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RESEARCH ARTICLE

Leveraging AI for a Greener Future: Exploring the Economic and Financial Impacts on Sustainable Environment in the United States

Mohammad Ridwan[1*], Shewly Bala[2], Sarder Abdulla Al Shiam[3], Afsana Akhter[1], Md Asrafuzzaman[3], Sarmin Akter Shochona[3], Shake Ibna Abir[4], Shaharina Shoha[4]

[1]Department of Economics, Noakhali Science and Technology University, Sonapur, Noakhali-3814, Bangladesh
[2]Department of Finance, University of Dhaka, Bangladesh
[3]Department of Management -Business Analytics, St Francis College, USA
[4]Department of Mathematics, Western Kentucky University, Bowling Green, KY, USA

Corresponding author: Mohammad Ridwan. Email: m.ridwan.econ@gmail.com
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Abstract
In response to increasing environmental challenges, the United States has deliberately adopted technical advancements to promote sustainable development. This includes efforts to decrease pollution, improve energy efficiency, and encourage the use of environmentally friendly technology in different industries. This study investigates the role of Artificial Intelligence (AI) technology in promoting environmental sustainability in the United States from 1990 to 2019. It also examines the impacts of financial development, ICT use, and economic growth on the Load Capacity Factor (LCF). Various unit root tests revealed no unit root issues and mixed integration orders among variables. The Autoregressive Distributive Lag (ARDL) model explored cointegration, indicating long-run relationships among the variables. The ARDL findings confirm the Load Capacity Curve hypothesis for the United States, with AI technology and ICT use positively correlating with LCF in both the short and long run. Conversely, financial development and population growth significantly reduce LCF. Robustness checks using FMOLS, DOLS, and CCR estimation approaches align with the ARDL results. Granger causality tests reveal unidirectional causality from economic growth, AI, financial development, and ICT use to LCF and bidirectional causality between population and LCF. Diagnostic tests confirm the results are free from heterogeneity, serial correlation, and specification errors. This study underscores the importance of AI and ICT in enhancing environmental sustainability while highlighting the adverse impacts of financial development and population growth on LCF.

Keywords: Artificial Intelligence; Financial Development; ICT Use; Load Capacity Factor; United States

Introduction

In the modern world, environmental deterioration is a reason to be concerned (Usman et al., 2020). The main driver of rising temperatures, which promotes climate change, is fossil fuel breakdown (Isfat and Raihan, 2022; Polcyn et al.2023). Our planet will suffer tremendously due to this temperature rise phenomenon, with severe weather events, increasing sea levels, and the eventual extinction of numerous species (Raihan and Tuspekova, 2022; Pattak et al.2023).

The implications of global warming and strategies to lessen their effects on the ecosystem as a whole were explained by Rafindadi et al.(2018), Alola et al.(2019a, 2019b), and Raihan et al.(2024a). To mitigate such catastrophic repercussions, organizations and lawmakers must set policies in effect focused on reducing emissions of carbon dioxide. This may be implemented by boosting the efficiency of energy usage as well as transitioning to a more sustainable power system (Tian et al., 2022; Voumik and Ridwan, 2023). The second-highest CO_2 generator in the globe, underlying China, with around 4833.1 million tons of emissions, and the third-largest transmitter of CO_2 per individual is the USA (Germanwatch, 2019). The USA has a 133% shortage in biological capacity, which indicates that the ecological footprint exceeds the biocapacity (Alola et al.,2020). By 2018, the contribution of primary power utilized globally derived from fossil fuels, nuclear power, and green energy sources was around 85%, 4%, and 11%, respectively (BP, 2019). Due to the burning of fossil fuels, this overreliance on natural energy sources creates severe ecological issues like air pollution, rising temperatures, and climate (Bilgili et al.2017; Danish and Ulucak 2020). Moreover, the country has the biggest GDP in the globe and spends a lot of money on its power system (Danish and Ulucak , 2021). Thus, the World Bank (2020) revealed that in 2018, the US economy's share of the global GDP (constant 2010 USD) was around 21.6%. The alarming data mentioned earlier inspired this author to investigate the environmental sustainability of the USA, even despite the nation's abundance of clean energy sources and the adoption of legal initiatives intended to promote environmental sustainability. In order to combat global warming and fostering sustain prosperity, policymakers must recognize the country's ability to minimize pollution. How the USA can cut emissions is an urgent issue, which might be accomplished by assessing the implications of financial development, ICT utilization, and AI innovation on the LCF. For monitoring, anticipating, and reducing ecological risks, artificial intelligence (AI) is now a transforming force (Rane, 2023; Kunduru, 2023; Ukoba and Jen, 2022; Bahroun et al., 2023). Nonetheless, ICT can decrease damage to the environment by boosting public awareness of sustainability issues while encouraging the utilization of innovative technologies (Plepys, 2002; Laschkarizadeh and Salatin, 2012).

Conversely, the ecological footprint solely considers the demand side of the natural ecosystem and ignores its supply side (Adebayo and Samour, 2024; Voumik et al.2023a). To get over this issue, multiple research studies such as Pata (2021), Shang et al. (2022), and Xu et al. (2022) considered the level of ecology by utilizing the LCF to provide precise information on the quality of the environment. Furthermore, Siche et al. (2010) and Pata (2021) considered an LCF less than one, suggesting that the present biodiversity condition is not green, but a value greater than 1 indicates that the current system is stable. As a result, the sustainability limit is 1 (Akadiri et al.,2022). According to Worldometer (2024), 339,996,563 people are expected to live in the United States by the halfway point of 2023. Furthermore, the population (281,984,165 in 2023) constitutes 4.23% of the global population, and about 82.9% of the people reside in urban areas. In 2022, the United States' GDP expanded by 2.1%, the highest yearly growth since 1984 in 2021 (ECLAC,2023). However, global carbon emissions must drop by 7.6% annually to stay beneath the 1.5 °C rise in temperatures beyond the era of industrialization, which signals the existence of the biggest disastrous ecological risks (Evan, 2020; UNEP, 2021 IPCC, 2018). Researchers in the fields of software development and digital innovation are growing increasingly engaged in using ICT to promote awareness and boost sustainable endeavors and behaviors (Adisa and Porras, 2024; Ridwan et al.2024). Asongu et al. (2018), for instance, underlined how modern technological solutions might encourage clean environments, specifically in poor nations, by rendering education more accessible and spreading ecological practices.

Using AI to its full potential will enable us to reduce ecological damage, maximize the utilization of resources, and uncover new insights (Akter,2024; Voumik et al.2023b). According to a 2018 Microsoft/PwC study, for instance, using AI for sustainability initiatives might raise global economic output by 3.1% to 4.4% while cutting GHG pollution by 1.5% to 4% by 2030 (Microsoft, 2018; Hasan et al.2024). Moreover, cities can shift toward a more circular economy model, minimizing environmental effects and boosting sustainability, by using AI for garbage reduction and recycling (Verma et al.,2022; Magazzino et al.,2021; Rana et al.2024). Artificial intelligence (AI) tools can also aid in predicting severe weather conditions that are getting more frequent due to global warming, such as forest fires (Jaafari et al. 2019), extreme rainfall damage (Choi et al. 2018), and the level of human movement (Robinson and Dilkina 2018; Shium et al.2024a). Frequently, artificial intelligence (AI) methods can boost present forecasting as well as prediction systems. For instance, they can be used to automatically label information obtained from climate simulations (Chattopadhyay et al. 2020) and distinguish across indicators and noise in the assessment of climate change (Barnes et al. 2019). Both developed and emerging nations' GDPs are greatly impacted by the monetary sector (Haseeb et al., 2018; Shium et al.2024b). An efficient financial system draws in investors, strengthens the stock market, and increases the productivity of economic activity (Sadorsky, 2011). Furthermore, a substantial amount of empirical research suggests that growth in finances is influencing the quality of the natural ecosystem (Khan et al., 2018; Charfeddine and Kahia, 2019). Our research contributed to several distinctive perspectives. First off, the United States' huge population has accelerated economic growth and exacerbated ecological concerns. Second, the environmental effects of these factors will fluctuate considerably depending on different levels of financial development and AI technology in the USA. Therefore, goals related to sustainability might shift as development moves forward. Thirdly, this research contrasts with other studies like Dahmani et al. (2023), which emphasized multiple environmental variables in that it examines the expected advantages of ICT, AI innovation, and financial development on LCF. Furthermore, compared to the Ecological Footprint (EF), LCF offers an advanced approach to accounting for biodiversity loss. The combined effect of ICT use and AI innovation is significant in the context of ensuring ecological viability in the USA, and its implementation of the LCC hypothesis offers an exceptional contribution. In conclusion, the ARDL method is adopted in this study to explore the implications of several indicators and to assure robustness. FMOLS, DOLS, and CCR techniques are also utilized. Depending on the outcomes, we discuss the policy implications for enhancing environmental sustainability.

This investigation is structured into several key sections. The "Literature Review" provides an overview of relevant studies. The "Data and Methodology" section details the data sources and empirical techniques used for analysis. Findings and their interpretations are presented in the "Results and Discussion" section. Finally, the "Conclusion and Policy Implications" section offers concluding insights and recommendations for further research on green ecosystems.

Literature Review

Numerous experiments looked at how the usage of ICT, financial development, and GDP expansion affect the LCF. While multiple studies have used the ARDL framework, most of the studies have focused on how population density and advances in technology affect environmental quality. Other studies examined the link between the globalization of finance, ICT usage, and LCF; however, the variable innovation in AI has received less attention in those studies. Thorough research remains inadequate in the US literature on AI innovation and environmental sustainability. Nonetheless, a few previous investigations have offered insight into the factors and techniques of investigation applied. The next part goes over a few of those queries.

Substantial monetary growth and resource wealth are related to higher ecological degradation (Hunjra et al., 2024). Achieving sustainable development goals, addressing environmental problems, and ensuring financial stability are all possible with a green growth approach (Ridwan et al.,2023, Urbee et al.2024). By utilizing the ARDL approach, Raihan et al. (2023) demonstrated that Mexico's LCF decreases when economic expansion occurs. Adebayo and Samour (2024) employed the PNARDL method and showed that economic development is a major reason for environmental damage in BRICS countries. Moreover, several investigations, for example, Nathaniel et al.(2019), Nathaniel et al.(2020), Ahmed et al.(2020a), Ahmed et al.(2020b); Raihan et al.(2022a), Raihan et al.(2022b)

Raihan et al.(2024b) and Sun et al.(2024) concluded that expansion of economy degrades ecosystem quality. In response to this, Solarin et al. (2021), who utilized the ARDL approach for Nigeria, discovered that although growth in the economy first degrades the environment, it eventually improves it. Additionally, the link between GDP growth and CO_2 emissions in India from 1965 to 2022 was investigated by Raihan et al. (2024a). The ARDL long-run elasticity's findings suggest that economic expansion helped to mitigate some emissions. Several works by Hassan et al. (2019) and, Baloch et al.(2021) in Pakistan and Bento and Moutinho (2016) in Italy show that economic expansion causes environmental unsustainability. Moreover, Balcilar et al. (2018) asserted that ecological quality in Germany and the UK is unaffected negatively by monetary expansion.

There is a substantial deficiency in achieving the SDG goals due to the absence of research on the use of AI for environmental concerns. AI is crucial in mitigating the urgent problems of global warming, biodiversity loss, and ecological loss, which are becoming increasingly evident as humanity struggles to solve these issues (Akter, 2024). AI, in its simplest form, comprises computers or other devices that imitate the cognitive functions regarding intelligence in humans, like learning and solving problems (Khanzode and Sarode, 2020). Four primary domains broadly define the intersection of AI and green environment: pollution and waste administration, preservation of natural assets, agricultural sustainability, and monitoring of pollution and treatment (Qian et al., 2018; Granata and Nunno, 2021). Leveraging artificial intelligence (AI) technological advances is an appropriate strategy to promote systemic modifications and advance sustainable development (Jarrahi, 2018; Jeste et al., 2020). According to Ray et al. (2024), pollution, especially contamination with heavy metals, can be detected, examined, and regulated by integrating environmental research with technological advances in AI, particularly machine learning, forecasting, and advanced algorithms. Similarly, Yadav and Singh (2023) demonstrated that artificial intelligence (AI) may improve ecological sustainability by mitigating global warming and enhancing agriculture, water availability, marine ecosystems, prediction of weather, and resilience to disasters.

