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Assessing the Role of Artificial Intelligence in Achieving Green Growth: A Panel Data Analysis for OECD countries

Salah ud Din
M.Phil, Quaid-i-Azam University, Islamabad, Pakistan
Email: salaheco99@gmail.com

Kashif Khan
BS Economics, Government Degree College Mingora, Pakistan
Email: kashii.eco@gmail.com

Dr. Faiza Hassan
Lecturer, Department of Economics, University of Malakand, Pakistan
Correspondence: faizahassan@uom.edu.pk

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Abstract

While higher economic growth can improve lives by reducing poverty, it often comes at the cost of environmental degradation. Over the last two centuries, technological advancements have been considered a key driver of economic growth. Technologies such as Artificial Intelligence (AI) are believed to be vital in reducing carbon emissions and fostering green growth (GGT). The study examines the relationship between investment in AI and GGT in the Organization for Economic Cooperation and Development (OECD) countries, which are almost all advanced and have invested more in AI than any other region. A decade comparison through maps revealed that the OECD region has invested more in AI development and deployment in recent years. The results of the Generalized Method of Moments (GMM) show that AI has a significant negative relationship with green growth in the linear form, while in the quadratic form, it exerts a significant positive impact on green growth. The dual effect of AI highlights that AI initially disrupts green growth due to high initial costs, and after a certain threshold, it impacts green growth positively. The study recommends policies and guidelines to ensure proper utilization of AI for green growth objectives.

Keywords: Artificial Intelligence, Green Growth, OECD, Regulatory Quality, GMM.

1. Introduction

Economic growth (EG) is critical for alleviating poverty and raising the living standards of the people. However, EG also causes environmental degradation. The growing speed of environmental degradation further complicates this relationship and demands policies that can balance economy and environment (Cole et al., 1997). The Intergovernmental Panel on Climate Change (IPCC) reported that the average global temperature increased by approximately 0.74°C (estimated range 0.56–0.92°C) between 1906 and 2005 (IPCC, 2007). EG causes environmental concerns, nations are struggling and transitioning toward sustainable development (Capasso et al., 2019; Liu et al., 2019). In order to accelerate EG while simultaneously maintaining environmental quality, the OECD developed the concept of "Green Growth" as an alternative approach to development (OECD,2011). According to the United Nations Environmental Program, green growth is an environmentally friendly economy that enhances human well-being and social equity while substantially mitigating environmental risks and ecological scarcities (UNEP, 2011). At the 2012 Rio+20 Conference on Sustainable Development, green growth emerged as a key theme for the global leaders. This theme is further emphasized in "The World We Want" a manifesto that advocated a green economy and sustained economic growth. Green growth emerged as a prominent global response to the growing environmental degradation and climate change (Hickel & Kallis, 2020; Dale et al., 2016). It raised concerns for research to develop new methods and techniques for sustainable development. A green economy emphasizes on resource preservation, economic growth and environmental friendliness as efficient approach to sustainability (Bagheri et al., 2018; Matraeva et al., 2019; Yang et al., 2019). Green growth fosters economic progress and advancement by striving for a long-term equilibrium between environmental risks and economic growth (Popp et al., 2011). Every country must develop environmentally friendly economic policies to improve social cohesion and achieve long-term economic growth and development. (Khan & Ozturk,2020). Governments worldwide view the pursuit of economic growth alongside environmental sustainability as a crucial policy objective (Hao et al., 2020). Sustainability and a low-carbon economy could only be possible in an environment with the involvement and development of high-end technologies. Technological developments are expected to change the process of carbon emissions significantly. An atmosphere that fosters technological innovation is being created to support environmental sustainability and economic progress (Kuntsman & Rattle, 2019). For over 250 years, the primary catalysts for economic expansion have been technological advancements. Among these, the most crucial are what economists refer to as general-purpose technologies. Artificial Intelligence (AI) is the most significant general-purpose technology of our time (Brynjolfsson & McAfee, 2017). AI is a general term for using computers to simulate intelligent behavior with little to no human intervention. AI's origins are frequently linked to the advancement of robotics. It is widely acknowledged that the development of robots represented the beginning of AI. The name comes from the Czech word robota; it represents a factory where forced work is performed by biosynthetic machines (Hamet & Tremblay, 2017). AI involves exploring enabling computers to perform tasks currently better executed by humans (Ertel, 2018). AI is a knowledge project focusing on acquiring, analyzing, and studying knowledge as its primary objective. It explores how knowledge is expressed and utilizes these methods to simulate human intellectual activities (Zhang & Lu, 2021). Simply put, AI seeks to advance humankind's capacity to manipulate nature and run society through intelligent machines to establish a peaceful coexistence of humans and robots. The ultimate objective of AI has always been to build computers with human-like intelligence (Liu et al., 2018). There are three key advantages of AI technologies. First, AI allows significant but time-consuming and repetitive jobs to be automated, freeing up human labor for higher-value work. Second, AI unlocks insights that would otherwise be hidden behind enormous volumes of unstructured data, such as information produced by emails, videos, images, written reports, business papers, social media posts, and so on, that traditionally require human administration and analysis. Third, AI can combine thousands of computers with additional resources to tackle even the most challenging issues. AI is utilized across various contexts in the social and economic spheres to improve resource integration capabilities and stimulate innovation in green technology (Wang et al., 2023). An ever-widening array of industries is being shaped by AI. For example, AI is anticipated to have short- and long-term effects on global productivity, equality and inclusion, environmental outcomes, and several other domains (Vinuesa et al., 2020).

