Article

Artificial Intelligence Adoption and Role of Energy Structure, Infrastructure, Financial Inclusions, and Carbon Emissions: Quantile Analysis of E-7 Nations

Shanwen Gu [1],* and Adil Javed [2],*

1   School of Marxism, Shanghai University of Finance and Economics, Shanghai 200433, China
2   Department of Economics, University of Management and Technology, Lahore 54770, Pakistan
*   Correspondence: 2022310159@stu.sufe.edu.cn (S.G.); adiljaved.umt@gmail.com (A.J.)

Abstract

The E-7 nations face significant challenges in harmonizing artificial intelligence (AI) adoption with sustainable economic and environmental goals. While AI holds transformative potential to revolutionize energy structures, modernize infrastructure, broaden financial inclusion, and reduce carbon emissions, its effective integration is frequently hindered by policy inertia, economic limitations, and long-standing institutional barriers. Using the multi-level perspective (MLP), this study employs the method of moments quantile regression (MMQREG) on panel data from 2004 to 2024 to investigate the determinants of artificial intelligence (AI) adoption, focusing on the roles of energy structure (ES), infrastructure (INFRA), financial inclusion (FI), economic growth (GDP), patent activity (Tpatent), population (TP), and carbon emissions (CE) across E-7 nations. The study findings reveal that economic growth and energy structure play a significant role in driving AI adoption, while inadequacies in infrastructure and limited financial inclusion significantly hinder AI progress. Additionally, the analysis reveals a positive relationship between AI adoption and CO_2 emissions, where early stages of technology uptake lead to increased emissions, but sustained integration eventually results in efficiency gains that help to reduce them. These findings underscore the need for E-7 nations to adopt targeted policies that modernize digital and physical infrastructure, broaden financial access, and expedite the transition to sustainable energy systems. This study offers actionable insights for policymakers to align digital innovation with sustainable development goals.

Keywords: artificial intelligence; energy structure; infrastructure; financial inclusion; sustainable development

1. Introduction

The rapid advancement of artificial intelligence (AI) is transforming multiple sectors worldwide, altering the fabric of energy systems, infrastructure development, financial markets, and innovation capabilities [1–3]. Emerging economies, especially those in the E-7 group such as China, India, Russia, Indonesia, Brazil, Mexico, and Turkey, face complex challenges and opportunities as they integrate AI into their development strategies [4]. AI-driven technologies offer considerable potential to optimize renewable energy management, improve infrastructure efficiency, expand access to digital finance, and accelerate GDP growth through innovation. However, these benefits are counterbalanced by growing concerns over energy consumption, carbon emissions, and unequal access to technology [5,6].

For E-7 countries at a transitional stage of development, the sustainability implications of AI adoption are multidimensional. While AI facilitates smarter energy distribution and reduces carbon footprints [6–8], its energy-intensive nature increases electricity demand, which may rely on fossil fuel sources, potentially exacerbating carbon emissions [9]. Similarly, AI-driven digital finance tools improve financial inclusion by lowering barriers to banking and credit access [10]. Yet their broader impact on GDP and patent generation in emerging economies remains underexplored.

AI technologies also have the potential to enhance the efficiency and integration of renewable energy sources significantly [11]. By optimizing energy consumption patterns and improving climate modeling, AI can facilitate the transition to cleaner energy systems, thereby reducing carbon emissions and mitigating the adverse effects of climate change. [12]. This is particularly pertinent for E7 countries, where escalating energy demand and the shift towards renewable energy are imperative for sustainable development. Studies have demonstrated that AI can play a significant role in advancing sustainability efforts and supporting the creation of carbon-neutral technologies [13].