Financial development (FD) has the potential to adversely affect the ecosystem and either raise or lower the need for energy (Usman et al.,2024). In addition, by expanding the financing facilities to projects in R&D, enlarging techno-financial support to businesses, and encouraging environmentally friendly innovations, the financial development intends to lower emissions of carbon and sustain the environment (Abid et al., 2021; Yao et al., 2021). The dynamic consequence of expansion in finances on ecological sustainability in China was investigated by Fu et al. (2022), who determined that monetary expansion is favorable to long-term environmental sustainability. Using yearly data from 1990 to 2020, Solaymani and Montes (2024) employ the ARDL approach. The empirical study reveals that New Zealand's FD considerably lowers carbon emissions and ensures a green ecosystem. In the same way, Ahmad et al. (2022) established that by raising the EFP, financial development causes environmental damage. Moreover, advancement in finance can promote environmental preservation in South Asia countries (Ozturk et al.,2024). Furthermore, Ramzan et al. (2022) investigated how financial development affected Pakistan's increased pollution levels. The financial sector's encouragement of the widespread industrial processes increases the environmental hazards (Yuxiang and Chen, 2010; Usman et al., 2022). Multiple researchers also indicated that development in finances degrades the level of natural health (Saqib et al.,2024; Petrović and Lobanov,2022; Khan et al.,2019).

Numerous investigations into the connection between ICT and harm to the environment have produced conflicting findings. According to certain research, using ICTs greatly reduces environmental pollution, improving the natural environment (Park et al. 2018). ICT expenditure, however, has a minimal effect, mostly on ecological sustainability, as Ziemba and Grabara (2024) discovered. Qayyum et al. (2024) illustrate how ICT protects the atmosphere by lessening its ecological effect by using CS-ARDL estimators. The results of the investigation show that ICT invention is required to achieve the goal of a green environment in the long run. Similarly, Mensah et al. (2024) found that IQ and ICT collaborate to improve the environment and reduce footprint by 0.0748%. The majority of research indicates that using ICT facilities helps lower pollution (Ozcan and Apergis 2018). Moreover, Coroama et al. (2012) state that ICT might mitigate GHG emissions by promoting energy-efficient production and consumption practices. Similar findings also concluded by Lu (2018) in 12 Asian countries, Ahmad et al.(2023) in OECD countries, N'dri et al.(2021) in developing countries, Sahoo et al.(2021) in India and Chien et al.(2024) in Indonesia. However, a small number of additional studies suggest that using ICT leads to increased environmental contamination and environmental degradation (Asongu et al. 2018). By adopting the ARDL approach, Lin and Ullah (2023) observed that ICT hinders environmental sustainability in Pakistan. Ulucak and Khan (2020) concluded that ICT has a detrimental implication on GHG pollution in the BRICS nations. Additionally, Salahuddin et al. (2016) indicated that a 1% expansion in internet use generates a spike in carbon emissions in the OECD nations of 0.16%.

Growing populations are considered to have an unfavorable impact on the environment as individuals need more places to live, healthcare, schooling, and transportation options (Isik et al., 2019; Wu et al., 2022b, Raihan, 2023). However, since it lessens carbon emissions, population growth (POP) which is planned leads to environmental sustainability (Katircioglu et al., 2018; Dogan et al., 2020, Oje, 2024). Voumik et al. (2023c) used the ARDL approach to evaluate the impact of the population on Kenya's carbon emissions. They proved that the country's CO_2 emissions may climb in tandem with its growing population. Similarly, using data from 1990 to 2019 in Malaysia, Raihan (2024) adopted the ARDL approach and concluded that population growth has an encouraging association with long-term carbon pollution. By using the recently developed LCC hypothesis, Erdogan (2023) observed that an ecosystem is diminished by a high population in Africa. Additionally, Adebayo (2023) used the BDS test to investigate Turkey's ecological impact. They found that high population density is the major cause of ecological destruction in the majority of quantiles. Using a geographic semi-parametric panel technique, Xie et al. (2023) found similar results in China's environment, demonstrating that the country's population growth exacerbates damage to the environment. Additionally, Bangladesh's ecology suffers from high population density (Rahman and Alam, 2021, Datta, 2024). Conversely, Wu et al. (2021a) noted that China's increasing population might also have a short- and long-term beneficial impact on the reduction in biodiversity loss.

Ultimately, our literature assessment has proven that a few studies explicitly examine the LLC hypothesis for the USA while considering the consequences of financial development, ICT use, economic expansion, population, and AI innovation. Many studies examined the LLC hypothesis in emerging economies, but their study has been specific and fails to take other economic sectors into account. It seems reasonable to investigate the LLC hypothesis as the USA is an expanding nation with distinctive ecological variables. The literature that is currently available on AI for environmental sustainability addresses several topics, including power, transport, water, and biological diversity. On the other hand, relatively no research is being done on the real-world uses of AI innovation on load capacity factor, especially when it comes to solving sustainability problems. Even though certain useful applications, such as the disposal of trash using sophisticated navigation strategies and protecting animals for increased biodiversity, have been seen in developed nations, additional studies and research are still required. The absence of knowledge on how AI might be used to effectively safeguard the environmental sustainability of the United States creates a research gap. Additional research is required to discover and develop innovative applications of AI that can help the chosen area achieve the Sustainable Development Goals (SDGs). By bridging the knowledge and implementation gaps, closing this research gap would make it possible to apply AI and ICT effectively to address ecological sustainability concerns across different regions.

Methodology

Data

Table 1 is an essential feature of the study as it offers a comprehensive overview of all the variables examined. It offers insightful details on their descriptions, units of measurement, and sources. The LCF information for the US is obtained from the Global Footprint Network (GFN, 2022). A higher LCF is representative of a better ecosystem as it incorporates EF and biocapacity in the denominator (Pata and Kartal, 2023). Numerous independent factors were also included in this research, all of which depended on meticulously gathered data. World Development Indicators (WDI, 2022) offered statistics on GDP, GDP squares, and population; trustworthy Our World in Data (2022) was implemented to gather information on other significant elements such as Artificial Intelligence innovation and ICT usage. However, data regarding financial development is collected from the IMF. Therefore, by improving the accessibility and reliability of the study's methodology, the thorough documentation guarantees a clear and coherent analysis.

Table 1: Source and Description of Variables

Variables	Description	Logarithmic Form	Unit of Measurement	Source
LCF	Load Capacity Factor	LLCF	Gha per person	GFN (2022)
GDP	Gross Domestic Product	LGDP	GDP per capita (current US$)	WDI (2022)
GDP^2	Square of Gross Domestic Product	$LGDP^2$	GDP per capita (current US$)	WDI (2022)
AI	Artificial Intelligence Innovation	LAI	Annual patent applications related to artificial intelligence	Our World in Data (2022)
FD	Financial Development	LFD	Financial Development Index	IMF (2022)
ICT	ICT use	LICT	ICT goods imports (% of total imports)	Our World in Data (2022)
POP	Population	LPOP	Population, total	WDI (2022)

Theoretical Framework

The LCC theory depends on the LCF statistic, which takes prospects for ecological provision and human-made demand for resources into consideration (Pata et al.,2023). Through a contrast of ecological footprint and biocapacity, the LCF offers an additional assessment of the environment (Dogan and Pata, 2022). By comparing EFP and biocapacity, the LCF examines a specific ecological threshold; an upward trend in the LCF indicates a better ecosystem and a fall in the LCF suggests a surge in environmental deterioration (Alola et al.,2023). Moreover, the LCC emphasizes the interdependence of sustainability problems, such as resource scarcity, destruction of natural assets, and temperature rise (Wu et al.,2024). Ulucak et al. (2020) revealed that manufacturing pollution and waste are exacerbated by economic expansion, and production procedures and emissions are influenced by sectoral composition. Countries all around the world use a variety of petroleum-based products, including natural gas, coal, and fuel, to encourage growth in GDP, growth in population, and industrialization, all of which harm the planet (Chen et al.,2022). Similarly, financial development can also degrade biodiversity.

Now, we have created the following equation (1) for LCC theory:

$$Load\ Capacity\ Factor = f(GDP, GDP^2, K_t) \quad (1)$$

In this case, the variables for wealth in equation (1) are GDP and GDP squared, while the parameter for other factors affecting the LCF is K_t. The purpose of equation (2) is to provide an expanded view of the factors changing the LCF by consisting of several relevant factors such as population, development in finances, ICT use, and AI innovation.

$$LCF = f(GDP, GDP^2, AI, FD, ICT, POP) \quad (2)$$

In equation (2), the load capacity factor is represented by LCF, GDP stands for economic growth, AI represents artificial intelligence innovation, FD refers to financial development, and POP indicates population. The econometric justification of equation (3) is given above.

$$LCF_{it} = \delta_0 + \delta_1 GDP_{it} + \delta_2 GDP_{it}^2 + \delta_3 AI_{it} + \delta_4 FD_{it} + \delta_5 ICT_{it} + \delta_6 POP_{it} \quad (3)$$

In scientific and financial research, logarithmic scaling is a particularly helpful adjustment for consolidating broad ranges as it efficiently stabilizes fluctuation. It improves perception and facilitates the formulation of conclusions based on statistics by bringing down complex connections into simpler linear forms. Equation (4) illustrates the variables' logarithmic values.

$$LLCF_{it} = \delta_0 + \delta_1 LGDP_{it} + \delta_2 LGDP_{it}^2 + \delta_3 LAI_{it} + \delta_4 LFD_{it} + \delta_5 LICT_{it} + \delta_6 LPOP_{it} \quad (4)$$

Here, within the parameter range of δ_0 to δ_6, the coefficients of the research variables are listed.

Econometric Framework

This research uses multiple stages in its estimate technique to address frequent problems. The ADF, P-P, and DF-GLS examinations are utilized to check stationarity and confirm independence among the variables. Next, the ARDL method is used to discover both immediate and long-term relationships. The research then makes use of the FMOLS, DOLS, and CCR to confirm the accuracy of the long-run estimation. The associated relationships between GDP, financial development, ICT use, AI innovation, population, and LCF in the USA were then examined using the Pairwise Granger causality test. Finally, we performed three diagnostic tests to check autocorrelation, heteroscedasticity, and multicollinearity.

Stationarity test

In order to provide accurate statistical modeling, non-stationary data must be used as non-stationary regressions might produce deceptive findings. A series with a unit root suggests that systemic shocks have a lasting impact on the series' long-term behavior (Ridwan, 2023). In order to attain stationarity and guarantee precise forecasting and inference, researchers can distinguish between stationary and non-stationary processes by identifying unit roots. This distinction helps researchers select the right models and transformations, such as differencing (Ridzuan et al.2023). Three stationarity tests were performed in this research: the Augmented Dickey-Fuller (ADF) test, which Dickey and Fuller (1981) introduced, the Phillips and Perron (1988), and the DF-GLS examination, which Elliot et al. (1996) suggested. When variables are stationary but have a root close to a non-stationary frontier, the ADF and Phillips-Perron tests have drawn criticism for their inadequate efficiency (Brooks, 2014). When serial correlation is present in the residuals, the Phillip-Perron test was designed to remove the asymptotic bias that was present in the original ADF test (Davidson and MacKinnon, 1993). According to Elliot et al. (1996), the DF-GLS assessment is more robust compared to the ADF and Phillips-Perron tests when there is an uncertain mean or trend. The Monte Carlo evidence given by Stock (1994) also demonstrates the improved performance of the DF-GLS evaluation.

