Received: 16 November 2024 | Revised: 20 February 2025 | Accepted: 18 March 2025

https://doi.org/10.56946/jeee.v4i1.537

Journal of Environmental and Energy Economics

Research Article

Role of AI Innovation, Clean Energy and Digital Economy towards Net Zero Emission in the United States: An ARDL Approach

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Abstract

The current paper investigates the influences of AI innovation, GDP growth, renewable energy utilization, the digital economy, and industrialization on CO_2 emissions in the USA from 1990 to 2022, incorporating the ARDL methodology. The outcomes observe that AI innovation, renewable energy usage, and the digital economy reduce CO_2 emissions, while GDP expansion and industrialization intensify ecosystem damage. Unit root tests (ADF, PP, and DF-GLS) reveal heterogeneous integration levels amongst components, ensuring robustness in the ARDL analysis. Complementary methods (FMOLS, DOLS, and CCR) validate the results, enhancing their reliability. Pairwise Granger causality assessments identify strong unidirectional connections within CO_2 emissions and AI innovation, as well as the digital economy, underscoring their significant roles in ecological sustainability. This research highlights the requirement for strategic actions to nurture equitable growth, including advancements in AI technology, green energy adoption, and environmentally conscious industrial development, to improve environmental quality in the United States.

Keywords: AI Innovation, Digital Economy, Industrialization, CO_2 Emission, United States

1. Introduction

The importance to ecological conservation and sustainability has attained unparalleled prominence [1,2]. Carbon dioxide (CO_2) is a prevalent greenhouse gas (GHG) that retains surface heat in the atmosphere, inhibiting its escape into space and contributing to the rise in global temperatures [3,4,5]. This has prompted countries and international organizations to seek global solutions for reducing carbon emissions and addressing climate change [6,7] . Recently, the USA, the second-largest producer of GHGs in 2017, has a target to reduce GHG emissions by around 27% by 2025, relative to 2005 emission levels [8].The US was selected based on several compelling factors. People regard the United States as the leading entity in energy usage. From 1980 to 2019, quantities of carbon monoxide, lead, and sulfur dioxide decreased by almost 80 percent; the particles had comparable reductions, although the surface levels of ozone diminished by about one-third [9,10]. The country uses the highest amount of renewable and non-renewable resources for each resident [11,12]. In 2020 the United States released emissions totaling 5,416 metric tonnes of CO_2 which constituted approximately 16% of worldwide emissions [13]. AI research among nations ranks both China and United States as major global forces in AI development [14]. The USA faces consider obligation in the ecological emergencies and rising temperatures because it ranks as one of the top greenhouse gas manufacturers worldwide thus assessing its environmental sustainability stands as a critical matter. It is essential to recognize the importance of economic growth, energy consumption, industrialization, AI innovation, and the digital economy, especially for a developing nation like the USA. The research drives from global climate crisis demands to reduce CO_2 emissions yet maintain economic development and advancing technology. As one of the top economies worldwide the United States requires methods to support industrial growth along with digital expansion while achieving lower ecological influence. This study investigates CO_2 emission effects from AI innovation together with digital economy power and renewable energy and traditional factors of GDP growth and industrial development. The relationships between these factors remain essential to create policies which support sustainable economic progress. The research bases its analysis on the ARDL framework by using tests for unit roots along with causality assessments for confirming the findings. This research provides policymakers with essential knowledge about AI innovations along with digital economies as emission reduction agents before examining the detrimental environmental effects of uncontrolled economic expansion and industrialization. These results demonstrate the necessity of directing financial resources towards sustainable AI applications and green energy transformation and environmentally friendly industrial expansion. The research findings contribute to environmental economic scholarship while giving the United States specific policies to reach sustainable ecological and economic harmony.

Studies indicate that both environmental resource depletion and the climate change crisis have strengthened the immediate need for energy efficiency advancements [15]. As the world's primary contributor, the United States assumes a fundamental part in bringing global carbon emissions to zero by 2050 by working to solve the upcoming climate emergency during the present and future times [16,17]. Habitable planet preservation relies on advancing social development and economic conditions together with renewable energy source expansion [18,19]. The Biden administration presents a $2 trillion plan for renewable energy development while enhancing infrastructure and conducting various climate-dependent projects to achieve net-zero emissions by 2050 [20]. Furthermore, the United States offers substantial fossil fuel subsidies, totaling approximately 0.6 trillion USD, making it the second-highest globally. To attain carbon neutrality by diminishing fossil fuel consumption, it is imperative to curtail policy support [21]. Moreover, the United States must promptly reduce its CO_2 emissions by employing carbon capture technologies at power and industrial sites, in conjunction with geological storage solutions [22,23].

