

Article

Decarbonizing Through Innovation: The Role of AI Investment in Reducing CO₂ Emissions in the Top AI-Investing Economies

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Abstract

This research explores the effect of artificial intelligence (AI) investment on carbon dioxide (CO₂) emissions relating to worldwide industrialization and environmental concerns. CO₂ emissions have risen due to fossil fuel usage, leading to global warming, environmental degradation, and climate change. While most previous studies have concentrated on components such as economic progress, energy consumption, and technological improvement, little attention has been given to the impact of artificial intelligence on the levels of carbon dioxide emissions. Artificial intelligence technology enables systems to perform complicated duties including reasoning and decision making. This article intends to fill this research gap by examining the impact of AI on carbon emissions in the eight highest AI-investing countries (the USA, China, the United Kingdom, Israel, Germany, India, Canada, and Korea) from 2012 to 2022. OECD data on average trade, AI investment, and consumption-based CO₂ emissions were analyzed in this study. The Augmented Mean Group (AMG) approach was employed to analyze the study findings, with the results showing that GDP had a beneficial influence on CO₂ emissions in the Top AI-Investing Economies. The results also showed that AI investment and trade had adverse impacts on CO₂ emissions. The findings supported the idea that investment on AI has a positive impact on decreasing CO₂ emissions, thus leading to a more sustainable environment.

Keywords: artificial intelligence; CO₂ emissions; innovation; top AI-investing economies



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1. Introduction

The importance of AI technology has grown significantly across modern industries and societies. Fundamentally, artificial intelligence can now perform tasks such as optical identification, understanding conversations, decision making, and language skills, activities previously achieved only through human intelligence. AI technology can now analyze vast amounts of complex data, recognize patterns, and make decisions using algorithms, mathematical models, and high-level calculation methods. A characteristic of AI systems is continuous learning processes which improve performance and can adapt to changing conditions, thus optimizing final outcomes. AI technology has impacted many sectors such as transportation, health, education, entertainment, and finance, delivering improved productivity and efficiency. For instance, in the manufacturing industry, automated AI-based systems help in completing repetitive (duplicative) duties thereby allowing humans

to perform more complicated and innovative duties [1]. Additionally, AI is improving personalization in e-commerce and on entertainment platforms like platforms Amazon and Netflix, offering user-tailored suggestions [2]. Investments and planning activities can be performed more effectively by following AI-designed strategies generated by analyzing patterns and trends across huge numbers of datasets. Further advantages of AI technology include improved security and lower vulnerability, for example, identifying unauthorized access and security threats more easily via AI systems such as facial recognition. Moreover, AI-powered drones can detect and intervene in disasters to aid environmental protection and save the lives of humans and other living creatures.

The relationship between AI, investment, and energy consumption has become more significant with AI's integration into various industries. AI technology can improve and optimize the consumption of energy through a range of systems and procedures. As an example, in the manufacturing industry, energy demand can be estimated by AI-driven technology, meaning usage can be adjusted to minimize unnecessary energy loss. Similarly, AI-powered smart grids are used in the energy sector to decrease energy waste [3]. AI technology is also a vital component in integrating renewable energy sources, thereby ultimately minimizing energy consumption. It is very important in improving the production, storage, and distribution of energy. AI can estimate electricity generation via renewable resources like wind and solar power; these prediction systems aids in achieving a supply–demand balance, leading to less dependence on fossil fuels and reduced need for excess energy storage. AI can also be used to predictively maintain energy infrastructure, thus reducing system outages.

