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Article

Artificial Intelligence: A Blessing or a Curse for Climate Action (SDG 13)? The Moderating Roles of Governance Quality and Digital Infrastructure

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Abstract: This study examines the dynamic relationship between the adoption of artificial intelligence (AI) and carbon dioxide (CO_2) emissions, focusing on the moderating roles of governance quality (GQI) and digital infrastructure (DII) across 104 countries from 2000 to 2023. Using two-step system GMM and two-stage least squares (2SLS) estimations, the findings reveal that AI, while enhancing innovation and productivity, currently contributes to higher CO_2 emissions, particularly in economies with weak governance and underdeveloped digital ecosystems. Strong institutional quality and advanced digital infrastructure significantly mitigate this effect, suggesting that GQI and DII are critical for realizing AI's potential as a sustainable technology. The results further reveal pronounced heterogeneity across energy-efficient and energy-inefficient countries as well as low-AI and high-AI stages, indicating that the environmental impact of AI is weaker in settings characterized by higher energy efficiency and early-stage AI diffusion, but stronger in energy-inefficient and AI-advanced contexts. These findings underscore the context-dependent nature of AI's environmental outcomes and highlight the importance of governance-driven digital transformation for achieving sustainable growth.

Keywords: Artificial Intelligence (AI); Climate Action; CO_2 Emissions; Governance Quality; Digital Infrastructure; SDG 13

1. Introduction

Climate change has become one of the most critical challenges of the twenty-first century, posing severe threats to ecosystems, economies, and human well-being [1]. The intensifying manifestations of this crisis, evidenced by rising global temperatures, frequent natural disasters, and deteriorating environmental conditions, have drawn growing attention from researchers and policymakers worldwide [2,3]. According to the World Health Organization [4], the impacts of Climate change are an escalating threat to human health and the broader goals of global sustainability. Rising greenhouse gas emissions largely drive global warming and associated environmental disruptions. Among these gases, CO_2 remains the dominant contributor to climate change and global temperature increases [5,6]. In response, countries worldwide are implementing policies and strategies to promote a greener, low-carbon transition [7]. Recognizing this urgency, the United Nations' Sustainable Development Goal 13 (SDG 13) emphasizes the need for urgent and coordinated efforts to reduce CO_2 emissions

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and enhance resilience against climate-related risks. Achieving these goals requires not only technological innovation but also the presence of robust institutional frameworks and advanced infrastructural systems.

Within this context, artificial intelligence (AI) has evolved into a transformative general-purpose technology of the Fourth Industrial Revolution, capable of reshaping production, communication, and decision-making processes on a global scale. However, its environmental implications remain contested, raising critical questions about whether AI will serve as a catalyst for climate action or exacerbate the challenges of global warming [8]. AI offers a diverse range of applications with both direct and indirect implications for emissions. On the positive side, AI-enabled systems enhance energy efficiency, optimize industrial processes, and stimulate green technological innovation. AI has triggered transformative changes across diverse economic and social domains globally. This technological evolution has permeated key sectors, including healthcare, finance, transportation, logistics, and manufacturing, among others [9]. Applications such as demand forecasting, energy optimization, and intelligent grid management have demonstrated their ability to reduce waste, facilitate the integration of renewable energy, and support cleaner energy transitions [10,11]. AI-driven robotics and automation also enhance abatement efficiency and reduce emissions intensity at both the firm and city levels [12-14]. However, the environmental footprint of AI itself complicates this picture. Training and deploying complex models require vast computational resources, data storage, and energy-intensive infrastructure, raising concerns about the carbon costs associated with AI adoption [15,16]. Thus, AI represents both an opportunity and a challenge—a “double-edged sword” whose impact on SDG 13 remains highly contested.

From a theoretical standpoint, AI’s role can be situated within the endogenous growth paradigm, which emphasizes that long-run economic growth is driven by technological innovation, human capital, and knowledge accumulation [17]. AI contributes to growth by raising productivity and enabling cleaner forms of production, potentially reducing the CI of economic activity [18]. However, endogenous growth theory also suggests rebound effects: efficiency-driven cost reductions may stimulate higher output and consumption, ultimately leading to increased aggregate emissions [9]. This paradox highlights the conditional nature of AI’s environmental impact, underscoring the importance of understanding the institutional and infrastructural contexts in which it is deployed.

Two contextual moderators are particularly salient in shaping this relationship: governance quality (GQI) and digital infrastructure (DII). GQI determines whether AI’s potential is steered toward sustainability. Strong governance frameworks can incentivize carbon pricing, support emissions trading, and discourage greenwashing, ensuring that efficiency gains translate into real environmental improvements [19-21]. Conversely, weak or rigid governance structures may limit experimentation, foster symbolic compliance, or exacerbate rebound effects. Similarly, DII constitutes the backbone for AI adoption and diffusion. Robust digital ecosystems enhance interconnectivity, facilitate real-time data optimization, and promote the spillover of green innovations across regions, thereby amplifying AI’s decarbonization potential [7,10,22]. However, DI is not costless: large-scale broadband expansion and data center operations generate significant transitional emissions [23], which complicates its net environmental role.

Despite these insights, the literature remains fragmented and inconclusive. Much of the empirical evidence is geographically concentrated in China, where quasi-natural experiments, such as the Broadband China program [22] and the Pilot Zones [24], provide strong causal evidence but limited external validity. Cross-national research, in turn, has been dominated by OECD economies [21], leaving developing countries underexplored. Furthermore, existing studies tend to examine AI, GQI, and DII in isolation rather than within an integrated framework. As a result, little is known about whether AI universally reduces emissions or whether its environmental role depends on governance and infrastructural conditions.

This study addresses these gaps by examining the impact of AI on CO_2 emissions within the framework of endogenous growth theory (EGT), while testing the moderating roles of GQI and DII. Drawing on a balanced panel of 104 countries over the period 2000–2023, this study employs the Two-step System GMM (SGMM) and two-stage least squares (2SLS) estimation techniques to rigorously examine the relationship between AI and CO_2 emissions. The analysis begins by considering the full sample and then examines potential heterogeneities across energy efficiency and AI development stages. This design enables systematic evaluation of whether AI's environmental effects are consistent across contexts or conditional upon institutional and infrastructural capacity.

The contribution of this study is threefold. Theoretically, it extends EGT by explicitly incorporating environmental externalities and embedding AI within broader institutional and infrastructural frameworks. Empirically, it provides the first large-scale cross-country analysis that integrates AI, GQI, and DII into a unified framework, offering comparative insights across different governance and development contexts. Practically, it offers actionable guidance for policymakers: AI's environmental benefits are not automatic but depend critically on digital readiness and governance strength. Leveraging AI for climate action, therefore, requires coordinated investment in digital ecosystems and institutional quality.

The rest of the paper is organized as follows. Section 2 provides a comprehensive review of existing literature on AI, CO_2 emissions, GQI, and DII, emphasizing significant insights, research gaps. Section 3 outlines the theoretical foundation of the study and formulates of hypotheses. Section 4 outlines the research methodology. Section 5 reports the empirical results, while Section 6 concludes by summarizing the study's key contributions, addressing its limitations, and proposing avenues for future research.

2. Literature Review

This section reviews existing literature on the relationship between AI and CO_2 emissions. It further examines how GQI and DII moderate this nexus. The review identifies key empirical gaps and conceptual inconsistencies in the current body of research.

