use rates in areas with greater populations which cause more pollutants [99-101].

Table 5. Results of ARDL short-run and long-run.

Variables	LR	SR
LGDP	0.361***(0.1062)	
LAI	-0.542***(0.3251)	
LENU	0.349***(0.3481)	
LINDUS	0.450***(0.3871)	
LPOP	0.761**(0.1087)	
D.LGDP		0.234***(0.6717)
D.LAI		-0.781**(0.2541)
D.LENU		0.145***(0.1345)
D.LINDUS		0.561***(0.1467)
D.LPOP		0.731**(0.1562)
ECT (Speed Adjustment)		-0.551***(0.0182)
Constant		10.865***(15.1782)
R-square	0.9821	

Table 6 shows that the ARDL results were shown to be reliable using three different estimating approaches: FMOLS, DOLS, and CCR. For each method, the expected LGDP coefficients are 0.354, 0.289, and 0.376. With the exception of FMOLS, that is significant at the 5% level, other estimators express significance at the 1% level. The conclusions are in line with the ARDL method's short- and long-term findings, indicating that growth in GDP has a negative impact on the US atmosphere. The LAI coefficient exhibits negative correlations with LEF in all calculations, demonstrating significance at the 1% level in each instance. Specifically, LEF diminishes by 0.321% in FMOLS, 0.276% in DOLS, and 0.326% in CCR for every percent increase in LAI. This result confirms what the ARDL simulation predicted and highlights how artificial intelligence breakthroughs have benefited the US environmental system.

Table 6. Result of robustness check.

Variables	FMOLS	DOLS	CCR
LEF dependent			
LGDP	0.354***(0.2361)	0.289**(0.6719)	0.376***(0.3543)
LAI	-0.321***(0.6793)	-0.276*(0.0453)	-0.326**(0.1345)
LENU	0.215***(0.2214)	0.164***(0.2654)	0.243***(0.3432)
LINDUS	0.765**(0.2309)	0.327**(0.4301)	0.275**(0.2654)
LPOP	0.652**(0.6345)	0.670***(0.2098)	0.446***(0.3411)
C	10.723**(4.0437)	10.291**(4.0451)	10.652**(7.8929)
R-squared	0.9801	0.9324	0.9591

Table 7 displays the results of the evaluation of diagnostics. The findings support the null hypothesis since no evaluation method was shown to be effective. A p-value of 0.1281 from the Jarque-Bera test indicates that the residuals follow a normal distribution. A p-value of 0.2041, as shown in the LM analysis, suggests that the

residuals do not exhibit serial correlation. Moreover, no evidence of heteroscedasticity is present in the residuals, as confirmed by the Breusch-Pagan-Godfrey test (p = 0.2039).

Table 7. The findings of diagnostic tests.

Diagnostic Tests	Coefficient	p-value	Decision
Jarque-Bera test	0.6761	0.1281	Residuals are normally distributed
LM test	0.2356	0.2041	No serial correlation exits
Breusch-Pagan-Godfrey test	1.1354	0.2039	No heteroscedasticity exists

In addition, we find intrinsic resilience in residuals throughout long and short time periods using the CUSUM and CUSUM-SQ measures. As seen in the following picture, the CUSUM-SQ plot constantly aligns with the critical line, indicating that the findings are inside the range that is required. It indicates that the requirements are well-defined and have sufficient consistency at the 5% level of significance.

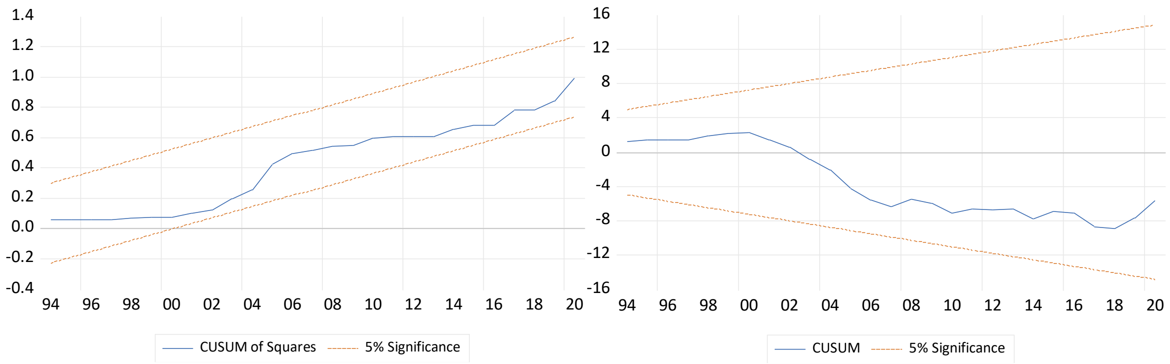

Fig. 1. CUSUM and CUSUMSQ test.

4 | Conclusion and Policy Implications

The present research investigated the complicated interrelationships between economic growth, AI innovation, energy usage, industrialization, and population growth, and the resulting effects on the EF in the USA between 1996 and 2022. The investigation used sophisticated econometric approaches to examine the EF and identify the elements impacting the ecological health of the area of choice. To ensure that the inquiry was rigorous, different unit root tests, such as ADF, P-P, and DF-GLS, were employed to test for non-stationarity of variables. This made it possible to assess short-term and long-term effects using the innovative ARDL methodology. The robustness tests using FMOLS, DOLS, and CCR validate the reasonability and reliability of the ARDL findings, therefore increasing the confidence in the results. Finally, three diagnostic tests were employed to test the concerns of heteroscedasticity and autocorrelation in the chosen dataset. The results of the ARDL study uncover several significant feedbacks, suggesting a positive association between environmental factors and GDP expansion, energy consumption, industrialization, and growing population both in the short and long term. The outcomes indicate that the economic operations, increased energy consumption, heightened industrialization, and population growth will result in more pollution due to the consumption of more fossil fuels and mineral assets. Nevertheless, we found a negative relationship between AI innovation and EF, suggesting that the use of modern AI technology could potentially increase the natural EF of the designated area. These links underscore the significance of developments in artificial intelligence, the adoption of sustainable energy, and eco-friendly manufacturing and production in enhancing ecological sustainability dynamics in the USA. As a result, authorities can develop special measures and regulations that will minimize ecological degradation and promote the progressive technical advancement, stable tendency of the population, and use of alternative sources of energy in the specified area.

In order to encourage ecological sustainability in the USA, policymakers are to focus on the implementation of advanced AI systems, renewable energy approaches, and sustainable industries. Considering that economic growth, energy consumption, industrialization, and expansion of the population are positively correlated with environmental deterioration, there is a necessity for strict regulations of environmentally friendly technologies and alternative sources of cleaner energy. To maximize effectiveness in production while decreasing energy consumption and garbage, lawmakers should offer financial incentives for the use of artificial intelligence. Additionally, to further lessen industrialization's toll on the natural world, it is essential to advocate for greener manufacturing practices, including switching to clean energy sources and getting enterprises to switch to more sustainable materials. Policies should also emphasize stabilizing population growth to reduce pressure on the environment in terms of exhaustion of natural resources and also a harmony between development and environmental conservation. By adopting these measures, the USA can advance both technological innovation and environmental sustainability, ensuring long-term ecological health.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

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