Despite the promise of energy efficiency, there remain concerns about the effects of AI on the environment when considering the processing power needed to develop and implement AI models, particularly deep learning models. Vast amounts of energy are required to enable large-scale learning, which may lead to significantly increased energy consumption. It is therefore important that research on artificial intelligence, cloud computing, and machine learning should pay special attention to AI technology's impact on the environment. In modern societies, the importance of AI in creating a more sustainable environment grows each day. Sectors like agriculture, urban planning, and waste management are transformed through effective AI-driven integration of renewable energy, carbon emission reductions, and resource efficiency. A sustainable environment can be achieved via AI technology in optimizing the integration of alternative sources of energy, such as water, solar, and wind turbines. AI algorithms are used to estimate energy production according to weather conditions, thus delivering a reliable and steady supply of energy. Moreover, to decrease peak demand and prevent grid overloads, AI-powered demand response systems facilitate real-time modifications to energy consumption. Additionally, AI is an important tool for decreasing carbon emissions by streamlining industrial operations and determining areas for improvement [4]. AI systems can evaluate information from multiple areas and sectors like transport and manufacturing to detect ineffectiveness and suggest methods to cut carbon emissions. In addition, policy and sustainability strategies can be developed more accurately via more precise estimations of climate change and its impacts. In the agriculture sector, resource use optimization of (water, fertilizer), reducing waste, and improving output processes are achieved via AI technology. AI's capacity to control energy storage systems is yet another significant advancement that improves the longevity and efficiency of batteries used to store renewable energy. AI technology is making cities better and healthier by improving energy use in waste disposal, transportation systems, and buildings [5]. AI, investment, and sustainability in the environment have an ongoing and changing relationship. Increasingly, companies are seeing how AI-powered machines can address global problems like environmental damage, climate change, and depleting assets.

Technical advancements in AI that reduce emissions, boost energy consumption, and aid in the shift to a carbon-neutral, sustainable future are therefore essential. Opportunities for artificial intelligence-based investment are particularly promising, with technologies for enhancing energy utilization from renewable sources, improving energy storage, and decreasing energy consumption becoming more and more common. Additionally, as a component of the greater movement for environmental consciousness, investment is being drawn toward artificial intelligence technology for integrating environmentally friendly alternatives in fields including handling waste, farming, and ecological diversity surveillance. Despite AI's many advantages for ecology, it is crucial to acknowledge the problems brought on through its high energy usage, especially in applications that require large amounts of data like deep learning, thus underscoring the need for continuous improvements in algorithm optimization and power-efficient processing. Future plans for investing in the AI and energy sectors will need to balance the environmental advantages of AI with its energy consumption.

Due to magnitude of effects brought on by increased manufacturing and use of energy, economic expansion has historically been linked to higher CO₂ emissions. In countries that rely on fossil fuels, emissions often increase when GDP grows, suggesting an upward growth–emissions link. This association can be altered via technological advancement, especially through investments in AI technology, which can help lower the carbon dioxide intensity of business operations by increasing productivity, efficiency, and allocation of resources. Theoretically, efficiency benefits should predominate, leading to decreased CO₂ emissions, even though AI may raise the demand for energy through the growth in technological infrastructure. The size and technology spread of trade also affects emissions. Trade may increase economic activity, but it also makes it easier for effective production techniques and greener technology to become widespread. The resulting effect will contribute to lower emissions in developed and innovative economies. In general, trade and AI investment reduce emissions by mitigating the intensity of carbon dioxide, but GDP influences emission release primarily via the scale effect. In accordance with macroeconomic and environmental theory, the empirical model used a logarithmic formulation to capture these proportional associations and interpret coefficients as elasticities.

CO₂ emissions are impacted by artificial intelligence in both positive and negative ways. AI reduces waste, forecasts the need for energy, and optimizes industrial operations to increase energy utilization. It facilitates the incorporation of energy from environmentally friendly sources like solar and wind power and assists the development of smart grids. AI reduces carbon footprints (carbon dioxide emissions per unit of GDP) by enhancing stored energy, balancing supply and demand, and decreasing reliance on petroleum and coal. AI also aids in identifying inefficiencies in industries such as manufacturing, transportation, agriculture, and urban systems, which reduces pollutants and resource consumption. Furthermore, via trade and innovation, investments in artificial intelligence encourage the adoption of greener technologies. On the other hand, AI systems demand significant energy and processing capacity, particularly deep learning and massive computation. AI infrastructure and data centers have the potential to increase the use of energy in general. Furthermore, increasing output and usage of energy could result in a scale effect that raises overall emissions if AI promotes growth in the economy. In summary, this study makes the case that investing in AI can result in a net decrease in CO₂ emissions if technology and efficiency advancements offset the effects of size and energy use.