Autoregressive Distributive Lag model

The cointegrating link between the variables is further captured in the research with the help of the ARDL bounds assessment. For series with a small sample size, this test is trustworthy. When the factors are only partially integrated, it is also advantageous (Akadiri, 2022). Examining the link between the aforementioned sustainable ecosystem indicators and the GDP, FA, AI, ICT, and POP using the ARDL model highlights the relevance of LCF. Pesaran et al. (2001) proposed the ARDL approach, an extensive dynamic regression model that combines the characteristics of autoregressive as well as distributed lag models. In comparison to conventional cointegration techniques, it has several benefits. First of all, variables can be integrated into various orders; variables integrated of order one, order zero, or even fractionally integrated, except for 1(2), can be supported. Second, this framework may be used for data analysis in situations when sample sizes are limited and small due to its efficiency (Kumar et al., 2024). Thirdly, Harris and Sollis (2003) have shown that the model yields unbiased estimates over an extended period. Finally, this model captures both short-term dynamics and long-run linkages by integrating short-run adjustments with long-run equilibrium through the derivation of the Error Correction Term (ECT) via a straightforward linear transformation (Ali et al., 2017). Equation (5) can be used to represent the ARDL Bound test:

$$\begin{aligned} \Delta LLCF_t = {} & \omega_0 + \vartheta_1 LCF_{\mathrm{t}-1} + \vartheta_2 LGDP_{t-1} + \vartheta_3 \mathrm{LGDP}^2{}_{t-1} + \vartheta_4 LAI_{t=1} + \vartheta_5 LFD_{t-1} + \vartheta_6 LICT_{t-1} + \vartheta_7 LPOP_{t-1} \\ & + \sum_{i=1}^{k} \omega_1 \, \Delta LLCF_{2_{\mathrm{t-i}}} + \sum_{i=1}^{k} \omega_2 \, \Delta \mathrm{LGDP}_{\mathrm{t-i}} + \sum_{i=1}^{k} \omega_3 \Delta \mathrm{lnGDP}^2{}_{\mathrm{t-i}} + \sum_{i=1}^{k} \omega_4 \Delta LAI_{t=1} \\ & + \sum_{i=1}^{k} \omega_5 \, \Delta \, LFD_{t-i} + \sum_{i=1}^{k} \omega_6 \Delta \mathrm{LICT}_{\mathrm{t-i}} + \sum_{i=1}^{k} \omega_7 \Delta \mathrm{LPOP}_{\mathrm{t-i}} + \varepsilon_t \qquad (5) \end{aligned}$$

The alternative hypothesis (H1) and the null hypothesis (H0) are represented by equations 6 and 7.The evidence supporting cointegration (the alternative hypothesis) is contrasted with the null hypothesis, which claims that there exit no cointegration. If the F-statistic exceeds both the lower and upper limit values, the null hypothesis cannot be accepted.

$$H_0 = \omega_1 = \omega_2 = \omega_3 = \omega_4 = \omega_5 = \omega_6 \neq \omega_7 \quad (6)$$

$$H_1 = \omega_1 \neq \omega_2 \neq \omega_3 \neq \omega_4 \neq \omega_5 \neq \omega_6 \neq \omega_7 \quad (7)$$

After confirming cointegration among the parameters, the short-run coefficient and the ECT are assessed using the Engle and Granger (1987) ECM. The ECM is included in the ARDL framework in the following ways to accomplish this:

$$\Delta LLCF_t = \omega_0 + \sum_{i=1}^{k} \vartheta_1 \Delta \mathrm{LCF}_{\mathrm{t-i}} + \sum_{i=1}^{k} \vartheta_2 \Delta \mathrm{LGDP}_{\mathrm{t-i}} + \sum_{i=1}^{k} \vartheta_3 \Delta \mathrm{lnGDP}^2{}_{\mathrm{t-i}} + \sum_{i=1}^{k} \vartheta_4 \Delta LAI_{t=1} + \sum_{i=1}^{k} \vartheta_5 \Delta\, LFD_{t-i} + \sum_{i=1}^{k} \vartheta_6\, \Delta \mathrm{LICT}_{\mathrm{t-i}} + \sum_{i=1}^{k} \vartheta_7 \Delta \mathrm{POP}_{\mathrm{t-i}} + \aleph ECT_{t-i} + \varepsilon_t \quad (8)$$

Here, the sign ℵ is used to denote the rate of adjustment.

Robustness Check

To assess the feasibility of ARDL results, we employed the FMOLS, DOLS, and CCR methodologies. When examining a single cointegrating link with a mixture of integrated orders of I(1) variables, the FMOLS approach is applied (Ahmad et al., 2019). The FMOLS analysis, a nonparametric method, has the benefit of simultaneously accounting for sequence correlation, endoplasmic error, and simultaneous bias (Hamit-Haggar.,2012). It also considers the possibility of heterogeneity in the long-run parameters (Phillips and Hansen, 1990). In the meanwhile, DOLS successfully combats potential endogeneity and sample bias difficulties and minimizes feedback in the cointegrating equation with its enhanced regression technique, which incorporates leads and lags of the initial differences of regressors (Idores et al., 2024). Kao and Chiang (1999) provided the DOLS as an alternative (parametric) estimator for predicting the long-run interaction of variables using first differenced regressor leads and lags. Additionally, the CCR approach established by Park (1992) could be utilized for testing for cointegrating vectors in a model with an integrated process of order I(1). Consistent estimates are produced by this approach in a variety of situations, including those involving extremely persistent time series. According to Kinnunen et al. (2024), CCR is particularly recognized for its flexibility in handling a wide range of difficulties that can be created with cointegrated regression analysis.

Granger Causality test

Our methodology is based on Granger (1969), who suggested using time-series data to establish the association between financial variables. Whether one factor may aid in the forecasting of another parameter is a usual inquiry in time series analysis (Kumo,2012). Granger causality has two main implications: either x must Granger cause Y or vice versa if two variables say x and y, are co-integrated (Awe,2012). Two variables are cointegrated if they have a shared stochastic trend (Engle and Granger, 1987). A pair of elements are considered cointegrated in a broader sense if their linear combinations are stationary (I(0)) and if they are not stationary in and of themselves but are stationary in their initial differences (Yousefi, 2015). It was possible to get a more complete and nuanced view of the links and linkages that occur in our analysis by incorporating pairwise Granger causality tests within our research.

Diagnostic test

To assess the accuracy of the information utilized for the factors selected in this work, we make use of the Breusch-Godfrey Lagrange Multiplier test to identify serial correlation issues, the Breusch-Pagan-Godfrey test is used to examine heteroskedasticity, and the Jarque-Bera test is used to confirm residual normality (Gupta and Singh, 2016). The sample skewness S and kurtosis K from the observed time series data are measured by the Jarque-Bera test statistics. According to the normality concept, S and K have values of 0 and 3, respectively (Thadewald & Büning 2007). Mokhtar (1994) argues that autocorrelation typically happens in both time-series and cross-sectional data. However, we know that time is the factor that causes autocorrelation in time series data. Unreliable research findings will emerge from a model with a heteroscedasticity issue, and the estimated model will not be appropriate for application (Lun and Samsudin, 2022).

Results and Discussion

Summary Statistics

Using the different results of many normality assessments (skewness, probability, kurtosis, and Jarque-Bera), Table 2 showcases the outcomes of the summary measurements among the variables. Additionally, it offers basic descriptive statistics for factors in the actual and logarithmic forms, including mean, standard error, median, standard deviation, and lowest and highest figures. Time series data for the USA from 1990 to 2019 is included in each parameter, with 32 observations. All of the elements appear to follow normality based on the negative values of skewness by the variables. In addition, the research used kurtosis to determine if the series exhibited a strong or weak tail compared to a normal distribution. Furthermore, the Jarque-Bera probability calculations demonstrate that every parameter is normal. We moved further with the component correlation assessment based on this information.

Table 2. Summary Statistics of the Variables

Statistic	LCLF	LGDP	$LGDP^2$	LAI	LFD	LICT	LPOP
Mean	-0.835416	10.64393	113.3917	2.625053	-0.167379	19.4995	7.505506
Median	-0.822656	10.71885	114.8942	7.157725	-0.096679	2.63119	19.50906
Maximum	-0.63269	11.15938	124.5318	9.724421	-0.081949	2.871059	19.62074
Minimum	-0.970971	10.08116	101.6297	6.320768	-0.520773	2.267549	19.33546
Std. Dev.	0.093945	0.318778	6.76113	1.035853	0.137067	0.132527	0.086792
Skewness	0.065531	-0.255693	-0.219087	1.155679	-1.662635	-0.270512	-0.311181
Kurtosis	1.965479	1.888894	1.876795	2.992345	4.273768	3.783686	1.894819
Jarque-Bera	1.449882	1.994763	1.938117	7.123243	16.90654	1.209162	2.14501
Probability	0.484353	0.368844	0.37944	0.128393	0.332213	0.546303	0.34215
Sum	-26.73331	340.6058	3628.534	240.1762	-5.356143	84.00168	623.984
Sum Sq. Dev.	0.273596	3.150205	1417.099	33.26275	0.582405	0.544463	0.233521
Observations	32	32	32	32	32	32	32

Stationarity test

The Table 03 below presents the findings of stationarity testing with the ADF, DF-GLS, and P-P procedures. The ADF test observations illustrated that after taking the first difference, LLCF, LGDP, $LGDP^2$, and LAI became stationary from their non-stationary values. On the other hand, LFD, LICT, and LPOP stayed stationary at their levels after first differencing. For each factor, the findings of the P-P and DF-GLS assessments were identical to those of the ADF test. Interestingly, at first differencing, every variable in the ADF, P-P, and DF-GLS tests is significant at the 1% level. After first differencing, the $LGDP^2$ variable in the DF-GLS analysis, however, is only significant at the 5% level. The stationarity examination findings reveal that the series is stationary at mixed levels of either level or first-order integration, I(0) or I(1), meaning that the ARDL bounds cointegration method might be applied to this study.

Table 3. Results of unit root tests

Variables	ADF		P-P		DF-GLS		Decision
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
LLCF	-0.799	-5.347***	-0.826	-5.345***	-1.475	-4.302***	I(1)
LGDP	-0.878	-4.841***	-0.953	-4.829***	-1.771	-3.137***	I(1)
$LGDP^2$	-0.614	-5.001***	-0.650	-4.968***	-1.142	-3.343**	I(1)
LAI	-2.014	-4.881***	-1.181	-3.676***	-2.047	-4.121***	I(1)
LFD	-3.071**	-4.381***	-3.108**	-4.551***	-3.184**	-4.221***	I(0)
LICT	-3.052**	-4.585***	-3.010**	-4.574***	-3.435**	-3.836***	I(0)
LPOP	-4.520***	-7.341***	-7.550***	-8.112***	-3.229**	-4.549***	I(0)

ARDL Bound test

We first determine the stationarity characteristics of the series and then perform the ARDL bounds technique for cointegration evaluation. The F-statistic was computed with suitable lag duration according to the lowest values of the Akaike Information Criterion in this investigation. The cointegration relationship between the variables was investigated using the ARDL bounds test, and the findings are displayed in Table 4. The outcomes are organized so that the existence of a long-term link between the variables is demonstrated if the estimated value of the F-test is greater than the values of both limits (upper and lower bound). Our findings support the rejection of the null hypothesis by indicating that the variables have a long-term connection. The approximate F-statistic value (9.129832) is greater than 10%, 5%, 2.5%, and 1% of the critical upper limit in the order zero and one, accordingly. Therefore, we conclude that variations in each of these factors have a consequence on the LCF in the USA.

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Table 4. Results of ARDL bound test

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	9.129832	10%	Asymptotic: n=1000	1.99
		6%	2.27	3.28
		2.50%	2.55	3.61
		1%	2.88	3.99

ARDL short-run and Long-run

The ARDL results for each variable can be seen in Table 5. The short and long-term dynamics' findings revealed that GDP has an adverse effect on the LCF; that is, for every 1% rise in LGD, the ecosystem's quality will decline by 0.899% and 0.360%, respectively. This suggests that when economies evolve, they correspondingly increase the need for goods, power, and natural assets, which leads to greater production of pollutants, which worsen environmental conditions. According to the expected outcomes, economic expansion is not an indication of a sustainable US atmosphere. Conversely, the coefficient $LGDP^2$ is positively and significantly correlated with LLCF. A 1% increase in $LGDP^2$ leads to corresponding increases of 0.652% and 0.969% in LCF. This finding suggests that the United States environmental quality will benefit from a short- and long-term increase in LGDP squared. According to He et al. (2024), increased economic activity deteriorates ecological conditions in OECD nations. Numerous studies by Ali et al. (2024), Ullah et al. (2024), Mughal et al. (2022), and Rahman et al. (2022) concurred that a rise in economic growth led to a heightened rate of destruction of the environment. However, GDP expansion may also enhance the ecosystem (Jabeen et al.,2024; Mohammed et al.,2024).

Likewise, there exists an encouraging correlation between the LAI coefficient and the LCF over both terms. An increase of 1% in AI innovation will result in an expansion of 0.030% and 0.036% of LCF. This result illustrates how AI innovation can benefit the natural world by reducing CO_2 emissions, improving the efficiency of resources, and cutting garbage creation. According to Hoang et al. (2022), AI has demonstrated its potential for usage in preventing pollution and managing the environment in the future. In a similar vein, Habila et al. (2023) agreed that (AI) improves human capacity to manage global warming to achieve sustainability while utilizing renewable resources. Furthermore, AI has a great deal of promise for tackling severe environmental issues (Bibri et al.,2024, Rasheed, 2024). However, over both short and long terms, there is a detrimental and significant relationship between the LFD and LLCF, suggesting that financial development does not help guarantee a sustainable environment. In particular, 1% more financial development will end up in 0.343% and 0.295% of LCF in response. According to (Katircioğlu and Taşpinar, 2017 Xu et al., 2018 Imamoglu, 2019 Kayani et al.,2020; Yang et al.,2023, Xulu, 2024), expansion in finance harms the environment. Furthermore, several empirical studies (Cheng et al., 2019; Omri et al., 2019; Seetanah et al., 2019) suggested no discernible correlation between the growth of the financial industry and ecosystem health. On the other hand, several researches provide evidence that mitigating the harm to the environment can be achieved through the creation of a robust and well-planned financial sector (Dar and Asif, 2018; Fakher, 2019; Zaidi et al., 2019; Saud et al., 2018; Baloch et al., 2019; Khan et al., 2019; Akadiri et al.,2022; Annor et al.,2024).