In addition, AI can significantly improve infrastructure quality by enabling predictive maintenance, smart city systems, and efficient energy use. Research shows that digital innovation supports infrastructure modernization and improves public service delivery, particularly in fast-urbanizing regions [14]. In the financial sector, AI fosters financial inclusion by providing innovative solutions that expand services to underserved populations, stimulating economic growth, and improving access to capital for small and medium-sized enterprises [15]. Additionally, the integration of green finance and fintech plays a vital role in supporting economic sustainability in developing countries [16]. However, the relationship between AI and sustainability is complex; while AI systems can increase carbon emissions due to their high energy consumption, they also present significant opportunities for emission reduction through enhanced efficiency [17]. Balancing these aspects is essential for E7 nations to achieve their environmental targets.

Moreover, technological innovation, measured by the number of patents (Tpatent), is a key factor in this study. Patents serve as indicators of research advancements and AI adoption, both of which influence environmental sustainability [18]. They reflect a country's technological progress and contribute to the development of energy-efficient solutions, AI-driven environmental monitoring systems, and smart energy grids [19]. Increased patent activity fosters innovation in renewable energy and carbon reduction strategies, strengthening AI's role in mitigating emissions and supporting sustainable economic growth. By incorporating Tpatent into this study, we gain a comprehensive understanding of how technological progress influences AI diffusion, energy efficiency, and environmental sustainability.

Figure 1 illustrates AI adoption levels across E-7 countries from 2004 to 2024. The data source is Statista [20], which reports the AI adoption index as a percentage of adoption across sectors and institutions within each country. The percentage represents the proportion of organizations or sectors adopting AI technologies, as estimated through Statista's industry surveys and technological adoption reports. The initial phase from 2004 to 2014 reflects a relatively stagnant level of AI interest, indicating limited integration of AI technologies within these economies. However, after 2015, a gradual, upward trend emerges, corresponding with increased digitalization efforts, policy-driven AI strategies, and advancements in computational capabilities. The acceleration becomes more pronounced after 2020, likely driven by the widespread adoption of AI-powered automation, digital finance, and remote working solutions, especially in response to the COVID-19 pandemic. The steepest growth trajectories are observed in China and India, suggesting their leadership in AI investment, infrastructure development, and innovation. [21]. The expo-

nential increase comes after 2021 in all E-7 nations, underscoring AI's transition from an emerging technology to a critical driver of economic and industrial transformation across these nations [4,22,23]. This trend reflects a transition from early niche experimentation to broader systemic integration, aligning with the multi-level perspective (MLP) framework applied in this study. This accelerating but heterogeneous adoption underscores a key research gap: the need to understand how determinants like infrastructure or emissions influence AI diffusion at different adoption stages. Addressing this issue motivates our use of a quantile-based empirical strategy to capture the varying effects across AI adoption levels in E-7 countries.
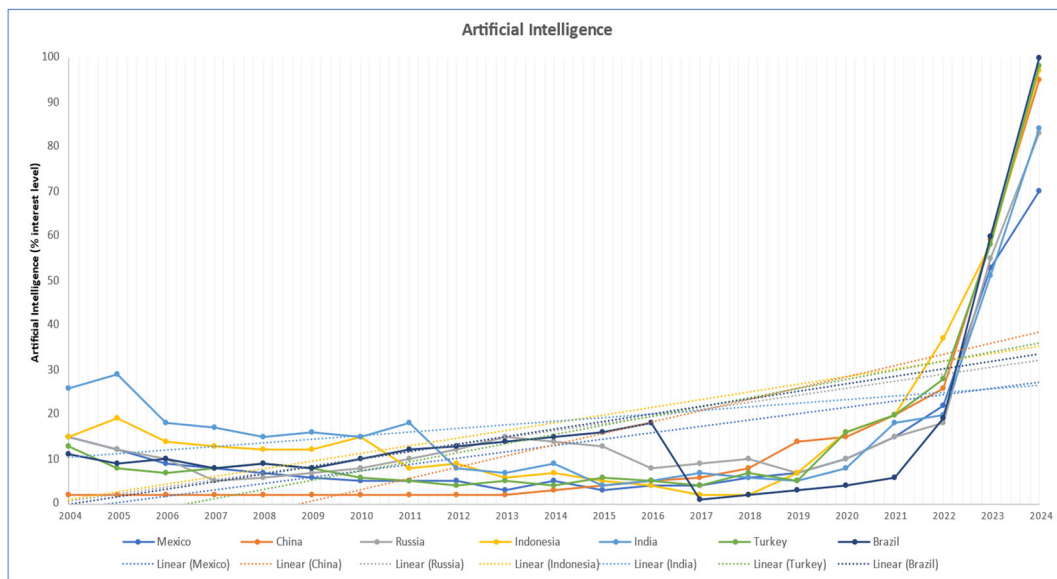

Figure 1. Trend of artificial intelligence adoption in E-7 nations from 2004 to 2024 (authors' illustrated plot).

