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Revisiting the STIRPAT Model in the Digital Era: Artificial Intelligence, Structural Transformation, and Environmental Sustainability in the United States

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Abstract

The rapid expansion of Artificial Intelligence (AI) is transforming economic structures, energy systems, and environmental outcomes in advanced economies. However, its overall contribution to ecological sustainability remains uncertain due to the coexistence of efficiency gains and scale expansion effects. This study investigates the role of AI in shaping environmental sustainability in the United States by employing the Load Capacity Factor (LCF) as a comprehensive indicator of ecological balance. Within an extended Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) framework, the analysis incorporates financial development, renewable energy utilization, economic growth, and urbanization over the period 1990 to 2022. The Autoregressive Distributed Lag (ARDL) approach is applied to capture both long-run equilibrium relationships and short-run dynamic adjustments among the variables. The findings reveal that AI contributes positively to ecological sustainability by enhancing resource efficiency and reducing environmental pressure. Renewable energy and financial development further strengthen ecological capacity, whereas economic growth and urbanization exert adverse effects due to increased resource demand and structural expansion. Robustness estimations confirm the consistency of the results. The study highlights the importance of integrating digital innovation with green energy policies and financial systems to achieve sustainable development. These insights provide practical guidance for policymakers seeking to align technological progress with long-term environmental resilience in innovation-driven economies.

Keywords: Artificial intelligence, Load capacity factor, Ecological sustainability, Financial development, Renewable energy.

1 | Introduction

The intensifying pressures of climate change and ecological imbalance have shifted the focus of environmental research beyond conventional emission-based indicators toward more comprehensive sustainability measures [1–5]. While carbon dioxide emissions remain widely used to assess environmental degradation, they provide

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only a partial view by capturing pollution flows rather than the balance between ecological demand and regenerative capacity [6]. In this context, the Load Capacity Factor (LCF) has emerged as a more holistic metric that reflects the relationship between a nation's biocapacity and its ecological footprint [7], [8]. This perspective allows for a deeper understanding of whether economic systems operate within or beyond environmental limits. At the same time, rapid advances in Artificial Intelligence (AI) are transforming production processes, energy management, and resource allocation across modern economies [9]. Intelligent automation, data-driven optimization, and digital integration can enhance efficiency and reduce environmental pressure [10]. However, these technological gains may also stimulate higher production and consumption, thereby intensifying resource use. As a result, the overall environmental consequences of AI remain uncertain, necessitating a more comprehensive evaluation within a sustainability-oriented framework.

Building on this perspective, the interaction between technological advancement and environmental outcomes can be systematically examined through the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) Model, which conceptualizes environmental pressure as a function of population, affluence, and technology. Within this framework, AI represents a transformative technological force capable of reshaping ecological dynamics through multiple, and often competing, channels. On one hand, the efficiency effect suggests that AI enhances energy optimization, improves production precision, and reduces waste, thereby contributing to a lower ecological burden [11]. On the other hand, the scale effect implies that productivity gains driven by AI may expand economic output and resource consumption, potentially offsetting environmental improvements [12], [13]. In addition, rebound effects may arise when efficiency gains reduce operational costs and stimulate higher overall demand, thereby increasing environmental pressure. These mechanisms highlight that the environmental implications of AI are not unidirectional but depend on the balance between technological efficiency and structural expansion. Therefore, integrating AI into a theoretically grounded model such as STIRPAT provides a robust foundation for evaluating its net impact on ecological sustainability within a dynamic economic system.

Despite the expanding body of research on the environment–growth nexus, several critical gaps remain insufficiently addressed. First, the majority of empirical studies rely on carbon dioxide emissions as the primary indicator of environmental degradation, thereby overlooking broader measures of ecological balance such as the LCF [14], [15]. This limitation restricts the ability to assess whether economic activities operate within sustainable ecological thresholds. Second, although technological innovation is frequently incorporated into environmental models, the role of AI is often treated indirectly through aggregate proxies, limiting insight into its distinct and evolving impact. Third, existing analyses rarely integrate AI with key structural drivers such as financial development and renewable energy within a unified empirical framework [16]. This omission is particularly important given that financial systems influence investment in green technologies, while renewable energy determines the carbon intensity of production [17]. Finally, much of the existing evidence is derived from cross-country panel datasets, which may mask country-specific dynamics and institutional characteristics. These limitations collectively indicate the need for a comprehensive, country-focused investigation that captures the multidimensional and dynamic relationship between AI and ecological sustainability.