Applications for AI-based technologies in environmental, sustainability, and climate science research are becoming increasingly popular. Examples include AI-augmented ecological monitoring, climate and Earth system modeling, autonomous underwater marine conservation actions, and data collection. AI technology can help and improve the development of a green, environmentally friendly economy (Yang & Liu, 2023). The use of AI applications can be used as a key instrument to sustain economic growth (Hussain et al., 2022). For green manufacturing and green economic development, AI helps in the industry's transition from an extended production mode to an intelligent and intensive one (Mao et al., 2019; Sarc et al., 2019). In time of higher environmental issues, the world is suffering from the consequences of economic growth, AI technologies offer efficient methods for sustained economic development (Baysan et al., 2019; Farghali et al., 2023). The development and development of AI can create both negative and positive consequences, therefore, the present study intended to explore the dual impact of AI on green growth. Furthermore, the study aims to develop possible mechanisms for the removal of negative AI consequences. This study contributes to the literature by providing a framework in which the dual impact of AI can be studied in a region where AI investment is higher than any other region. It also highlights the role of regulatory quality in minimizing the adverse impact of AI on green growth.

2. Literature Review

2.1. Theoretical Backgrounds

The endogenous growth theory overcomes the shortcomings in the Solow-Swan model of exogenous growth, which could not sufficiently explain sustained long-term growth based solely on external technological advancements. In response, Paul Romer and Robert Lucas developed models in the latter stages of the 1980s and early 1990s that argued that growth is driven by internal economic drivers such as human capital development, knowledge accumulation, and innovation (Romer, 1986; Lucas, 1988). Another important driver of endogenous growth theory is the role of Human Capital (HC), which is considered an essential component of the endogenous growth model. Lucas (1988) argued that HC accumulation is important for long-term economic growth. Investments in education and training promote workers' productivity, resulting in a higher level of output. This, in turn, causes further monetary expansion, creating a virtuous growth cycle. Endogenous growth models often assume increasing returns to scale, particularly in sectors related to knowledge and innovation. Romer (1986) highlighted that in industries where knowledge and technology are vital inputs, increasing returns occur because the marginal cost of producing additional units of knowledge or innovation is low once the initial investment is made. This concept challenges the traditional view of diminishing returns in classical economic models and provides a mechanism for sustained growth without the need for external technological shocks. The main idea of the endogenous growth theory is that knowledge accumulation and technological innovation are important factors leading to growth (Romer, 1990). Romer (1990) expanded on his earlier work by introducing the concept that technological change is an outcome of intentional investment in knowledge. In this framework, firms' investment in Research and Development (R&D) can lead to innovations that generate positive externalities for the economy. New knowledge and information may be used at minimal or no cost, fostering further economic growth.

2.2. Impact of AI on Economic Growth

Wang et al. (2024) studied the impact of AI on China’s economic growth. The study concentrated on technology, value, and application pathways within the population's external system. The study found a significant positive impact of AI on China’s economic growth for the entire sample period; however, the impact of AI on economic growth varies across China. Focusing on the regional differences and variations in the impact, Plikas et al. (2023) studied the association between AI and economic growth, as measured by GDP, from a European perspective (EU27). The study investigated two channels by which AI may affect GDP, digital penetration, and labor productivity, and considered critical drivers of AI. The study employed econometric methods like panel OLS, including country-fixed effects and stepwise regression, for the period between 2010 and 2020. The study's findings indicate that AI has a significant positive impact on GDP. The digital inclusion (DI) measures positively affect labor productivity (LB) but do not directly influence GDP. The study concluded that as labor productivity increases, adopting various digital measures enhances the workers' skills, leading to economic development. To support the argument of the positive impact of AI on economic growth, Gonzales (2023) studied the effect of AI on economic variables. The study aimed to observe the influence of AI on long-term economic growth, considering a positive relationship between the two. The study employed fixed effects and GMM estimation methods using a panel dataset from 1970 to 2019. The results revealed a stronger positive correlation between AI and economic growth than overall patent counts. The influence of AI on growth is more pronounced in advanced economies and gets stronger over time. To study the job market in more detail with a specific focus on AI and job issues, Makridis and Mishra (2022) analyzed 343 cities job market with AI growth. The study highlighted the increasing presence of AI in the job market. It argued that the percentage of AI job postings in the total proportion of the US market has increased from 0.20% to nearly 1% between 2010 and 2019, with variations across cities. The study found a positive relationship between AI job growth and economic growth, with cities having more AI jobs and economic growth. AI job growth affects well-being through its impact on economic growth. The study argued that AI-driven economic growth could contribute to well-being and social welfare. Nxumalo et al. (2022) analyzed how AI influences economic growth using AI data from 20 subregions in Hungary from 2004 to 2021. The study employed Panel data econometrics models like pooled OLS, fixed effects, and random effects to estimate the results. The study argued the positive impact of AI on economic growth along with factors like inflation, consumption, investment, and government spending—variations in AI impact globally and within a country. Similarly, He (2019) examined the impact of AI on economic growth using neoclassical growth and task-based models. The theoretical and empirical literature analysis showed a positive relationship between AI and economic growth. The study suggested that governments should increase investment in AI development to stimulate economic growth further.

