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THE ENVIRONMENTAL IMPACT OF AI-DRIVEN INNOVATION: EVIDENCE FROM THE UNITED STATES

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Abstract. This study investigates how Artificial Intelligence (AI)-related patents, income, trade openness, renewable energy generation and energy intensity influence carbon dioxide (CO_2) emissions in the United States. The empirical analysis is conducted using Canonical Cointegration Regression (CCR), Dynamic Ordinary Least Squares (DOLS), and Fully Modified Ordinary Least Squares (FMOLS) estimators. The empirical findings show that AI- related patents, income, trade openness, and energy intensity have positive and statistically significant effects on CO_2 emissions, whereas renewable energy generation contributes to reducing emissions. Furthermore, the interaction term between renewable energy generation and AI-related patents is negative and statistically significant, indicating that renewable energy generation moderates the emissions-increasing effect of AI-related technological innovation. This result suggests that the environmental implications of AI depend critically on the energy structure supporting its development and deployment. Accordingly, the study recommends that policymakers promote the integration of AI with renewable energy systems, reduce energy intensity in industry and transport through AI-enabled efficiency improvements, prioritize energy-efficient AI projects, and strengthen trade in AI-based green technologies. These measures are essential for ensuring that AI contributes to decarbonization rather than reinforcing carbon-intensive growth.

Keywords: US; CO2 Emissions; AI-related patents, Economic Growth; Renewable Energy Generation; Sustainable Development

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1. Introduction. In recent years, the negative impacts of climate and environment related issues have increased. Accordingly, the interest of all countries and communities in environmental issues has been developing. In this context, the related parties have been considering a set of factors, including both economic and non-economic, to empirically understand the causes of negative progress over the years [1].

According to the current, both economic growth [2] and energy intensity [3] have been among the causes of environmental change. Also, some literature has considered the role of trade openness [4]. Although those factors have been used in the literature, contemporary literature has recently begun to consider the role of AI [5, 6] due to its growing prominence. However, the current use of AI algorithms is mainly driven by technological issues, leading to high energy consumption and harming the environment. On the other hand, AI-related patents have largely focused on environmental progress. Nevertheless, it is not certain whether the use of AI is beneficial or not for environmental progress.

Artificial intelligence (AI) is a set of technologies that enable computer systems to perform functions such as perception and reasoning, using machine learning, deep learning, and other techniques. As a result of these functions, AI is becoming capable of replacing some human tasks and assisting in others [7]. In recent years, AI, which has significantly impacted life, not only increases productivity but also encourages complementary innovations [8]. From this perspective, the importance of AI cannot be ignored, and examining its fields of study is crucial. While the scope of artificial intelligence (AI) is broad today, its effects on the economy vary. Its impact on production processes, productivity, competitiveness, trade, energy, and labor creates both risks and opportunities in economic activity. AI, which has a general impact on growth and prosperity, can support growth by increasing production capacity, economies of scale, and the pace of innovation. According to UNCTAD [9], this situation also includes some drawbacks. The report emphasizes that because AI development is being undertaken by a small number of countries and companies, it may create inequality between countries. From this perspective, the greatest benefit is obtained by countries with strong digital infrastructure and high-tech investments. Globally, the inclusive role of artificial intelligence needs to be addressed through global cooperation. The WTO [10] highlights that artificial intelligence can increase trade in services and affect foreign trade by improving firms' international production-sharing and logistics processes. Artificial intelligence emerges as a key driver of international trade, reducing trade costs and increasing productivity through two main channels. AI-based tools can facilitate international trade by optimizing logistics, reducing language barriers, and automating customs procedures. Simulations conducted by the WTO suggest that AI can increase efficiency in international trade, potentially boosting global trade by 34% by 2040. Therefore, AI stands out as a crucial technology in international trade. In addition to production processes, efficiency, and international trade, the potential of artificial intelligence to transform the energy sector is a prominent issue. While it is well known that AI depends on energy, its development requires a cost-effective, sustainable electricity supply.

