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AI-DRIVEN GROWTH IN AN ENVIRONMENTAL CONTEXT: ANALYZING THE EFFECTS OF ENVIRONMENTAL POLICY STRINGENCY AND TAXES IN G19 COUNTRIES

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ABSTRACT
The impacts of technological progress and its adoption, especially in the shape of AI, have been unprecedented in changing the socioeconomic landscapes of the economies. However, the socioeconomic impacts of AI may differ from country to country and region to region depending on the socioeconomic structure and levels of socioeconomic development of the economies or regions. One of the major contributions of the AI adoption is its driving potential for economic growth (EG). The contribution of AI to EG warrants further data-driven evidence-based insights for the formulation of macroeconomic policies ensuring sustainable economic growth. The primary focus of the current study is to examine the impact of AI on EG in G-19 economies from 2011 to 2023. In addition, the study also includes Environmental Degradation (ED), Environmental Policy Stringency (EPS), and Environmental Tax (ET) as control variables. The estimates of the Panel Corrected Standard Errors (PCSE) and Kernel-Regularized Least Squares (KRLS) Machine Learning Method (MLM) show that AI and EPS have a positive and significant impact on EG, while ED and ET have a negative impact on EG. Policymakers should promote economic growth, reduce environmental degradation, and leverage AI adoption to achieve a more sustainable and prosperous future.
Keywords: *Artificial intelligence; Environmental sustainability; Environmental Policy; Economic development; Sustainability.*

INTRODUCTION
Unprecedented technological innovation and its adoption in every sphere of life have changed the socio-economic landscape of the economies. Especially the pace with which the adoption of AI has taken place, it has changed economic activities and enhanced productivity (Gonzales, 2023; Kalyani & Hogan, 2024). The studies have shown that AI has macroeconomic implications for the economies (Acemoglu, 2024). Whereas, some studies unveil that the impact of AI on macroeconomic productivity is unclear (Morikawa, 2025). A stream of studies on AI-macroeconomic growth supports the argument that AI has huge potential to increase productivity growth, but it may have different implications for the labor market (Furman & Seamans, 2019). However, there is a heated debate on the patterns in aggregate productivity growth consequent upon leaps in AI. On one hand, there are surprising instances of potential transformation that modern technologies bring by enhancing productivity and economic welfare. On the other hand, there are some examples of low productivity growth in recent decades despite

technological progress and its adoption in economic activities (Brynjolfsson et al., 2017).
The G20 countries, which account for 80% of GDP, have been at the forefront of this digitalization transformation. However, this digitalization drive has also raised concerns about its impacts on energy consumption and macroeconomic performance. Digitalization plays a potential role in improving energy efficiency to reduce carbon emissions and promote sustainable economic growth. In recent years, several authors have studied the impact of digitalization on GDP, including per capita GDP. However, their research focused on digital empowerment (Evangelista et al., 2014). Digitalization, the increasing application of information and communication technology (ICT) throughout the economy and society, has triggered great hopes of reducing energy demand and emissions (Gesi & Deloitte, 2019). Digitalization is one of those key processes that are undergoing dramatic development and transforming all aspects of contemporary society. Digitalization, in a nutshell, is an ever-increasing application of information and communication technologies across all sectors of the economy and everyday life of the population as well. It covers the great bulk of digital technologies such the Artificial Intelligence, the Internet of Things (IoT), and Industry 4.0, and contributes to intensifying the interactions between digital and physical worlds (Galperova & Mazurova, 2019).
The growing adoption of AI has sparked many concerns worldwide that AI can affect EG and employment. The influence is assumed to be substantial because the adoption of AI technology may lead to increased productivity, lower wages, prices, and labor substitution (Wang et al., 2021). Technological progress serves as a crucial mechanism for the growth of GDP per capita. This study provides helpful insights to policymakers, business leaders, and scholars seeking to promote sustainable and inclusive EG in the digital age. The objective of this study is to explore the impact of Artificial intelligence on EG. Industry 4.0 is characterized by a convergence of digital, biological, and physical innovations that are profoundly affecting various sectors globally (Vijayakumar, 2021). AI plays a pivotal role in this transformation, offering unprecedented opportunities for enhancing productivity, creating new business models, and driving economic growth (Liao et al., 2018). AI has an inherent capability to process massive datasets, allowing for more effective decision-making, automation of routine tasks, and even the development of intelligent systems capable of learning and improving over time. These advancements are not limited to any particular industry; rather, they have far-reaching implications across healthcare, manufacturing, finance, and many other domains (Rashid & Kausik, 2024; Varnosfaderani & Forouzanfar, 2024).
In addition to labor productivity, another significant channel through which technology, particularly AI, stimulates economic growth is data analysis. AI algorithms can analyze enormous datasets to provide insights that are actionable and strategically beneficial for businesses. For instance, machine learning algorithms can analyze consumer data to predict market trends, enabling companies to tailor their services or products more effectively. These analytical capabilities help in optimizing various aspects of business, such as supply chain efficiency, customer engagement, and pricing strategies (Aghion et al., 2018).
The objective of the study is to explore how AI contributes to EG. It is also pertinent to note that the model estimated in the current study also includes environmental degradation, environmental policy stringency, and environmental tax. In addition to AI, the study also considers environmental degradation, environmental policy stringency, and environmental tax as control variables in the model. Notably, the inclusion of these variables in the model would help to understand how AI contributes to economic growth in conditions of environmental degradation, stringent environmental policy, and environmental tax regimes in the economy. The findings of the study provide guidelines for policymakers in formulating a comprehensive AI adoption policy to stimulate sustainable growth.