Despite technological advancements and persistent efforts to implement climate policies, worldwide emissions of carbon dioxide are still rising, especially in heavily industrialized countries. Simultaneously, AI has emerged as a key force behind technological advancement, drawing significant global investment. However, there is still little and

conflicting empirical data regarding whether investing in AI aids national decarbonization. Current studies mostly ignore the unique significance of AI as a capital-intensive breakthrough in favor of focusing on conventional factors that determine emissions or on overall technical advancement. The need to determine whether making investments in AI can be a successful innovation-led approach to lowering CO₂ emissions among the world's top AI-investing economies is what spurred this study. The effect of investments in AI on carbon dioxide emissions for the eight nations with the highest AI spending has never before been extensively investigated. This investigation adds to the literature by addressing the knowledge gap in this field of research. An in-depth analysis of artificial intelligence investments (in the energy sector) is lacking, and the objective is to close this hole in the field of knowledge. Utilizing an approach that uses econometrics, our objective was to perform a quantitative assessment. The goal of this study is to broaden the range of studies that utilize this method of inquiry considering the lack of it, especially on machine learning.

Some primary contributions are made in this study. Moving beyond research focused on the adoption of AI or general technical progress, it first presents AI investment as a unique explanatory variable in the carbon footprint–technology nexus. Second, it concentrates on the leading economies that devote resources to AI, where the technology has reached a mature stage and its effects on the natural environment are more likely to be structural than speculative. Third, this study offers solid empirical proof that investing in AI reduces CO₂ emissions by focusing on consumption-based CO₂ emissions and utilizing the AMG estimator, providing fresh perspectives for innovative industrial and climate policies.

2. Literature Survey

The existing literature examining the relationship between technological innovation, AI, energy consumption, and CO₂ emissions can be grouped according to methodological approaches, regional focus, and empirical findings, revealing both common patterns and important differences.

A large portion of the literature relies on econometric and panel-data methods to analyze the long- and short-run dynamics between economic activity, technology, and environmental outcomes. Ref. [6] investigated South Asian economies and emphasized the critical role that utilization of energy and fossil fuel usage play in generating carbon dioxide emissions, along with discussing other atmospheric greenhouse gas issues. Ref. [7], employing multivariate adaptive regression splines (MARS) with long-run data, concluded that coal, natural gas, and oil are the primary sources of atmospheric greenhouse gases and that a global strategy to address ecological harm is ineffective due to cross-country heterogeneity. Similarly, Ref. [8] applied asymmetric ARDL approaches for Sweden and demonstrated that positive technological shocks reduce CO₂ emissions, whereas negative shocks increase them. Another strand of the literature employs AI-based, machine learning, and optimization-oriented approaches. Ref. [9], analyzing Chinese manufacturing industries, found that employing AI considerably lowers carbon dioxide emissions, especially in robotics and academic AI research, with effects differing by industry and stage of development. Ref. [5] examined intelligent waste management technologies and showed that machine learning-powered trash identification devices significantly improved efficiency and reduced carbon dioxide emissions. Ref. [10] focused on AI-enhanced energy management systems and concluded that optimizing energy usage and system performance leads directly to reduced CO₂ emissions. Ref. [11] used AI forecasting models to analyze U.S. data centers and found that while emissions may rise without intervention, AI-based optimization and renewable energy use can drastically decrease emissions. A smaller number of studies adopt conceptual or integrative frameworks. Ref. [12] proposed a system-of-systems approach, arguing that AI can substantially lower carbon emissions when used

to coordinate energy, transportation, industry, and governance systems, provided that institutional coordination and regulatory frameworks are in place.

Regionally, a significant portion of the literature concentrates on China. Ref. [13] found that technological advancement supports sustainable development in China by reducing pollutants while stimulating economic expansion. Ref. [14], using data from 269 Chinese towns, reported that smart manufacturing dramatically lowers PM_{2.5} (Particulate Matter 2.5) and total environmental pollution through optimal resource use. Ref. [15], focusing on China's clothing industry, identified a positive but statistically insignificant relationship between investment in technological advancement and environmental outcomes, highlighting sector-specific differences. Ref. [16] analyzed China over a long time span and demonstrated that green finance and renewable energy investment positively affect clean energy development in both the short and long run. Ref. [17] showed that AI reduces CO₂ emissions in China mainly through industrial structure optimization, with stronger effects in technologically advanced regions.