In the same way, population density has a destructive but significant link to the LCF, which is detrimental to the ecological condition of the United States. The LCF will drop by 0.836% and 0.335%, respectively, with a 1% rise in LPOP. One explanation might be that when the population grows, there is a greater demand for materials, resulting in the exploitation and depletion of assets; this, in turn, causes environmental damage such as loss of wildlife, deforestation, and boosting contamination. According to Yeh and Liao (2017), Taiwan's population increase was the main contributor to carbon emissions, and a 16–29% reduction in population growth would result in lower emissions of carbon. Wu et al. (2021), however, dispute this claim and conclude that China's population growth can both slow down the short- and long-term boost to emissions and enhance the environment. Finally, there is a significant and beneficial association between ICT use and LCF. If LICT expands by 1% in a shorter time, LCF increases by 0.279% on average. Similarly, over time, a 1% increase in ICT will allow the LCF to boost by 0.106%. This conclusion is observed by (Asongu et al.,2017 Ahmed and Le,2021 Lahouel et al. 2024, Zhang and Liu,2015 Chen et al.,2019; Danish, 2019 and, Megbetor and Boateng, 2023), who concluded that ICT might be utilized to lessen the negative consequences of CO_2 emissions and enhance the environmental quality.

Conversely, Appiah-Otoo and Chen (2024), Raheem et al.(2020), and Haseeb et al.(2019) claimed that the elevation in GHG pollution is caused by ICT use and hampers environmental sustainability.

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

Long-run Estimation				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGDP	-0.360	3.177805	-6.72179	0.0000
$LGDP^2$	0.969	0.151067	6.416285	0.0000
LAI	0.036	0.012913	-2.81781	0.0130
LFD	-0.295	0.132515	-2.2324	0.0413
LICT	0.106	0.040101	2.64342	0.0184
LPOP	-0.335	0.518045	7.76546	0.0000
C	8.14243	2.36632	1.785167	0.0945
Short-run Estimation				
Variable	Coefficient	Std. Error	t-Statistic	Prob
D(LLCF(-1))	0.172	0.072349	2.384869	0.0307
D(LGDP)	-0.899	2.906232	-5.12658	0.0001
D($LGDP^2$)	0.652	0.133748	4.881989	0.0002
D(LAI)	0.030	0.013241	-2.32651	0.0344
D(LFD)	-0.343	0.067581	-5.07745	0.0001
D(LICT)	0.279	0.032765	8.538319	0
D(LPOP)	-0.836	0.733377	1.140186	0.2721
CointEq(-1)*	-1.44956	0.140053	-10.35	0
R^2=0.9687				
Adjusted R^2 =0.9588				

Robustness Check

To confirm the consistency of the ARDL estimation, we implemented the FMOLS, DOLS, and CCR approaches. The outcomes for these models are shown in Table 6. The LCF is typically reduced by 0.708%, 0.467%, and 0.716% in the FMOLS, DOLS, and CCR models for each 1% improvement in the LGDP. This coefficient agrees with the results of the ARDL calculation and is significant in each case at the 1% level. In a similar vein, the notable and encouraging outcomes for $LGDP^2$ support the ARDL findings. The robustness of the ARDL estimation for the LAI and LICT variables is further demonstrated by the FMOLS, DOLS, and CCR conclusions. These factors are also significant at the 1% level and have a positive correlation with LCF.

However, the data shows that there is a detrimental and substantial link between LCF and financial development (LFD). To be more precise, under the FMOLS, DOLS, and CCR models, a 1% spike in LFD yields a 0.542%, 0.535%, and 0.510% drop in LCF, respectively. The variable is significant at the 1% level of significance in all cases. Finally, in the scenario of LPOP, the FMOLS, DOLS, and CCR results demonstrate an advantageous relationship. A 1% boost in LPOP in each model creates an average jump in LCF of 1.223%, 1.759%, and 1.148%, in that order. For FMOLS and CCR, the coefficient is significant at the 1% level; for DOLS, it is only significant at the 10% level of significance. However, this result is not aligned with the conclusions of the ARDL estimation.

So overall, the abovementioned information indicates the robustness of the outcomes of the ARDL short and long-run methodology.

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Table 6. Results of Robustness check

Variables	FMOLS	DOLS	CCR
LGDP	-0.708***(0.2708)	-0.467***(0.2045)	-0.716***(0.7166)
$LGDP^2$	0.693***(0.1049)	1.805***(0.9846)	0.689***(0.1312)
LAI	0.016***(0.0382)	0.089***(0.0687)	0.013***(0.0121)
LFD	-0.542***(0.1026)	-0.535***(0.9805)	-0.510***(0.1048)
LICT	0.132***(0.0345)	0.036***(0.2609)	0.101***(0.0367)
LPOP	1.223***(0.3095)	1.759*(0.4805)	1.148***(0.3775)
C	-9.261***(1.059)	-7.055*(1.432)	-9.359***(1.8912)

Pairwise Granger Causality test

Table 7 presents the findings of the causal links across different chosen variables. It is evident from an F-statistic of 3.38826 and a p-value of 0.0399 that LGDP doesn't Granger cause of LLCF. This implies that, at the 5% significance level, the null hypothesis that there exists no link between these variables is rejected. Furthermore, the presence of one-way causation from $LGDP^2$, LAI, LFD, and LICT to LLCF is confirmed by the p-values that are less than the conventional significance threshold. Thus, we rule out the null hypothesis that there is no causal connection under these circumstances. Nonetheless, a significant bidirectional causal association emerged between LPOP and LLCF. On the other hand, p-values greater than the traditional significance criterion for each case show that there is no meaningful causal association between LLCF and LGDP, $LGDP^2$, LAI, LFD, and LICT. These results imply that changes in LCF do not influence ICT usage, financial development, artificial intelligence, or economic growth. So, it is not possible to rule out the null hypothesis that there is no causality in these interactions.

Table 7. Results of Granger Causality test

Null Hypothesis	Obs	F-Statistic	Prob.
LGDP $\neq$ LLCF	30	3.38826	0.0399
LLCF $\neq$ LGDP		0.44313	0.647
$LGDP^2 \neq$ LLCF	30	3.4843	0.0463
LLCF $\neq LGDP^2$		0.44696	0.6446
LAI $\neq$ LLCF	30	2.38966	0.0123
LLCF $\neq$ LAI		1.48366	0.2461
LFD $\neq$ LLCF	30	6.00742	0.0074
LLCF $\neq$ LFD		0.25365	0.7779
LICT $\neq$ LLCF	30	13.581	0.0001
LLCF $\neq$ LICT		0.02088	0.9794
LPOP $\neq$ LLCF	30	4.3606	0.0237
LLCF $\neq$ LPOP		0.50808	0.0177

Diagnostic Test

The findings from three separate diagnostic examinations are displayed in Table 8. The results show that no diagnostic approach can rule out the null hypothesis since they are all contradictory. A p-value of 0.5621 from the Jarque-Bera test illustrates that the residuals have a normal distribution. Then, with a corresponding p-value of 0.2412, over the traditional threshold for significance, the Lagrange Multiplier analysis shows no serial correlation in the residuals. The Breusch-Pagan-Godfrey test, which yields a p-value of 0.4658, ultimately verifies that the residuals do not exhibit a heteroscedasticity problem.

Table 8. The results of diagnostic tests

Diagnostic tests	Coefficient	p-value	Decision
Jarque-Bera test	2.3412	0.5621	Residuals are normally distributed
Lagrange Multiplier test	1.5136	0.2412	No serial correlation exits
Breusch-Pagan-Godfrey test	0.9695	0.4658	No heteroscedasticity exists

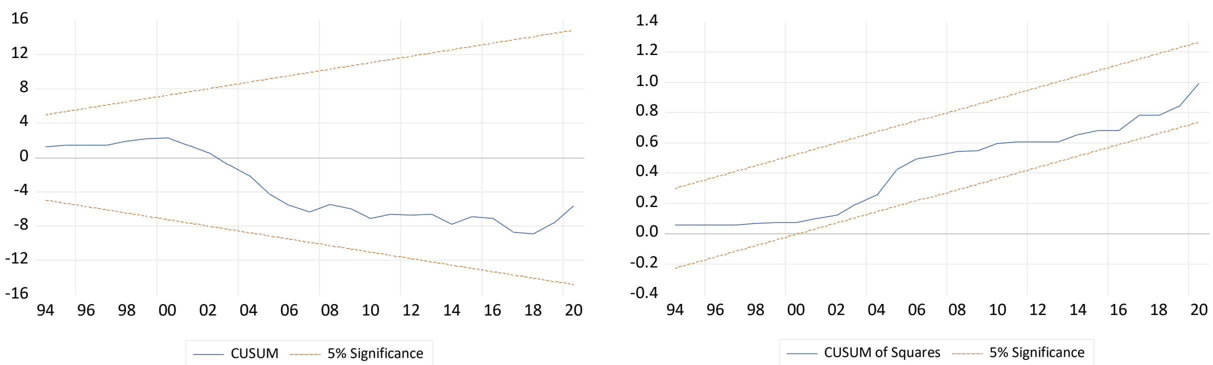

Figure 1. The plots of the CUSUM and CUSUMQ tests (critical bounds at a 5% significance level)

Moreover, CUSUM and CUSUM-SQ statistics are utilized to perform the stability assessment. For residuals of functions that show structural stability over the long and short terms, use the CUSUM and CUSUM-SQ testing. The statistical findings in this case fall between the upper and lower limits. The plot of the CUSUM-SQ test is located within the crucial line, as shown in Figure 1, which indicates that the parameters are stable and well-specified at a 5% percent significance threshold.

Conclusion and Policy Recommendation

Our investigation seeks to understand the long- and short-term implications of population growth, financial development, economic expansion, AI innovation, and ICT use on load capacity factor (LCF) in the United States using data from 1990 to 2019. This investigation used the ADF, DF-GLS, and P–P unit root tests to determine the dataset's integration order. The variables in question showed long-term cointegration, as demonstrated by the ARDL bounds examination. While population growth, financial development, and short-term economic expansion would increase environment degradation in the chosen location, the ARDL long-run relationship showed that $LGDP^2$, innovations in artificial intelligence (AI), and utilization of ICT improve the environment over time by lowering GHG emissions. Based on the CCR, FMOLS, and DOLS estimators, the projected findings are robust and validated. The LLCF of the USA may be granser caused by $LGDP^2$, LAI, LFD, LIT, and LPOP, owing to the Granger causality test. Additionally, the diagnostic test indicates that there is no autocorrelation or heteroscedasticity issue and that the analysis residuals are distributed correctly. This article makes further policy recommendations for reducing pollution while encouraging sustainable development through the funding of green ICT, equitable progress, and more application of AI innovation. Lastly, to prevent resource depletion, reduce the generation of waste, and ensure a sustainable environment and growth, the government should offer incentives to individuals for integrating green AI innovation and the latest information technologies.

To enhance environmental sustainability while promoting economic growth in the United States, policies should capitalize on the link between GDP and the environment. Key actions include adopting renewable energy, enforcing strict emissions standards, and supporting sustainable agriculture. As GDP grows, focus on sustainable development by investing in eco-friendly infrastructure, promoting energy efficiency, and improving public transportation. Foster innovation through research grants for clean technologies and assist industries in adopting greener practices. Additionally, invest in environmental education to cultivate a culture of sustainability, ensuring economic growth aligns with environmental goals.

Policymakers should leverage artificial intelligence (AI) and information and communication technologies (ICT) to boost environmental sustainability. These technologies can reduce emissions, optimize resource use, and monitor environmental impacts in real-time. Encourage AI and ICT adoption in sectors like industry, energy, and agriculture through tax incentives and subsidies. Support the development of smart grids and AI-driven energy management to enhance energy efficiency and integrate renewables. Invest in R&D for ICT and AI applications in environmental monitoring and precision agriculture. Establish legal frameworks for data sharing and public-private cooperation to maximize environmental benefits. Promote AI in urban planning to design sustainable cities with green infrastructure and efficient waste management. Ensure AI and ICT growth adheres to ethical standards, addressing concerns like data privacy and job displacement through comprehensive policies and worker transition programs.

Addressing the environmental impacts of population growth and financial development in the U.S. requires targeted measures. Regulate financial markets to encourage green investments and discourage environmentally harmful projects. Introduce green bonds and incentives for sustainable investment, and promote ESG standards in financial institutions. Implement laws to manage population growth by developing sustainable cities, improving resource efficiency, and reducing environmental impacts. Enhance public awareness through family planning and education initiatives. Improve public transportation and enforce strict land use laws to curb urban sprawl and protect natural areas. Invest in energy efficiency and renewable to meet the rising energy demand. Strengthen waste management and recycling systems to handle increased waste. These strategies will balance economic and demographic growth with environmental sustainability.