1. Literature review

In recent years, technological innovations, especially in the field of AI, have shown unprecedented progress. Similarly, the impacts of this progress have started shaping the economic spheres by contributing to the progress and productivity of the economies. Some of the

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studies have shown that AI has the potential to stimulate the economy by replacing labor (Aghion et al., 2017). However, (Zeira, 1998) showed that the economic growth model adopting technological innovation does reduce labor input but warrants more capital. Another study represented AI as a driver of productivity and growth. According to this, AI enhances efficiency and enormously improves the decision-making process as it enables the analysis of large amounts of data (Trabelsi, 2024). According to Gonzales (2023), AI helps in multiple ways to increase productivity by helping in production, customer acquisition, marketing, and consumer reach. In Gonzales (2023), the author finds the positive impact of AI on economic growth. However, this positive impact of AI is more robust in advanced countries.

Investigating the impact of AI on economic growth in thirty European economies. Kalai et al. (2024) show that there is a positive link between AI and economic growth. The results of NARDL estimates show that positive shocks to the AI positively impact economic growth. Whereas, negative shocks have a negative impact on economic growth. The authors also point out that AI stimulates growth by increasing efficiency, enhances economies of scale, and enriches the quality of the goods and services, and working conditions. Some studies focus on the implications of financial technology (Fintech) on environmental sustainability. Tan et al. (2023) discussed Fintech development, renewable energy consumption, government effectiveness, and management of natural resources along the Belt and Road countries. This study used 22 selected countries covering the period 2006 to 2021, applying the PCSE approach. Results show that fintech development positively influences natural resource management, while renewable energy consumption and FDI also significantly influence indicators of natural resource management. The study also revealed the positive role of government effectiveness in managing natural resources, while urbanization was found to be negative.

Solangi et al. (2024) exploring the influence of digital technology innovation on air quality: insights from developed and developing economies. This study used panel data from 85 developed and developing countries. Air pollution (AP) was used as the dependent variable, while digital technology innovation (DTI), green energy (GE), economic growth (GDP), governance (GOV), and social performance (ESRP) were used as independent variables. Pooled regression and generalized least squares (GLS) methods showed that DTI significantly reduced air pollution, while green energy, governance, and economic-social performance were major factors contributing to air pollution reduction. (Zhang et al., 2024) examined renewable energy and natural resource protection in developing economies. This study used natural resource protection as a dependent variable while renewable energy consumption, governance effectiveness estimate, financial technology, GDP per capita, urban population, and foreign direct investment as independent variables. Pre-diagnostic tests, pooled regression with Driscoll-Kraay standard errors, generalized least squares, and Bayesian regression techniques are used to find the results of 22 developing countries. Results reveal that U-shaped association between GDP per capita and natural resource protection. Further, governance effectiveness, financial technology, and foreign direct investment contribute to natural resource protection, while urbanization has a negative effect on natural resource protection.