Other studies adopt a cross-country or global perspective. Ref. [18] employed cross-country panel data and found that AI technologies significantly reduce global carbon dioxide emissions. Ref. [19] compared high- and low-income countries and demonstrated that the macroeconomic factors influencing CO₂ emissions vary substantially with income level. Country-specific analyses outside China are also present. Ref. [6] focused on South Asia, Ref. [20] examined the United States, and [8] analyzed Sweden, collectively highlighting regional heterogeneity in the emissions–technology relationship. Across the literature, there is strong agreement that fossil fuel consumption and energy use are major contributors to CO₂ emissions. Studies such as [6,7,9] consistently emphasize the emissions-increasing role of conventional energy sources and economic expansion. At the same time, many studies report that technological innovation and AI contribute to emission reduction. Empirical evidence from [5,9,10,18,21] shows that AI improves efficiency, lowers emissions, and enhances environmental performance across sectors. However, several studies highlight conditional and heterogeneous effects. Refs. [15,22] found that the environmental impact of technology and AI may be statistically insignificant or mixed in certain contexts. Ref. [19] emphasized that the effectiveness of AI in reducing emissions depends on income level, industrial structure, and economic composition. Ref. [17] further showed that regulatory quality, education, and technological infrastructure condition AI's emissions-reduction potential.

Overall, the literature demonstrates broad consensus that AI and technological innovation generally mitigate environmental degradation, but it also reveals important differences across methods, regions, and economic contexts. These differences underscore the complexity of the technology–emissions relationship and highlight the need for carefully designed empirical models that account for heterogeneity and context-specific dynamics.

3. Data, Model and Method

3.1. Data

Data on GDP, average trade, AI investment in energy, raw materials, and utilities consumption-based CO₂ emissions is collected for 8 countries leading on artificial intelligence investment (USA, China, United Kingdom, Israel, Germany, India, Canada, Korea), covering the years between 2012 and 2022. GDP is collected for current prices as USA Dollars for the 8 countries (collected from the World Bank Dataset). Data on trade, including the summation of goods being imported and exported divided by two, is collected for the same countries as USA Dollars (collected from World Bank Dataset). Consumption-based CO₂ emissions, which means the emissions generated in the production of goods and services according to where they were consumed rather than where they were produced, is

also collected for the 8 countries (collected from Our World in Data). Finally, AI investment in energy, raw materials and utilities is collected as USA Dollars (collected from OECD.AI).

3.2. Model

The aim of this study is to investigate the effect of AI investment on CO₂ emissions regarding worldwide industrialization and environmental concerns.

$$LCCO_2 = F(LGDP, LTRO, LAIENERGY)$$

$$LCCO_2 = \beta_0 + \beta_1 LGDP + \beta_2 LTRO + \beta_3 LAIENERGY$$

where LCCO₂ LGDP, LTRO, and LAIENERGY denote the natural logarithm of consumption-based CO₂ emissions, natural logarithm of gross domestic product, natural logarithm of trade, and natural logarithm of AI investment in energy, raw materials, and utilities, respectively. In addition, β_0 indicates the intercept, while β_1 , β_2 , and β_3 indicate the slope coefficients.

Three hypotheses have been established in this research and tested empirically.

Hypothesis 1. *AI investment in energy, raw materials and utilities decreases consumption-based carbon dioxide emissions in the top AI-Investing economies. AI investment in energy, raw materials, and utilities is expected to lower consumption-based CO₂ emissions by reducing the carbon footprint of power generation, increasing energy utilization in carbon-intensive upstream industries, and streamlining worldwide distribution networks. Similar results were found by [9], who analyzed Chinese manufacturing industries and found that employing AI considerably lowers carbon dioxide emissions, especially in robotics and academic AI research, with effects differing by industry and stage of development.*

Hypothesis 2. *Economic growth increases consumption-based carbon dioxide emissions in the top AI-Investing economies. Economic development in the leading AI-investing economies is expected to raise consumption-based carbon dioxide emissions by increasing consumption by households and the importation of commodities that release more emissions.*

Hypothesis 3. *Increasing trade decreases consumption-based carbon dioxide emissions in the top AI-Investing economies. Increasing average trade can reduce consumption-based CO₂ emissions in the leading AI-investing nations by enabling nations to import products from less polluting and more efficient manufacturers. By moving manufacturing towards less environmentally damaging activities and more effective worldwide supply chains, it also lowers pollutants that are imbedded in consumption.*

3.3. Method

The Methodology section describes the statistical techniques employed to analyze the time-series data, particularly focusing on tests for stationarity, cointegration, and estimation in panel data analysis. To ascertain if a time series is stationary or not, unit root checks are utilized. Since non-stationary data might produce inaccurate regression model results, stationarity is essential. When performing unit root tests, the alternative hypothesis (H₁) suggests that the series is stationary, compared to the null hypothesis (H₀), which claims the series is non-stationary.