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Consent to participate: Informed consent was obtained from all individual participants included in the study. Participants were fully informed of the study's purpose, procedures, and their rights, including the right to withdraw at any time without penalty.

Consent for publication: All participants provided consent for the publication of data and findings derived from their participation in the study. The consent forms are available upon request from the corresponding author.

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Authors' contributions: Mohammad Ridwan contributed to the study's conception and design. Material preparation, data collection, and analysis were performed by Shewly Bala, Sarder Abdulla Al Shiam, Afsana Akhter, Md Asrafuzzaman, Sarmin Akter Shochona, Shake Ibna Abir, Shaharina Shoha. All authors read and approved the final manuscript.

References

Abid, A., Majeed, M. T., & Luni, T. (2021). Analyzing ecological footprint through the lens of globalization, financial development, natural resources, human capital, and urbanization. Pakistan Journal of Commerce and Social Sciences (PJCSS), 15(4), 765-795.

Adebayo, T.S. Assessing the environmental sustainability corridor: linking oil consumption, hydro energy consumption, and ecological footprint in Turkey. Environ Sci Pollut Res 30, 18890–18900 (2023). https://doi.org/10.1007/s11356-022-23455-1

Adebayo, T.S., Samour, A. Renewable energy, fiscal policy and load capacity factor in BRICS countries: novel findings from panel nonlinear ARDL model. Environ Dev Sustain 26, 4365–4389 (2024). https://doi.org/10.1007/s10668-022-02888-1

Adisa, M. O., Oyedeji, S., & Porras, J. (2024). The nexus between ICT, top-down and bottom-up approaches for sustainability activities: A systematic mapping study. Journal of Cleaner Production, 141768. https://doi.org/10.1016/j.jclepro.2024.141768

Ahmad, M., Ahmed, Z., Yang, X., Hussain, N., & Sinha, A. (2022). Financial development and environmental degradation: Do human capital and institutional quality make a difference? Gondwana Research, 105, 299–310. https://doi.org/10.1016/J.GR.2021.09.012

Ahmad, M., Kuldasheva, Z., Nasriddinov, F., Balbaa, M. E., & Fahlevi, M. (2023). Is achieving environmental sustainability dependent on information communication technology and globalization? Evidence from selected OECD countries. Environmental Technology & Innovation, 31, 103178. https://doi.org/10.1016/j.eti.2023.103178

Ahmad, S., Raihan, A., & Ridwan, M. (2024). Role of economy, technology, and renewable energy toward carbon neutrality in China. Journal of Economy and Technology. https://doi.org/10.1016/j.ject.2024.04.008

Ahmed Z, Asghar MM, Malik MN, Nawaz K (2020b) Moving towards a sustainable environment: the dynamic linkage between natural resources, human capital, urbanization, economic growth, and ecological footprint in China. Res Policy 67:101677

Ahmed Z, Zafar MW, Ali S (2020a) Linking urbanization, human capital, and the ecological footprint in G7 countries: an empirical analysis. Sustain Cities Soc 55:102064

Ahmed, Z., Le, H.P. Linking Information Communication Technology, trade globalization index, and CO2 emissions: evidence from advanced panel techniques. Environ Sci Pollut Res 28, 8770–8781 (2021). https://doi.org/10.1007/s11356-020-11205-0

Akadiri, S.S., Adebayo, T.S., Riti, J.S. et al. The effect of financial globalization and natural resource rent on load capacity factor in India: an analysis using the dual adjustment approach. Environ Sci Pollut Res 29, 89045–89062 (2022). https://doi.org/10.1007/s11356-022-22012-0

Akter, M. S. (2024). Harnessing technology for environmental sustainability: utilizing AI to tackle global ecological challenge. Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023, 2(1), 61-70.

Al Shiam, S. A., Hasan, M. M., Nayeem, M. B., Choudhury, M. T. H., Bhowmik, P. K., Shochona, S. A., ... & Islam, M. R. (2024b). Deep Learning for Enterprise Decision-Making: A Comprehensive Study in Stock Market Analytics. Journal of Business and Management Studies, 6(2), 153-160.

Al Shiam, S. A., Hasan, M. M., Pantho, M. J., Shochona, S. A., Nayeem, M. B., Choudhury, M. T. H., & Nguyen, T. N. (2024a). Credit Risk Prediction Using Explainable AI. Journal of Business and Management Studies, 6(2), 61-66.

Ali, M., Kirikkaleli, D. & Altuntaş, M. The nexus between CO2 intensity of GDP and environmental degradation in South European countries. Environ Dev Sustain 26, 11089–11100 (2024). https://doi.org/10.1007/s10668-023-03217-w

Ali, W., Abdullah, A., & Azam, M. (2017). Re-visiting the environmental Kuznets curve hypothesis for Malaysia: Fresh evidence from ARDL bounds testing approach. Renewable and sustainable energy reviews, 77, 990-1000. https://doi.org/10.1016/j.rser.2016.11.236

Alola AA, Saint Akadiri S, Akadiri AC, Alola UV, Fatigun AS (2019a) Cooling and heating degree days in the US: the role of macroeconomic variables and its impact on environmental sustainability. Sci Total Environ 695:133832 https://doi.org/10.1016/j.scitotenv.2019.133832

Alola, A. A., Bekun, F. V., & Sarkodie, S. A. (2019b). The dynamic impact of trade policy, economic growth, fertility rate, renewable and non-renewable energy consumption on the ecological footprint in Europe. Science of the Total Environment, 685, 702-709. https://doi.org/10.1016/j.scitotenv.2019.05.139

Alola, A.A., Arikewuyo, A.O., Ozad, B. et al. A drain or drench on biocapacity? Environmental account of fertility, marriage, and ICT in the USA and Canada. Environ Sci Pollut Res 27, 4032–4043 (2020). https://doi.org/10.1007/s11356-019-06719-1

Annor, L.D.J., Robaina, M. & Vieira, E. Climbing the green ladder in Sub-Saharan Africa: dynamics of financial development, green energy, and load capacity factor. Environ Syst Decis (2024). https://doi.org/10.1007/s10669-023-09959-2

Appiah-Otoo, I., Chen, X. Exploring the Environmental Impact of Information and Communication Technologies, Population, Economic Growth, and Energy Consumption in MENA Countries. Environ Model Assess (2024). https://doi.org/10.1007/s10666-024-09979-5

Arif, M., Hasan, M., Al Shiam, S. A., Ahmed, M. P., Tusher, M. I., Hossan, M. Z., ... & Imam, T. (2024). Predicting Customer Sentiment in Social Media Interactions: Analyzing Amazon Help Twitter Conversations Using Machine Learning. International Journal of Advanced Science Computing and Engineering, 6(2), 52-56.

Asongu SA, Le Roux S, Biekpe N (2018) Enhancing ICT for environmental sustainability in sub-Saharan Africa. Technol Forecast Soc Chang 127:209–216. https://doi.org/10.1016/j.techfore.2017.09.022

Asongu, S. A., Le Roux, S., & Biekpe, N. (2017). Environmental degradation, ICT and inclusive development in Sub-Saharan Africa. Energy Policy, 111, 353-361. https://doi.org/10.1016/j.enpol.2017.09.049

Asongu, S. A., Le Roux, S., & Biekpe, N. (2018). Enhancing ICT for environmental sustainability in sub-Saharan Africa. Technological Forecasting and Social Change, 127, 209-216. https://doi.org/10.1016/j.techfore.2017.09.022

Awe, O. O. (2012). On pairwise granger causality modelling and econometric analysis of selected economic indicators. Interstatt journals. net/YEAR/2012/articles/1208002. pdf.

Bahroun, Z., Anane, C., Ahmed, V., & Zacca, A. (2023). Transforming education: A comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis. Sustainability, 15(17), 12983. https://doi.org/10.3390/su151712983

Balcilar, M., Ozdemir, Z. A., Ozdemir, H., & Shahbaz, M. (2018). Carbon dioxide emissions, energy consumption and economic growth: The historical decomposition evidence from G-7 countries. Work Pap.

Baloch, A., Shah, S.Z., Habibullah, M.S. et al. Towards connecting carbon emissions with asymmetric changes in economic growth: evidence from linear and nonlinear ARDL approaches. Environ Sci Pollut Res 28, 15320–15338 (2021). https://doi.org/10.1007/s11356-020-11672-5

Baloch, M. A., Zhang, J., Iqbal, K., & Iqbal, Z. (2019). The effect of financial development on ecological footprint in BRI countries: Evidence from panel data estimation. Environmental Science and Pollution Research, 26(6), 6199–6208. https://doi.org/10.1007/s11356-018-3992-9

Baloch, M.A., Zhang, J., Iqbal, K. et al. The effect of financial development on ecological footprint in BRI countries: evidence from panel data estimation. Environ Sci Pollut Res 26, 6199–6208 (2019). https://doi.org/10.1007/s11356-018-3992-9

Barnes EA, Hurrell JW, Ebert-Uphoff I, Anderson C, Anderson D (2019) Viewing forced climate patterns through an AI lens. Geophys Res Lett 46(22):13389–13398. https://doi.org/10.1029/2019GL084944

Ben Lahouel, B., Taleb, L., Managi, S. et al. The threshold effects of ICT on CO2 emissions: evidence from the MENA countries. Environ Econ Policy Stud 26, 285–305 (2024). https://doi.org/10.1007/s10018-022-00346-w

Bento, J. P. C., & Moutinho, V. (2016). CO2 emissions, non-renewable and renewable electricity production, economic growth, and international trade in Italy. Renewable and sustainable energy reviews, 55, 142-155.

Bibri, S. E., Krogstie, J., Kaboli, A., & Alahi, A. (2024). Smarter eco-cities and their leading-edge artificial intelligence of things solutions for environmental sustainability: A comprehensive systematic review. Environmental Science and Ecotechnology, 19, 100330. https://doi.org/10.1016/j.ese.2023.100330

Bilgili F, Kocak E, Bulut U, Kuskaya S (2017) Can biomass energy be an efficient policy tool for sustainable development? Renew Sustain Energy Rev 71:830–845

BP (2019) BP statistical review of world energy. https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2019-full-report.pdf. Accessed 14 Feb 2020.

Charfeddine, L., & Kahia, M. (2019). Impact of renewable energy consumption and financial development on CO2 emissions and economic growth in the MENA region: a panel vector autoregressive (PVAR) analysis. Renewable energy, 139, 198-213. https://doi.org/10.1016/j.renene.2019.01.010

Chattopadhyay A, Hassanzadeh P, Pasha S (2020) Predicting clustered weather patterns: a test case for applications of convolutional neural networks to spatio-temporal climate data. Sci Rep 10(1):1317. https://doi.org/10.1038/s41598-020-57897-9

Chen X, Gong X, Li D, Zhang J (2019) Can information and communication technology reduce CO2 emission? A quantile regression analysis. Environ Sci Pollut Res 26:32977–32992. https://doi.org/10.1007/s11356-019-06380-8

Chen, H., Tackie, E.A., Ahakwa, I. et al. RETRACTED ARTICLE: Does energy consumption, economic growth, urbanization, and population growth influence carbon emissions in the BRICS? Evidence from panel models robust to cross-sectional dependence and slope heterogeneity. Environ Sci Pollut Res 29, 37598–37616 (2022). https://doi.org/10.1007/s11356-021-17671-4

Cheng, Z., Li, L., & Liu, J. (2019). The effect of information technology on environmental pollution in China. Environmental Science and Pollution Research, 26(32), 33109-33124. https://doi.org/10.1007/s11356-019-06454-7

Chien, F., Hsu, CC., Moslehpour, M. et al. A step toward sustainable development: the nexus of environmental sustainability, technological advancement and green finance: evidence from Indonesia. Environ Dev Sustain 26, 11581–11602 (2024). https://doi.org/10.1007/s10668-023-03424-5

Choi C, Kim J, Kim J, Kim D, Bae Y, Kim HS (2018) Development of heavy rain damage prediction model using machine learning based on big data. In: Research article. Advances in meteorology. Hindawi. https://doi.org/10.1155/2018/5024930

Coroama VC, Hilty LM, Birtel M (2012) Effects of Internet-based multiple-site conferences on greenhouse gas emissions. Telemat Informatics 29:362–374. https://doi.org/10.1016/j.tele.2011.11.006

Dahmani, M., Mabrouki, M., & Ben Youssef, A. (2023). The ICT, financial development, energy consumption and economic growth nexus in MENA countries: dynamic panel CS-ARDL evidence. Applied Economics, 55(10), 1114-1128. https://doi.org/10.1080/00036846.2022.2096861