2.3. Impact of AI on Green Growth

Studies have highlighted the vital role of AI in economic growth and its growing influence across various sectors. Zhao et al. (2022) studied the impact of AI on green growth by using total factor productivity for China. The result of GMM indicates a U-shaped relationship between AI and GGT. Additionally, Qian et al. (2022) studied the influence of AI on green economic growth in China. The results found that AI can potentially increase local green growth but has behaved differently in neighboring regions. In the short run, AI has a low effect on green growth in the nearby areas but can significantly enhance the green growth of the nearby regions in the long run. The study argued that increased human capital can minimize AI's negative impact. AI has a weak positive effect on green growth in resource-rich areas. Liu et al. (2022), while using the STIRPAT model, investigated the impact of AI on the environment in China following Chinese industrial data. The study focused on how AI influences carbon intensity and found that AI significantly reduces carbon intensity with varying effects by industry and period. The study argued that AI has a more carbon-reducing effect in labor-intensive sectors than in capital-intensive industries. To study the role of AI in the United States, Vijayakumar (2021) studied the relationship between the annual growth of the US Gross Domestic Product (GDP) and private investments in AI and AI inventions in the US from 2010 to 2020. Random Forest Regression (RFR) and Correlation analysis (CA) were employed as analytical techniques (research methods) for both current and lag values. The findings observed that the correlation between GDP growth and AI-related activities varies across various fields. The field that showed the strongest correlation is life sciences. On the other hand, the most significant lagged correlation was seen in the Physical Sciences and Engineering domains; it might indicate that their influence is reflected over some period. The study observed that datasets of AI investment, whether current or lag, have the most influence on predicting GDP growth. The study revealed that the benefits related to AI patents that can impact economic growth can be seen immediately or with a lag.

2.4. Impact of other Determinants on Green Growth

Different studies utilize different essential factors to investigate their relationship with green growth. For example, Hussain et al. (2022) studied the impact of green technology and environmental factors on green growth in high-GDP countries. Using an advanced econometric method, they analyzed GDP's linear and nonlinear effects on green growth. Results showed a positive linear effect of GDP on green growth, while the nonlinear effect was negative. Green technology had a positive impact, while energy consumption had a negative influence. Environmental factors like emissions also decreased green growth. The study recommended that high-GDP countries manage their economic and ecological activities to enhance green growth and protect the environment. Expanding the literature on the role of education and ICT, Li et al. (2022) examined the impact of higher education and ICT on green growth in China. Results showed a significant positive effect of both higher education and ICT on green growth in the short and long term. Financial inclusion and renewable energy consumption were also positively associated with green growth. The findings suggested promoting human capital and ICT infrastructure to enhance green growth. Similarly, Zhou et al. (2022) created a comprehensive index to analyze the effect of green finance and fintech innovation on green growth. The study followed China's panel provincial data from 2011 to 2018. The empirical results showed that both green finance and fintech innovation have significant positive effects on promoting green economic growth. Analyzing the role of financial factors, Cao et al. (2022) used the Spatial Durbin Model to study the impact of economic development and technological innovation on China green growth using panel data from 30 provinces. The Entropy Weight Method measured the green growth index. The study's findings indicate that local financial institution development has an inverse association with local green growth but positive impacts on neighboring provinces. The local stock market scale positively correlates with green growth in both local and neighboring regions. Local technological innovation has a positive effect on local green growth, but not on surrounding provinces. The interaction between financial development and technological innovation worsens the negative impact on green growth, suggesting low integration efficiency. More financial support and institutional innovation will help China achieve green growth. Degbedji et al. (2024)

investigated how institutions impact green economic growth in the West African Economic and Monetary Union (WAEMU) countries to contribute to Sustainable Development Goals. Data from WDI and WGI for 2002 to 2017 for eight WAEMU countries were used, and the FMOLS method was employed to find the empirical results. The study found varying influences of Institutional quality on green growth across various countries. Institutions promote green growth in some countries like Cote d'Ivoire, Mali, Niger, Senegal, and Togo but suppress it in Benin and Burkina Faso.

Literature Gap:

Most of the literature discussed the relationship between AI and economic growth, with few studies specifically analyzing the influence of AI on green growth in regions like China and other areas. Still, more research is needed to study the impact of AI on advanced economies, particularly in the case of the OECD (Zhao et al., 2022; and Qian et al., 2022). This gap highlights the need for further studies into integrating AI technologies into sustainable development goals and the potential for AI to drive green economic growth in advanced economies.

3. Model and Methodology

3.1. The model

Following Zhao et al. (2022), the present study analyzed the relationship between green growth, AI, and technological development. Information Communication Technology (ICT) and Renewable Energy Consumption are the control variables. We can set the following model for our study,

$$GGT = \propto + \beta i(AI_{it} + TECD_{it} + ICT_{it} + REC_{it}) + \epsilon_i + \cup_{it} \quad (1)$$

In equation 1, the "i", The subscript represents a cross-section in time t. The intercept is represented by $\propto$. βi Represent the coefficients of explanatory variables. AI_{it} reflects the value of AI as the main explanatory and $TECD_{it}$Is the technological development. $ICT_{it} + REC_{it}$, All these are the control variables. ϵ_iIs the individual fixed effect? As the theoretical analysis concluded that AI has a dual impact or "U Shape" nonlinear effect on GGT, we proposed a squared term for AI to construct a nonlinear regression model.

$$GGT = \propto + \beta i(AI_{it} + AI_{it}^2 + TECD_{it} + ICT_{it} + REC_{it}) + \epsilon_i + \cup_{it} \ . \quad (2)$$