The Im, Pesaran, and Shin (IPS) test considers the heterogeneity in the panel data; the Levin, Lin, and Chu (LLC) test relies on the standard unit root procedure across the panel; and the ADF-Fisher Chi-square and PP-Fisher Chi-square analyses aggregate *p*-values from separate tests to evaluate unit roots throughout a panel, adjusting for heteroscedasticity and serial relationship in the information being examined. To provide dependable findings

for further examination, such tests assist in identifying whether transformation, such as differentiation, is necessary to render the series stable.

A long-term equilibrium connection between time series that are not stationary is referred to as cointegration. The Pedroni Residual Cointegration Test and the Kao Residual Cointegration Test are two frequently used cointegration tests in panel data. The Pedroni Residual Cointegration Test (1999, 2004) considers panel diversity when determining cointegration.

It offers seven test results that consider both short- and long-run panel patterns and variations. The Kao Residual Cointegration Test employs just one test statistic and concentrates on homogenous correlations between the time series throughout the dataset. It works well in circumstances in which the investigator believes that the elements in the group have a common long-term connection. Both of these methods can be applied to determine whether the time series in the dataset have cointegration, which indicates that although the data are not stable, they do have a strong long-term relationship when taken independently. For forecasting, the AMG estimator, which performs effectively across a variety of datasets, panel data is used. This estimating technique is especially helpful whenever the parameters have long-term, reliable relations (cointegration) and when the reactions of the cross-sectional units to the factors that describe them are different. It captures more general trends in the available data while enabling the evaluation of specific deviations.

For datasets with significant variation, the AMG estimator produces reliable findings and is perfect for handling non-stationarity and cointegration problems across several panel elements. Overall, the approach outlined stresses the use of unit root analysis and cointegration checks to guarantee that information gathered over the period is appropriately examined, as well as the use of the AMG estimator to account for cointegration and variety among data collectors for panel units.

4. Results

This study investigates, in light of ecological issues and worldwide advancement, how AI expenses affect CO₂ emissions. Initially, a unit root analysis was performed. The data's stationary patterns were examined at level and first difference.

As shown in Table 1, when Levin, Lin, and Chu; Im, Pesaran and Shin W-stat; ADF-Fisher Chi-square; and PP-Fisher Chi-square unit root tests were applied, *p*-values for all dependent and independent variables were found to be bigger than 5%, which means they were all non-stationary. First difference was therefore taken for all variables, and the variables became stationary.

Table 1. Unit root test.

LTRO			DLTRO		
Method	Statistic	Prob.	Method	Statistic	Prob.
Levin, Lin, and Chu <i>t</i>	−0.11682	0.4535	Levin, Lin, and Chu <i>t</i>	−6.17183	0.0000
Im, Pesaran, and Shin W-stat	2.28415	0.9888	Im, Pesaran, and Shin W-stat	−2.98361	0.0014
ADF-Fisher Chi-square	4.41006	0.9925	ADF-Fisher Chi-square	36.3091	0.0009
PP-Fisher Chi-square	2.70691	0.9995	PP-Fisher Chi-square	43.7087	0.0001

Table 1. Cont.