2.1. AI and CO_2 Emissions

AI has increasingly been positioned as an important determinant of CO_2 emissions; however, the existing literature provides mixed and context-specific evidences. Empirical literature highlights the potential of AI in achieving emission abatement through improvements in energy efficiency, industrial upgrading, and technological innovation. Using city-level data from China, Shen et al. [10] demonstrate that digital technologies have a significant negative direct and indirect effect on carbon intensity through fostering green innovation, reducing energy intensity. Similar conclusions were drawn at broader scales, where Cao et al. [11] and Tian et al. [18] report that emission reductions due to AI are strongest in regions with improved industrial structure and higher human capital. At the cross-country level, Wang et al. [25] demonstrate that energy transition and emission reduction are promoted by AI, with trade openness acting as a mediating channel.

Evidence from micro and firm level studies also corroborates the perception of AI being a process-optimizing technology. Firm-level studies have consistently demonstrated that the adoption of AI leads to the reduction in pollution intensity and improvements in environmental performance by efficiency gains and green technological upgrading [12,13,26,27]. Collectively, these studies suggest that AI makes the environment better as it reduces the emissions per unit of output and contributes to cleaner production practices. In contrast, a growing strand of macro-level and cross-country research suggests that AI may have a positive impact on aggregate emissions, especially when institutional and technological conditions are not conducive to an AI revolution. Alhares [28] finds that expansion of AI is related to higher CO_2 emissions within diverse economies, whereas Alnafrah [9] shows that AI causes higher emissions beyond certain diffusion thresholds, though this effect can be mitigated by GQI and DII.

The divergence between micro- and macro-level results indicates the existence of scale and rebound effects. While AI benefits efficiency at the firm level, such gains may be offset at the country level by increased production, consumption, and energy demand. Dian et al. [14] offer supporting evidence to the idea by showing that AI simultaneously promotes innovation-driven emission reductions and generates spatial spillovers that complicate aggregate outcomes.

Overall, the literature documents the environmental effects of AI are not uniform, but critically depend on the governance quality and digital infrastructure. However, the existing literature focuses hardly on examining these moderating mechanisms together in a causal approach.

2.2. GQI As a Moderator

The effectiveness of AI in reducing emissions is not solely shaped by technology, but is contingent upon governance frameworks. GQI determines whether efficiency gains from AI are translated into genuine environmental benefits or lost to rebound effects and institutional rigidities. For example, Cao et al. [11] demonstrate that flexible regulation enhances the carbon-reducing effects of AI, whereas poorly designed governance undermines them. Similarly, Shen et al. [10] find that carbon trading schemes and big data pilot zones in China enhanced the mitigation impact of digital technologies, underscoring the enabling role of supportive policy environments. These findings align with broader governance-based arguments: Smuha [19] emphasizes that “trustworthy AI” governance is crucial for accelerating sustainable adoption, while Traverso et al. [29] demonstrate how rigid institutions, such as strict labor protections in nineteen Western countries, have constrained robot adoption—an analogy equally applicable to AI in green transitions.

Cross-national studies further reinforce the moderating role of governance quality. Using data of OECD countries, Dehdar et al. [30] demonstrate that policy instruments and environmental patents reduce CO_2 emissions when supported by strong institutions. Similarly, the authors in [31], report that government effectiveness consistently reduces emissions, particularly when combined with the adoption of renewable energy sources. Generalizing this to a global sample of 134 countries, Stef et al. [21] emphasize the importance of the rule of law, political participation, and corruption control in reducing emissions. More AI-specific studies add nuance: Gan and Pi [20] show that AI policy uncertainty encourages corporate greenwashing in China. Similarly, AlHares [28] and Alnafrah [9] show that while AI can increase emissions at the aggregate level, effective governance redirects its impact toward sustainability.

Overall, the literature indicates that high levels of governance are needed in order to realize the efficiency gains of AI, enabling them to translate into real environmental benefits, while weak institutions have the potential to neutralize, and even reverse, these gains. Despite this growing body of evidence, the cross-national consistency and causal strength of the role of governance as a moderator in the AI-emissions relationship are not sufficiently explored, providing a motivation for the present study.

2.3. DII As a Moderator

Research increasingly highlights the importance of DII in shaping the environmental effectiveness of AI, positioning DI as a key moderator in the AI–CO_2 emissions nexus. Rather than having a direct impact by itself, DII increasingly seems to be a key conditioning factor determining whether the adoption of AI, leads to emission reductions or increases environmental pressures. Much of the empirical evidence to support this role comes from China, where rapid digitalization has made detailed subnational analysis possible. For instance, Chen et al. [7], using spatial econometric models on 275 Chinese cities, show that DII improves carbon emission efficiency, particularly in resource-dependent and central regions. Similarly, Li et al. [22], applying a multiphase difference-in-differences design around the Broadband China program (2013–2016), report that DI reduces emissions through industrial optimization, innovation, and eco-friendly lifestyles, though the effect size remains modest. Similarly, Wang et al. [24], examining 273 prefecture-level cities, find that Big Data Comprehensive Pilot Zones enhance environmental quality by stimulating green innovation and energy efficiency, albeit with short-term construction-related emissions.

Beyond city-level evidence, firm- and country-level studies reinforce DI's enabling role. Ma et al. [32] demonstrate that Chinese listed firms benefit more from AI adoption when embedded in robust digital ecosystems, suggesting that the potential for emissions reduction is also conditioned by digital capacity. Slimani et al. [33] find that AI improves environmental performance primarily via renewable transitions, with the digital economy amplifying these effects. Broader technological studies also confirm that DI accelerates the diffusion of AI's environmental benefits: Shen et al. [10] highlight cross-city spillovers in green innovation, while Vorozheykina [34] shows that AI, IoT, and big data reduce emissions more effectively in regions with strong digital foundations. Nonetheless, the literature cautions that DII is not costless, as broadband rollouts and data centers generate substantial short-term emissions [23]. However, over time, DI functions as a double-edged moderator, on the one hand amplifying AI's potential to reduce emissions through efficiency gains and green innovation, while on the other producing heterogeneous effects across regions, energy mixes, and policy contexts.

In essence, DII emerges as a decisive yet complex moderator in the AI–CO_2 relationship. Its environmental outcomes depend on ecosystem maturity and governance alignment, pointing to the need for cross-country analyses that capture these multidimensional interactions. Nevertheless, the literature that analyzes digital infrastructure, the quality of governance, and AI altogether in a causal context across countries is relatively few, providing a clear motivation for the present study.

2.4. Research Gap

Although the literature has advanced understanding of how AI shapes CO_2 emissions, important limitations remain. Much of the existing evidence is geographically concentrated, with China serving as the dominant case due to quasi-natural experiments such as Broadband China [22] and Big Data Pilot Zones [24]. While these studies offer strong causal insights, their external validity is limited, and cross-national analyses have disproportionately focused on OECD economies [21]. As a result, the dynamics of AI adoption in other countries, where institutional capacity and infrastructure differ significantly, remain underexplored. Equally, prior work tends to examine AI, GQI, and DII in isolation. Governance has been shown to determine whether AI adoption reduces or increases emissions [9,28], while DII enables efficiency gains and the diffusion of innovation [7]. However, these factors are rarely integrated into a unified framework, despite their interdependence in shaping outcomes. This study addresses these gaps by examining 104 countries and comparing the economies of developed and developing nations.