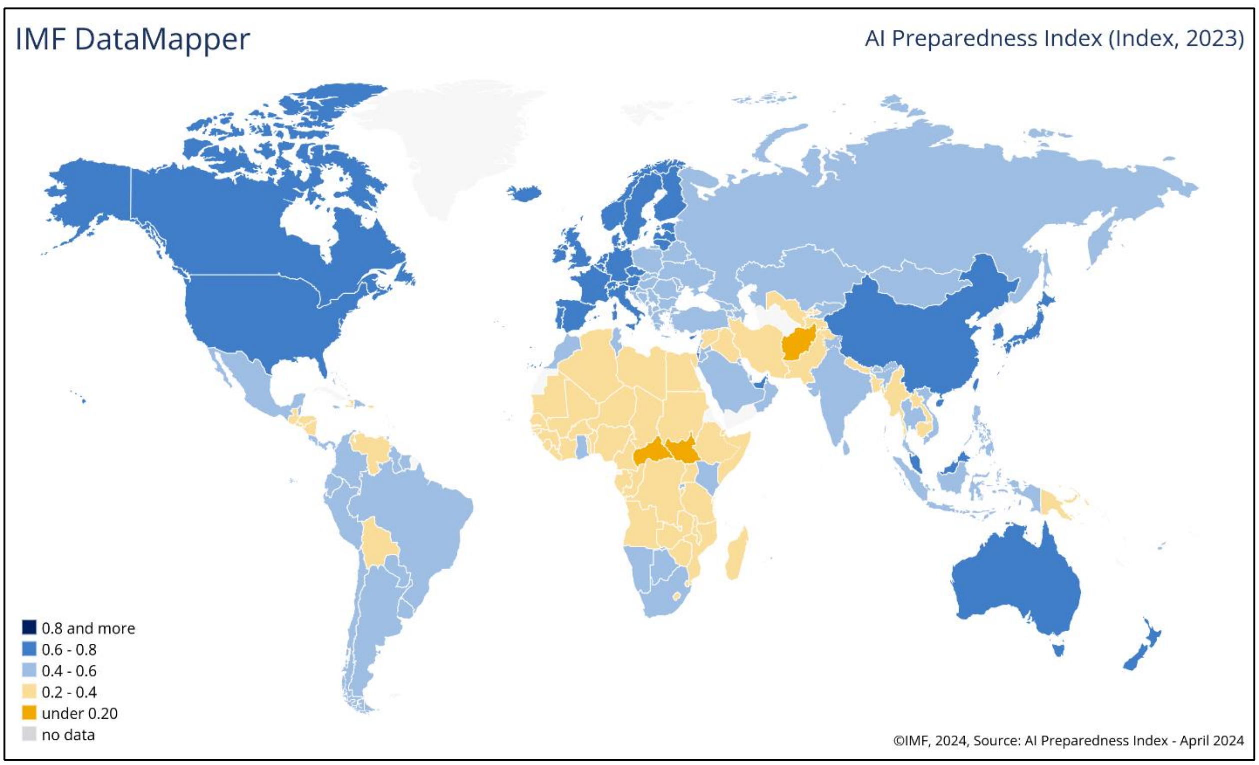
The model now includes the interaction between AI and RQ, which was introduced to demonstrate how AI influences GGT when the authorities implement regulations.

$$GGT = \propto + \beta i(AI_{it} + AI_{it}^2 + (AI \times RQ)_{it} + TECD_{it} + ICT_{it} + REC_{it}) + \epsilon_i + \cup_{it} \ . \quad (3)$$

Our study is based on country-level data, and each country has its own fixed individual effect. There may be omitted variables that affect dependent and independent variables, so the problem of endogeneity in our study exists. Lastly, our data is Short Panel, meaning we have a small time (10 years) and large cross sections (27 OECD countries). Equation (3) contains the individual fixed effect; therefore, applying the ordinary least squares will produce panel bias (Nickell, 1981). Hence, in panel estimation, when cross sections are more significant than a period, and when there is endogeneity and fixed individual effects, generalized method of moment can be used to solve the problems of endogeneity, heteroskedasticity, and autocorrelation. This can be done with the first difference transformation (Difference GMM) and system GMM (two types of GMM) developed by Blundell and Bond. The difference GMM uses lag variables as instrument variables (the only available instruments for our study are internal instruments) to estimate the difference equation and deal with first-order difference processing. At the same time, the GMM system contains first-difference and level equations (Roodman, 2009). Although our model is static, the difference transformation removes the fixed effect, and our data is balanced, so difference GMM could be the right option to estimate the model. As Roodman (2009) stated, difference transformation magnifies the gaps in unbalanced panels, and the selection estimation method also depends on the number of instruments and groups, i.e., the number of instruments must not be less than the number of groups. For these reasons, we have estimated a step difference in GMM.