Theoretically, the link within the digitalized economy and environmental quality is complex and multifaceted. Digital transformation enhances ICT utilization; thereby imposing greater environmental strain through increased energy consumption is related to the manufacturing, and usage of ICT-related items [24]. Enhancing economic growth is the foremost priority for many nations, particularly developing and developing region, to improve their citizen's quality of life [25]. Despite the benefits, heightened industrial productivity is the primary contributor to trash generation and energy consumption [26]. In 2020, the digital economy of the USA amounted to US$13.6 trillion [27]. The prevailing perspective posits that economic expansion adversely impacts the environment during the initial phases of development and then benefits it in later stages [28,29,30]. Public opinion toward these issues parallels the way people respond to climate change since the observable pattern represents an unavoidable trend [31]. Throughout the past 50 years, academic scientists have resurfaced their interest in AI research [32]. It can be anticipated that artificial intelligence will significantly impact global environmental outcomes, productivity, inclusivity, and equity. The influence of AI on sustainable development has been ambiguous. Artificial intelligence (AI) has developed as a formidable instrument across various industries and presents significant potential for government, society, and the economy [33].

The primary aim is to analyze the implication of GDP, the digital economy, clean power usage, industrialization and AI innovation on CO_2 emission levels in the USA from 1990 to 2022. After a comprehensive examination of current academic literature, we assert the innovative nature of this research study, substantiated by several foundational ideas. This research presents three notable contributions: Currently, academic research has not specifically analyzed the consequences of green energy utilization, the digital economy, and AI innovation on CO_2 emissions in the USA, despite the country's crucial function in the climate change agenda. The USA merits specific scrutiny in the analysis owing to its position as a highly industrialized country that utilizes substantial natural resources, hence imposing considerable environmental strain. Consequently, the USA ranks as the second-highest polluter of CO_2 [34]. The data indicates that the USA possesses considerable potential to enhance its energy portfolio by using renewable energy sources. Therefore, the USA's carefully designed and judicious nuclear energy policy could successfully mitigate its air pollution challenges in the near future. Furthermore, we scrutinize the link within industrialization and biodiversity condition. Unlike previous researches, this analysis employs a newly developed econometric technique known as ARDL simulation. The extended IPAT models, which incorporate renewable energy, AI innovations, and a digitalized economy, employ this technique. This methodology obtains, activates, and autonomously produces charts that show misleading changes in the endogenous factor based on the exogenous variable, all while accounting for other elements.

In the second part, we look at research that has been done on certain factors by looking at methodology, theoretical frameworks, the building of empirical models, and the estimation methods that were used. A thorough breakdown of the model results appears in "Results and Discussion," and the final segment covers the analysis together with the proposed action.

2. Literature Review

Numerous empirical studies investigate how the three factors of GDP growth, industrialization, and sustainable power usage affect CO_2 emission levels. Various studies have analyzed the ARDL model, yet most of them examine how GDP growth, together with urbanization and renewable energy consumption, drives environmental outcomes. Most individuals fail to notice how AI technology, together with the digital economy, affects environmental contaminations. There is limited previous research on ecological deterioration in the United States because this field is new to scientific investigation. Previous research enabled the inquiry to choose variables and methodologies while conducting its study. The subsequent part of this work examines multiple query points.

2.1. GDP and CO2

Many research activities concentrate on the link between growing GDP and biodiversity health. Many experts hold the position that GDP growth usually leads to higher CO_2 emission levels. The analysis of environmental quality using CO_2 emissions records complicates the current situation. The study of economic growth's (GDP) effect on China's environmental sustainability uses ARDL methodology according to Raihan et al. [35]. Data collected from multiple sources show that the expansion of national economies causes strong increases in CO^2 emissions. Sheraz et al. [36] conducted research on G20 carbon dioxide emission responses to GDP variables from 1986 to 2018. Results obtained through the FE-OLS method demonstrated that GDP led to an upsurge in CO_2 releases throughout the examined period. Koengkan et al. [37] established through their research that economic progress leads to deterioration of environmental quality. Aslam et al. [38] presents an investigation of industrialization as well as its impact on CO_2 emissions when coupled with GDP growth. The research evaluates the environmental Kuznets curve by establishing that per capita GDP drives CO_2 emissions increases over time Findings by Raihan et al. [39] and Sikder et al.[40] together with Abbasi et al.[41] and Magazzino et al.[42] showed parallel outcome. Using ARDL modeling throughout 1977 to 2016 Solarin et al. [43] discovered that Nigerian economic growth inflicts damage on the environment in the beginning but eventually shows favorable consequences. Mohsin et al. [44] studied the ecological and economic relationship in European and Central Asian regions. Analysis through ARDL technique demonstrated that CO_2 emissions and GDP show an opposite sustained link and a positive short-term connection thus indicating GDP expansion damages the ecosystem.