The IEA [11] report indicates that electricity consumption in data centers has increased by 12% from 2017 to the present. This shows that not only economic growth and efficiency, but also energy demand and infrastructure costs are affected. The report also states that different energy sources will be needed to meet the increasing electricity demand in data centers. It is predicted that renewable energy sources and systems, such as battery storage, will meet this increased electricity demand. Another prominent issue in the field of artificial intelligence and the energy sector is the use of AI to optimize energy and mineral supply, electricity generation, and consumption, thereby supporting energy efficiency [12]. However, alongside its potential benefits, the high electricity consumption of data centers raises concerns that AI will increase emissions and worsen environmental pollution [13,14]. Currently, data center emissions are estimated at 180 million tons of CO_2, and if current trends continue, this figure is projected to reach 300 million tons by 2035 [11]. From this perspective, the impacts of AI on emissions vary. Positive impacts depend on regulatory frameworks and the management of the impact of energy supply on carbon intensity.

The increase in carbon emissions, in addition to the environmental problems it creates in countries, also leads to significant problems such as global warming and climate change worldwide. Therefore, minimizing the environmental damage caused by carbon emissions generated to meet energy demands has become an important issue [15]. On a global scale, countries have also accepted the need to minimize environmental damage and have set targets to increase energy efficiency [16]. The literature contains widespread findings indicating that renewable energy sources reduce carbon emissions by decreasing dependence on fossil fuels [17-20]. Therefore, increasing the use of renewable energy sources in line with the Sustainable Development Goals is of great importance today [21].

Beyond their environmental significance, renewable energy sources also affect countries' production and foreign trade structures. In this context, renewable energy production and trade deficits become closely related issues [22]. Increasing renewable energy production reduces countries' dependence on energy imports, thereby reducing trade deficits and increasing competitiveness [23]. However, this may not always be the case. The transition to renewable energy, due to the high initial investment costs, may create dependence on imported technology and equipment in the initial stages [24]. When both situations are considered together, the relationship between renewable energy and trade openness is shaped by countries' technological capacities and policies. At this point, artificial intelligence forms a common framework with its multifaceted impacts on international trade, the energy sector, production channels, and environmental sustainability.

Considering the rising critical importance of AI use in many areas, along with the aforementioned factors, this research aims to uncover the role of AI on CO_2 emissions. In doing so, the study focuses on the USA as the leading economy in the world, uses yearly data from 1985 to 2021, and applies cointegration-based regression methods (i.e., CCR, DOLS, & FMOLS) for empirical analysis. The results of the econometric estimations reveal that AI- related patents, income, trade openness, and energy intensity have a positive impact on CO_2 emissions in the USA. In contrast, the interaction between AI-related patents and REG has a negative impact. By considering these determinations, the study discusses various policy recommendations that can help the USA benefit from AI to support decarbonization.

The remaining parts of the study are as follows: Section 2 explains the methodology and data used; Section 3 presents the empirical results; and Section 4 concludes with policy recommendations.

2. **Materials and methods.** A large body of studies investigates the factors influencing CO_2 emissions, mostly using the Environmental Kuznets Curve (EKC) and STIRPAT frameworks, which primarily focus on income and population impacts. Yet these approaches face well-documented shortcomings, as noted by Ezzati et al. [25], Tisdell [26], Dinda [27], Brock and Taylor [28], and Berk et al. [29]. In light of these limitations, scholars such as Brock and Taylor [28], Criado et al. [30], and Berk et al. [29] argue for adopting broader, theoretically stronger modeling strategies. Recent empirical literature increasingly integrates AI into analytical frameworks. Notably, scholars such as Wang et al. [12, 16], Xia and Ahmad [31], Yang et al. [32], and Kartal et al. [33] systematically employ AI indicators to evaluate its environmental impacts.

AI technology alone may not necessarily lower or increase carbon emissions. The real impacts depend on several factors, including how and where the technology is used. AI technologies may make energy use much more efficient, but they also consume significant energy, particularly in data centers and cloud computing. If renewable sources primarily power the energy system, the growing energy demand for AI applications may not significantly increase carbon emissions. But if the energy system is heavily dependent on fossil fuels, the same AI technology may have the opposite effect, causing emissions to rise. Therefore, the incorporation of interaction terms is grounded in both theoretical and practical reasoning. Considering that the impact of AI patents on CO_2 emissions may depend on the level of renewable energy, an interactive model specification is proposed below. This model aims to empirically evaluate whether the impact of AI technologies on CO_2 emissions varies across energy structures. Additional economic, energy, and trade-related variables have also been included in this model. Considering the above-mentioned facts, the following model specification is proposed:

$$LCO2_{,t} = \alpha 0 + \alpha 1 LAIP t + \alpha 2 LGDP t + \alpha 3 LTO t + \alpha 4 LEI t + \alpha_5 REG_t + \alpha_6 LREG_t * LAIP_t + \varepsilon_t \qquad (1)$$