3.2. Data

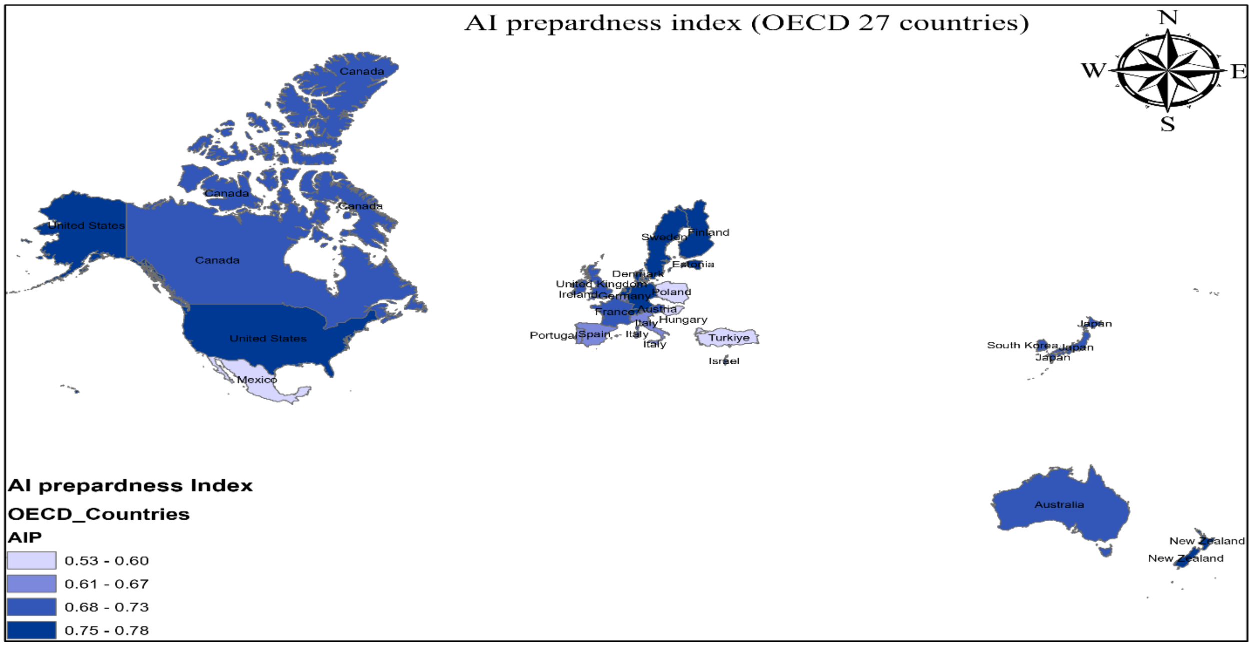
Nations worldwide realize that AI and robotics have the potential to drive economic growth and development. Investing in and developing AI- and robot-based environments in every economic sector is vital in a rapidly evolving global economy. Investing in AI technologies positions countries at the top of innovation and highlights their competitive nature and concerns for economic prosperity and environmental sustainability. To visualize the global preparedness and interest in AI development and deployment, the AI preparedness index published by the IMF shows variation in AI preparedness across the globe (see Map 1). The AI preparedness index is based on a rich set of macro-structural indicators that cover the countries' digital infrastructure, human capital, and labor market policies, innovation and economic integration, and regulation and ethics. The map shows that some global economies have invested in AI and are ready to invest and adopt AI, while most countries are still not ready to embrace AI. Moving from dark blue to light blue indicates less preparedness for AI.



Map 1 AI Preparedness Index

Source: IMF, https://www.imf.org/external/datamapper/AI_PI@AIPI/ADVEC/EME/LIC?year=2023

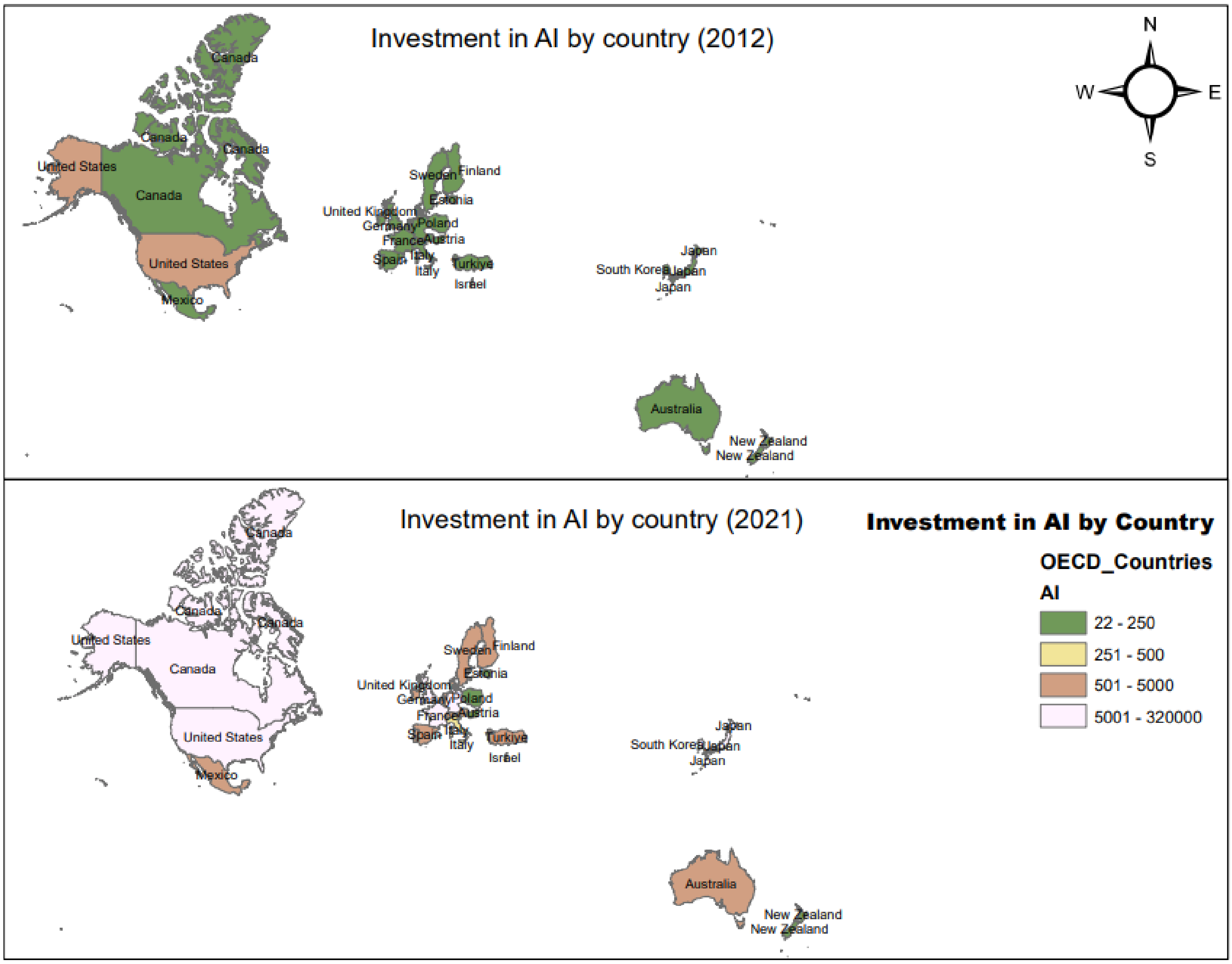
To identify the region that has invested more in AI and who is more ready to adopt AI technology, we have visualized only those countries that have high preparedness index values (0.53 to 0.78) (see Map 2). The visual of highly AI-prepared countries revealed that only OECD nations have invested more in AI and are more ready to adopt and deploy AI technologies than any other region or group of countries. The OECD nation with a high index score is well prepared to achieve sustainable development. Countries like the United States, Canada, the United Kingdom, Germany, France, Japan, South Korea, Australia, and Finland are in an excellent position to use AI for Sustainable development. Countries like Italy, Spain, the Netherlands, Belgium, Austria, Norway, Denmark, and New Zealand have moderate index scores. However, these countries are progressing in fully utilizing the potential of AI. Countries like Greece, Turkey, and Mexico are less prepared to develop and deploy AI in their economies. From this, it can be observed that only high-income OECD countries have invested and are ready to adopt AI technologies.