2.2. AI innovation and CO_2

The significant impact of AI technologies, such as machine learning (ML), deep learning (DL), and big data, can improve environmental quality by decreasing pollutant levels [45]. The global economy faces huge strain from ecological issues and the need for more durable infrastructure, making the integration of AI, ML, and DL in manufacturing operations a crucial component of a comprehensive strategy to adhere to long-term sustainability goals [46, 47]. As research progresses, certain researchers have identified the possible environmental ramifications of AI [48,49,50]. Vinuesa et al. [51] examined the effects of AI on the 17 goals and 169 specific targets specified in the UN's "2030 Agenda for Sustainable Development," demonstrating that AI can aid in the realization of the majority of these targets. Dhar [52] examined the dual function of AI in CO_2 emission reduction, emphasizing its position as both a means to combat global warming and a notable source of carbon emissions. Moreover, Chen et al. [53] found that the impact of AI innovation on reducing CO_2 emissions is more pronounced in large cities, major urban areas, well-developed infrastructure, and technologically advanced cities, based on 270 Chinese cities.

2.3. Renewable Energy use and CO_2

The long-term cost benefits of alternative or green energy sources will enhance the general standard of living [54]. Environmental disasters arose from increasing fossil fuel usage so green power needs to replace them to protect ecosystems and obtain secure reliable power [55]. Energy efficiency methods work for ensuring green ecosystem and develop equitable growth through the deployment of sustainable and clean energy resources [56]. Baloch et al. [57] analyzed the connection within renewable energies and CO_2 emissions in BRICS countries by using the AMG estimator from 1990 to 2015. Research findings demonstrated that clean energy caused decreased CO_2 emissions throughout the entire BRICS coalition except for South Africa. Dogan and Ozturk [58] study the implication of renewable and non-renewable energy utilization on CO_2 emissions throughout the 1980-2014 periods in the United States. Research findings demonstrate that raising renewable energy usage creates effective reduction of environmental harm throughout extended periods. A research conducted by Salahuddin et al.[59] focused on SSA countries and Kartal et al.[60] worked with USA while Dagar et al. [61] did their study with the OECD economies all reaching similar findings. Numerous experimental studies show renewable energy implementation produces minor effects on CO_2 emissions while producing possible adverse environmental consequences from increased GHG output. The research by Apergis and Payne [62] demonstrates that renewable energy technology failed to reduce emissions within a short-term period across 19 developing economies and industrial nations. In the short term Farhani [63] finds that REN output creates a causal link to CO_2 emissions yet this effect disappears in the long term. Several studies demonstrate renewable energy utilization brings adverse effects to ecosystems according to Murshed et al.[64] in G-7 countries as well as Abbas et al. [65] in BRICS region and Silva et al.[66] in Africa.

2.4. Digital Economy and CO_2

The modernization of the nature hypothesis demonstrates how digital technological advancement offers solutions to ecological problems while producing theoretical analysis for digital economy-based sustainability [67]. The paper of Wang et al. [68] introduces a multifaceted digital economy index that tracks Chinese provincial data from 2006 to 2017 while studying digital commerce connections with levels of CO_2 emissions. Through their analysis, which used system-GMM, they found evidence that DE operations create negative effects on CO_2 emissions. Ma et al. [69] examined China's digital economy capability for minimizing pollutants. The study indicates that the DE of China plays a substantial role in reducing CO_2 emissions. The digital economy emerges as both a promising and innovative environmental sustainability strategy because of rising environmental awareness and a growing economic need for sustainable solutions [70]. Shobande and Ogbeifun [71] replicated the findings along with Kovacikova et al. [72] in their own regional studies. Xu et al. [73] explored the current and quantitative patterns that relate the DE to natural world throughout China's 287 prefecture-level cities from 2008 to 2018. Research outcomes demonstrate that the relationship between the DE and ecological damage runs in reverse directions as it displays complex spatial and temporal patterns. According to Nguyen et al. [74], the increasing scale of economic activities facilitated by the DE increases environmental emissions by using more energy. Research by Li and Wang [75] established that the correlation between the DE and CO_2 releases followed an inverted U pattern.

2.5. Industrialization and CO_2

The detailed linkage between industrial development and biodiversity reduction became a major topic when nations aim to expand their economic base without causing environmental deterioration. In their study Sumaira and Siddique [76] investigated how industrialization creates cause and effect patterns with CO_2 emissions which operate in both directions. The investigations took place in the SAARC area from 1984 to 2016. Through their analysis Ahmed et al. [77] evaluated how industrialization affects environmental condition in the Asia-Pacific region. The results using ARDL methods showed that industrial growth has a major beneficial impact on environmental conditions. Opoku and Aluko [78] conducted research that analyzed various environmental results of industrialization from 2000 to 2016 across 37 African nations. The researchers established that national industrial growth decreases environmental destruction. Sikder et al. [40] investigated emissions based on industrial development among 23 developing nations during the period from 1995 to 2018. According to the ARDL model industrialization grows by 0.54% when CO_2 emissions increase by 1% throughout the long-term period. Research by Nasir et al. [79] investigates ecological damage elements in Australia throughout the 1980-2014 periods. Their analysis using EKC and STIRPAT adopted complete framework to demonstrate that industrial development shows no significant link with CO_2 emissions. Mentel et al.[80] researched Africa while Kermani et al. [81] investigated Iran, Xu and Lin [82] studied China and Farooq et al.[83] analyzed India and all these studies demonstrated that CO_2 emissions rise because of industrial growth and harm environmental health.