3. Theoretical Framework & Hypothesis Development

3.1. Theoretical Framework

The study is anchored in three theoretical foundations: EGT, Institutional Theory (IT), and Technological Ecosystem Theory (TET). From the perspective of EGT [17], AI can act as a catalyst for knowledge accumulation, resource efficiency, and productivity growth, thereby lowering the carbon and energy intensity of economic activity [18]. By fostering innovation spillovers and enabling structural transformation, AI has the potential to support long-term decarbonization pathways. However, EGT also cautions that technological advances can generate rebound effects [9] as efficiency gains may lead to increased production and consumption. This aligns with emerging evidence that AI's impact on CO_2 emissions is mixed: positive at the micro-level [10], [28] but often ambiguous or even harmful at the aggregate level [9]. IT [35] helps explain this conditionality. GQI determines whether AI is steered toward sustainability outcomes or diverted into pathways that exacerbate emissions. Effective governance through carbon pricing, emissions trading, and green innovation incentives amplifies the environmental benefits of AI [19]. Conversely, weak or rigid institutions may foster greenwashing or symbolic adoption, diluting potential gains [29]. Similarly, TET [36] highlights the role of DII. Strong infrastructure enhances AI's efficiency by supporting data flows, interconnectivity, and the diffusion of innovation [34,37]. However, the expansion of digital systems is not costless, as it generates short-term emissions that complicate their net effect [23]. Taken together, these perspectives conceptualize AI as a conditional and context-dependent driver of SDG 13 outcomes [38]. Its environmental impact is inherently mixed, hinging on governance and infrastructure that shape whether efficiency gains translate into genuine decarbonization.

3.2. Hypothesis Development

AI can impact environmental performance in both efficiency-improving and energy-intensive ways. Some studies claim that the adoption of AI lowers the emission levels through both technological innovation and increased productivity [12-14], although others also claim that the intensive adoption of AI can increase emissions both through the increased energy demand and the commodities of computational processes [9,28]. These contradictory results suggest that the environmental implications of AI depend on the specific situation in each respective country, including governance and infrastructure. In line with this, the hypothesis is as follows:

H_1**:** *AI has a significant impact on CO_2 emissions*

GQI also influences the impacts of AI on the environment. Studies on OECD and global samples suggest that excellent institutions and governance frameworks enhance the pursuit of green innovation and the reduction of emissions [21,30]. On the other hand, the challenge of weak governance may also result in the inefficiency of regulations and greenwashing, which undermines the sustainability advantages of AI [20]. Empirical findings also suggest that AI can lead to a reduction in emotions in cases of high institutional quality and effective policy enforcement [32]. Therefore, this study hypothesizes:

H_2**:** *GQI moderates the relationship between AI and CO_2 emissions.*

Similarly, DII improves AI-based environmental technologies and the scaling paradigm. Strong digital ecosystems enhance the capability of AI to mitigate carbon by further connecting data and inducing technological spillovers [10,34,37]. In contrast, the poor infrastructure may also limit the effectiveness of AI. Thus, the study hypothesizes:

H_3**:** *DII moderates the relationship between AI and CO_2 emissions.*

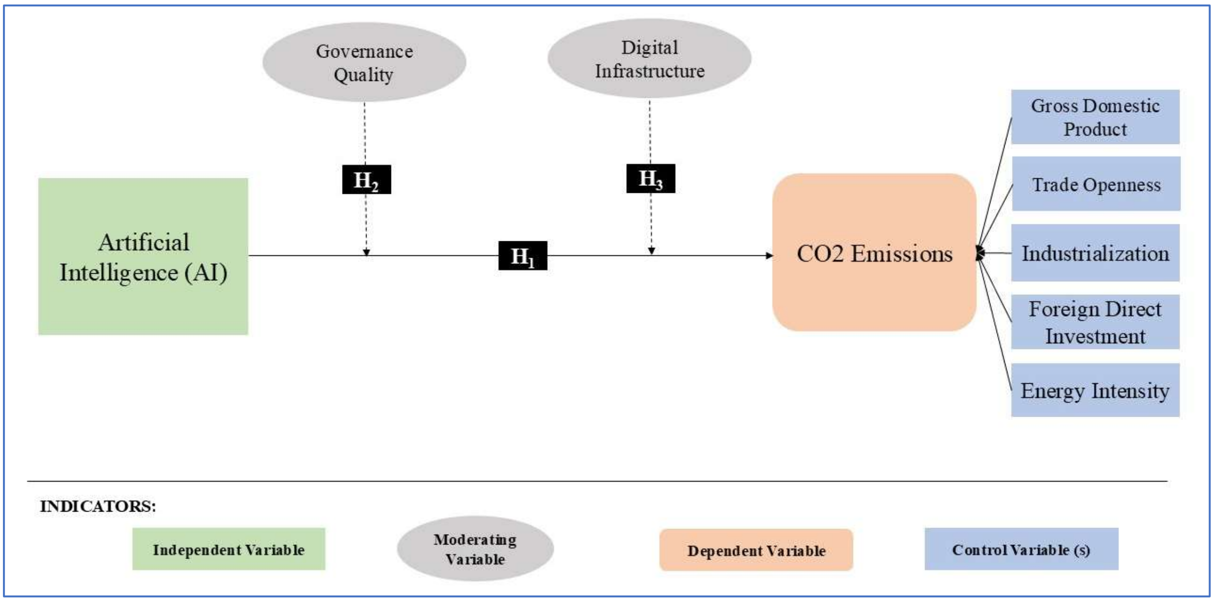

Figure 1. Conceptual Framework (Sources: authors' own creation).

4. Research Design

4.1. Data & Sources

This study employs a panel dataset of 104 countries (2000-2023) to examine the influence of AI, GQI, and DII on environmental sustainability, measured through CO_2 emissions per capita. The selection of the countries and time period is subject to data availability. Table A1 presents the list of countries included in the sample. The data used in this study are mainly obtained from the World Development Indicators (WDI) and the Organization for Economic Co-operation and Development

(OECD) databases. The dependent variable, CO_2 emissions per capita, is represented by the 'natural logarithm of carbon dioxide emissions (in tonnes per person)' and is employed as a measure of environmental degradation. The key explanatory variable, AI, is proxied by AI-related publications per capita from the OECD, reflecting the intensity of AI research and adoption in each country. The DII and GQI are constructed using Principal Component Analysis (PCA) based on four and six indicators, respectively (see Table 1), derived from the WDI. Both indices capture the multidimensional nature of digital and governance systems. The results of the index formation are presented in Table A2. These two variables are also considered as moderating factors because the impact of AI on environmental outcomes is expected to depend on the level of digital readiness and institutional capacity.

Table 1. Variable Description & their Sources.

Variable	**Label**	**Measurement**	**Source**	**Expected Sign**
CO_2 emission per capita	CO_2	Natural log of CO_2 emissions tonnes per person	WDI	NA
Artificial Intelligence	AI	Publication related to AI per capita	OECD	+/-
Digital Infrastructure	DII	DI Index consolidation of 4 parameters through PCA ('Fixed Telephone Subscriptions, Mobile Cellular Subscriptions, Fixed Broadband Subscriptions, Individuals Using Internet')	Authors' calculation using data from WDI	+/-
Governance Quality	GQI	Governance Quality Index consolidation of 6 parameters through PCA ("CC: Control of Corruption; GE: Government Effectiveness; PV: Political Stability and Absence of Violence/Terrorism; RL: Rule of Law; RQ: Regulatory Quality; VA: Voice and Accountability")	Authors' calculation using data from WDI	-
Foreign Direct Investment	FDI	Natural log FDI inflow (% of GDP)	WDI	+/-
Gross Domestic Product	PGDP	'Natural log of GDP per capita (constant US$2015)'	WDI	+/-
Trade Openness	TO	Natural log of Export plus Import divided by GDP	WDI	+/-
Industrialisation	INDUS	Natural log of Industrial Value Added (% of GDP)	WDI	+
Energy Intensity	EI	'Natural log of Energy intensity level of primary energy (MJ/$2017 PPP GDP)'	WDI	+

Source: Author(s) creation.