Map 2 Top AI-Prepared Countries

Source: *Author Elaboration*

The OECD high-income group is well prepared to adopt AI. Still, to gauge their consistency in AI investment and developing AI technologies, we have prepared two maps to compare AI investments since 2012 (see Map 3). Different combinations of four colors represent the investment level; green color represents the investment range of 0-250 million dollars, yellow color represents the 251-500 million dollars of investment, brown color represents 501-5000 million dollars, and light pink color represents the upper range of investment 5000-10000 million dollars. In 2012, except for the United States, all other countries were in the range of 0-250 million dollars of investment. These countries showed early investment in AI technologies, indicating initial readiness to adopt and integrate AI into their economies. This early investment laid the groundwork for later developments and applications of AI-driven solutions. After a decade, by 2021, the investment landscape in AI has grown significantly. The countries that were early investors in 2012 devoted more capital to AI projects. This increase might be due to the increased awareness of AI's potential and the recognition of the high economic returns of AI investment. From Map 3, we can observe that in 2021, most countries moved towards higher AI investments. Poland, Estonia, and New Zealand are still in the range of 0-250 million dollars of investment, as represented by the green color. Italy is moving towards a higher investment range of 500 million dollars, while all other countries have shown a significant transfer to the 500-5000 million dollars range. This means these countries have realized the potential of AI and robots for their economies. The United States, Canada, the United Kingdom, France, and Germany are at the top of the list as they have invested more than 5000 million dollars in AI technologies.



Map 3 Comparison of a decade's investment in AI

Source: *Author Elaboration*

These OECD countries have shown their interest in AI development and deployment. The decade comparison suggests that OECD countries are more interested in incorporating AI into their economies. Countries with more AI investment might have developed digital infrastructure, skilled workforces, and better policies to encourage the deployment of AI for growth. The map indicates that the United States, the United Kingdom, Canada, France, and Germany are the leaders in developing AI technologies. AI helps countries advance their productivity and efficiency and can revolutionize economies. AI can do repetitive tasks in the manufacturing sector and help in the health, agriculture, environment, energy, and logistics industries. Due to its transformative potential, OECD countries are investing in AI for higher productivity and economic prosperity. Therefore, this study is intended to analyze the revolutionary impact of AI on green growth in OECD countries. AI can have both positive and negative effects; for this reason, the study also investigates AI's linear and non-linear impact on green growth. The negative consequences of AI need to be corrected at times; therefore, it is essential to analyze the role of regulatory quality or regulatory bodies

Our analysis is based on ten years, covering 2012–2021, for 31 OECD countries. The dependent variable is the green growth index taken from Sarkodie et al. (2023). The independent AI variable, investment in AI, has been taken from the OECD. The remaining variables (control) are Technological development, renewable energy consumption, and Information and Communication technology. We control other variables that are likely to influence green growth. The number of Patents on technology related to the environment from the OECD has been used as a proxy for Technological development. At the same time, the data on renewable energy consumption and Information Communication Technology has been obtained from World Development Indicators (WDI). The interaction term between quality and AI captures the combined effect of regulatory quality and AI development and deployment. The data for regulatory quality has been taken from the World Governance Indicators (WGI). The years and countries mentioned are chosen based on the availability of data. The variables' definitions and sources are displayed in Table 1.

Table 1: *Variable Description*

Variables	Description	Measure	Data Source
GGT	Green Growth	Index	Sarkodie et al., (2023)
AI	Artificial Intelligence	Investment in AI in Million US$	OECD.ailibrary
ICT	Information and Communication Technology	Index	WDI
TECD	Technological development	Number of patent technologies related to the environment	OECD
RQ	Regulatory Quality	Regulatory Quality: Estimate	WGI
REC	Renewable energy consumption	% of total final energy consumption	WDI

4. Results and Discussion

4.1. Descriptive Statistics

Table 2: *Descriptive Statistics*

Variable	Observations	Mean	Std. Dev.	Min	Max
GGT	270	0.58	0.132	0.21	0.896
AI	270	4485.21	26221.93	0	316593
REC	270	18.25	12.26	1.61	58.4
TECD	270	1340.10	2588.38	3.67	10805.97
AIRQ	270	6299.44	36833.38	-288.57	456196.97
ICT	270	0.12	0.98	-2.51	2.03

Table 2 consists of the summary Statistics showing the dispersion and central trends of the variables GGT, AI, REC, TECD, AIRQ, and ICT. GGT and REC have minimum and maximum values between 0.216 and 0.896 and 1.61 and 58.4, respectively. AI has a minimum value of 0 and a maximum value of 316593 in the data, with a wide range and high standard deviation. TEC proves to be highly variable, as observed by its wide range and high mean. AIRQ has minimal negative values and very observable variability, pointing to more comprehensive data points.