Nuţă et al. (2024) investigated the relationship among urbanization, economic growth, renewable energy consumption, and environmental degradation comparative view of European and Asian emerging economies. Carbon emission (CO_2) was used as the dependent variable to measure environmental degradation while economic growth, urbanization, renewable energy consumption (RE), financial development and services value added per worker were used as independent to measure the quadratic association between economic growth and carbon emissions in selected emerging European and Asian countries during the years 1995 to 2019. This study used feasible generalized least squares (FGLS) and PCSE models to examine the correlation.

Asghar et al. (2024) analyzed energy transition in newly industrialized countries' policy paradigm in the perspective of technological innovation and urbanization using PCSE regression and quantile regression on data from 1985-2020. Results show that technological innovations increase renewable energy and decrease non-renewable

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energy, while urbanization and trade liberalization decrease renewable energy but accelerate non-renewable energy, so an increase in output positively impacts both renewable and non-renewable energy. Iqbal et al. (2023) examined asymmetric determinants of renewable energy production in Pakistan: do economic development, environmental technology, and financial development matter? This study used linear and non-linear versions of the ARDL methods by collecting data during the period 1990 to 2020. Results of the linear model show that improvement in renewable energy production is affected by GDP, environmental advancements CO_2 emissions, financial development, and foreign direct investment, while results attained from the non-linear model confirm that positive shocks in GDP, environmental-related technologies, and financial development promote renewable energy production.

Nan et al. (2023) highlighted a comparative analysis of the impact of policy uncertainty, agricultural output, and renewable energy on environmental sustainability by using pooled ordinary least squares and panel quantile regression to analyze data from 2001 to 2019. Findings show that economic policy uncertainty negatively and significantly affects environmental sustainability as it increases GHG emissions. Additionally, findings also support the pollution haven hypothesis, while renewable energy consumption has a positive impact on environmental sustainability, as it significantly diminishes greenhouse gas emissions. (Asghar et al., 2025) examined ecological resilience in crisis: analyzing the role of urban land use and institutional policies using panel data from 15 environmentally failed states during the period 2009-2022. This study used static and panel econometric techniques to obtain results, and the results were generalized to the system-generalized methods of moments (GMM). Findings showed that increased urban land use, financial inclusion, and output deteriorate ecological sustainability, while effective policies, quality institutions for combating ecological footprint, and green energy improve ecological footprint.

2. Theoretical Underpinnings

The macroeconomic theory is enriched with the theoretical approaches that support the argument that technological progress plays a pivotal role in the economic growth trajectories of the economies. For instance, the Solow Growth Model (SGM) emphasized that technological advancement drives economic growth (Solow, 1962). Endogenous Growth Theory (EGT) (Romer, 1990) puts forth the argument that technological innovation is endogenously determined within the economic ecosystem. It is driven by the public and private sectors. It implies that technological progress in the economy advances perpetually with private and public investment in research and development, and enhances human capital skills. Either the traditional growth model or EGT provides support for growth growth-enhancing impact of technological progress.

The integration of AI into the various sectors of the economy, especially in recent years, has significantly sparked its potential impact on economic growth. Theoretical and empirical models provide insightful findings on the mechanisms through which AI impacts growth outcomes. Studies show that AI replaces the limited resource labor with the unlimited resource capital both in for production of goods, services, and ideas (Aghion et al., 2017). One of the channels through which AI drives productivity and growth is a significant improvement in the decision-making process, as it provides the opportunity for the analysis of a large amount of data. On the other hand, it creates the risks of job market polarization, a rise in inequality, causes structural unemployment, and warrants new industrial structures, which may be undesirable (Trabelsi, 2024). Studies also show that technological progress in the shape of AI increases productivity and efficiency as it provides the opportunity for routine task automation, enables innovation, and improves decision-making, which enables the improvement in total factor productivity, which is a key driver for long-term growth (Wu & Zhu, 2025).

Developing a 3-sector endogenous growth model, Lu (2021) investigated how AI along the transitional dynamics path (TDP) and balance growth path (BGP), and showed that progress in AI increased economic growth along TDP. Furthermore, it also showed that AI had the ability to increase household short-run utility, provided the accumulation of AI was due to an increase in productivity in the goods or AI sector.