where CO_2 denotes emissions per capita, GDP denotes GDP per capita, OP denotes international oil price, REG denotes renewable energy generation, and εt is an error term of the econometric model. Given its status, the signs of $\alpha 1$, $\alpha 2$, $\alpha 3$, and $\alpha 4$ are anticipated to be positive for the United States while the sign of $\alpha 5$ is expected to be negative. In addition, the objective of this study is to empirically estimate whether the impact of AI technologies on CO_2 emissions varies across levels of renewable energy. Therefore, the sign of $\alpha 6$ is expected to be negative and statistically significant. This means that as the share of renewable energy increases, the emission-reducing impact of AI patents becomes stronger. Eq. (1) may be assessed using traditional econometric methods (see, for example, Jin, [34]; Jin & Kim, [35]; Mukhtarov et al. [36]).

Specifically, the Canonical Cointegration Regression (CCR) [37], Dynamic Ordinary Least Squares (DOLS) [38, 39], and Fully Modified Ordinary Least Squares (FMOLS) [40, 41] were utilized.

The stationarity properties of the variables under investigation were analyzed through the Augmented Dickey-Fuller (ADF) test by Dickey and Fuller [42]. Furthermore, cointegration among the variables was assessed using the Engle-Granger cointegration test [43].

The study utilizes data from 1985 to 2021. CO_2 is measured in tons per person. The total number of AI-based patents indicates the presence of AIP. GDP is represented as gross domestic product per capita in US dollars at 2015 values. The REG represents the total amount of renewable energy production (trillion Btu). Trade Openness (TO) is the ratio of total trade to GDP. It is calculated as the sum of exports and imports, both expressed as proportions of GDP. Energy intensity (EI) is expressed as the ratio of total primary energy consumption to GDP (Btu per 2015 US $). Data on CO_2 emissions is sourced from Global Carbon Atlas [44] while REG and total primary energy consumption are sourced from the US Energy Information Administration [45]. The AIP data are collected from the OECD [46]. The GDP and TO are sourced from the World Bank database [47].

3. Results and discussion. Initially, the stationarity of the variables was evaluated using the Augmented Dickey-Fuller (ADF) test. The results of ADF are given in the Table 1. According to the unit root test results, all the variables under investigation became stationary after taking first differences.

Table 1. Unit root test results

	level	**1st difference**
CO2	1.528471	4.268422***
AIP	1.950514	-3.711620***
REG	0.708423	-4.662544***
GDP	-1.138991	-3.448411***
TO	-1.963913	-5.645272***
EI	0.084540	-6.173263***
AIP*REG	2.074959	-3.628488**

Notes: * and *** represent a rejection of the null hypothesis at 10% and 1% significance levels, respectively.

Hence, it becomes appropriate to assess the long-run relationships among these variables. To this end, the Engle-Granger cointegration test was employed, and the results are presented in the Table 2. The outcomes confirmed the existence of a long-run cointegrating relationship among the examined variables.

Table 2. Results of the Cointegration Test

Engle-Granger			
Tau-statistics	-6.434405 (0.020)	Z-statistics	-118.7638(0.000)
Notes: *p-values are in parenthesis.*			

Lastly, the Canonical Cointegration Regression (CCR), Dynamic Ordinary Least Squares (DOLS), and Fully Modified Ordinary Least Squares (FMOLS) methods were applied to estimate the long-run coefficients. The results obtained from these estimation techniques are presented in the Table 3.

Table 3. Findings of the Econometric Estimations

	CCR	DOLS	FMOLS
AIP	0.47^{***}	0.18^{***}	0.47^{***}
GDP	1.40^{***}	1.22^{***}	1.39^{***}
TO	0.01^{***}	0.01^{**}	0.01^{***}
REG	-0.20^{***}	-0.02^{***}	-0.20^{***}
EI	1.56^{***}	1.20^{***}	1.56^{***}
*REG*AIP*	-0.06^{**}	-0.02^{***}	-0.05^{***}
Constant	-14.7^{***}	-10.8^{***}	-14.6^{***}
Trend	-0.01^{***}	-0.01^{*}	-0.01^{***}

Notes: ****, **, and * display rejecting the null hypothesis at a 1%, 5%, and 5% significance level, respectively.*