4.2. Matrix of Correlation

The correlation matrix with a correlation coefficient ranging from -1 to 1 shows the relationship between various pairs of variables. A value of 1 indicates a perfectly positive correlation, -1 indicates a perfectly negative linear correlation, and 0 indicates no linear correlation. The higher the absolute value of the correlation coefficient, the stronger the relationship between the variables. Below in Table 2 is the correlation matrix for different variables, each representing different aspects related to "GGT", "ai", "ai2", "rec", "tec", and "airq".

Each cell in the matrix represents the correlation between two variables in the table (3).

Table 3: *Correlation Matrix*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)GGT	1.000						
(2) AI	0.0073	1.000					
(3) AI2	-0.012	0.941	1.000				
(4) REC	-0.080	-0.098	-0.063	1.000			
(5) TEC	0.108	0.377	0.249	-0.324	1.000		
(6) AIRQ	0.009	0.997	0.940	-0.096	0.378	1.000	
(7) ICT	-0.130	0.061	0.043	0.162	0.152	0.064	1.000

GGT shows a negative correlation with ICT, AI2, and REC and positive correlations with other variables, with TEC's highest correlation. AI and AIRQ, AI and AI2 show a strong positive relationship between these variables, suggesting that the other tends to increase as one increases. REC and TEC have a negative correlation, suggesting that the other decreases as one increases. REC and AI- A weak negative correlation, indicating a slight inverse relationship. Overall, the matrix shows several strong positive correlations, particularly involving the "ai," "ai2," and "air" variables, while the "rec" variable tends to have negative correlations with other variables.

4.3. Diagnostic Tests:

4.3.1. Arellano-Bond Test for Autocorrelation:

The Arellano and Bond test of AR (1) and AR (2) has been used to check serial autocorrelation of the first and second order and is applied to the differenced residuals. Its null hypothesis is,

Table 4: *Test for Autocorrelations*

	Probability Value
AR (1)	0.462
AR (2)	0.182

The probabilities of AR (1) and AR (2) are 0.462 and 0.182, respectively, which is more significant than 0.05 and greater than 0.01, showing that we fail to reject the null hypothesis and there is no first-order serial correlation and no second-order serial correlation in residuals.

4.3.2. Sargan and Hansen Tests of Over identification

We report on Sargan and Hansen tests for the validity of instruments used in this analysis. Both tests have the same null hypothesis.

Table 5: *Test for Over Identification*

	Probability value
Sargan test	0.836
Hansen test	0.429

The probability value of the Sargan test is 0.836, which is more significant than 0.05, which tells us that we fail to reject the null hypothesis that all the over identification restrictions are valid and there is no over identification. The Sargan test suggests that the over identifying restrictions are not violated, meaning the instruments are appropriately exogenous. The probability of the Hansen test is 0.429, which shows that all the restrictions are valid and that there is no ground to reject the null hypothesis. The Hansen test suggests that the instruments are valid.

4.4. GMM Results:

The two-step difference GMM is employed to examine how AI affects green growth by adapting preceding equations 2 and 3. The results of the difference GMM are shown in Table 3. The coefficient values represent the strength and direction of the relationship between each independent and dependent variable (GGT). The AI in the linear form shows a negative and highly significant association with GGT, which indicates that as the use of AI increases, GGT decreases. The negative association of AI with GGT in linear form could be due to the initial high investments in AI costs and job disruption by AI implementation, which may divert the current investments from green growth. Some of the AI deployment and development may require high energy consumption, contributing to the environmental impact. Poor research and testing can lead to negative impacts on AI systems. The utilization of AI in finance brings a risk of systemic disruptions and faults. Limited data and research bias could hamper understanding AI's practical implications. The AI technology must be evaluated for ethics, efficiency, and sustainability to avoid negative effects before its widespread use and adaptation. Economic incentives may prioritize profitable AI projects over socially valuable ones, exacerbating inequalities; profitable AI projects might take preference over socially beneficial ones due to more returns, profits, and economic incentives, worsening investment inequality (Vinuesa et al., 2020).

Table 5: *Generalized Method of Moments Results*

Variables	Coefficient	Standard error	t-value	Prob value
Ai	-0.000167***	.0000245	-6.81	0.000
AI2	1.46e-10***	2.98e-11	4.90	0.000
TEC	-0.000235**	.0000845	-2.78	0.005
REC	0.0124*	.0055541	2.22	0.026
ICT	0.181**	.0587293	3.08	0.002
AIRQ	0.0000567***	.0000119	4.75	0.000

*, **, *** represents level of significance at 10%, 5% and 1%.