(Kalai et al., 2024) pointed out that AI-driven innovation stimulates economic growth by increasing overall productivity, increasing returns on capital, and fostering technological spillovers across industries. In a recent study, Plikas et al. (2024) showed that AI technologies positively contributed to economic growth. Furthermore, the study also revealed that digital inclusion significantly enhanced labor productivity. However, the direct impact of the former on GDP was not observed. Moreover, AI methodology adoption, technology adoption practices, and reskilling of employees significantly contributed to labor productivity which ultimately stimulated growth. The model used in the current study is given in Figure 1.

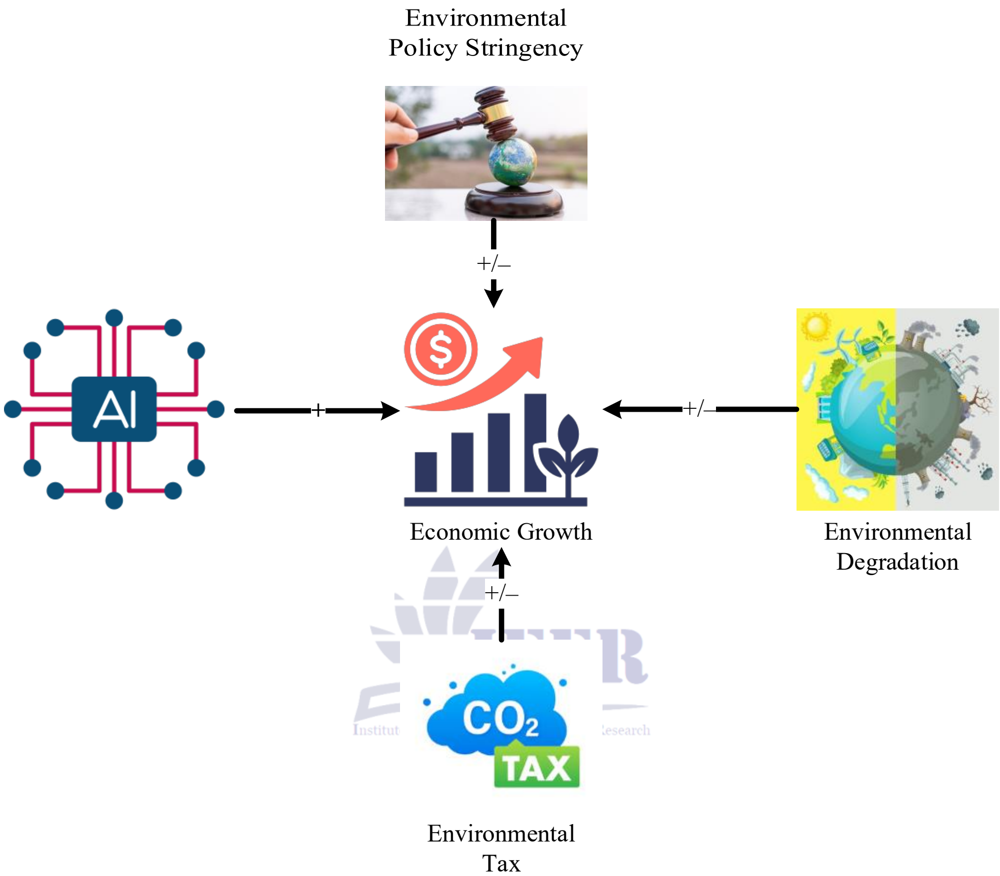

Figure 1: The Model

3. Research Methodology

4.1 The Model

This study used the_PCSE test by using economic growth as the dependent variable while artificial intelligence, environmental degradation, environmental policy stringency, and environmental tax as independent variables during the years 2011 to 2023 for G19 countries.

$$LEG_{it} = a_0 + a_1 LAI_{it} + a_2 LED_{it} + a_3 LEPS_{it} + a_4 LET_{it} + u_{it} \quad (1)$$