Several control variables are included to mitigate omitted variable bias and capture the broader economic and structural dynamics that affect emissions. Foreign Direct Investment (FDI), is included because cross-border capital flows can introduce either green technology ("pollution halo") or pollution-intensive production ("pollution haven"). Gross Domestic Product (GDP) controls for the level of economic development and potential non-linear effects predicted by the Environmental Kuznets Curve (EKC). Trade Openness (TO), computed as the capture of the effect of globalization and trade-related emissions or efficiency gains. Industrialization (INDUS) represents the structural composition of the economy, as industrial sectors are typically energy-intensive. Lastly, Energy Intensity (EI) accounts for energy efficiency; higher values indicate less efficient production and greater environmental stress. Overall, this combination of technological, institutional, and macroeconomic variables provides a comprehensive framework for analyzing how AI interacts with digital readiness and governance structures to influence environmental outcomes across economies. The detailed description of the variables is presented in Table 1.

4.2. Empirical Models

4.2.1. Baseline Model

CO_2 emissions demonstrate dynamic persistence, as long-standing economic structures, energy use patterns, and technological pathways influence them. Once carbon-intensive systems are established, they tend to endure, making current emissions highly dependent on past levels. To capture this inertia and avoid biased estimates, the study employs Two-step SGMM, as developed by Arellano and Bond [39] and Blundell and Bond [40]. This approach effectively addresses endogeneity, autocorrelation, and heteroskedasticity. Within this framework, the study empirically examines how AI, GQI, and DII influence environmental sustainability. The dynamic specification allows for the persistence of CO_2 emissions while accounting for potential endogeneity arising from simultaneity, reverse causality, and omitted variables. The baseline model is expressed as follows:

$$\mathrm{CO2_{it}} = \gamma_0 + \gamma_1 \cdot \mathrm{CO2_{it-1}} + \gamma_2 \cdot \mathrm{AI_{it}} + \gamma_3 \cdot \mathrm{PGDP_{it}} + \gamma_4 \cdot \mathrm{TO_{it}} + \gamma_5 \cdot \mathrm{INDUS_{it}} + \gamma_6 \cdot \mathrm{FDI_{it}} + \gamma_7 \cdot \mathrm{EI_{it}} + \mathrm{v_{it}} + \epsilon_{\mathrm{it}} \tag{1}$$

where $CO2_{it}$ represents the natural logarithm of CO_2 emissions per capita for country I at time t; AI_{it} denotes AI activity; $PGDP_{it}$ *denotes* GDP per capita, TO_{it} refers to Trade Openness, FDI_{it} Denotes Foreign Direct Investment, $INDUS_{it}$ denotes industrialization, and EI_{it} Refers to Energy Intensity. The term v_{it} captures unobserved country-specific effects, and ϵ_{it} is the idiosyncratic error term.

4.2.2. Moderation Models

To assess the moderating influence of GQI and DII, the baseline model is augmented by incorporating relevant interaction terms. Accordingly, two distinct specifications are estimated. The first extended model introduces the interaction between AI and GQI. $(AI \times GQI)_{it}$, as presented in Equation (2), while the second model explores the interaction between AI and DII $(AI \times DII)_{it}$, as shown in Equation (3).

Equation 2: Moderating Role of GQI:

The moderation model incorporating GQI is specified as follows:

$$\mathrm{CO2_{it}} = \gamma_0 + \gamma_1 \cdot \mathrm{CO2_{it-1}} + \gamma_2 \cdot \mathrm{AI_{it}} + \gamma_3 \cdot \mathrm{GQI_{it}} + \gamma_4 \cdot (\mathrm{AI} \times \mathrm{GQI})_{\mathrm{it}} + \gamma_5 \cdot \mathrm{PGDP_{it}} + \gamma_6 \cdot \mathrm{TO_{it}} + \gamma_7 \cdot \mathrm{INDUS_{it}} + \gamma_8 \cdot \mathrm{FDI_{it}} + \gamma_9 \cdot \mathrm{EI_{it}} + \mathrm{v_{it}} + \epsilon_{\mathrm{it}} \tag{2}$$

Here, the interaction term $(AI \times GQ)_{it}$ captures how the marginal impact of AI on CO_2 emissions varies with the level of GQI. A negative and statistically significant coefficient for γ_4 would suggest that strong governance enhances AI's contribution to emission reduction by promoting sustainable technological deployment and institutional accountability.

Equation 3: Moderating Role of DII:

The moderation model incorporating DII is therefore formulated as:

$$\mathrm{CO2}_{\mathrm{it}} = \gamma_0 + \gamma_1 \cdot \mathrm{CO2}_{\mathrm{it}-1} + \gamma_2 \cdot \mathrm{AI}_{\mathrm{it}} + \gamma_3 \cdot \mathrm{DII}_{\mathrm{it}} + \gamma_4 \cdot (\mathrm{AI} \times \mathrm{DII})_{\mathrm{it}} + \gamma_5 \cdot \mathrm{GDP}_{\mathrm{it}} + \gamma_6 \cdot \mathrm{TO}_{\mathrm{it}} + \gamma_7 \cdot \mathrm{INDUS}_{\mathrm{it}} + \gamma_8 \cdot \mathrm{FDI}_{\mathrm{it}} + \gamma_9 \cdot \mathrm{EI}_{\mathrm{it}} + \mathrm{v}_{\mathrm{it}} + \epsilon_{\mathrm{it}} \quad (3)$$

In this specification, the interaction term $(AI \times DII)_{it}$ reflects how the effect of AI on emissions depends on the level of DII development. A negative and significant γ_4 would indicate that stronger DII amplifies AI's potential to reduce emissions by facilitating technological diffusion and resource efficiency. Together, these models provide a robust empirical framework to assess how AI, supported by digital and governance structures, influences environmental sustainability across countries.

4.3. Estimation Strategy

The empirical analysis began with a preliminary examination that included descriptive statistics, the correlation matrix, and the Variance Inflation Factor (VIF) tests to check for multicollinearity among variables. To assess cross-sectional dependence (CSD), the Pesaran [41] and Frees [42] tests were conducted, followed by panel cointegration tests using the Pedroni [43] and Kao [44] approaches to confirm the presence of long-run relationships among the variables. Pre-estimation diagnostics, such as the Hausman [45] test, the 'Wooldridge [46], test for autocorrelation', and the 'Modified Wald test for groupwise heteroskedasticity [47]', were also performed. The detection of autocorrelation, CSD, and heteroskedasticity justified the use of robust estimation techniques. Consequently, the study adopted the two-step SGMM estimator, which provides consistent and efficient estimates in dynamic panel settings characterized by potential endogeneity, unobserved heterogeneity, and autocorrelation. In this approach, lagged levels and differences of endogenous regressors serve as internal instruments, and the instrument matrix is collapsed to prevent instrument proliferation. The Windmeijer [48] finite-sample correction was applied to obtain robust standard errors.

Model validity was ensured through several post-estimation diagnostic tests. The Arellano–Bond AR (1) and AR (2) tests were conducted to detect first- and second-order serial correlation in the differenced residuals; as expected, AR (1) was significant by construction, while the insignificance of AR (2) confirmed the absence of higher-order autocorrelation and supported the model's dynamic validity. The Hansen J-test of overidentifying restrictions was used to evaluate the overall validity of the instruments, with a non-significant result indicating that the instruments were appropriate and uncorrelated with the error term.

Following the main analysis, the study performed Heterogeneity analysis by dividing the sample on the basis of energy efficiency (energy efficient and energy inefficient countries) and AI development stages (high-AI and low-AI economies). For robustness analysis, assuming potential endogeneity of AI, the study further employed the 2SLS estimator. To address potential endogeneity, AI publication stock is constructed using a perpetual inventory method with a 15% depreciation rate, following Parteka and Kordalska [49], and employed as an instrument for AI development. This served as an additional robustness check to validate the consistency and stability of the GMM results. The methodological flowchart is presented in Figure 2.