2.6. Literature Gap

The research addresses critical information deficiencies by examining the United States and its distinct macroeconomic and environmental attributes. Despite the global focus on equitable growth, there have been limited, thorough studies conducted in the USA that investigate the cumulative implication of industrialization, AI innovation, and the digital economy on carbon intensity. Comprehensive assessments of the complex interrelations among these factors are frequently absent in the current literature, especially with the ARDL framework. Conflicting findings continue on the relationship among DGE, AI innovation, and CO_2 emissions, despite earlier research acknowledging the necessity for more thorough examinations of these associations. It is essential to recognize that technical growth, along with the adoption of alternative energy and a digital economy, can promote the utilization of cutting-edge, environmentally friendly technologies, thereby facilitating a sustainable world. Therefore, the objective of the article is to address these inadequacies and provide policymakers with essential data to develop sustainable plans for decarbonizing emissions.

3. Methodology

3.1. Data and Variables

This analysis utilized time series data from 1990 to 2020 for the United States. The World Development Indicator (WDI) supplied the data on CO_2 emissions, which is employed as an endogenous variable. Likewise, information regarding AI innovation and the digital economy is sourced from Our World in Data. Furthermore, the statistics on GDP, renewable energy utilization, and industrialization are sourced from WDI. Table 1 distinguishes the factors, their logarithmic forms, units of measurement, and sources of data.

3.2. Theoretical framework

Dietz and Rosa [84,85] developed a revised "Stochastic Impacts by Regression on Population, Affluence, and Technology" (STIRPAT) model to resolve problems with IPAT format [86]. The method predicts irregular functional connections between variables which affect the ecosystem environment [87]. The STIRPAT model enables researchers to add extra independent factors like energy usage when tracking environmental influences [88]. The basic model structure appears in Equation (1).

$$I \equiv P.A.T \quad \ldots\ldots (1)$$

In this case, "P" denotes population number, "A" denotes wealth, "T" denotes advances in technology, and "I" denotes an ecological impact. Researcher examines the following formulation:

$$I_{it} = CP_{it}^{\gamma_1} A_{it}^{\gamma_2} T_{it}^{\gamma_3} \varepsilon_{it} \quad \ldots\ldots (2)$$

Table 1. Data and variables.

Variables	Description	Logarithmic Form	Unit of Measurement	Source
CO_2	CO_2 Emission	LCO_2	CO_2 Emission (kt)	WDI
GDP	Gross Domestic Product	LGDP	GDP per capita (current US$)	WDI
AI	AI Innovation	LPAI	Estimated Investment in AI (US$)	Our World in Data
REN	Renewable Energy Use	LREN	Renewable Energy Use (% of total energy use)	WDI
DGE	Digital Economy	LDGE	ICT good imports (% of total goods imports)	Our World in Data
INDUS	Industrialization	LINDUS	Industry (including construction), value added (current US$)	WDI

The logarithmic transformation can stabilize data, compress variable scales, and reduce model heteroscedasticity and collinearity while maintaining data structure and correlation. Understanding unit differences in factors affecting carbon intensity is crucial for the research topic. Equation (3) presents the logarithmic representation.

$$LnI_{it} = C + \gamma_1 LnP_{it} + \gamma_2 LnA_{it} + \gamma_3 LnT_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

In this context, P symbolizes the population of a nation, A its affluence, and T its technology at time t. The random error component is denoted by ε, while the constant component in the STIRPAT methodology is C. Eqn.(4) is the mathematical framework for this study:

$$CO_{2it} = f(GDP_{it}, AI_{it}, REN_{it}, DGE_{it}, INDUS_{it}) \ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

The explanatory variables in this instance are GDP, AI innovation, renewable energy use, digital economy and industrialization whereas the dependent variable is CO_2 emission. An alternate way to describe the empirical model in logarithmic form is as follows:

$$LnCO_{2it} = \beta_0 + \beta_1 LnGDP_{it} + \beta_2 LnAI_{it} + \beta_3 LnREN_{it} + \beta_4 LnDGE_{it} + \beta_5 LnINDUS_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(5)}$$

Here, β_0 to β_5 is used as the coefficient of five different selected independent variables.

3.3. Empirical Framework

The fundamental purpose of this inquiry analyzes the connection among AI innovation and GDP growth, industrialization and digital economy and energy usage on CO_2 emissions in the USA region. The research study will execute the following sequence of steps towards its objective. Tests including ADF and P-P and DF-GLS were used to perform unit root examinations. We utilize ARDL modeling to discover the connection patterns in the variables both in the short and long term. The robustness tests were done with various techniques which included FMOLS and DOLS and CCR. Multiple diagnostic assessments were also applied to confirm that the model contained no disturbing factors.

3.4. Unit Root Test

It is imprudent to check the stability of the data prior to examining any correlations between the eras [89]. Whether the dataset exhibits stationarity in integrated order zero (I(0)) or integrated order one (I(1)), the current study first examines the links between the response and its independent factors. The evasion of the I(2) sequence is considered invalid and may lead to erroneous results [90]. This study employs the ADF test [91], DF-GLS test [92] and PP test [93] to assess the stability of the variables.