Dam, M. M., Durmaz, A., Bekun, F. V., & Tiwari, A. K. (2024). The role of green growth and institutional quality on environmental sustainability: A comparison of CO2 emissions, ecological footprint and inverted load capacity factor for OECD countries. Journal of Environmental Management, 365, 121551. https://doi.org/10.1016/j.jenvman.2024.121551

Danish (2019) Effects of information and communication technology and real income on CO2 emissions: The experience of countries along Belt and Road. Telemat Informatics 45:101300. https://doi.org/10.1016/j.tele.2019.101300

Danish, Ulucak R (2020) The pathway toward pollution mitigation: does institutional quality make a difference? Bus Strategy Environ 29:3571-3583

Danish, Ulucak R (2021) A revisit to the relationship between financial development and energy consumption? Is globalization paramount? Energy 227:1-8

Dar, J. A., & Asif, M. (2018). Does financial development improve environmental quality in Turkey? An application of endogenous structural breaks based cointegration approach. Management of Environmental Quality: An International Journal, 29(2), 368-384. https://doi.org/10.1108/MEQ-02-2017-0021

Datta, R. K. (2024). Bangladesh towards green growth: a review of environmental sustainability indicators. Journal of Environmental Science and Economics, 3(2), 17–40. https://doi.org/10.56556/jescae.v3i2.889

Davidson, R., & MacKinnon, J. G. (1993). Estimation and inference in econometrics (Vol. 63). New York: Oxford.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica: journal of the Econometric Society, 1057-1072. https://doi.org/10.2307/1912517

Dogan, A., & Pata, U. K. (2022). The role of ICT, R&D spending and renewable energy consumption on environmental quality: Testing the LCC hypothesis for G7 countries. Journal of Cleaner Production, 380, 135038. https://doi.org/10.1016/j.jclepro.2022.135038

Dogan, E., Ulucak, R., Kocak, E., & Isik, C. (2020). The use of ecological footprint in estimating the environmental Kuznets curve hypothesis for BRICS by considering cross-section dependence and heterogeneity. Science of the Total Environment, 723, 138063. https://doi.org/10.1016/j.scitotenv.2020.138063

Economic Commission for Latin America and the Caribbean (ECLAC), United States economic outlook: 2022 year-in-review and early 2023 developments (LC/WAS/TS.2023/2), Santiago, 2023. https://repositorio.cepal.org/server/api/core/bitstreams/4fc6db6a-0f7a-452f-ae3f-0f5b3ee16cae/content

Elias Megbetor, & Boateng, S. (2023). Examining the Implications of Climate Change and Adaptation Technologies on the Livelihood of Cocoa Farmers in Offinso Municipalities, Ghanas. Journal of Environmental Science and Economics, 2(3), 86–108. https://doi.org/10.56556/jescae.v2i3.641

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1992). Efficient tests for an autoregressive unit root.

Engle RF, Granger CW (1987) Co-integration and error correction: representation, estimation, and testing. Econometrica: Journal of the Econometric Society 251–276

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. Econometrica: journal of the Econometric Society, 251-276. https://doi.org/10.2307/1913236

Erdogan, S. (2023). Linking natural resources and environmental sustainability: a panel data approach based on the load capacity curve hypothesis. Sustainable Development. https://doi.org/10.1002/sd.2836

Evans, S. Analysis: Coronavirus Set to Cause Largest Ever Annual Fall in CO2 Emissions. Carbon Brief. 2020. Available online: https://www.carbonbrief.org/analysis-coronavirus-set-to-cause-largest-ever-annual-fall-in-CO2-emissions/ (accessed on 13 March 2021).

Fakher, HA. Investigating the determinant factors of environmental quality (based on ecological carbon footprint index). Environ Sci Pollut Res 26, 10276–10291 (2019). https://doi.org/10.1007/s11356-019-04452-3

Fu, H., Huang, P., Xu, Y., & Zhang, Z. (2022). Digital trade and environmental sustainability: The role of financial development and ecological innovation for a greener revolution in China. Economic Research-Ekonomska Istrazivanja. https://doi.org/10.1080/1331677X.2022.2125889

Germanwatch (2019). Largest producers of territorial fossil fuel CO2 emissions worldwide in 2018, based on their share of global CO2 emissions [Graph]. In Statista. Retrieved December 23, 2019, from https://www.statista.com/statistics/271748/the-largest-emitters-of-co2-in-the-world

Global Footprint Network (GFN, 2022). Accessed on 20th March 2024. Available at: https://www.footprintnetwork.org/

Granata, F., Di Nunno, F. Artificial Intelligence models for prediction of the tide level in Venice. Stoch Environ Res Risk Assess 35, 2537–2548 (2021). https://doi.org/10.1007/s00477-021-02018-9

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica: journal of the Econometric Society, 424-438. https://doi.org/10.2307/1912791

Gupta, P. and Singh, A. (2016), "Causal nexus between foreign direct investment and economic growth: A study of BRICS nations using VECM and Granger causality test", Journal of Advances in Management Research, Vol. 13 No. 2, pp. 179-202. https://doi.org/10.1108/JAMR-04-2015-0028

Hamit-Haggar, M. (2012). Greenhouse gas emissions, energy consumption and economic growth: A panel cointegration analysis from Canadian industrial sector perspective. Energy Economics, 34(1), 358-364.

Harris, R., & Sollis, R. (2003). Applied Time Series Modelling and Forecasting.

Haseeb A, Xia E, Saud S, Ahmad A, Khurshid H (2019) Does information and communication technologies improve environmental quality in the era of globalization? An empirical analysis. Environ Sci Pollut Res 26:8594–8608. https://doi.org/10.1007/s11356-019-04296-x

Haseeb, A., Xia, E., Danish et al. Financial development, globalization, and CO2 emission in the presence of EKC: evidence from BRICS countries. Environ Sci Pollut Res 25, 31283–31296 (2018). https://doi.org/10.1007/s11356-018-3034-7

Hassan ST, Baloch MA, Mahmood N, Zhang J (2019) Linking economic growth and ecological footprint through human capital and biocapacity. Sustain Cities Soc 47:101516

He, B., Jie, W., He, H., Alsubih, M., Arnone, G., & Makhmudov, S. (2024). From resources to resilience: How green innovation, fintech and natural resources shape sustainability in OECD countries. Resources Policy, 91, 104856. https://doi.org/10.1016/j.resourpol.2024.104856

Hoang, TD., Ky, N.M., Thuong, N.T.N., Nhan, H.Q., Ngan, N.V.C. (2022). Artificial Intelligence in Pollution Control and Management: Status and Future Prospects. In: Ong, H.L., Doong, Ra., Naguib, R., Lim, C.P., Nagar, A.K. (eds) Artificial Intelligence and Environmental Sustainability. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-19-1434-8_2

https://www.worldometers.info/world-population/us-population/. Accessed 1 July 2024.

Hunjra, A. I., Bouri, E., Azam, M., Azam, R. I., & Dai, J. (2024). Economic growth and environmental sustainability in developing economies. Research in International Business and Finance, 70, 102341. https://doi.org/10.1016/j.ribaf.2024.102341

Idroes, G.M., Hardi, I., Rahman, M.H. et al. The dynamic impact of non-renewable and renewable energy on carbon dioxide emissions and ecological footprint in Indonesia. Carbon Res. 3, 35 (2024). https://doi.org/10.1007/s44246-024-00117-0

Imamoglu, H. The role of financial sector in energy demand and climate changes: evidence from the developed and developing countries. Environ Sci Pollut Res 26, 22794–22811 (2019). https://doi.org/10.1007/s11356-019-05499-y

International Monetary Fund (IMF, 2022). Accessed on 20th March 2024. Available at: https://data.imf.org/?sk=4c514d48-b6ba-49ed-8ab9-52b0c1a0179b&sId=-1

IPCC. Summary for Policymakers. In Global Warming of 1.5 °C; IPCC: Geneva, Switzerland, 2018.

Isfat, M., & Raihan, A. (2022). Current practices, challenges, and future directions of climate change adaptation in Bangladesh. Journal homepage: www. ijrpr. com ISSN, 2582, 7421.

Isik, C., Ongan, S., & Özdemir, D. (2019). The economic growth/development and environmental degradation: Evidence from the US state-level EKC hypothesis. Environmental Science and Pollution Research, 26(30), 30772–30781. https://doi.org/10.1007/s11356-019-06276-7

Jaafari A, Zenner EK, Panahi M, Shahabi H (2019) Hybrid artificial intelligence models based on a neuro-fuzzy system and metaheuristic optimization algorithms for spatial prediction of wildfire probability. Agric for Meteorol 266–267(March):198–207. https://doi.org/10.1016/j.agrformet.2018.12.015

Jabeen, Gul, Dong Wang, Cem Işık, Rafael Alvarado, and Serdar Ongan. "Role of energy utilization intensity, technical development, economic openness, and foreign tourism in environmental sustainability." Gondwana Research 127 (2024): 100-115. https://doi.org/10.1016/j.gr.2023.03.001

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business horizons, 61(4), 577-586. https://doi.org/10.1016/j.bushor.2018.03.007

Jeste, D. V., Graham, S. A., Nguyen, T. T., Depp, C. A., Lee, E. E., & Kim, H. C. (2020). Beyond artificial intelligence: exploring artificial wisdom. International Psychogeriatrics, 32(8), 993-1001. https://doi.org/10.1017/S1041610220000927

Kao, C., & Chiang, M. H. (2001). On the estimation and inference of a cointegrated regression in panel data. In Nonstationary panels, panel cointegration, and dynamic panels (pp. 179-222). Emerald Group Publishing Limited. https://doi.org/10.1016/S0731-9053(00)15007-8

Katircioğlu, S. T., & Taşpinar, N. (2017). Testing the moderating role of financial development in an environmental Kuznets curve: empirical evidence from Turkey. Renewable and Sustainable Energy Reviews, 68, 572-586. https://doi.org/10.1016/j.rser.2016.09.127

Katircioglu, S., Katircioglu, S., & Kilinc, C. C. (2018). Investigating the role of urban development in the conventional environmental Kuznets curve: Evidence from the globe. Environmental Science and Pollution Research, 25(15), 15029–15035. https://doi.org/10.1007/s11356-018-1651-9

Kayani, G. M., Ashfaq, S., & Siddique, A. (2020). Assessment of financial development on environmental effect: implications for sustainable development. Journal of Cleaner Production, 261, 120984. https://doi.org/10.1016/j.jclepro.2020.120984

Khan, A.Q., Saleem, N. & Fatima, S.T. Financial development, income inequality, and CO2 emissions in Asian countries using STIRPAT model. Environ Sci Pollut Res 25, 6308–6319 (2018). https://doi.org/10.1007/s11356-017-0719-2

Khan, M. K., Teng, J. Z., Khan, M. I., & Khan, M. O. (2019). Impact of globalization, economic factors and energy consumption on CO2 emissions in Pakistan. Science of the total environment, 688, 424-436. https://doi.org/10.1016/j.scitotenv.2019.06.065

Khan, M. T. I., Yaseen, M. R., & Ali, Q. (2019). Nexus between financial development, tourism, renewable energy, and greenhouse gas emission in high-income countries: A continent-wise analysis. Energy Economics, 83, 293-310.

Khanzode, K. C. A., & Sarode, R. D. (2020). Advantages and disadvantages of artificial intelligence and machine learning: A literature review. International Journal of Library & Information Science (IJLIS), 9(1), 3.

Kinnunen, J., Georgescu, I., & Nica, I. (2024). Evaluating the Environmental Phillips Curve Hypothesis in the STIRPAT Framework for Finland. Sustainability, 16(11), 4381. https://doi.org/10.3390/su16114381

Kumo, W. L. (2012). Infrastructure investment and economic growth in South Africa: A granger causality analysis. African development bank group working paper series, 160.

Kunduru, A. R. (2023). Artificial intelligence usage in cloud application performance improvement. Central Asian Journal of Mathematical Theory and Computer Sciences, 4(8), 42-47.

Lashkarizadeh, M., & Salatin, P. (2012). The effects of information and communications technology (ICT) on air pollution. Elixir Pollut, 46, 8058-8064.