EG is economic growth, AI is artificial intelligence, ED is environmental degradation, EPS is environmental policy stringency, and ET is environmental tax. The purpose of this study is to assess the impact of AI on EG. The prevalent conditions of the ED provide strong reasons to adopt AI-driven solutions in the economy. Furthermore, it is also pertinent to mention that a country facing severe environmental degradation may either hinder AI adoption due to a lack of resources or accelerate technology adoption, including AI-based technologies (Olawade et al., 2024). The inclusion of EPS in model (1) is based on the argument that it is more likely that countries with stringent environmental policy regimes might invest in sustainable technologies to ensure the regulatory requirements (Bettarelli, 2023). Controlling for the EPS, model (1) enables the prevention of overestimating the impacts of AI in conditions where improvements in environmental sustainability may be stimulated more by policy stringency than the AI-technology adoption. Since the environmental tax provides economic incentives to reduce resource use and emissions (Qi et al., 2023), it may be productive in affecting the behaviour of the firms, innovation decisions, and AI adoption for sustainability. Studies show that environmental tax promotes technological innovation (Karmaker et al., 2021). Controlling for ET will help to understand the observed effects on environmental outcomes, not only because of fiscal pressures but more profoundly attributed to AI adoption initiatives.

4.2 Description of variables

The study used data from the G-19 economies, including Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Russia, Saudi Arabia, South Africa, South Korea, Türkiye, the UK, and the USA. The description and sources of variables used in the model are given in Table 1.

Table 1: Variables, symbols, description, and data sources

Variables	Symbol	Description	Data Source
Economic growth	EG	Real GDP per capita	(OECD, 2024)
Artificial intelligence	AI	Contributions to all public AI projects with Very High Impact percentage (>100 forks)	(OECD.AI, 2024)
Environmental degradation	ED	CO2 emissions from the transport sector (MtCO2e)	(OECD, 2024)
environmental policy stringency	EPS	Environmental Policy Stringency Index	(OECD, 2024)
Environmental tax	ET	Environmentally related taxes, % total tax revenue	(OECD, 2024)

4.3 Econometric methodology

PCSE approach (Beck & Katz, 1995; Hoechle, 2007) is an alternative to FGLS to fit the linear cross-sectional time series models, especially when the error terms are no longer independent or identically distributed. The error terms may be either heteroskedastic across panels or contemporaneously correlated across panels. Furthermore, the error terms may also be autocorrelated across panels, and the autocorrelated parameters may be constant across panels or may be different for each panel (Hoechle, 2007). Suppose the model:

$$y_{it} = x_{it}\varphi + \mu_{it} \quad (2)$$

In model (2), $i = 1, \dots, m$ is number of panels, where $t = 1, \dots, T_i$. T_i = number of periods in each panel i and μ_{it} is a disturbance term.

This model can be expressed in matrix form as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix} \varphi + \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_m \end{bmatrix} \quad (3)$$

The model with heteroskedastic error terms and contemporaneous correlation but no autocorrelation, the error term covariance matrix can be written as:

$$E[uu'] = \theta = \begin{bmatrix} \sigma_{11}I_{11} & \sigma_{12}I_{12} & \cdots & \sigma_{1m}I_{1m} \\ \sigma_{21}I_{21} & \sigma_{22}I_{22} & \cdots & \sigma_{2m}I_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{m1}I_{m1} & \sigma_{m2}I_{m2} & \cdots & \sigma_{mm}I_{mm} \end{bmatrix} \quad (4)$$

In equation (4), σ_{ii} is the variance of the disturbance term for ith panel, σ_{ij} is the covariance of the error term between panels i and j. This study utilizes the PCSE regression for model estimation. This estimation simultaneously corrects autocorrelation, cross-sectional dependence, and heteroscedasticity to improve parameter efficiency (Hoechle, 2007).

4. Analysis of the Impact of Artificial Intelligence on Economic Growth

4.1 Descriptive Analysis

In the second column mean values of each variable are given. The mean value of EG is 10.2579, AI mean value is -5.0198, ED mean value is 4.9351, EPS mean value is 0.8395, and ET mean value is 1.6964 (Table 2). In the third column, the standard deviation is given, which measures the spread of values. The economic growth standard deviation is 0.5452, AI is 2.6113, ED is 0.8105, EPS is 0.5922, and ET is 0.8778. In the fourth column minimum value of each variable is given. The minimum value of economic growth is 9.0320, AI is -12.4753, ED is 3.5374, EPS is -1.7918, and ET is -3.9750. In the fifth column, the maximum value of each variable is given. Economic growth's maximum value is 11.0351, AI maximum's value is 0.8470, ED maximum value is 7.3217, EPS maximum's value is 1.6100, and ET maximum value is 2.9653.