A positive and highly significant relation between the quadratic term of AI and GGT indicates AI's dual and non-linear influence on GGT. Initially, AI reduces the green growth as confirmed by the linear term of AI, and after a certain as the level of AI increases, the negative effect diminishes, and the positive effect of AI starts, which increases GGT. The dual impact of the quadratic term of AI is consistent with the study of Zhao et al. (2022). A possible explanation for this pattern is that AI is still developing and in the initial stages, which is characterized by inefficiencies in some of its applications, which could initially constrain green growth. However, with the development of new AI models and technologies, their integration has become more prominent, and it has started to improve green growth by balancing and improving resource efficiency and green technologies. The resource-rich and labor-intensive areas experience a productivity paradox where AI does not promote GGT until it reaches a particular level of AI sophistication, so in resource-rich areas, a high level of AI is required to increase GGT (Zhao et al., 2022). Among the control variables, AIRQ is the interaction term between AI and regulatory quality, which has a positive and statistically significant relationship with GGT. The positive AIRQ suggests the role of policies, rules, and regulations to control the negative impact of AI in the initial phase. These effective regulations can guide AI to more sustainable development, as observed by immediate positive signs in a linear form. The policies and laws should ensure that AI development and deployment are implemented in a way that is more environmentally sustainable. Technological development has a negative association with green growth, which is against the study of Ulucak (2020) for BRICS countries. The possible reason for this could be that the patents claiming to be environmentally sustainable still need to be optimized for environmental sustainability and are adversely affecting the environment and reducing green economic growth. The other possible reason could be attributed to the fact that technology development may contribute to more resource consumption and emissions unless it leads to more sustainable development. There are also the region differences in both studies as BRICS countries consist of diverse economies while OECD region consist of almost the same economies. The renewable energy consumption has positive and statistically significant relationship with green growth indicating that as one increases the other also tends to increase and the result is backed by Taşkın et al., (2020) in OECD region and Hao (2021) in G7 countries by reporting that renewable energy reduces CO2 emissions and hence promote green growth. The ICT has a positive and statistically significant association with GGT, which indicates that information communication technology has a positive impact on green growth. The result is supported by Chen et al. (2022) in their study, arguing that ICT is crucial for transforming human society. The internet has revolutionized lifestyles, converting traditional items like books into digital formats. Online activities such as shopping, e-commerce, and teleworking save time and resources. The shift to information economies improves the environment and reduces energy consumption. This transformation reduces reliance on physical resources, decreasing pollution emissions. Online shopping and virtual meetings decrease transportation and energy use, benefiting the environment. Overall, ICT has reshaped societies, economies, and daily life, leading to more sustainability and efficiency in various aspects of human activity.

5. Conclusion and Policy Recommendation

The advanced economies mostly invested more in AI and Green Growth in this era. To examine the influence of AI on GGT, this study used panel data from 2012 to 2021 for OECD countries. Utilizing the Environmental Kuznets Curve as a theoretical framework, the empirical analysis employed a two-step difference generalized method of moments (GMM) to account for small period, large cross-section, endogeneity, and fixed effect issues. The results highlighted several findings that there is an immediate negative relation of AI, as confirmed by AI in linear form with GGT, indicating that initially AI reduces GGT. This could be high initial cost, job disruption, Investment in high-return AI projects, and maybe due to high energy consumption in initial AI deployment. The quadratic term of AI shows a statistically highly significant non-linear effect with GGT, indicating the initial negative association of AI with GGT. However, as AI sophistication increases, the impact of AI becomes positive, hence improving GGT. The interaction between AI and regulatory quality has a positive and significant relation with GGT, highlighting the importance of policies and regulations in the initial stage of developing such regulation that guides AI towards sustainable development. Surprisingly, technological development has a negative relation with GGT, which is contrary to the previous study of Ulucak (2020) conducted for BRICS countries, which might be due to the technological patents related to the environment not yet being optimized for environmental sustainability, or due to the differences in the region, as in our case, the OECD. Both renewable energy consumption and Information Communication Technology showed a positive association with GGT, highlighting their importance in sustainable development. The diagnostic tests, the Arellano-Bond test for autocorrelation, indicate no first or second-order serial correlation in residuals. Sargan and Hansen tests confirm the instruments' validity, suggesting the selected instruments are valid.

5.1. Policy Proposal

This policy proposal aims to guide advanced economies in utilizing AI for environmentally sustainable development. Government and policymakers should impose strict criteria for energy efficiency and sustainability during the early stages of AI adoption or deployment. The governments should give grants or tax exemptions to AI projects that show a clear route to lowering environmental impact and enhancing sustainability as financial incentives. To avoid the negative impact of AI at the initial stage, Policies and regulations should be adopted that can quickly respond to the new developments in AI and how these developments affect the environment. It is essential to monitor and assess the environmental impact of AI, establish ongoing evaluation systems, and mandate companies implementing AI to report on their environmental impact for sustainability. AI computing frameworks and analysis are typically led by professionals from advanced economies. Further research activities are necessary to expand the development of AI applications on a global scale, specifically concerning the negative climate impact on emerging economies. Renewable energy consumption can promote green growth, so investment in more renewable energy can not only enhance green growth but also meet the growing energy demand for AI in the initial phase. Monitoring technological patents related to the environment is also necessary to observe their effect on the environment and whether they are optimized for sustainability. Adopting ICT solutions and investing in digital infrastructure can lower resource consumption and emissions.

5.2. Limitations of the Study and Future Study Direction:

Our study only focused on advanced economies. Future studies can be conducted to analyze the diverse influence that AI might have across various geographical regions. There is a need for more comparative studies, particularly in the case of developed vs developing economies. Our study concluded that policies and regulations can reduce the negative impact of AI; therefore, more research is required to explore how different governance structures and policies can enhance or reduce the positive impact of AI on green growth. Our study used data for a short panel of 10 years; further research can be conducted to check the influence of AI on long panel data. Studies need to explore the long-term impacts of AI and other variables on green growth, especially in how these relationships evolve.

Conflict of Interest

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