Lin, B., & Ullah, S. (2023). Towards the goal of going green: Do green growth and innovation matter for environmental sustainability in Pakistan. Energy, 285, 129263. https://doi.org/10.1016/j.energy.2023.129263

Lu W (2018) The impacts of information and communication technology, energy consumption, financial development, and economic growth on carbon dioxide emissions in 12 Asian countries

Magazzino, C., Mele, M., Schneider, N., & Sarkodie, S. (2021). Waste generation, wealth and ghg emissions from the waste sector: is denmark on the path towards circular economy?. The Science of the Total Environment, 755, 142510. https://doi.org/10.1016/j.scitotenv.2020.142510

Microsoft (2018) The carbon benefits of cloud computing: a study on the Microsoft Cloud

Mohammed, S., Gill, A. R., Ghosal, K., Al-Dalahmeh, M., Alsafadi, K., Szabó, S., ... & Harsanyi, E. (2024). Assessment of the environmental kuznets curve within EU-27: Steps toward environmental sustainability (1990–2019). Environmental Science and Ecotechnology, 18, 100312. https://doi.org/10.1016/j.ese.2023.100312

Mokhtar A. 1994. Regression Analysis. Kuala Lumpur: Dewan Bahasa dan Pusaka.

Mughal, N., Wen, J., Zhang, Q., Pekergin, Z. B., Ramos-Meza, C. S., & Pelaez-Diaz, G. (2024). Economic, social, and political determinants of environmental sustainability: Panel data evidence from NEXT eleven economies. Energy & Environment, 35(1), 64-87. https://doi.org/10.1177/0958305X221124224

N'dri, L. M., Islam, M., & Kakinaka, M. (2021). ICT and environmental sustainability: any differences in developing countries?. Journal of Cleaner Production, 297, 126642. https://doi.org/10.1016/j.jclepro.2021.126642

Nathaniel S, Anyanwu O, Shah M (2020) Renewable energy, urbanization, and ecological footprint in the Middle East and North Africa region. Environ Sci Pollut Res 27:14601–14613 1-13. https://doi.org/10.1007/s11356-020-08017-7

Nathaniel S, Nwodo O, Adediran A, Sharma G, Shah M, Adeleye N (2019) Ecological footprint, urbanization, and energy consumption in South Africa: including the excluded. Environ Sci Pollut Res 26:27168–27179 1-12

Oje, G. (2024). The Threshold level of Institutional Quality in the Nexus between Financial Development and Environmental Sustainability in Nigeria. Journal of Environmental Science and Economics, 3(1), 42-64.

Omri, A., Euchi, J., Hasaballah, A. H., & Al-Tit, A. (2019). Determinants of environmental sustainability: evidence from Saudi Arabia. Science of the Total Environment, 657, 1592-1601. https://doi.org/10.1016/j.scitotenv.2018.12.111

Opoku-Mensah, E., Chun, W., Ofori, E. K., Ampofo, S. A., Chen, W., & Appiah-Otoo, I. (2024). Revisiting the role of ICT and green institutional governance in environmental sustainability and proposing an ecological footprint mitigation pathway using a volatility-driven model. Journal of Cleaner Production, 434, 139824. https://doi.org/10.1016/j.jclepro.2023.139824

Our World in Data (2022). Accessed on 20th March 2024. Available at: https://ourworldindata.org/

Ozcan B, Apergis N (2018) The impact of internet use on air pollution: evidence from emerging countries. Environ Sci Pollut Res 25(5):4174–4189. https://doi.org/10.1007/s11356-017-0825-1

Ozturk, I., Farooq, S., Majeed, M. T., & Skare, M. (2024). An empirical investigation of financial development and ecological footprint in South Asia: Bridging the EKC and pollution haven hypotheses. Geoscience Frontiers, 15(4), 101588. https://doi.org/10.1016/j.gsf.2023.101588

Park Y, Meng F, Baloch MA (2018) The effect of ICT, financial development, growth, and trade openness on CO2 emissions: an empirical analysis. Environ Sci Pollut Res 25(30):30708–30719. https://doi.org/10.1007/s11356-018-3108-6

Park, J. Y. (1992). Canonical cointegrating regressions. Econometrica: Journal of the Econometric Society, 119-143. https://doi.org/10.2307/2951679

Pata, U. K. (2021). Do renewable energy and health expenditures improve load capacity factor in the USA and Japan? A new approach to environmental issues. The European Journal of Health Economics, 22(9), 1427–1439. https://doi.org/10.1007/s10198-021-01321-0

Pata, U. K., & Kartal, M. T. (2023). Impact of nuclear and renewable energy sources on environment quality: Testing the EKC and LCC hypotheses for South Korea. Nuclear Engineering and Technology, 55(2), 587-594. https://doi.org/10.1016/j.net.2022.10.027

Pata, U. K., Kartal, M. T., Erdogan, S., & Sarkodie, S. A. (2023). The role of renewable and nuclear energy R&D expenditures and income on environmental quality in Germany: Scrutinizing the EKC and LCC hypotheses with smooth structural changes. Applied Energy, 342, 121138. https://doi.org/10.1016/j.apenergy.2023.121138

Pattak, D. C., Tahrim, F., Salehi, M., Voumik, L. C., Akter, S., Ridwan, M., ... & Zimon, G. (2023). The driving factors of Italy's CO2 emissions based on the STIRPAT model: ARDL, FMOLS, DOLS, and CCR approaches. Energies, 16(15), 5845. https://doi.org/10.3390/en16155845

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of applied econometrics, 16(3), 289-326. https://doi.org/10.1002/jae.616

Petrović, P., Lobanov, M.M. Impact of financial development on CO2 emissions: improved empirical results. Environ Dev Sustain 24, 6655–6675 (2022). https://doi.org/10.1007/s10668-021-01721-5

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. biometrika, 75(2), 335-346. https://doi.org/10.1093/biomet/75.2.335

Plepys, A. (2002). The grey side of ICT. Environmental impact assessment review, 22(5), 509-523. https://doi.org/10.1016/S0195-9255(02)00025-2

Polcyn, J., Voumik, L. C., Ridwan, M., Ray, S., & Vovk, V. (2023). Evaluating the influences of health expenditure, energy consumption, and environmental pollution on life expectancy in Asia. International Journal of Environmental Research and Public Health, 20(5), 4000. https://doi.org/10.3390/ijerph20054000

Qayyum, M., Zhang, Y., Ali, M., & Kirikkaleli, D. (2024). Towards environmental sustainability: The role of information and communication technology and institutional quality on ecological footprint in MERCOSUR nations. Environmental Technology & Innovation, 34, 103523. https://doi.org/10.1016/j.eti.2023.103523

Qian, Y., Song, K., Hu, T., & Ying, T. (2018). Environmental status of livestock and poultry sectors in China under current transformation stage. Science of the Total Environment, 622, 702-709. https://doi.org/10.1016/j.scitotenv.2017.12.045

Rafindadi AA, Muye IM, Kaita RA (2018) The effects of FDI and energy consumption on environmental pollution in predominantly resource-based economies of the GCC. Sustainable Energy Technologies and Assessments 25:126–137 https://doi.org/10.1016/j.seta.2017.12.008

Raheem ID, Tiwari AK, Balsalobre-Lorente D (2020) The role of ICT and financial development in CO2 emissions and economic growth. Environ Sci Pollut Res 27:1912–1922. https://doi.org/10.1007/s11356-019-06590-0

Rahman, M. M., & Alam, K. (2021). Clean energy, population density, urbanization and environmental pollution nexus: Evidence from Bangladesh. Renewable Energy, 172, 1063-1072. https://doi.org/10.1016/j.renene.2021.03.103

Rahman, M. M., & Halim, M. A. (2024). Does the export-to-import ratio affect environmental sustainability? Evidence from BRICS countries. Energy & Environment, 35(2), 904-926. https://doi.org/10.1177/0958305X221134946

Raihan, A. (2023). A review of the global climate change impacts, adaptation strategies, and mitigation options in the socio-economic and environmental sectors. Journal of Environmental Science and Economics, 2(3), 36-58.

Raihan, A. (2024). The influence of tourism on the road to achieving carbon neutrality and environmental sustainability in Malaysia: The role of renewable energy. Sustainability Analytics and Modeling, 4, 100028. https://doi.org/10.1016/j.samod.2023.100028

Raihan, A., & Tuspekova, A. (2022). Dynamic impacts of economic growth, energy use, urbanization, agricultural productivity, and forested area on carbon emissions: New insights from Kazakhstan. World Development Sustainability, 1, 100019. https://doi.org/10.1016/j.wds.2022.100019

Raihan, A., Atasoy, F. G., Atasoy, M., Ridwan, M., & Paul, A. (2022). The role of green energy, globalization, urbanization, and economic growth toward environmental sustainability in the United States. Journal of Environmental and Energy Economics, 1(2), 8-17. https://doi.org/10.56946/jeee.v1i2.377

Raihan, A., Bala, S., Akther, A., Ridwan, M., Eleais, M., & Chakma, P. (2024b). Advancing environmental sustainability in the G-7: The impact of the digital economy, technological innovation, and financial accessibility using panel ARDL approach. Journal of Economy and Technology. https://doi.org/10.1016/j.ject.2024.06.001

Raihan, A., Rashid, M., Voumik, L. C., Akter, S., & Esquivias, M. A. (2023). The dynamic impacts of economic growth, financial globalization, fossil fuel, renewable energy, and urbanization on load capacity factor in Mexico. Sustainability, 15(18), 13462. https://doi.org/10.3390/su151813462

Raihan, A., Tanchangya, T., Rahman, J., & Ridwan, M. (2024a). The Influence of Agriculture, Renewable Energy, International Trade, and Economic Growth on India's Environmental Sustainability. Journal of Environmental and Energy Economics, 37-53. https://doi.org/10.56946/jeee.v3i1.324

Raihan, A., Tanchangya, T., Rahman, J., Ridwan, M., & Ahmad, S. (2022). The influence of Information and Communication Technologies, Renewable Energies and Urbanization toward Environmental Sustainability in China. Journal of Environmental and Energy Economics, 1(1), 11-23. https://doi.org/10.56946/jeee.v1i1.351

Raihan, A., Voumik, L. C., Ridwan, M., Ridzuan, A. R., Jaaffar, A. H., & Yusoff, N. Y. M. (2023). From growth to green: navigating the complexities of economic development, energy sources, health spending, and carbon emissions in Malaysia. Energy Reports, 10, 4318-4331. https://doi.org/10.1016/j.egyr.2023.10.084

Ramzan, M., Raza, S. A., Usman, M., Sharma, G. D., & Iqbal, H. A. (2022). Environmental cost of non-renewable energy and economic progress: do ICT and financial development mitigate some burden?. Journal of Cleaner Production, 333, 130066.

Rana, M. N. U., Al Shiam, S. A., Shochona, S. A., Islam, M. R., Asrafuzzaman, M., Bhowmik, P. K., ... & Asaduzzaman, M. (2024). Revolutionizing Banking Decision-Making: A Deep Learning Approach to Predicting Customer Behavior. Journal of Business and Management Studies, 6(3), 21-27.

Rane, N. (2023). ChatGPT and Similar Generative Artificial Intelligence (AI) for Smart Industry: role, challenges and opportunities for industry 4.0, industry 5.0 and society 5.0. Challenges and Opportunities for Industry, 4. https://dx.doi.org/10.2139/ssrn.4603234

Rasheed, M. (2024). Renewable energy adoption and CO2 emissions in G7 economies: In-depth analysis of economic prosperity and trade relations. Journal of Environmental Science and Economics, 3(2), 41–66. https://doi.org/10.56556/jescae.v3i2.839

Ravi Kumar, K. N., Reddy, K. G., Mohan Reddy, M. J., & Shafiwu, A. B. (2024). Unveiling the interplay between climate variability and economic growth in India: an auto regressive distributed lag (ARDL) framework. Cogent Social Sciences, 10(1), 2352507. https://doi.org/10.1080/23311886.2024.2352507

Ray, R. K., Chowdhury, F. R., & Hasan, M. R. (2024). Blockchain Applications in Retail Cybersecurity: Enhancing Supply Chain Integrity, Secure Transactions, and Data Protection. Journal of Business and Management Studies, 6(1), 206-214. Doi: https://doi.org/10.32996/jbms.2024.6.1.13

Ridwan, M. (2023). Unveiling the powerhouse: Exploring the dynamic relationship between globalization, urbanization, and economic growth in Bangladesh through an innovative ARDL approach.

Ridwan, M., Raihan, A., Ahmad, S., Karmakar, S., & Paul, P. (2023). Environmental sustainability in France: The role of alternative and nuclear energy, natural resources, and government spending. Journal of Environmental and Energy Economics, 2(2), 1-16. https://doi.org/10.56946/jeee.v2i2.343

Ridwan, M., Urbee, A. J., Voumik, L. C., Das, M. K., Rashid, M., & Esquivias, M. A. (2024). Investigating the environmental Kuznets curve hypothesis with urbanization, industrialization, and service sector for six South Asian Countries: Fresh evidence from Driscoll Kraay standard error. Research in Globalization, 8, 100223.