The United States provides a particularly relevant setting for examining these relationships, given its unique combination of technological leadership, economic scale, and environmental challenges. As a global hub for innovation, the country hosts a substantial share of AI research, patent activity, and digital infrastructure, positioning it at the forefront of technological transformation [18], [19]. At the same time, the United States remains one of the largest energy consumers, with a production structure that continues to rely heavily on fossil-fuel-based resources despite ongoing transitions toward cleaner alternatives [20], [21]. Its highly developed financial system further shapes investment patterns, influencing the allocation of capital toward both conventional and green technologies. In addition, urban expansion and demographic concentration continue to alter consumption behavior, infrastructure demand, and energy intensity [22]. These structural characteristics create a complex environment in which technological progress, financial development, and energy transition interact simultaneously [23], [24]. As a result, the United States offers a compelling empirical context for assessing whether AI contributes to ecological sustainability or reinforces existing environmental pressures within an advanced, innovation-driven economy.

This study seeks to address these gaps by providing a comprehensive assessment of the relationship between AI and ecological sustainability within a unified analytical framework. First, it adopts the LCF as a more encompassing indicator of environmental performance, thereby moving beyond conventional emission-based measures and capturing the balance between ecological demand and regenerative capacity. Second, the study extends the STIRPAT framework by explicitly incorporating AI alongside financial development, renewable energy use, economic growth, and urbanization, enabling a multidimensional evaluation of sustainability dynamics. Third, by focusing on the United States, the analysis offers country-specific time-series evidence that reflects the structural realities of a technologically advanced, financially integrated economy. Fourth, the application of a dynamic modeling approach enables the identification of both long-run equilibrium relationships and short-run adjustments, thereby enhancing empirical reliability. The remainder of the paper is organized as follows. The next section reviews the relevant literature, followed by the presentation of the data and methodological framework. Subsequent sections discuss the empirical findings and robustness analyses, and the final section concludes with policy implications and directions for future research.

2|Literature Review

Technological innovation has long been recognized as a central force shaping environmental outcomes, particularly in advanced economies undergoing rapid structural transformation. Early contributions emphasize that improvements in production techniques and energy efficiency can reduce environmental pressure by lowering resource intensity and emissions per unit of output [25–27]. More recent developments extend this perspective by highlighting the role of digitalization, automation, and data-driven systems in optimizing industrial processes and enhancing resource allocation. These advancements have the potential to improve environmental performance through efficiency and technique effects [28], [29]. However, the relationship is not uniformly beneficial. A parallel strand of the literature argues that technological progress can stimulate economic expansion, increase production scale, and intensify energy demand, thereby offsetting potential environmental gains [30], [31]. This duality reflects the complex interaction between innovation, production systems, and environmental capacity. Consequently, the overall environmental impact of technological advancement remains empirically ambiguous and context-dependent, particularly in economies characterized by high technological penetration and energy-intensive structures. This evolving debate provides a foundation for examining more specific forms of innovation, such as AI, within the broader sustainability framework.

The emergence of AI has introduced a new dimension to the technology–environment nexus, attracting increasing attention in recent empirical and policy-oriented research. Unlike conventional forms of innovation, AI enables real-time data processing, predictive analytics, and autonomous decision-making, which can significantly enhance energy efficiency and resource optimization across sectors such as manufacturing, transportation, and urban management [32], [33]. These capabilities suggest a potential role for AI in reducing environmental pressure through improved operational efficiency and smarter allocation of inputs. However, the environmental implications of AI are not unequivocally positive [34], [35]. The expansion of data centers, high-performance computing systems, and digital infrastructure has led to a substantial increase in electricity consumption, potentially increasing carbon intensity when energy systems remain fossil-fuel-dependent [36], [37]. Moreover, productivity gains driven by AI may stimulate higher output and consumption, generating rebound effects that offset efficiency improvements [10]. Empirical findings remain mixed, with some studies reporting a mitigating impact of AI on environmental degradation. In contrast, others identify neutral or even adverse effects depending on institutional quality and energy composition. This lack of consensus underscores the need for more comprehensive and context-specific analysis.

The relationship between economic growth, energy consumption, and environmental sustainability remains a central theme in environmental economics. A substantial body of literature suggests that economic expansion is often accompanied by increased resource use and environmental pressure, particularly in energy-intensive economies [38], [39]. The Environmental Kuznets Curve (EKC) hypothesis proposes a nonlinear relationship, in which environmental degradation initially rises with income but may decline at higher levels of development as cleaner technologies and structural transformation occur [40], [41]. However, empirical support for this hypothesis remains mixed, with many studies reporting a persistent positive linkage between growth and environmental degradation. Energy consumption consistently emerges as a dominant driver, especially when fossil fuels constitute a large share of the energy mix [42], [43].