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	JB	Chi (2)
EG	10.2579	0.5452	9.0320	11.0351	24.300	5.3e-06
AI	-5.0198	2.6113	-12.4753	- 0.8470	31.650	1.3e-07
ED	4.9351	0.8105	3.5374	7.3217	108.400	2.8e-24
EPS	0.8395	0.5922	-1.7918	1.6100	94.660	2.8e-21
ET	1.6964	0.8778	-3.9750	2.9653	21.26	2.4e-05

Note: JB = Jarque-Bera normality test

The correlation matrix (Table 3) showed the correlation between the coefficients of each variable, which ranges from -1 (negative correlation) to 1 (positive correlation), and a value close to zero showed no correlation. EG is positively correlated with AI and EPS, while negatively correlated with ED and ET. AI positively correlated with EPS and negatively correlated with ED. EPS is positively correlated with economic growth and AI, while negatively correlated with ET. Variance-inflating factor (VIF) measures the effect of multicollinearity on the variance of coefficients high VIF value greater than 5 or 10 shows strong issues with multicollinearity. AI has a moderate VIF value (2.11) and shows some multicollinearity. EPS has a moderate VIF value is 1.30, which shows some multicollinearity. The mean VIF value is 1.64, which is relatively low and shows multicollinearity is not a major concern.

Table 3: Pairwise Correlations

Correlation Matrix						VIF	1/VIF
	EG	AI	ED	EPS	ET		
EG	1.0000					-	-
AI	0.3393	1.0000				2.1100	0.4750
ED	0.1736	0.5919	1.0000			1.7600	0.5675
EPS	0.7159	0.3620	0.1393	1.0000		1.3000	0.7678
ET	-0.0372	-0.1610	-0.2505	0.1942	1.0000	1.4000	0.7130
					Mean VIF	1.6400	

5.2 Pre-Diagnostic Tests

Pre-diagnostic tests are used to check the cross-sectional dependence of data. In section a, variables have a p-value less than 0.05, indicating that variables have cross-sectional dependence (Table 4). In our results, all variables have significant cross-sectional dependence because their p-values < 0.01, so the null hypothesis of no cross-sectional dependence is rejected and shows a significant correlation between economic growth, ED, ET, and ET. While the AI p-value (0.308) is greater than 0.01 and does not show significant cross-sectional dependence, and no cross-sectional dependence null hypothesis is accepted. In section b slope heterogeneity test examines whether slope coefficients vary significantly across cross-sectional dependence. Delta and adjusted delta have significant p-values < 0.01, which shows slope heterogeneity, so the homogeneity test's null hypothesis is rejected. In section c LR test is used to check the heteroskedasticity. LR test is a statistically significant p-value < 0.01 that shows heteroskedasticity, so the null hypothesis of homoscedasticity is rejected.

Table 4: Pre-diagnostic Tests

Variable	CSD test
a. Cross-Sectional Dependence Test	
EG	16.30 (0.00)
AI	-1.02 (0.308)
ED	15.03 (0.00)
EPS	5.36 (0.00)
ET	1.63 (0.00)
b. Slope Heterogeneity Test	
Delta	6.2940 (0.00)
Adjusted Delta	8.8000 (0.00)
c. Heteroskedasticity Test	
LR test	285.8000 (0.00)

Note: Values in parentheses are p-values.

4.2 Inferential Analysis

The PCSE method is used to produce the estimation of the model and is summarized in Table 5. In this, GDP per capita, a measure of economic growth, is the dependent variable. In the first column, coefficients are given, second column, standard errors are given, and in the third column, p-values are given. A p-value of artificial intelligence is 0.022, so the coefficients are positive and statistically significant at level 5% and indicate that a 1% increase in AI results in a 0.0133% increase in EG. ED p-value < 0.01. Coefficients are negative and significant at level 1% associated with a 1% increase in ED and a -0.0701% decrease in EG. EPS is positive and statistically significant at level 1% p-value < 0.01, which is associated with a 1% increase in EPS 0.6683% increase in economic growth.