LCCO ₂			DLCCO ₂		
Method	Statistic	Prob.	Method	Statistic	Prob.
Levin, Lin, and Chu t	−0.32003	0.3745	Levin, Lin, and Chu t	−8.91290	0.0000
Im, Pesaran, and Shin W-stat	1.46590	0.9287	Im, Pesaran, and Shin W-stat	−4.90575	0.0000
ADF-Fisher Chi-square	10.0450	0.8643	ADF-Fisher Chi-square	58.3936	0.0000
PP-Fisher Chi-square	12.7123	0.6937	PP-Fisher Chi-square	72.2966	0.0000
LAIENERGY			DLAIENERGY		
Method	Statistic	Prob.	Method	Statistic	Prob.
Levin, Lin, and Chu t	4.60650	1.0000	Levin, Lin, and Chu t	−11.5370	0.0000
Im, Pesaran, and Shin W-stat	1.48556	0.9313	Im, Pesaran, and Shin W-stat	−4.85978	0.0000
ADF-Fisher Chi-square	9.06920	0.8266	ADF-Fisher Chi-square	44.7432	0.0000
PP-Fisher Chi-square	10.4801	0.7263	PP-Fisher Chi-square	57.7878	0.0000
LGDPC			DLGDPC		
Method	Statistic	Prob.	Method	Statistic	Prob.
Levin, Lin, and Chu t	−0.19025	0.4246	Levin, Lin, and Chu t	−7.54745	0.0000
Im, Pesaran, and Shin W-stat	1.69570	0.9550	Im, Pesaran, and Shin W-stat	−5.32148	0.0000
ADF-Fisher Chi-square	10.4613	0.8415	ADF-Fisher Chi-square	60.2836	0.0000
PP-Fisher Chi-square	12.3323	0.7208	PP-Fisher Chi-square	65.8094	0.0000

Secondly, cointegration tests were applied to determine whether two or more non-stationary time series variables have a long-term equilibrium relationship. We applied two commonly used cointegration tests in panel data analysis: Pedroni Residual Cointegration Test; Kao Residual Cointegration Test.

As shown in Table 2, when cointegration tests were applied, 6 out of 11 results for the Pedroni Residual Cointegration Test and Kao Residual Cointegration Test were found to have *p*-values lower than 5% meaning the hypothesis assuming no long-term linkage among dependent and independent variables is rejected. This result reveals that cointegration between the variables exists.

Thirdly, the Augmented Mean Group (AMG) estimator is applied to estimate long-run relationships in panel data. The interaction between AI, energy expenditures, and ecological effects is complex. While AI has the potential to drive energy efficiency improvements, its widespread adoption and the infrastructure supporting it also contribute to increased energy demand and environmental concerns. Balancing these aspects necessitates careful consideration of energy sources, creative thinking in technology, and policy interventions to ensure that AI development aligns with environmental sustainability objectives.

According to the study results, the *p*-value of LGDPC is lower than 5%, and the *p*-values of LAIENERGY and LTR are equal to or lower than 10%. This data is therefore suitable for use by the AMG model at 5% for some variables and at 10% for others. In this study, as Table 3 shows, AI investment in energy, raw materials, and utilities negatively affects CO₂ emissions, which means that as AI investment in energy, raw materials, and utilities increases, CO₂ emissions decrease. When AI is used in the energy, raw materials, and utilities industries, CO₂ emissions tend to fall due to improved process efficiency and integration of more environmentally friendly products and technologies. AI allows companies to reduce waste, make better predictions about demand, and use their assets with higher efficiency. The transition to ecologically friendly manufacturing and consumption

is made possible through these advancements, especially in sectors that have historically produced a lot of emissions. In addition, AI accelerates the shift towards additional green methods as markets and sectors grow by lowering expenditures and increasing the accessibility of ecologically sound alternatives. Overall, the above supports the results of this study which shows that as AI investment in energy, raw materials, and utilities increases, CO₂ emissions tend to decrease in the Top AI-Investing Economies.

Table 2. Cointegration tests.

Pedroni Residual Cointegration Test				
Series: LCCO ₂ LGDPC LTR LAIENERGY				
Alternative hypothesis: common AR coefs. (within-dimension)				
Weighted				
Statistic	Prob.	Statistic	Prob.	
−1.006706	0.8430	−1.445601	0.9259	Panel v-Statistic
0.912186	0.8192	0.918908	0.8209	Panel rho-Statistic
−2.157759	0.0155	−2.822570	0.0024	Panel PP-Statistic
−1.948119	0.0257	−2.628934	0.0043	Panel ADF-Statistic
Alternative hypothesis: individual AR coefs. (between-dimension)				
Statistic		Prob.		
Group rho-Statistic		1.880048	0.9699	
Group PP-Statistic		−2.288437	0.0111	
Group ADF-Statistic		−2.110184	0.0174	
Kao Residual Cointegration Test				
Series: LCCO ₂ LGDPC LTRO LAIENERGY				
			t-Statistic	Prob.
ADF			−2.757761	0.0029
Residual variance			0.000276	
HAC variance			0.000282	

Table 3. Augmented Mean Group estimator.