The optimal lag length is determined using the Akaike information criterion (AIC). Table 3 demonstrates consistent results across all applied estimation methods, with parameters exhibiting similar signs and magnitudes. Specifically, the interaction term between renewable energy production and AI-related patents consistently shows a negative and statistically significant impact across methods. This means that when the share of renewable energy is high, the emission-reducing impact of AI patents is stronger. This evidence suggests that enhanced renewable energy deployment mitigates the sensitivity of the United States' CO_2 emissions to fluctuations in AI-related patents. This pattern demonstrates that the carbon-reduction potential of AI-based technologies is realized only when the energy system is sufficiently "green". In other words, technological advancement alone is not enough. Its environmental benefits are conditional on the sustainability of the underlying energy infrastructure. Moreover, AI-related patents, GDP, trade openness, and energy intensity individually exhibit positive and statistically significant impacts on CO_2 emissions, while REG has a negative impact on CO_2 emissions for the United States.

4. Conclusions. The findings of this study offer valuable insights into the complex relationships linking AI-related patents, GDP, trade openness, energy intensity, REG, and CO_2 emissions in the United States. Consistently, the results show that the interaction between AI-related patents and renewable energy production has a negative, statistically significant impact on CO_2 emissions. This notable finding underscores the potential of renewable energy production to mitigate the impact of AI technologies on CO_2 emissions. Furthermore, the study also detects a positive and statistically significant influence of AI-related patents, GDP, trade openness, and energy intensity on CO_2 emissions. On the other hand REG has a negative effect on CO_2 emissions.

Based on these results, the recent literature's findings suggesting that the environmental impacts of artificial intelligence are not one-sided are supported [48-50]. It is observed that if energy systems are not green, artificial intelligence technologies can increase environmental pollution due to their production processes, data processing infrastructure, and energy- intensive use, as well as the energy demand created by data centers. The relationship between carbon emissions and artificial intelligence is not direct; it varies depending on the application areas. When considered alongside green energy systems, artificial intelligence's ability to reduce carbon emissions underscores the importance of supporting energy systems with renewable resources. For the results of artificial intelligence to be positive, investments in renewable energy need to increase. The necessity of transitioning to green energy for artificial intelligence to effectively reduce environmental pollution is also consistent with the literature [51-53]. In this context, the results obtained show that artificial intelligence has a conditional role in reducing environmental pollution. If artificial intelligence applications are implemented within a fossil fuel-based system, the expected positive effect is reversed. Data centers, infrastructure, technologies that require high processing power, and digital networks increase carbon emissions when powered by a fossil-fuel-based energy system.

Another subject of study, GDP, is associated with increased carbon emissions. This supports the literature's findings that increased production, consumption, and energy demand contribute to environmental pollution [54, 55]. In economies with high production capacity, such as the US, economic growth does not reduce environmental costs despite increased energy efficiency. While there are expectations that artificial intelligence will reduce carbon emissions, this needs to be supported by a transition to green energy. Therefore, to mitigate the environmental damage caused by economic growth, it must be supported by renewable energy use and energy efficiency policies.

Another variable underpinning this research is trade openness. The positive impact of trade openness on carbon emissions is noteworthy. The results show that increased trade openness can lead to higher carbon emissions due to larger production scale, greater energy use, and higher energy intensity in the global supply chain. There is no consensus in the literature regarding the environmental impact of trade openness. Reasons for this include differences between country groups, production structures, foreign trade content, and measurement differences [56]. However, pressure on carbon emissions is higher in areas where production growth comes from non-renewable energy sources, environmental regulations are weak, and especially where the export structure is based on energy-intensive sectors. The findings of this study are consistent with the literature, which provides evidence that trade openness increases carbon emissions [57-59].

Based on the obtained results, the following policy recommendations are proposed: a) As can be seen from the estimation results, AI technologies have an emission-reducing impact only when the energy system is "green". Therefore, AI applications should primarily be used in renewable energy infrastructure and energy management (e.g., smart grids and energy forecasting). In this context, AI strategies integrated with renewable energy should be developed. b) The finding that trade openness increases emissions indicates that the structure of imports and exports needs to be regulated. The transfer of AI-based technologies should be promoted jointly with green technologies. c) Green-oriented incentives should be provided for AI innovations. Specifically, government policies should prioritize support for energy- efficient and carbon-neutral AI projects. d) Considering the impact of energy intensity on CO_2 emissions, AI applications should be used to promote process optimization, reduce energy losses, and encourage automation.

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Declarations

Conflict of Interest. The authors declare that they have no competing interests or conflicts of interest.

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