5. Empirical Results

This section presents the empirical findings on the relationship between AI and CO_2 emissions, with a particular focus on the moderating roles of GQI and DII. The analysis integrates results from the SGMM and 2SLS estimations to ensure robustness against potential endogeneity and dynamic panel bias. The findings offer insights into how AI adoption impacts environmental outcomes and how governance and infrastructure conditions can either amplify or mitigate these effects.

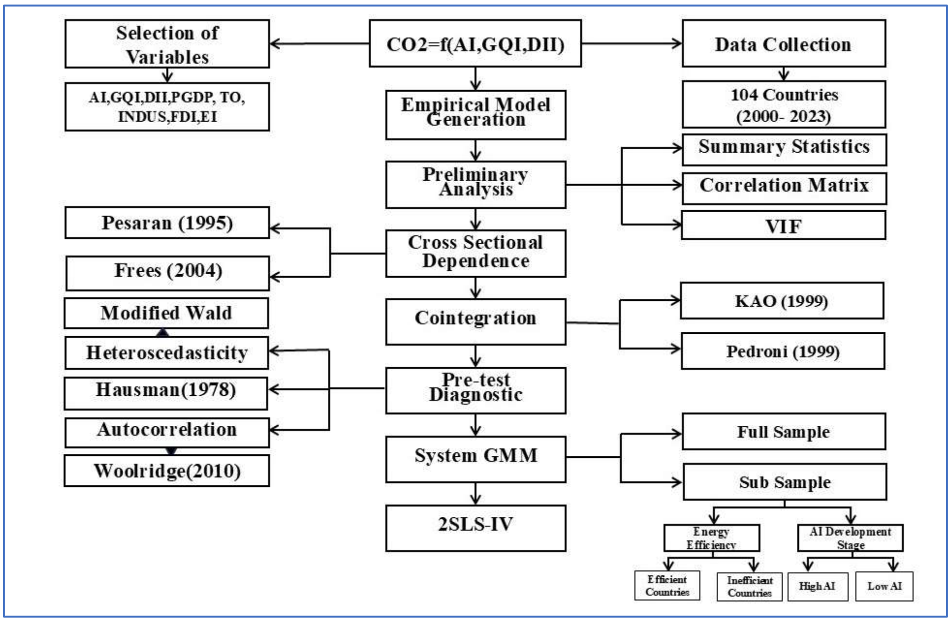

Figure 2. Methodological Flowchart (Sources: authors' own creation).

Table 2. Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
CO_2	2496	1.259	1.338	-3.72	3.982
AI	2496	0.94	2.952	0	30.254
GQI	2496	0	2.295	-5.314	4.237
DII	2496	0	1.666	-2.732	4.654
PGDP	2496	9.055	1.404	5.533	11.63
TO	2496	4.355	0.567	0.906	6.093
INDUS	2496	3.262	0.425	0.735	4.462
FDI	2496	6.111	0.128	0.257	6.8
EI	2496	1.47	0.525	-1.05	3.292

Source: Author(s) estimation.

The descriptive statistics reported in Table 2 provide an overview of the distributional characteristics and variability of the variables used in this study, based on 2,496 country-year observations. The dependent variable, CO_2, records a mean of 1.259 with a standard deviation of 1.338, indicating moderate dispersion around the mean. The wide range (–3.72 to 3.982) reflects substantial heterogeneity in emission profiles, capturing both low-emission and high-emission economies, which is important for identifying cross-country environmental disparities. The main explanatory variable, AI, exhibits a low mean (0.94) and a large standard deviation (2.952), suggesting a highly uneven distribution of AI research intensity. This disparity suggests that only a few advanced economies make significant contributions to global AI knowledge production, while many others remain at the early stages of technological development. GQI is standardized around zero (SD

= 2.295), reflecting balanced variations across countries with differing institutional strengths. Similarly, DII (mean = 0; SD = 1.666) highlights considerable variation in digital readiness, which may moderate the diffusion of AI technologies and their environmental effects. PGDP averages 9.055 (SD = 1.404), indicating wide economic heterogeneity among the sampled countries. TO and INDUS exhibit moderate means (4.355 and 3.262, respectively) with limited dispersion, indicating relatively stable integration into global trade and consistent industrial contributions across nations. FDI shows a mean of 6.111 with very low variation (SD = 0.128), indicating a stable inflow of capital relative to GDP across the sample. EI averages 1.47 (SD = 0.525), reflecting moderate differences in energy efficiency. Overall, the descriptive analysis reveals substantial cross-sectional diversity in AI adoption, GQI, and DII, all of which may play critical roles in explaining variations in CO_2 emissions.

Table 3. Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) CO_2	1.000								
(2) AI	0.190*	1.000							
(3) GQI	0.606*	0.150*	1.000						
(4) DII	0.623*	0.143*	0.706*	1.000					
(5) PGDP	0.842*	0.176*	0.847*	0.799*	1.000				
(6) TO	0.355*	-0.25*	0.353*	0.336*	0.344*	1.000			
(7) INDUS	0.273*	0.018	-0.22*	-0.21*	-0.011	-0.036	1.000		
(8) FDI	0.003	-0.010	0.020	0.012	0.003	0.033	-0.018	1.000	
(9) EI	-0.07*	0.064*	-0.33*	-0.37*	-0.37*	-0.17*	0.328*	-0.014	1.000

Source: Author(s) estimation; Note: '*<p (0.05)'.

The pairwise correlation matrix in Table 3 presents the linear relationships among the key variables included in the analysis. The correlation between CO_2 emissions and PGDP (0.842) is particularly strong and positive, consistent with the EKC hypothesis, which posits that higher income levels are typically associated with greater energy use and emissions during the early development stages. Likewise, CO_2 emissions show strong positive correlations with GQI (0.606) and DII (0.623), indicating that better institutional quality and advanced digital infrastructure often coincide with higher emissions, likely due to increased industrial and digital activities in more developed economies. The positive but weaker association between AI and CO_2 (0.190) suggests that while implementation of AI expands alongside development, its environmental impact may still depend on how AI technologies are deployed either for industrial growth or sustainability-oriented innovation. GQI and DII exhibit a very high correlation ($r = 0.706$), highlighting that nations with stronger institutions tend to have more developed digital ecosystems. Similarly, PGDP correlates strongly with both GQI ($r = 0.847$) and DII ($r = 0.799$), reinforcing the notion that governance and digitalization are key attributes of economic growth and development. Trade openness (TO) exhibits moderate positive correlations with CO_2 (0.355), GQI (0.353), and PGDP (0.344), suggesting that more open economies tend to be wealthier and more emission-intensive, possibly due to increased industrial and trade-related activities. In contrast, industrial value added (INDUS) exhibits weak and mixed correlations, suggesting that its contribution to emissions varies across different contexts. Interestingly, energy intensity (EI) is negatively correlated with PGDP (–0.365), DII (–0.371), and GQI

(–0.333), indicating that higher-income and better-governed countries tend to be more energy-efficient. The near-zero correlation between FDI (FDI) and most variables implies limited direct association with either economic or environmental indicators. The VIF results (Table A3) confirm the absence of multicollinearity in the dataset. Overall, the correlation results suggest interconnectedness between development, governance, and environmental performance, while also emphasizing the potential mediating roles of digital and AI-related progress. The moderate-to-strong correlations also warrant caution for potential multicollinearity in regression analyses.

Table 4. CSD & Cointegration Test.