Dependent Variable: LCCO₂	Coefficient	Std. Err.	z	p > z
LAIENERGY	−0.0036657	0.002021	−1.81	0.07
LTRO	−0.2728458	0.165809	−1.65	0.1
LGDPC	0.3942837	0.087105	4.53	0
_cons	−0.798301	1.801544	−0.44	0.658

Note: Wald chi2(3) = 25.21 Prob > chi2 = 0.0000.

Table 3 shows that this study found a positive relationship between LGDPC and CO₂ emissions. As LGDPC increases, the amount of CO₂ emissions also increases. When the effect of GDP is analyzed theoretically, carbon dioxide release can be affected by increased GDP. Releases typically rise during economic expansion due to higher energy consumption, manufacturing activities, and dependency on petroleum and coal. This analysis supports the result of this study, which states that as GDP increases, CO₂ release also increases in the Top AI-Investing Economies.

In theory, trade makes greener technology more accessible, fostering innovation, and allowing nations to focus on environmentally friendly industries; trade might therefore re-

duce emissions. Table 3 shows that trade has negative relationship with CO₂ emissions. As trade increases, the amount of CO₂ emissions decreases in the Top AI-Investing Economies, and this result is in line with the theory mentioned above.

When the results of the study are summarized, it can be seen that GDP had a beneficial influence on CO₂ emissions in the Top AI-Investing Economies. The results also showed that investment on AI and trade had adverse impacts on CO₂ emissions. The findings supported the idea that investment on AI has a positive impact on decreasing CO₂ emissions, which will thus have positive effect on securing a sustainable environment.

5. Conclusions

AI has the potential to significantly impact energy efficiency and environmental sustainability, offering solutions to some of the most pressing challenges facing the global economy. From optimizing energy consumption and improving renewable energy integration to reducing carbon emissions and supporting sustainable agriculture, AI is at the forefront of environmental change. However, the environmental costs of training and deploying AI models must be carefully considered, with investment in energy-efficient AI technologies being a key priority moving forward. AI will be crucial in determining the direction of the energy industry and international environmental programs as the need for environmentally friendly options grows. A cleaner, more effective future will require sustained spending on environmentally friendly innovations and artificial intelligence-driven energy-efficient technologies.

AI can assist in reducing CO₂ emissions through optimization, forecasting, smart grids, incorporation of energy from renewable sources, efficient supply chains, and environmental surveillance. However, its advantages cannot be ensured because artificial intelligence systems require significant processing power, which might raise the need for electrical power and thus mitigate emission reductions if powered by conventional energy sources, i.e., fossil fuels. Accurate and trustworthy data used for training is also necessary for its efficacy; inadequate data might result in inaccurate forecasts, ineffective choices, or skewed monitoring. Rebound effects, disparities in technology capability, issues related to cybersecurity, and governance difficulties are further threats. As a result, investing in AI should not be viewed as a substitute for conventional emission reduction strategies including fuel switching, carbon pricing, energy conservation, green energy, regulation, and sustainable transportation. Rather, the primary reason for concentrating on investments in artificial intelligence is to investigate if this new type of technological advancement might supplement and enhance the effectiveness of well-established decarbonization measures, thereby contributing to emission reduction in the most prominent AI-investing nations.

In the major AI-investing economies—the US, China, the UK, Israel, Germany, India, Canada, and South Korea—this analysis shows that GDP expansion raises CO₂ emissions, while trade and investments in artificial intelligence lower emissions. The following recommendations for policy are made solely based on these factors.

Policymakers must ensure that future economic growth continues to be powered by investments in artificial intelligence instead of through emission-intensive development, as GDP growth is found to have a beneficial effect on CO₂ emissions. Incorporating AI-intensive industries into expansion plans may lessen the emissions–GDP connection as AI investment reduces emissions. The proportion of artificial intelligence-related activities in the overall GDP should therefore be increased.

It is advised to increase AI investment to support economic growth. Increased investments in artificial intelligence can counteract the adverse environmental impacts of GDP development, as evidenced by the negative correlation between AI investment and CO₂ emissions. As a result, investment in AI should increase at least proportionately to GDP,

and ideally more quickly. It is advised to maintain steady rises in AI spending in parallel with economic expansion. During times of GDP growth, AI investment stagnation or fall should be avoided.