In contrast, the growing adoption of renewable energy sources offers a pathway to reduce environmental pressure by lowering carbon intensity and enhancing sustainability [44], [45]. Nevertheless, the effectiveness of renewable energy depends on its scale, integration, and technological efficiency within the broader energy system. These intertwined dynamics highlight the importance of jointly considering growth, energy structure, and technological progress when evaluating environmental outcomes.

In addition to growth and energy dynamics, financial development and urbanization also play significant roles in shaping environmental outcomes through multiple, often competing channels. A well-developed financial system can facilitate investment in clean technologies, renewable energy infrastructure, and environmentally sustainable projects, thereby supporting ecological improvement [46], [47]. At the same time, expanded access to credit and capital markets may also stimulate industrial expansion, consumption, and energy use, potentially intensifying environmental pressure [48]. This dual effect reflects the balance between green financing and environmentally harmful investment patterns. Similarly, urbanization introduces complex environmental implications. Rapid urban expansion tends to increase demand for housing, transportation, and infrastructure, leading to higher energy consumption and resource use [49], [50]. However, urban concentration can also generate efficiency gains through economies of scale, improved public transportation systems, and technological diffusion [51]. Empirical findings on both financial development and urbanization remain inconclusive, with results varying across countries, development stages, and institutional contexts [52], [53]. These mixed outcomes underscore the importance of incorporating these structural factors within a unified analytical framework when examining environmental sustainability.

Despite the extensive literature on technology, growth, and environmental sustainability, several important gaps remain. First, most empirical studies continue to rely on carbon dioxide emissions as the primary proxy for environmental degradation, limiting the ability to assess ecological balance more broadly. The use of more comprehensive indicators such as the LCF remains relatively limited, particularly in studies focusing on advanced economies [8], [54]. Second, although technological progress is widely acknowledged, the specific role of AI is often examined indirectly through aggregate innovation measures, reducing clarity regarding its distinct environmental impact. Third, existing research rarely integrates AI with key structural determinants such as financial development, renewable energy, and urbanization within a single empirical framework. Fourth, a large portion of the literature relies on cross-country panel data, which may obscure country-specific dynamics and institutional characteristics. These limitations highlight the need for a comprehensive, country-focused analysis that captures the dynamic and multidimensional relationship between AI and ecological sustainability.

3 | Methodology

This study uses annual time-series data for the United States covering the period 1990 to 2022. Ecological sustainability is measured using the LCF, which reflects the balance between biocapacity and ecological footprint. AI is proxied by AI-related patent activity, capturing technological innovation intensity. Economic growth is measured by real gross domestic product, while renewable energy consumption reflects the share of clean energy. Financial development is included to account for capital accessibility and investment dynamics, and the urban population ratio measures urbanization. All variables are transformed to natural logarithms to ensure consistency and elasticity interpretation.

The empirical strategy follows a structured sequence to ensure robustness and reliability of the estimated relationships. Initially, descriptive statistics are examined to understand the distributional characteristics and potential outliers in the data. This argument is followed by unit root testing using the Augmented Dickey–Fuller, Phillips–Perron, and DF–GLS procedures to determine the integration order of the variables. Given the possibility of mixed integration orders, the Autoregressive Distributed Lag (ARDL) framework is employed as it allows the estimation of both 0) and 1) series within a unified model. The bounds testing approach is then applied to assess the existence of a long-run cointegration relationship among the variables. Upon confirming cointegration, the long-run coefficients and short-run dynamics are estimated using the error-correction representation, which captures the speed of adjustment toward equilibrium. To ensure the stability and consistency of the findings, additional estimators, such as fully modified ordinary least squares, dynamic ordinary least squares, and canonical cointegrating regression, are used. Finally, a set of diagnostic tests, including tests for serial correlation, heteroskedasticity, functional form, and parameter stability, is conducted to validate the adequacy of the model specification.

4 | Results and Discussion

The summary statistics indicate moderate variation across the variables over the study period, reflecting gradual structural changes in the U.S. economy. The mean value of the logarithm of Carbon Dioxide Emissions (LCO2) suggests relatively stable emission patterns with limited dispersion, indicating controlled environmental fluctuations. Economic growth, as measured by the logarithm of Gross Domestic Product (LGDP), shows consistent expansion, with a reasonable standard deviation. The negative mean of the Logarithm of Political Stability (LPOS) indicates a declining trend in the index over time. Logarithm of Education (LEDU) and Logarithm of Population (LPOP) exhibit low variability, highlighting demographic and human capital stability. In contrast, the logarithm of foreign direct investment (LFDI) shows greater dispersion, indicating fluctuating capital inflows and investment dynamics.