CSD			
Pesaran		21.362***	
Frees		22.996***	
Cointegration			
KAO		Pedroni Test	
MDF	-4.2675***	MPP	5.4274***
DF	-4.9758***	PP	-19.1561***
ADF	-15.1890***	ADF	-20.3510***
UMDF	-0.0826		
UDF	-2.8336***		

Source: Author(s) Estimation; Note: '***<p (0.01)'.

The results from the CSD and panel cointegration diagnostics in Table 4 provide key insights into the interdependencies and long-run relationships among the study variables. The Pesaran (21.362) and Frees (22.996) statistics strongly reject the null hypothesis of cross-sectional independence, indicating significant CSD. This suggests that shocks or policy interventions in one country may influence others, necessitating estimation techniques that explicitly account for these dependencies. The subsequent Kao and Pedroni cointegration test results provide robust evidence of a long-run equilibrium relationship among CO_2 emissions, AI and macroeconomic and institutional variables. These consistent findings suggest that the variables move in tandem over time, indicating stable long-term relationships between economic growth, digital transformation, and environmental outcomes.

Table 5. Diagnostic tests.

Tests	**Results**
Hausman	Chi2: 1004.30***
Autocorrelation	F: 250.660***
Heteroscedasticity	Chi2: 65366.12(0.0000)

Source: Author(s) Estimation; Note: '***<p (0.01)'.

The diagnostic tests confirm the robustness of the model specification. The Hausman test (χ^2 = 1004.30***) indicates that the fixed effects model is appropriate, as individual effects are correlated with the explanatory variables. The 'Wooldridge test for autocorrelation' (F = 250.660 ***) reveals the presence of first-order serial correlation, suggesting temporal dependence in the data. The 'Modified Wald test' (χ^2 = 65,366.12***) confirms significant heteroskedasticity across countries. Together, these results justify the use of robust or dynamic panel estimators that correct for heteroskedasticity, autocorrelation, and CSD to ensure reliable and efficient estimates.

Table 6. Two-Step SGMM Outcome.

Variables	**Eq(1)**	**Eq(2)**	**Eq(3)**
L.CO_2	0.977***	0.985***	0.975***
	(0.00984)	(0.00934)	(0.0107)
AI	0.00156***	0.00149***	0.00196***
	(0.000472)	(0.000334)	(0.000333)
GQI		0.00203	
		(0.00181)	
GQIXAI		-0.000495***	
		(0.000118)	
DII			-0.000139
			(0.00266)
DIIXAI			-0.000850***
			(0.000255)
PGDP	0.00844	0.000823	0.0113
	(0.00813)	(0.00978)	(0.00878)
TO	0.0121***	0.00901**	0.0121***
	(0.00405)	(0.00431)	(0.00413)
INDUS	0.0337***	0.0317***	0.0336***
	(0.00837)	(0.00732)	(0.00912)
FDI	0.0171***	0.0169***	0.0171***
	(0.00244)	(0.00275)	(0.00233)
EI	0.0156**	0.0109*	0.0170***
	(0.00629)	(0.00627)	(0.00658)
Constant	-0.311***	-0.223**	-0.335***
	(0.102)	(0.112)	(0.108)
P(AR1)	0.000	0.000	0.000
P(AR2)	0.101	0.101	0.103
P (Hansen)	0.158	0.158	0.154
Observations	2,392	2,392	2,392
Number of id	104	104	104
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
No of Groups	104	104	104
No of instruments	32	34	34

Source: Author(s) Estimation; Note: standard errors in parentheses, “*** p<0.01, ** p<0.05, * p<0.1”.

The baseline dynamic panel estimation results (Table 6) reveal key determinants of CO_2 emissions using the Two-step SGMM framework to control for endogeneity and dynamic persistence.

The lagged dependent variable ($L.CO_2 = 0.977$, $p < 0.01$) is highly significant, indicating a strong persistence of emissions over time, which suggests that countries with higher past emissions tend to sustain elevated levels due to structural and energy-use inertia. AI (0.00156, $p < 0.01$) exhibits a positive and significant association with emissions, indicating that the rise in AI research activity initially contributes to higher CO_2 levels, likely due to the energy-intensive nature of computation and industrial expansion. This result validates our central hypothesis (H1). Similar findings were observed in the study of Alhares [28]. The positive and significant coefficients for TO, INDUS, FDI, and EI indicate that these factors are key drivers of CO_2 emissions across countries. In essence, as economies become more open to trade, expand their industrial base, and attract greater foreign investment, production and energy consumption rise, often powered by fossil fuels, leading to higher emissions. Trade liberalization and globalization can stimulate industrial activity and export-oriented manufacturing; however, without strict environmental regulations or the adoption of clean technology, these processes tend to increase CI. Similar findings were observed in the study by Mahmood et al. [50], who noted that increasing TO has a positive effect on CO_2 emissions in the context of Turkey. Similarly, higher industrial value added reflects the dominance of energy-intensive sectors such as manufacturing and heavy industry, which contribute significantly to CO_2 output [51]. The positive effect of FDI implies that inflows of foreign capital often fuel industrial expansion and technological deployment, which may not always be environmentally efficient, especially in developing economies that prioritize growth over environmental compliance [52]. This validates the Pollution Haven hypothesis in these sample countries. The positive coefficient of energy intensity reinforces this view: greater energy use per unit of output directly translates into higher emissions, underscoring inefficiencies in energy utilization and dependence on non-renewable sources [53]. However, the impact of PGDP is insignificant (0.00844), suggesting that economic growth alone does not directly affect emissions when structural and technological factors are taken into account. Diagnostic tests [p{AR (1)} = 0.000; p{AR (2)} = 0.101; Hansen p = 0.158] confirm robustness and valid instrumentation. These results suggest that AI currently aligns with development-driven increases in emissions, while institutional and technological moderators likely determine whether AI serves as a complement or corrective mechanism for sustainability—a relationship examined in the subsequent models.

Eq. (2), which incorporates the interaction between GQI and AI, provides deeper insights into governance's moderating role. The lagged dependent variable ($L.CO_2 = 0.985$, $p < 0.01$) remains strongly significant, confirming persistence. The coefficient of AI (0.00149, $p < 0.01$) remains positive, indicating that AI diffusion in isolation still raises emissions due to energy-intensive innovation. Crucially, the interaction term (–0.000495, $p < 0.01$) is negative and highly significant, demonstrating that strong governance mitigates AI's emission-enhancing impact. This result validates our central hypothesis (H2). These results indicate that Effective institutions, environmental regulations, and enforcement mechanisms enable AI to promote sustainability and decarbonization [9,21,28], whereas weak governance contexts can amplify pollution through the use of productivity-focused AI. The direct effect of GQI (0.00203) is positive but insignificant, indicating its influence operates mainly through interaction with technological dynamics. Control variables remain positive and significant, with PGDP still insignificant. Post-test estimations confirm the validity of the model. Overall, Model (2) highlights GQI as a key moderating factor transforming AI from an emission-enhancing to an emission-mitigating force as institutional strength improves, emphasizing the need for governance reforms and environmental policy frameworks to leverage AI for sustainable transitions.