Table 5: Model Estimates

Dependent Variable: EG				
Variable		**PCSE Estimates**		
		Coef.	**Std. Err.**	**p-value**
Artificial Intelligence	AI	0.0133	0.0058	0.0220
Environmental Degradation	ED	-0.0701	0.0115	0.0000
Environmental Policy Stringency	EPS	0.6683	0.0385	0.0000
Environmental Taxes	ET	-0.1725	0.0349	0.0000
	_cons	10.4368	0.0906	0.0000
R-squared	0.5393	Wald Chi^2 (4)	494.10	0.0000

ET p-value < 0.01, so coefficients are significant at level 1% which tells that 1% increase in ET -0.1725% decrease in economic growth. R-squared measures the goodness of fit of a regression model. If it is closer to 1, it is the goodness of fit, and if it lies between 0.5, it's also the goodness of fit. The R-squared value is 0.5393, a moderate portion of the variance is explained by R-squared. Wald Chi-Squared test describes the significance of regression coefficients, whether the estimated coefficients are statistically significant or not. The Wald Chi-squared value is 494.10, and the p-value < 0.01, indicating the model is statistically significant. Artificial intelligence has a positive impact on economic growth, carbon emissions negative impact on economic growth, environmental policy stringency positive impact on economic growth, and environmental tax negative impact on economic growth.

5.3 Robustness Analysis

The artificial intelligence coefficient (0.0381) is positive and statistically significant as the p-value < 0.01 (Table 6). This suggests that a 1% increase in AI is associated with a 0.0381% increase in GDP growth. The environmental degradation coefficient (-0.1501) is negative, and the statistically significant p-value is < 0.01. This suggests that a 1% increase in ED is associated with a -0.01501% decrease in economic growth. The EPS coefficient is (0.2925) is positive and statistically significant with a p-value < 0.01, which shows that a 1% increase in EPS leads 0.2925% increase in economic growth. ET coefficient (-0.3769) is negative and statistically significant as p-value < 0.01, which suggests that a 1% increase in environmental tax would be a -0.3769% decrease in economic growth. The R^2 value is 0.91, which shows that 91% of variations in economic growth are explained by AI, ED, EPS, and ET. Lambda's value is 0.30, which controls the trade-off between model complexity and goodness of fit. Sigma is the kernel parameter that controls the spread of the kernel, and its value is 8.00. The effective degree of freedom (eff.df) is 16.13, which is the measure of model complexity. Looloss value is 10.02, which is the measure of the model's predictive performance.

Table 6: Robust Analysis Based on Kernel-Regularized Least Squares (KRLS) Machine Learning Method

Dependent Variable: EG								
Variables		Avg.	SE	t	P>t	P25	P50	P75
Artificial Intelligence	AI	0.0381	0.0103	3.6950	0.000	0.0056	0.0282	0.0694
Environmental Degradation	ED	-0.1501	0.0289	-5.1870	0.000	-0.4931	-0.1808	0.0880
Environmental Policy Stringency	EPS	0.2925	0.0445	6.5800	0.000	0.1069	0.2686	0.5510
Environmental Taxes	ET	-0.3769	0.0289	-13.0410	0.000	-0.4887	-0.3955	-0.1878
R^2	0.91							
Lambda	0.30							
Sigma	8.00							
Eff. df	16.13							
Looloss	10.02							

5. DISCUSSIONS ON RESULTS

Artificial intelligence has a positive impact on economic growth. When people adopt AI in the economy, it increases productivity by improving efficiency and enhancing decision-making, improves innovations through the development of new products, services, and business models, and increases economic growth by creating new industries, jobs, and opportunities. Technological progress serves as a crucial mechanism for the growth of GDP per capita. Its importance lies in its ability to enhance productivity, thus allowing for an increase in output that outpaces the contributions of labor and capital. One salient way that technology achieves this is by reducing the labor hours required to generate a unit of output (Ilkka, 2018). For example, automation technologies in manufacturing can significantly reduce the need for human intervention in repetitive tasks, thereby reducing labor costs and time. Similarly, advanced software can automate administrative processes, freeing up human resources for more complex tasks. The implications of these productivity gains are far-reaching, not just for the organization but also for the workforce (Krugman, 1996; Thierer et al., 2017). Skilled workers who can adapt to new technologies often see the most significant wage increases, while those in jobs that become automated may face unemployment or wage stagnation. This widening gap can offset some of the societal gains made through increases in GDP per capita and can lead to social and economic stratification. Therefore, any discussion of technological progress as a driver for economic growth must also consider measures to address inequality (Russell et al., 2015).