3.5. *A*RDL Structure

Pesaran et al. [94] introduced the ARDL limits analysis as a cointegration method that we used for assessing the lasting associations between factors. The cointegration test provides superior sequencing of integration when compared to traditional methods. This analytical method applies when parameters demonstrate I(1) and I(0) stability or an I(1)/I(0) combination status [95]. The ARDL framework determines cointegration through the ARDL F-statistic which computes its results using variable lag structures optimized for individual variables [96]. Cointegration between the parameters becomes evident when the values of the ARDL F-statistic exceed the predefined upper threshold. The absence of cointegration exists among the variables when the ARDL F-statistic falls beneath the lower critical boundary [97]. Eq. (6) applies the ARDL bound analysis to determine cointegration.

$$\begin{aligned}\Delta LCO_{2t} = {} & \tau_0 + \tau_1 LCO_{2t-1} + \tau_2 LGDP_{t-1} + \tau_3 LAI_{t-1} + \tau_4 LREN_{t-1} + \tau_5 LDGE_{t-1} + \tau_6 LINDUS_{t-1} \\ & + \sum_{i=1}^{q} \gamma_1\, \Delta LCO_{2t-i} + \sum_{i=1}^{q} \gamma_2\, \Delta LGDP_{t-i} + \sum_{i=1}^{q} \gamma_3\, \Delta LAI_{t-i} + \sum_{i=1}^{q} \gamma_4\, \Delta LREN_{t-i} + \sum_{i=1}^{q} \gamma_5\, \Delta LDGE_{t-i} \\ & + \sum_{i=1}^{q} \gamma_6\, \Delta LINDUS_{t-i} + \varepsilon_t\end{aligned} \tag{6}$$

where Δ is the first difference operator, and q indicates the length of the lag that is optimal.

The ECM method produces consistent outcome even with comparatively small samples [98]. The ECM amalgamates short-term nuances with long-term stability to maintain a comprehensive perspective [99]. The symbol θ represents the coefficient of ECM. Equation (7) is used to explore short run associations of the variables.

$$\begin{aligned}\Delta LCO_{2t} = {} & \tau_0 + \tau_1 LCO_{2t-1} + \tau_2 LGDP_{t-1} + \tau_3 LAI_{t-1} + \tau_4 LREN_{t-1} + \tau_5 LDGE_{t-1} + \tau_6 LINDUS_{t-1} \\ & + \sum_{i=1}^{q} \gamma_1\, \Delta LCO_{2t-i} + \sum_{i=1}^{q} \gamma_2\, \Delta LGDP_{t-i} + \sum_{i=1}^{q} \gamma_3\, \Delta LAI_{t-i} + \sum_{i=1}^{q} \gamma_4\, \Delta LREN_{t-i} + \sum_{i=1}^{q} \gamma_5\, \Delta LDGE_{t-i} \\ & + \sum_{i=1}^{q} \gamma_6\, \Delta LINDUS_{t-i} + \theta ECM_{t-1} + \varepsilon_t\end{aligned} \tag{7}$$

3.6. Robustness Check

The study evaluated ARDL results through alternative cointegration regression methods that included FMOLS by Hansen and Phillips [100] as well as DOLS methodology by Stock and Watson [101] and CCR test by Park [102]. The adoption of these methods emerged because of two main requirements [103]. The I(1) parameters need to exhibit cointegration before implementing any of FMOLS, DOLS, or CCR methods. The application of these methods produces consistent parameters while using small sample sizes in testing. The methods address endogeneity and serial correlation and omitted variable bias and measurement errors of parameters. The results produced by these methods become more and more efficient as the sample size increases [104].

3.7. Pairwise Granger Causality Test

The research utilized Granger-causality test developed by Granger [105] to verify connections among its components. The concept stands as a predictive statistical procedure that brings multiple benefits compared to other approaches when working with time series data [106]. This test provides the crucial benefit of simultaneous analysis of multiple lags by reducing the impact of elevated lag orders [107]. A time series Y demonstrates "Granger-causality" to another time series X through its ability to enhance future prediction of X values. At time t the time series values for both variables are denoted by Xt and Yt. The bivariate autoregressive model successfully demonstrates how the variables X and Y operate.

$$X_t = \beta_1 + \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{i=1}^{n} \mu_i X_{t-1} + e_t \quad (8)$$

$$Y_t = \beta_2 + \sum_{i=1}^{n} \Omega_i Y_{t-1} + \sum_{i=1}^{n} \infty_i X_{t-i} + u_t \quad (9)$$

3.8. Diagnostic Tests

The research employed diagnostic assessments such as the Jarque-Bera test, Lagrange Multiplier test, and Breusch-Pagan-Godfrey test to verify model assumptions and guarantee robust outcomes. The Jarque-Bera test evaluates the normality of residuals, whereas the Lagrange Multiplier test identifies serial correlation within residuals. The Breusch-Pagan-Godfrey test assesses heteroscedasticity, which may result in erroneous estimates and standard errors. Mitigating heteroscedasticity enhances model precision and inference dependability.