Ridzuan, A. R., Rahman, N. H. A., Singh, K. S. J., Borhan, H., Ridwan, M., Voumik, L. C., & Ali, M. (2023, May). Assessing the Impact of Technology Advancement and Foreign Direct Investment on Energy Utilization in Malaysia: An Empirical Exploration with Boundary Estimation. In International Conference on Business and Technology (pp. 1-12). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-55911-2_1

Robinson C, Dilkina B (2018) A machine learning approach to modeling human migration. In: Proceedings of the 1st ACM SIGCAS conference on computing and sustainable societies. COMPASS '18. Association for Computing Machinery, Menlo Park and San Jose, pp 1–8. https://doi.org/10.1145/3209811.3209868

Sadorsky P (2011) Financial development and energy consumption in central and eastern European frontier economies. Energy Policy 39:999–1006. https://doi.org/10.1016/j.enpol.2010.11.034

Sahoo, M., Gupta, M., & Srivastava, P. (2021). Does information and communication technology and financial development lead to environmental sustainability in India? An Empirical Insight. Telematics and Informatics, 60, 101598.

Salahuddin M, Alam K, Ozturk I (2016) The effects of Internet usage and economic growth on CO2 emissions in OECD countries: a panel investigation. Renew Sustain Energy Rev 62:1226–1235

Saqib, N., Usman, M., Ozturk, I., & Sharif, A. (2024). Harnessing the synergistic impacts of environmental innovations, financial development, green growth, and ecological footprint through the lens of SDGs policies for countries exhibiting high ecological footprints. Energy Policy, 184, 113863. https://doi.org/10.1016/j.enpol.2023.113863

Saud, S., Chen, S., Danish et al. Impact of financial development and economic growth on environmental quality: an empirical analysis from Belt and Road Initiative (BRI) countries. Environ Sci Pollut Res 26, 2253–2269 (2019). https://doi.org/10.1007/s11356-018-3688-1

Seetanah, B., Sannassee, R. V., Fauzel, S., Soobaruth, Y., Giudici, G., & Nguyen, A. P. H. (2019). Impact of economic and financial development on environmental degradation: evidence from small island developing states (SIDS). Emerging Markets Finance and Trade, 55(2), 308-322. https://doi.org/10.1080/1540496X.2018.1519696

Shang, Y., Razzaq, A., Chupradit, S., Binh An, N., & Abdul-Samad, Z. (2022). The role of renewable energy consumption and health expenditures in improving load capacity factor in ASEAN countries: Exploring new paradigm using advance panel models. Renewable Energy, 191, 715–722. https://doi.org/10.1016/j.renene.2022.04.013

Siche R, Pereira L, Agostinho F, Ortega E (2010) Convergence of ecological footprint and energy analysis as a sustainability indicator of countries: Peru as case study. Commun Nonlinear Sci Numer Simul 15(10):3182–3192

Solarin, S.A., Nathaniel, S.P., Bekun, F.V. et al. Towards achieving environmental sustainability: environmental quality versus economic growth in a developing economy on ecological footprint via dynamic simulations of ARDL. Environ Sci Pollut Res 28, 17942–17959 (2021). https://doi.org/10.1007/s11356-020-11637-8

Solaymani, S., & Montes, O. (2024). The role of financial development and good governance in economic growth and environmental sustainability. Energy Nexus, 13, 100268. https://doi.org/10.1016/j.nexus.2023.100268

Stock, J. H. (1994). Unit roots, structural breaks and trends. Handbook of econometrics, 4, 2739-2841. https://doi.org/10.1016/S1573-4412(05)80015-7

Sun, Y., Usman, M., Radulescu, M., Pata, U. K., & Balsalobre-Lorente, D. (2024). New insights from the STIPART model on how environmental-related technologies, natural resources and the use of the renewable energy influence load capacity factor. Gondwana Research, 129, 398-411. https://doi.org/10.1016/j.gr.2023.05.018

Tan, K. L., & Samsudin, H. B. (2022). Relationship between foreign direct investment (FDI) of the service sector and GDP in Malaysia. Journal of Quality Measurement and Analysis, 18(3), 95-109.

Thadewald, T., & Büning, H. (2007). Jarque–Bera test and its competitors for testing normality–a power comparison. Journal of applied statistics, 34(1), 87-105.

Tian, J., Yu, L., Xue, R., Zhuang, S., & Shan, Y. (2022). Global low-carbon energy transition in the post-COVID-19 era. Applied energy, 307, 118205. https://doi.org/10.1016/j.apenergy.2021.118205

Ukoba, K., Fadare, O., & Jen, T. C. (2019, December). Powering Africa using an off-grid, stand-alone, solar photovoltaic model. In Journal of Physics: Conference Series (Vol. 1378, No. 2, p. 022031). IOP Publishing. https://doi.org/10.1088/1742-6596/1378/2/022031

Ullah, A., Dogan, M., Pervaiz, A., Bukhari, A. A. A., Akkus, H. T., & Dogan, H. (2024). The impact of digitalization, technological and financial innovation on environmental quality in OECD countries: Investigation of N-shaped EKC hypothesis. Technology in Society, 77, 102484. https://doi.org/10.1016/j.techsoc.2024.102484

Ulucak ZŞ, İlkay SÇ, Burcu Özcan AG (2020) Financial globalization and environmental degradation nexus: evidence from emerging economies. Resour Policy. https://doi.org/10.1016/j.resourpol.2020.101698

Ulucak, R., & Khan, S. U. D. (2020). Does information and communication technology affect CO2 mitigation under the pathway of sustainable development during the mode of globalization? Sustainable Development, 28(4), 857–867. https://doi.org/10.1002/sd.2041

UNEP. Emissions Gap Report 2019. United Nations Environment Programme, Nairobi. 2019. Available online: http://www.unenvironment.org/emissionsgap (accessed on 26 October 2021).

Urbee, A. J., Ridwan, M., & Raihan, A. (2024). Exploring Educational Attainment among Individuals with Physical Disabilities: A Case Study in Bangladesh. Journal of Integrated Social Sciences and Humanities. https://doi.org/10.62836/jissh.v1i1.181

Usman, M., Chughtai, S., Rashid, A. et al. Disaggregated financial development and ecological sustainability: the critical role of urbanization, energy utilization, and economic growth in next 11 economies. Environ Dev Sustain 26, 11455–11474 (2024). https://doi.org/10.1007/s10668-023-03368-w

Usman, M., Jahanger, A., Makhdum, M. S. A., Balsalobre-Lorente, D., & Bashir, A. (2022). How do financial development, energy consumption, natural resources, and globalization affect Arctic countries' economic growth and environmental quality? An advanced panel data simulation. Energy, 241, 122515. https://doi.org/10.1016/j.energy.2021.122515

Usman, O., Akadiri, S.S. & Adeshola, I. Role of renewable energy and globalization on ecological footprint in the USA: implications for environmental sustainability. Environ Sci Pollut Res 27, 30681–30693 (2020). https://doi.org/10.1007/s11356-020-09170-9

Verma, D., Okhawilai, M., Dalapati, G., Ramakrishna, S., Sharma, A., Sonar, P., … & Sharma, M. (2022). Blockchain technology and ai-facilitated polymers recycling: utilization, realities, and sustainability. Polymer Composites, 43(12), 8587-8601. https://doi.org/10.1002/pc.27054

Voumik, L. C., & Ridwan, M. (2023). Impact of FDI, industrialization, and education on the environment in Argentina: ARDL approach. Heliyon, 9(1). https://doi.org/10.1016/j.heliyon.2023.e12872

Voumik, L. C., Akter, S., Ridwan, M., Ridzuan, A. R., Pujiati, A., Handayani, B. D., ... & Razak, M. I. M. (2023a). Exploring the factors behind renewable energy consumption in Indonesia: Analyzing the impact of corruption and innovation using ARDL model. International Journal of Energy Economics and Policy, 13(5), 115-125. https://doi.org/10.32479/ijeep.14530

Voumik, L. C., Rahman, M. H., Rahman, M. M., Ridwan, M., Akter, S., & Raihan, A. (2023b). Toward a sustainable future: Examining the interconnectedness among Foreign Direct Investment (FDI), urbanization, trade openness, economic growth, and energy usage in Australia. Regional Sustainability, 4(4), 405-415. https://doi.org/10.1016/j.regsus.2023.11.003

Voumik, L. C., Ridwan, M., Rahman, M. H., & Raihan, A. (2023c). An investigation into the primary causes of carbon dioxide releases in Kenya: Does renewable energy matter to reduce carbon emission?. Renewable Energy Focus, 47, 100491. https://doi.org/10.1016/j.ref.2023.100491

World Bank (2020) World Bank open data. https://data.worldbank.org/. Accessed 24 Mar 2020.

World Development Indicator (WDI, 2022). Accessed on 20th March 2024. Available at: https://databank.worldbank.org/source/world-development-indicators

Worldometer (2024) worldometer (United States Population open data).

Wu L, Jia X, Gao L, Zhou Y (2021a) Effects of population flow on regional carbon emissions: evidence from China. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-021-15131-7

Wu, R., Wang, J., Wang, S., & Feng, K. (2021b). The drivers of declining CO2 emissions trends in developed nations using an extended STIRPAT model: A historical and prospective analysis. Renewable and Sustainable Energy Reviews, 149, 111328. https://doi.org/10.1016/j.rser.2021.111328

Wu, Y., Anwar, A., Quynh, N.N. et al. Impact of economic policy uncertainty and renewable energy on environmental quality: testing the LCC hypothesis for fast growing economies. Environ Sci Pollut Res 31, 36405–36416 (2024). https://doi.org/10.1007/s11356-023-30109-3

Xie, Q., Yan, Y. & Wang, X. Assessing the role of foreign direct investment in environmental sustainability: a spatial semiparametric panel approach. Econ Change Restruct 56, 1263–1295 (2023). https://doi.org/10.1007/s10644-022-09470-9

Xu, D., Salem, S., Awosusi, A. A., Abdurakhmanova, G., Altuntaş, M., Oluwajana, D., Kirikkaleli, D., & Ojekemi, O. (2022). Load Capacity Factor and Financial Globalization in Brazil: The Role of Renewable Energy and Urbanization. Frontiers in Environmental Science. https://doi.org/10.3389/fenvs.2021.823185

Xu, Z., Baloch, M.A., Danish et al. Nexus between financial development and CO2 emissions in Saudi Arabia: analyzing the role of globalization. Environ Sci Pollut Res 25, 28378–28390 (2018). https://doi.org/10.1007/s11356-018-2876-3

Xulu. (2024). Digital transformation and enterprise dual innovation: Evidence from China's A-share listed companies. Journal of Environmental Science and Economics, 3(2), 67–89. https://doi.org/10.56556/jescae.v3i2.897

Yadav, M., & Singh, G. (2023). Environmental sustainability with artificial intelligence. EPRA International Journal of Multidisciplinary Research (IJMR), 9(5), 213-217. https://doi.org/10.36713/epra13325

Yang, M., She, D., Abbas, S., Ai, F., & Adebayo, T. S. (2023). Environmental cost of financial development within the framework of the load capacity curve hypothesis in the BRICS economies: Do renewable energy consumption and natural resources mitigate some burden?. Geological Journal, 58(10), 3915-3927. https://doi.org/10.1002/gj.4817

Yao, X., Yasmeen, R., Hussain, J., & Shah, W. U. H. (2021). The repercussions of financial development and corruption on energy efficiency and ecological footprint: evidence from BRICS and next 11 countries. Energy, 223, 120063. https://doi.org/10.1016/j.energy.2021.120063

Yeh, J. C., & Liao, C. H. (2017). Impact of population and economic growth on carbon emissions in Taiwan using an analytic tool STIRPAT. Sustainable Environment Research, 27(1), 41-48. https://doi.org/10.1016/j.serj.2016.10.001

Yousefi, A. (2015). A Panel Granger causality test of investment in ICT capital and economic growth: Evidence from developed and developing countries. Economics World, 3(5-6), 109-127. https://doi.org/10.17265/23287144/2015.0506.001

Yuxiang, K., & Chen, Z. (2010). Financial development and environmental performance: evidence from China.

Zaidi, S. A. H., Zafar, M. W., Shahbaz, M., & Hou, F. (2019). Dynamic linkages between globalization, financial development and carbon emissions: evidence from Asia Pacific Economic Cooperation countries. Journal of cleaner production, 228, 533-543. https://doi.org/10.1016/j.jclepro.2019.04.210

Zhang C, Liu C (2015) The impact of ICT industry on CO2 emissions: a regional analysis in China. Renew Sust Energ Rev 44:12–19. https://doi.org/10.1016/j.rser.2014.12.011

Ziemba, E. W., & Grabara, D. (2024). Sustainability affected by ICT adoption in enterprises. Journal of Computer Information Systems, 1-19. https://doi.org/10.1080/08874417.2024.2321529