Environmental degradation negative impact on economic growth when the environment is affected by carbon. Many negative impacts on economic growth, such as decreased agricultural productivity through soil erosion, decreased fertility, and changing weather patterns, ED also increases the cost of industries. Furthermore, the ED also creates issues related to healthcare, tourism, and infrastructure, diminishing their competitiveness. Increased healthcare issues exert an extra burden on the government expenditure by shifting resources from investment projects to additional health expenditure. It is also pertinent to note that environmental degradation lowers productivity, especially in areas with higher levels of productivity. Higher levels of poverty, in such conditions, increase reliance on natural resources, which further stimulates environmental degradation. Natural resource depletion has the huge potential to reduce the prospects of economic growth (Singh et al., 2024). As part of climate change mitigation and environmental pollution strategies, initiatives also call for the replacement of non-renewable energy sources with renewable energy (Khan et al., 2025). Empirical research on the interaction between environmental degradation and economic growth in developing economies is therefore crucial to their short and long-run energy policies (Debachi et al, 2020).

EPS has a positive impact on economic growth by improving resource efficiency through recycled materials, reducing waste, increasing energy efficiency, and increasing investment in clean technologies, renewable energy, and energy efficiency. However, China's ambitious economic growth policies are leading the emissions trend upward in the country. The study by Chen & Lei (2017) analyzes the impact path of the factors of CO_2 emissions in China and suggests that the government needs to devise effective policy measures to achieve sustainable development goals. Although a certain level of stringency has been observed in China's environmental regulatory framework in the recent past, to what extent these policies help to achieve China's ambitious emissions reduction targets requires debate. Meanwhile, there is a growing literature emphasizing the importance of predictive analysis to support the policies that are designed to achieve the commitments made by the countries towards sustainable global (Adamović et al., 2017). Environmental tax negatively impacts economic growth through increased production costs for industries and reduced profits, through reduced investment in industries, new projects, and technologies, and ET also reduces government revenue.

Environmental taxes have a negative effect on economic performance (Roegen, 1971; Meadows et al., 1972; Daly, 1991). According to the majority of economists, environmental taxes negatively affect economic growth. In empirical analyses such as Gollop & Roberts (1983), McDougall (1993), Van Der Ploeg & Ligthart (1994), Labandeira et al. (2004), Labandeira et al. (2004), and Siriwardana et al. (2011), environmental regulations have frequently been regarded as the main source of the productivity slowdown. This situation is described as follows. Environmental taxes, especially carbon taxes, curtailing the use of fossil fuels as a source of energy for production purposes, and, with a decline in the use of one of the factors of production, there is a reduction in national output compared to the case where there are no restrictions. Economic costs of a carbon tax are, therefore, usually measured as the percentage change of future GDP (Gandhi & Cuervo, 1998). It is notable that though the environmental tax policies may be targeted to achieve environmental and social objectives, such policies should be designed adequately. Furthermore, environmental taxes are deemed to necessary to mitigate the impacts of climate change but the implementation of such policies should be accompanied by complementary policies that are productive in mitigating their negative impact on economic growth. adequately designed environmental tax policy would be productive in smoothing the transition to sustainability.

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6. Conclusion

This study examined the impact of AI on EG in G19 countries during the period 2011 to 2023. To check the impact of AI, ED, EPS, and ET on EG, this study used the PCSE regression for estimation. Furthermore, the study also used MLM-based KRLS for robustness analysis. The results indicate that artificial intelligence and environmental policy stringency have a positive and significant impact on economic growth, while environmental degradation and environmental tax have a negative impact on economic growth. This study provides evidence that AI has a positive impact on economic growth while also reducing environmental degradation. Policymakers can leverage these findings to promote AI, reduce environmental degradation, and foster sustainable economic growth. Based on these results, this study has the following recommendations: Policymakers should promote AI by encouraging the adoption of AI in every field of life. Policymakers should implement policies for reducing environmental degradation viz, increasing energy efficiency, promoting renewable energy sources, and implementing carbon pricing mechanisms. At last, policymakers should prioritize economic growth by investing in human capital and innovations.

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