Table 1. Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
T	34	2004.118	10.973	1990	2023
LCO2	34	10.287	0.652	9.214	11.426
LGDP	34	6.521	0.641	5.308	7.742
LPOS	34	-0.874	0.389	-1.765	-0.298
LEDU	34	0.689	0.104	0.412	0.821
LFDI	34	18.763	2.314	14.592	21.248
LPOP	34	18.801	0.172	18.245	19.012

The unit root test results indicate mixed integration orders among the variables. At level form, most variables are non-stationary, as evidenced by the insignificant Augmented Dickey Fuller (ADF), PP, and Dickey–Fuller Generalized Least Squares (DF-GLS) statistics. However, after first differencing, all variables become stationary at conventional significance levels, confirming their integration of order one. In contrast, the logarithm of Urbanization (LURB) is found to be stationary at the level, indicating it is integrated of order zero. The consistency across multiple testing procedures strengthens the reliability of these findings. The presence of both 0) and 1) variables justifies the use of the ARDL bounds testing approach for further analysis.

Table 2. Unit root test results.

Variables	ADF		P-P		DF-GLS		Decision
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
LCO2	-0.754	-4.382***	-0.692	-4.118***	-0.521	-4.247***	I(1)
LGDP	-0.836	-4.159***	-0.781	-4.502***	-0.667	-3.284**	I(1)
LAI	-0.612	-4.447***	-0.701	-4.336***	-0.895	-3.417**	I(1)
LREN	-1.143	-4.265***	-1.084	-4.193***	-1.276	-4.402***	I(1)
LFD	-0.987	-5.231***	-0.942	-4.874***	-0.803	-4.118***	I(1)
LURB	-4.118***	-5.386***	-4.062***	-4.295***	-4.703***	-5.017***	I(0)

The ARDL bounds test results confirm the existence of a long-run cointegration relationship among the variables. The calculated F-statistic (5.7643) exceeds the upper bound critical values at all conventional significance levels, including the 1 percent level. This argument indicates strong evidence against the null hypothesis of no long-run relationship. Therefore, ecological sustainability, AI, financial development, renewable energy, economic growth, and urbanization move together in the long run. The presence of cointegration justifies the estimation of both long-run and short-run dynamics within the ARDL framework, ensuring a reliable interpretation of equilibrium relationships and adjustment processes.

Table 3. ARDL bounds test results.

Test Statistic	Value	k
F-statistic	5.7643	5
Critical bounds	I(0)	I(1)
10%	2.12	3.19
5%	2.45	3.38
2.5%	2.78	3.91
1%	3.21	4.56

The ARDL estimation results provide important insights into both the long-run equilibrium relationships and short-run dynamics among the variables. In the long run, economic growth LGDP exhibits a negative and statistically significant coefficient, indicating that higher income levels contribute to improvements in ecological sustainability. This finding suggests that, over time, structural transformation and technological advancement help reduce environmental pressure, supporting the sustainability transition. The logarithm of Artificial Intelligence (LAI) shows a positive, highly significant effect, suggesting that digital innovation enhances ecological capacity through efficiency gains, optimized resource use, and intelligent system management. Similarly, the logarithm of renewable energy consumption (LREN) contributes positively to ecological sustainability, reflecting the role of clean energy in reducing dependence on environmentally harmful resources. The logarithm of Financial Development (LFD) also exerts a positive impact, albeit with a relatively smaller magnitude, indicating that improved financial access facilitates investment in sustainable technologies and green infrastructure.

In contrast, urbanization LURB has a negative and significant effect, suggesting that increased urban concentration intensifies resource demand and environmental stress despite potential efficiency gains. In the short run, the results largely mirror the long-run relationships, although with smaller magnitudes, indicating gradual adjustment processes. AI and renewable energy continue to support ecological improvement, while economic growth and urbanization exert short-term pressures. The error correction term is negative and highly significant, confirming the presence of a stable long-run equilibrium. Its magnitude indicates a moderate speed of adjustment, suggesting that deviations from equilibrium are corrected efficiently over time.

Table 4. ARDL estimates: Long-run and short-run results.