It has been demonstrated that trade lowers CO₂ emissions, indicating that open economies gain from the global spread of AI-related technology. Policymakers should therefore avoid trade restrictions that can impede the expansion of the advantages of AI investment. It is advised to maintain and increase trade to facilitate worldwide movement of capital, expertise, and goods relevant to artificial intelligence. Trade regulations should be in line with AI investment goals to maximize carbon reductions.

Balanced growth strategies that combine expansion of trade with economic expansion are crucial since GDP raises releases while trade lowers them. The impact on the environment due to GDP growth can be somewhat mitigated by trade. It is advised to promote strategies for growth that are trade-integrated and export-oriented and to stay clear of internal-focused growth plans that only focus on local development.

The results of this study indicate that whereas GDP alone raises CO₂ emissions, trade and AI investment together lower releases in the Top AI-Investing Economies. Rather than treating these three factors as separate policy goals, policymakers should therefore view them as interrelated components and align economic expansion goals with AI development pathways. It is advised to ensure artificial intelligence-powered economic activity is supported by trade and to avoid growth policies that enhance GDP without also increasing trade and AI investment.

Policymakers may encourage AI technology for optimal utilization of energy in infrastructure, homes, and businesses, which will lower power use and increase network effectiveness. Intelligent technology could enhance cooling and heating processes, regulate power use, and increase the use of renewable energy sources by predicting tendencies and improving storage options. Policies should comprise tax breaks or benefits for businesses that use AI to transition to greener sources of electricity, in addition to benefits for advancing AI applications that use less energy. To separate economic development from CO₂ emissions, strategies ought to promote the adoption of energy-efficient practices and eco-friendly technology. AI can reduce pollutants and increase output, promoting long-term growth in the economy. Authorities can establish environmental fiscal initiatives, such as taxing carbon dioxide and cap-and-trade schemes, and the money raised could then be used to fund research and development on sustainable technology. Furthermore, encouraging environmentally friendly industries like renewable energies, EVs, and environmentally friendly farming can boost GDP and cut pollution.

To lower worldwide emissions of CO₂, policymakers should promote worldwide collaboration and the trade of environmentally friendly innovations driven by AI. Nations can assist one another in adopting greener alternatives by reducing restrictions on trade and encouraging the interchange of environmentally friendly technologies. Additionally, AI can enhance carbon boundary adjustment systems, guaranteeing the equitable introduction of emission taxes. Worldwide development and optimal procedures might be additionally shared through multilateral partnerships centered on AI for tackling climate change.

To accelerate the creation of environmentally friendly approaches, authorities should use private and public resources to make investments based on artificial intelligence utilizing clean technology. Regulations may have revised in such a way that companies must use AI to improve supply networks' sustainability by cutting waste and streamlining logistics. Encouraging AI-driven environmentally friendly behaviors will contribute to a cleaner economy by lowering the carbon emissions of multinational corporations.

AI can improve carbon monitoring and trading processes by offering immediate analysis for effective carbon credit verification and pollutants monitoring. To assist businesses

and countries in achieving climate change objectives, authorities ought to promote the creation of AI networks for carbon pricing and emissions trading. By increasing the efficiency and transparency of carbon markets, such networks would encourage environmentally friendly behaviors and provide incentives for reducing pollutants.

In conclusion, according to the results of this research, while AI investment and trade offer efficient pathways for carbon reduction, economic expansion without adequate AI investment and trade runs the risk of raising CO₂ emissions in the Top AI-Investing Economies. To achieve environmentally friendly economic growth with reduced carbon emissions, policymakers in the top AI-investing countries should therefore give priority to artificial intelligence-driven, trade-integrated development.

This research analyzed the eight nations with the largest investments in AI by applying data from 2012 to 2022. If datasets covering an extended duration were available and applied or if further nations had been included, more comprehensive results might have been obtained. Having additional data might facilitate a more comprehensive examination of different countries' AI investment programs. This study may be extended with new information and applied to different countries. By expanding the analysis to additional countries and utilizing more recent or comprehensive data, a more complete understanding of global trends in AI spending may be achievable.

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