4. Results and Discussion

4.1. Summary Statistics

Table 1 contains descriptive statistics that have been presented as a summary. The evaluation and analysis of collected data reveal identical median and mean values across all variables. The distribution of all variables remains normal because their skewness approaches zero points and kurtosis stays below 3 while their Jarque-Bera test statistics fall under their thresholds.

Table 02: Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
T	34	2003.676	11.726	1990	2021
LCO_2	34	10.376	.732	9.29	11.472
LGDP	34	6.402	.72	5.145	7.807
LPOS	34	-.985	.428	-1.864	-.371
LEDU	34	.627	.123	.355	.798
LFDI	34	19.031	2.589	14.145	21.764
LPOP	34	18.708	.2	18.105	18.948

4.2. Unit Root test

The analysis shows the stationarity findings of unit root test using both I(0) and I(1) first-difference forms in Table 03. It indicates that industrialization serves as the sole variable showing stationarity at level I(0) while CO_2, GDP, AI innovation, green power utilization and digital economy exist in non-stationary form before subtracting the first differences. The differently integrated series require us to initiate assessment then proceed with applying the ARDL modeling framework.

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)	
LCO_2	-0.644	-4.647***	-0.625	-4.014***	-0.427	-4.302***	I(1)
LGDP	-0.732	-4.271***	-0.740	-4.739***	-0.761	-3.051**	I(1)
LAI	-0.502	-4.615***	-0.597	-4.523***	-0.872	-3.365**	I(1)
LREN	-1.321	-4.321***	-1.034	-4.320***	-1.431	-4.623***	I(1)
LDGE	-1.025	-5.713***	-1.011	-5.166***	-0.806	-4.453***	I(1)
LINDUS	-4.340***	-5.787***	-4.120***	-4.243***	-4.981***	-5.462***	I(0)

Table 4. Results of ARDL bound test.

	Test Statistics	*Value*	*K*	
	F statistics	*5.0348*	*5*	
	Significance level			
Critical Bounds	*10%*	*5%*	*2.50%*	*1%*
I(0)	*1.98*	*2.29*	*2.60*	*2.98*
I(1)	*3.01*	*3.24*	*3.71*	*3.99*

4.3. ARDL bound test

Following the verification of the variable's unit roots, this investigation employed the ARDL bounds test to examine the nature of the long-term relationship between the variables. Table 4 presents the empirical findings derived from the ARDL-limits testing methodologies for cointegration. The calculated F-statistic (5.10348) was higher than the upper critical bound values. This means that there was long-term cointegration within the selected factors.

4.4. ARDL result

Table 5 utilizes the ARDL model to examine short-term and long-term influences of LGDP, LAI, LREN, LDGE, LINDUS on LCO_2 found within the United States. A 1% boost in LGDP leads to a rise of 0.332% in LCO_2 levels during the long-term period along with a short-term impact of 0.142%. The findings demonstrate that rising GDP levels produce increased CO_2 emissions because financial growth brings about more manufacturing operations and energy consumption and asset deployment. Several researchers have shown that economic expansions through increased GDP production create negative environmental consequences. Research evidence supporting this connection can be found in publications by Voumik and Sultana [108] Majeed et al. [109] Kirikkaleli et al.[110] and Qayyum et al.[111]. Research from Zubair et al.[112], Ali et al.[113], Halliru et al.[114] opposed the positive connection within GDP and CO_2 emission. A 1% boost in LAI causes to a decline of LCO_2 in both time scenarios by 0.115% and 0.076%. The use of AI technologies in the United States generates substantial environmental sustainability benefits based on these research findings. Thus the research from Cifuentes et al.[115], Ridwan et al.[116], Ham et al.[117] alongside Chattopadhyay et al.[118] shows that customized AI techniques must be developed to foster global sustainability goals. Moreover, Awan et al.[119] shows innovation leads to increased pollution while recommending the adoption of pollution-minimized technologies. The analysis shows that LREN positively affects LCO_2 in both time periods with confirmed statistical importance. The USA ecosystem benefits from renewable energy consumption according to the research findings. The relation between LREN and LCO_2 demonstrates that LCO_2 decreases by 0.193% in the long term and by 0.102% in the short term when there is a 1% increase in LREN. Green energy offers a substitute for fossil fuels through environmentally friendly sustainable power technologies that produce negligible greenhouse gas emissions. The research findings of Sharmin [120] support the findings alongside those of Waheed et al.[121] and Sharif et al.[122]. According to Silva et al.[66] and Yurtkuran [123] and Lee [124] researchers reported negative correlations between clean energy usage and pollutant level in African countries as well as Turkey and European economies respectively.