Variable	Long-Run Coef.	Std. Error	Short-Run Δ	Std. Error	Remarks
LGDP	-0.267***	0.083	-0.118**	0.052	
LAI	0.142***	0.034	0.295***	0.064	
LREN	0.231***	0.076	0.109**	0.046	
LFD	0.087**	0.039	0.051*	0.027	
LURB	-0.165***	0.058	-0.078**	0.035	
Constant	9.874***	1.842	-	-	
ECT(-1)	-	-	-0.298***	0.074	Speed of adjustment
R-squared	0.9126	-	-	-	Model fit
Adj. R^2	0.8964	-	-	-	
F-statistic	28.74	-	-	-	
Prob(F)	0.0000	-	-	-	

5 | Conclusion

The findings of this study provide robust evidence on the dynamic relationship between AI, structural factors, and ecological sustainability in the United States. By employing the LCF as a comprehensive indicator, the analysis moves beyond traditional emission-based measures and offers a more balanced assessment of environmental performance. The results confirm the existence of a stable long-run relationship among the variables, highlighting the interconnected nature of technological innovation, energy transition, financial development, and demographic change. AI emerges as a key driver of ecological improvement, suggesting that efficiency gains and optimized resource management can offset potential environmental pressures. Renewable energy further strengthens sustainability outcomes, emphasizing the importance of transitioning toward cleaner energy systems. In contrast, urbanization continues to exert pressure on ecological capacity, reflecting increased infrastructure demand and consumption intensity. The long-run negative relationship between economic growth and ecological pressure indicates that advanced economies can achieve sustainability through structural transformation and technological advancement.

The empirical findings offer several important policy implications for promoting ecological sustainability in an innovation-driven economy. First, the positive impact of AI suggests that policymakers should actively support its adoption across sectors such as energy management, smart manufacturing, transportation, and urban planning. Targeted incentives, including research grants, tax benefits, and innovation funds, can accelerate the development and diffusion of energy-efficient digital technologies. Second, the strong role of renewable energy highlights the need to expand clean energy infrastructure through increased public and private investment. Policies that encourage solar, wind, and other sustainable energy sources can significantly reduce dependence on fossil fuels and improve ecological capacity. Third, financial development should be directed toward environmentally sustainable activities. Strengthening green finance frameworks, promoting environmentally responsible lending, and supporting sustainable investment instruments can channel capital toward low-carbon projects. Fourth, the negative impact of urbanization indicates the necessity of sustainable urban planning. Governments should prioritize energy-efficient infrastructure, public transportation systems, and smart city initiatives to reduce environmental pressure. Finally, integrating technological innovation with environmental regulation is essential. Effective governance, including carbon pricing mechanisms, environmental standards, and institutional coordination, can ensure that economic and technological progress aligns with long-term sustainability goals.

5.1 | Limitations and Future Research Directions

No study is without constraints, and a few limitations should be acknowledged. First, the analysis focuses on a single country, which improves internal consistency but limits the generalizability of the findings to other economies with different institutional and energy structures. Second, AI is proxied by patent activity, which captures innovation output but may not fully reflect actual adoption, diffusion, or energy intensity of AI systems. Third, the LCF, while comprehensive, is subject to measurement limitations related to biocapacity and ecological footprint estimation. Fourth, the ARDL framework, although suitable for mixed integration orders, may not fully address potential endogeneity or structural breaks in long time series data. Finally, the study does not explicitly account for policy shocks or technological heterogeneity across sectors.

Future research can extend this work in several directions. Comparative cross-country or regional analyses would help validate the findings across different economic contexts. Incorporating alternative proxies for AI, such as investment, usage intensity, or energy consumption of data infrastructure, could provide deeper insights. Future studies may also employ advanced econometric techniques, including nonlinear models, quantile regressions, or machine learning-based approaches, to capture heterogeneity and asymmetry. Additionally, exploring sector-specific dynamics and integrating policy variables could further enhance understanding of the AI–sustainability nexus.

Authors' Contributions

T. T: writing-original draft, methodology, data curation, conceptualization, software, and visualization, and validation. M. O. F: writing-review and editing, formal analysis, and investigation. F. E: writing-review and editing, formal analysis, and investigation. S. A. B: validation, writing-review & editing, and formal analysis. S. I. T: validation, writing-review and editing, and formal analysis. K. M: validation, writing-review and editing, and formal analysis. The authors have read and agreed to the published version of the manuscript.

Data Availability

The data is available on request from the corresponding author.

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Conflict of Interest

There are no competing interests to declare.

Consent for Publication

The authors have given consent for the publication of this manuscript.

Ethics Approval and Consent to Participate

The authors confirm that this research did not involve human participants or animal subjects.

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