Equation (3) introduces the interaction between DII and AI, providing further evidence of the moderating effect of digital readiness. The lagged dependent variable (L.CO2 = 0.975, $p < 0.01$) remains highly significant, confirming the strong persistence of emissions. The direct effect of AI (0.00196, $p < 0.01$) remains positive, reinforcing the initial correlation between AI activity and higher emissions resulting from energy-demanding digital expansion. However, the interaction term (–0.000850, $p < 0.01$) is negative and highly significant, showing that better DII reduces AI's emission-increasing effects. Countries with advanced digital ecosystems, characterized by efficient data management, broadband access, and intelligent energy systems, utilize AI to enhance environmental efficiency and carbon monitoring. This result validates our central hypothesis (H3). Similar findings were observed in the studies of Slimani et al. [33] and Ma et al. [32]. In contrast, those with weaker infrastructure experience rebound effects from energy use. The main effect of DII (–0.000139) is negative but insignificant, suggesting its impact manifests through synergy with AI. Control variables retain positive significance, while PGDP remains insignificant. Post-test estimations confirm the validity of the model. Collectively, the results underscore that while AI development alone tends to heighten emissions, effective governance and robust DII substantially alter this trajectory, transforming AI into a tool for sustainable, low-carbon innovation and highlighting the pivotal role of institutional and technological capacity in shaping AI's environmental outcomes.

Table 7 presents the heterogeneity analysis across energy efficiency status (energy-efficient vs. energy-inefficient countries) and AI development stages (low-AI vs. high-AI stages), showing the systematic difference in the determinants of CO_2 emissions. Within all sub-samples, the lagged CO_2 emissions is positive and highly significant, confirming the persistence of elevated emissions. The degree of persistence is greater in energy-efficient (0.987) and low-AI economies (0.978), indicating stronger carbon lock-in where existing production systems and patterns of technological adoption are more gradual. In contrast, energy-inefficient nations (0.957) and high-AI economies (0.957) exhibit relatively less persistence, indicating a marginally greater scope for emission adjustment despite higher energy intensity and advanced digitalization. The impact of AI also varies significantly across dimensions. AI is statistically insignificant in energy-efficient countries and low AI economies, suggesting that low AI penetration and efficiency-focused energy systems limit its immediate environmental impact. By contrast, AI leads to a significant increase in emissions in energy-inefficient countries (0.002, $p<0.01$) and in high-AI economies (0.002, $p<0.01$), suggesting that in an advanced stage of AI diffusion, the energy required to achieve productivity gains and computations is amplified, creating rebound effects that dominate over efficiency improvements. This parallel pattern highlights the fact that the environmental footprint of AI is strongly conditioned by the energy structure and technological maturity. Additionally, PGDP is insignificant in energy-efficient countries and in low-AI economies, and becomes positive and statistically significant in energy-inefficient countries (0.024, $p<0.1$) and in AI-developed stage economies (0.031, $p<0.01$), reflecting growth-driven emissions when economic growth is embedded in energy-intensive and technology-driven production structures. This symmetry across both classifications highlights that growth-related environmental pressure is increasing as economies move towards higher levels of AI adoption without complementary increases in energy efficiency. However, TO and INDUS have consistently positive impacts on emissions across all sub-samples, and these impacts are potentially larger for energy-inefficient countries and AI-developed stage economies. This means that globalization and industrial growth increase the pressure on the environment when coupled with inefficient energy usage or the enhancement of digitalization. FDI exhibits significant heterogeneity: FDI is highly emission-enhancing in energy-efficient countries and in economies at the high-AI development stage, but not in energy-inefficient countries, suggesting that capital inflows only enhance emissions when they are associated with large-scale industrial and AI-intensive activities, accompanied by no parallel transitions in energy efficiency. However, EI is one of the strongest determinants of emissions for all sub-samples, and has consistently positive and significant coefficients.

Table 7. Heterogeneity Analysis.

Variables	Low EI	High EI	Low AI	High AI
L.CO_2	0.987***	0.957***	0.978***	0.924***
	(0.012)	(0.014)	(0.010)	(0.012)
AI	-0.001	0.002***	0.018	0.002***
	(0.001)	(0.001)	(0.040)	(0.000)
PGDP	-0.001	0.024*	0.013	0.031***
	(0.008)	(0.013)	(0.010)	(0.008)
TO	0.009**	0.008	0.015**	0.015***
	(0.004)	(0.007)	(0.007)	(0.004)
INDUS	0.010*	0.058***	0.022***	0.027**
	(0.006)	(0.017)	(0.008)	(0.012)
FDI	0.019***	0.231	0.012***	0.181***
	(0.002)	(0.184)	(0.004)	(0.035)
EI	0.039***	0.031***	0.012*	0.082***
	(0.015)	(0.008)	(0.007)	(0.015)
Constant	-0.178**	-1.861	-0.32***	-1.55***
	(0.088)	(1.193)	(0.115)	(0.249)
P(AR1)	0.000	0.000	0.000	0.000
P(AR1)	0.117	0.370	0.187	0.101
P(Hansen)	0.171	0.446	0.389	0.299
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1196	1196	1196	1196
Number of id	52	52	52	52
No of Instruments	32	32	32	32

Source: Author(s) Estimation; Note: standard errors in parentheses, “*** $p<0.01$, ** $p<0.05$, * $p<0.1$”.

Diagnostic statistics show the robustness of the estimations, with no signs of second-order serial correlation, valid outcomes of the Hansen statistic, and consistent numbers of instruments used in models. Overall, the heterogeneity results indicate that the energy efficiency status and the stage of AI development have equally important and mutually reinforcing effects on emission trajectories, underscoring the importance of combining both the deployment of AI and energy efficiency-oriented climate policies, rather than focusing solely on digitalization in relation to climate change.

Table 8. 2SLS Outcome.

VARIABLES	**Eq(1)**	**Eq(2)**	**Eq(3)**
AI	0.021**	0.025**	0.024**
	(0.009)	(0.010)	(0.009)
GQI		-0.112***	
		(0.038)	
GQIXAI		-0.008***	
		(0.002)	
DII			0.072
			(0.066)
DIIXAI			-0.007***
			(0.003)
PGDP	0.828***	1.077***	0.817***
	(0.045)	(0.068)	(0.073)
TO	0.255***	0.364***	0.312***
	(0.088)	(0.081)	(0.090)
INDUS	0.707***	0.420***	0.615***
	(0.122)	(0.098)	(0.129)
FDI	0.039	-0.046	-0.031
	(0.037)	(0.046)	(0.046)
EI	0.485***	0.503***	0.440***
	(0.137)	(0.117)	(0.131)
Constant	-10.612***	-11.781***	-9.836***
	(0.707)	(0.769)	(0.842)
Year FE	Yes	Yes	Yes
F	49.85***	37.33***	43.16***
KP LM	3.134*	3.091*	3.107*
CD Wald F	13000	13000	13000
KP Wald F	771.039	763.375	767.460
Observations	2,496	2,496	2,496
R-squared	0.828	0.865	0.840

Source: Author(s) Estimation; Notes: Standard errors are clustered at the country level. In the 2SLS estimations, AI development is instrumented using AI publication stock, constructed with a 15% annual depreciation rate following Parteka and Kordalska [49]; "*** p<0.01, ** p<0.05, * p<0.1".

2SLS estimations with country-level clustered standard errors, presented in Table 8, provide further evidence to the robustness of the results. Across all the specifications, AI shows positive and statistically significant results (0.021-0.025; $p < 0.05$). This indicates that the 1% increase in AI is associated with a 0.025% increase in CO_2 emissions. This effect is consistent with the idea that digitalization through AI increases energy demand and electricity consumption, especially in energy systems with high carbon intensity.