At the same way, there is a favorable link within LDGE and LCO_2, with each 1% increment in DGE mitigates the CO_2 emission by 0.057% over time and 0.061% immediately. It is significant 1% level and indicating that DGE is beneficially for the ecosystem of the USA. The digital economy leads to reduce CO_2 emissions by fostering energy-efficient innovations and decreasing the reliance of conventional industrial operations. Shahbaz et al.[125] and Song et al.[126] corroborated with this conclusion . However, Kuntsman and Rattle [127] assert that digital devices have inflicted significant harm on the ecosystem throughout the manufacturing, preservation, and disposal processes. Similarly, Guo and Liang [128] and Ozturk and Ullah [129] observed same conclusions. Statistical analysis shows that both time frames LURBA growth negatively affects environmental quality according to the LINDUS coefficients. Additional levels of LINDUS result in a 0.7182% increase in LCO_2 within the long-term period while generating a 0.204% rise in the short term. Due to higher energy use and reliance on petroleum and natural gas in manufacturing operations, modernization most likely results in more CO_2 emissions. Multiple research studies including Sikder et al.[40], Mahmood et al.[130], Khan et al.[131] illuminated how industrialization harmed natural world health. Industrialization achieves environmental sustainability through decreased CO_2 releases according to studies performed by Zafar et al.[132], Pong et al.[133] and Elfaki et al.[134].

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

VARIABLES	LR	SR
LGDP	0.332***(0.4321)	
LAI	-0.115***(0.0313)	
LREN	-0.193***(0.3412)	
LDGE	-0.057**(0.5431)	
LINDYS	0.182***(0.1337)	
D.LGDP		0.142**(0.4534)
D.LAI		-0.462***(0.0074)
D.LREN		-0.102***(0.1540)
D.LDGE		-0.061***(0.0074)
LINDUS		0.204***(0.5464)
ECT (Speed Adjustment)		-0.243***(0.6512)
Constant		10.910***(11.2423)
R-square	0.8950	

4.5. Robustness Check

The results of the ARDL test are confirmed by three other methods, shown in Table 6: DOLS, FMOLS, and CCR. The coefficients from the FMOLS analysis show statistical significance at the 1% level while producing positive values. A single percentage increment of GDP triggers a 0.443% boost in CO_2 emission levels. When LAI increases by one percentage point, the USA experiences a decrease of 0.145 percent in CO_2 emissions. A 1% increase in LREN together with LDGE can reduce LCO_2 by 0.253% and 0.027%, respectively. The relationship between LCO_2 and LINDUS shows a positive trend because elevating LINDUS by 1% generates a 0.168% increase in CO_2 emissions. The results confirm that both GDP growth and industrial development produce damaging impacts on the natural environment of the USA. The findings match those obtained from both the short-term and long-term ARDL estimations.

The DOLS model indicates that LCO_2 increases by 0.315% and 0.671% on average when LGDP and LINDUS rise by 1%. The CO2 emission levels decrease by 0.156% when LAI increases by 1% along with equivalent increases of 0.258% from LREN and 0.068% from LDGE. According to the CCR analysis, LGDP, LINDUS, and LDGE have effects on LCO_2 changes that are, on average, 0.136%, 0.045%, and 0.096%. LCO2 decreased by an average of 0.341% and 0.236% per 1% rise in LAI and LREN, respectively, which matched the ARDL results except for the LAI data. This model confirms the significance of all components at the 5% level with an additional 1% level of significance for LGDP, LREN, and LINDUS. The results from all three assessments demonstrate that the ARDL model reaches reliable conclusions about the data patterns.

Table 6. Results of Robustness Check.

Variables	FMOLS	DOLS	CCR
LCO_2 dependent			
LGDP	0.443***(0.8623)	0.315**(0.4352)	0.136***(0.4526)
LAI	-0.145***(0.0562)	-0.156**(0.0731)	-0.3413**(0.0762)
LREN	-0.253***(0.1718)	-0.258***(0.5214)	-0.236***(0.1345)
LDGE	-0.027**(0.0823)	-0.068*(0.6720)	0.045**(0.0820)
LINDUS	0.168**(0.2345)	0.671**(0.4591)	0.096***(0.8327)
C	10.708**(6.0127)	11.3101**(8.5372)	10.294**(8.9783)
R-squared	0.8913	0.9041	0.8965

4.6. Pairwise granger causality test

Table 7 delineates the outcomes of the causal linkages across diverse determinants. The results of an F-statistic 4.65823 and p-value .0499 indicate no Granger-causal link between LLGDP and LCO_2 because the test rejects the null hypothesis at a 5% significance level. The data indicates single-directional cause-effect relationships between LAI and LDGE and LCO_2 since their p-values lie below the standard significance threshold. A two-way causal connection exists within LCO_2 and INDUS. The analyzed p-values which exceed the significance threshold demonstrate LCO_2 has no statistically significant impact on LGDP, LAI or LDGE. For these interactions we lack enough evidence to deny the null hypothesis stating causality does not exist.

Table 7. Causality test.

Null Hypothesis	Obs	F-Statistic	Prob.
LGDP $\neq$ LCO	30	4.65823	0.0499
LCO_2 $\neq$ LGDP		0.76382	0.647
LAI $\neq$ LCO_2	30	3.78341	0.0027
LCO_2 $\neq$ LAI		0.67394	0.7692
LREN $\neq$ LCO_2	30	6.67381	0.0072
LCO_2 $\neq$ LREN		0.46839	0.0283
LDGE $\neq$ LCO_2	30	3.89923	0.0071
LCO_2 $\neq$ LDGE		0.67892	0.1381
LINDUS $\neq$ LCO_2	30	2.78290	0.0077
LCO_2 $\neq$ LINDUS		3.39028	0.0154

4.7. Diagnostic Test

The diagnostic assessment results appear in Table 8. The experimental results proved that all diagnostic procedures yielded minimal effectiveness rates during which the null hypothesis maintained its validity. The JB test results show that the residuals follow a normal distribution since the calculated p value stands at 0.2078. Analysis through the LM method shows that the residuals do not show serial correlation since the p-value stands at 0.5698. The BPG test validates that the residuals show no heteroscedasticity because its p-value reaches 0.7830.

Table 8. The findings of diagnostic tests.

Diagnostic tests	Coefficient	p-value
Normality test	0.26531	0.2078
Serial Correlation test	0.78901	0.5698
Heterocedasicity test	1.3245	0.7830

The structural reliability assessment of residuals at extended and brief intervals uses CUSUM and CUSUM-SQ statistics. The CUSUM-SQ plot graphically displays results within accepted critical limits through its position on the crucial line as shown in figure 01. The tests support the acceptability and coherence of parameters at a 5% significance level.

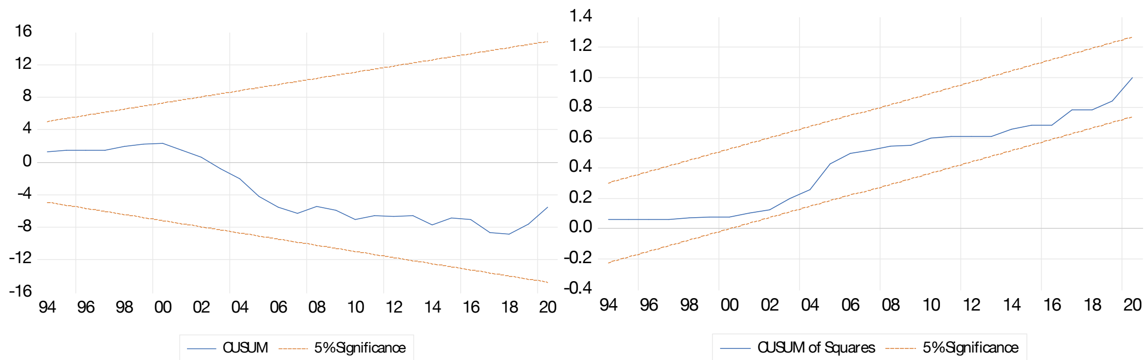

Figure 1. CUMSUM and CUSUM-SQ.

5. Conclusion

A thorough examination has studied the implications of AI innovation, GDP growth, cleanenergy usage, digital economy, and industrialization on CO_2 emissions in the USA from 1990 to 2022. The research confirms through the ARDL framework that AI innovation, along with the digital economy and renewable energy production, lowers environmental stress, yet GDP growth, together with industrialization, worsens environmental issues. The results from ADF, PP, and DF-GLS tests verify that these variables possess different levels of integration status without existing unit root issues. The analysis through ARDL methodology shows positive relationships among AI innovation and green power adoption and the digital economy toward USA CO_2 emissions reduction. The successful deployment of sustainable energy systems and a digitalized economy together with AI technology brings positive results to environmental quality. Economic development, along with industrial evolution, generates an opposing reaction with CO_2 emissions, indicating that these activities destructively affect environmental quality. The implementation of energy-efficient approaches and environmentally friendly industrial methods allows the development of innovative rivalries, which lead to sophisticated technology access. The reliability of ARDL results gains additional credibility through robustness assessments that use the combination of FMOLS, DOLS, and CCR. The Granger causality tests reveal that unidirectional causal effects run from LCO_2 to LAI and from LCO_2 to LDGE. The relationships between economic developments and advancements in AI, together with digitalization, demonstrate extensive effects on environmental sustainability within the USA. The study provides multiple suggested laws to enhance America's sustainable economic growth through technical innovation implementation alongside greener energy consumption methods and sustainable industrial installation.

Declarations

Ethics approval: Not applicable.

Consent to participate: Not applicable.

Consent for publication: Not applicable.

Acknowledgment: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

Data availability: Data will be available upon reasonable request from corresponding author.

Author's contribution: Adita Sultana and Abdullah Al Abrar Chowdhury were responsible for the conceptualization and design of the study, as well as conducting the literature review. Azizul Hakim Rafi led the development of the methodology and performed the data analysis. Abdulla All Noman contributed to the interpretation of the findings and the drafting of the discussion. All authors contributed to manuscript revision and approved the final version, ensuring the integrity and quality of the work.

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