Additionally, the moderation effects provide insight into the AI-CO_2 nexus. The governance interaction term (GQIxAI) is negative and highly significant (-0.008, $p < 0.01$), indicating that the improved institutional frameworks associated with increasing AI mitigate the emission-increasing effect of AI through enhanced regulatory enforcement, stricter environmental standards. In line with this, GQI itself has a direct mitigating effect on emissions (-0.112, $p < 0.01$), which further confirms its pivotal role in promoting environmentally sustainable results. Similarly, DIIxAI is negative and statistically significant (-0.007, $p < 0.01$), suggesting that more advanced digital ecosystems enable AI applications to be implemented more efficiently. this leads to a decrease in their carbon footprint. Although the direct impact of DII is statistically insignificant (0.072), its interaction with AI underlines that digital maturity can transform AI into a potential efficiency-enhancing mechanism. The control variables remain consistent across models. PGDP, TO, INDUS, and EI are all positive and statistically significant, pointing to the predominance of economic scale, structural transformation, and energy use in emissions. However, FDI is not significant, indicating a limited role for FDI in the direct environment framework. All models exhibit high explanatory power (R^2: 0.828-0.865) and robust coefficient signs across specifications.

Diagnostic statistics are used to validate the 2SLS estimations. The Kleibergen-Paap LM tests reject under-identification, the large KP Wald F-statistics rule out weak instruments concerns, and the high F-statistics further support model reliability. Overall, the results of the 2SLS show strong causal evidence that, although AI development on its own aggravates CO_2 emissions, the environmental impact of AI development is systematically moderated by the GQI and DII. These findings underpin the need for a focus on achieving sustainable growth through AI while ensuring parallel progress in GQI and DII.

6. Conclusion

The present study explores the association between AI and CO_2 emissions, taking into account the moderating effects of GQI and DII. The empirical findings suggest that, on average, the proliferation of AI is linked to increased CO_2 emissions, which is an energy-consuming aspect of data processing and automation, due to the current economic and regulatory environment. Furthermore, the GQI and DII play significant roles as moderating variables in the AI-CO_2 emissions nexus. Strong governance largely undermines the emission-enhancing impact of AI, which underscores the importance of regulatory performance, policy coordination, and institutional capacity in guiding AI adoption to more sustainable results. Meanwhile, a more advanced digital infrastructure further modulates such association, indicating that trusted connectivity, efficient data infrastructure, and current digital networks enable AI applications to operate with a reduced carbon intensity. Combined, the results suggest that AI is a conditional general-purpose technology, the environmental impact of which is contingent upon the complementary capabilities of an institution and its digital capacity. The AI application is likely to strengthen the carbon-based growth trends in the context of poor governance and inadequate digital infrastructure. On the other hand, when the GQI is improved and DII is established, it creates the possibility of achieving the productivity benefits of AI at a lower environmental cost. To match AI-based growth with climate goals, it thus needs to be coupled with synchronized advances in GQI and DII.

6.1. Theoretical Implications

The findings of this study extend existing theoretical frameworks by integrating insights from EGT, IT, and TET. From the standpoint of EGT, the results confirm that AI acts as a driver of innovation, learning, and productivity, while also validating the presence of rebound effects, where, efficiency gains from AI lead to increased energy consumption and expansion of production. This finding refines the theory by illustrating that technological progress does not automatically yield environmental efficiency; it must be accompanied by policy mechanisms that internalize environmental costs. Grounded in IT, the results affirm that GQI serves as a critical determinant of whether AI's diffusion contributes to decarbonization or exacerbates emissions. Effective governance, through mechanisms such as carbon pricing, innovation incentives, and regulatory enforcement, directly reduces emissions and creates a policy environment conducive to sustainable AI deployment. Conversely, weak institutions lead to symbolic or uncoordinated adoption of AI, diluting its potential environmental benefits. The results also advance TET, demonstrating that DII functions as a pivotal enabler of AI's environmental efficiency. The significant negative interaction between AI and DII supports the argument that robust digital ecosystems, encompassing broadband connectivity, data integration, and intelligent energy systems, enhance AI's contribution to energy optimization and emission reduction. Together, these findings establish AI as a conditional and context-dependent technology whose environmental impact is contingent upon GQI and DII.

6.2. Policy Implications

This study offers several policy implications. First, AI strategies should be integral to national and global frameworks regarding climate, with AI integration aligned with SDG 13. The priority of AI applications should be those that are energy-efficient, can track carbon, and improve resource utilization. Second, there is a need to enhance systems of governance in a bid to channel AI innovation into sustainable directions. To avoid backlash, policymakers should enhance the quality of regulation, incorporate environmental principles, and ensure transparency in AI-based industrial procedures. Thirdly, it is crucial to invest in DII to harness the potential of AI in the environment. Smart grids, green logistics, and predictive energy management can be supported by advanced digital systems, which can significantly reduce emissions. Fourth, fertile grounds such as green FDI and technology transfer should be promoted in favour of AI-based low-carbon innovations, especially in developing nations with limited technological capacities. Lastly, a coordinated global approach is necessary to ensure that the benefits of AI are distributed equitably and that its environmental footprint is minimized through international cooperation, shared standards, and sustainable technology policies.

6.3. Limitations and Future Scope

While this study provides robust empirical evidence, several limitations warrant attention. First, the measure of AI development, AI-related publications per capita, captures research intensity but not the full extent of AI deployment or the diversity of AI applications across sectors. Future research could incorporate alternative indicators, such as AI patents, digital automation indices, or industrial adoption metrics of AI. Second, the use of country-level data may mask subnational disparities in AI infrastructure, energy systems, and governance effectiveness. Regional or firm-level analyses could provide more granular insights into the relationship between AI and emissions. Third, although the analysis accounts for endogeneity, unobserved factors such as renewable energy integration, AI regulation maturity, or data center efficiency may still influence the results. Finally, future studies could employ nonlinear or threshold models to examine whether GQI and DII exhibit critical tipping points beyond which AI's impact on emissions shifts from positive to negative.

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Data Availability: The dataset used in this study will be made available on reasonable request to the corresponding author.

Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1. List of Countries.

Developed Countries					
Australia	Austria	Belgium	Canada	Cyprus	Czech Republic
Denmark	Estonia	Finland	France	Germany	Greece
Hong Kong (China)	Iceland	Ireland	Israel	Italy	Japan
Kuwait	Latvia	Lithuania	Luxembourg	Macau (China)	Malta
Netherlands	New Zealand	Norway	Poland	Portugal	Qatar
San Marino	Saudi Arabia	Singapore	Slovakia	Slovenia	South Korea
Spain	Sweden	Switzerland	United Kingdom	United States	
Developing Countries					
Algeria	Argentina	Armenia	Azerbaijan	Bahrain	Bangladesh
Belarus	Bosnia and Herzegovina	Brazil	Brunei Darussalam	Bulgaria	Burundi
Cambodia	Cameroon	Chile	China	Colombia	Costa Rica
Croatia	Egypt	Ethiopia	Fiji	Georgia	Ghana
Hungary	India	Indonesia	Iran	Iraq	Jamaica
Jordan	Kazakhstan	Kenya	Lebanon	Libya	Malaysia
Mexico	Moldova	Mongolia	Morocco	Myanmar	Nepal
Nigeria	North Macedonia	Oman	Pakistan	Peru	Philippines
Romania	Russia	South Africa	Sri Lanka	Sudan	Tajikistan
Thailand	Tunisia	Türkiye	Uganda	Ukraine	Uruguay
Vietnam	Yemen	Zimbabwe			

Source: Author(s) own work.

Table A2. PCA and Eigenvectors.

Variables	**GQI**	**DII**
Highest Eigenvector	5.2696	2.7747
Proportion	0.8782	0.6937
KMO	0.9230	0.7070

Source: Author(s) estimation.

Table A3. VIF Outcome.

Variables	VIF	1/VIF
PGDP	6.580	0.152
GQI	4.310	0.232
DII	3.170	0.315
INDUS	1.500	0.669
EI	1.360	0.738
TO	1.330	0.754
AI	1.200	0.836
FDI	1.000	0.998
Mean VIF	2.550	

Source: Author(s) estimation.

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