The study selected the E-7 group, Brazil, China, India, Indonesia, Mexico, Russia, and Turkey, which comprises the world's largest emerging economies, expected to lead global GDP by 2050. Unlike BRICS, which centers on geopolitical cooperation, the E-7 focuses on scalable economic transitions, digitalization, and the sustainability challenges of rapid industrialization. This study emphasizes the E-7 as key laboratories for AI-driven sustainability in resource-constrained, high-growth contexts. A comparative summary of E-7 and BRICS indicators (GDP, renewable energy, AI adoption, and population) is presented in Appendix A Table A1. Considering the rapid urbanization and digital transformation characteristic of the E-7 economies, this multidimensional analysis offers crucial insights for policymakers and stakeholders to balance technological progress with inclusive, sustainable development [24–27].

The study aim is to investigate the complex relationship of the determinants of artificial intelligence (AI) adoption in E-7 nations by focusing on key variables such as energy structure (ES), infrastructure quality (INFRA), financial inclusion (FI), economic growth (GDP), carbon emissions (CE), population size (TP), and technological innovation T(Patents). It examines how these factors influence AI diffusion across different adoption levels. The analysis captures both direct effects and interdependencies, offering insights for policymaking in digitally transforming, high-growth economies.

In this study, AI adoption is the dependent variable, while energy structure, infrastructure, financial inclusion, GDP, carbon emissions, population, and patent activity are independent variables. Utilizing the method of moments quantile regression (MMQREG), from 2004 to 2024, this study analyzes how the heterogeneous impacts of AI vary across

different stages of energy transition and economic development. Specifically, the study addresses the following research questions:

RQ1. How do renewable energy transition, economic growth, and carbon emissions influence AI adoption in E7 nations?
RQ2. What role do infrastructure quality, financial inclusion, and innovation capacity play in accelerating or hindering AI diffusion across E7 economies?
RQ3. What policy frameworks can mitigate AI's sustainability trade-offs, such as emissions, labor displacement, while maximizing its benefits for E7 nations?

This study provides empirical evidence on the drivers of AI adoption in E-7 nations, emphasizing its links with renewable energy, infrastructure, financial inclusion, and carbon emissions. Grounded in the multi-level perspective (MLP), and using quantile regression, it captures nonlinear effects across different stages of development. The findings offer valuable insights for aligning AI diffusion with sustainability goals in emerging economies.

2. Literature Review

The use of artificial intelligence (AI) across various sectors has garnered significant attention in academic and policy-making circles, particularly regarding its potential to promote sustainable development in emerging economies. This literature review synthesizes existing research on the impact of AI adoption within the E7 nations, including Brazil, China, India, Indonesia, Mexico, Russia, and Turkey, concentrating on renewable energy, infrastructure quality, financial inclusion, environmental sustainability, and innovation outputs.

Recent studies have explored the multifaceted impact of artificial intelligence (AI) adoption across economic, infrastructural, and environmental domains. The authors of [28] highlighted that AI technologies can optimize energy systems, promoting a higher share of renewable energy in national energy structures. The research of [29] emphasized that AI-driven digital platforms enhance infrastructure efficiency, especially in transport and ICT networks. Similarly, [30] found that AI-enabled financial services, including algorithmic credit scoring and mobile banking, improve financial inclusion, particularly in emerging markets. On the environmental front, [11] reported that AI tools can reduce CO_2 emissions through smart grids and emission-monitoring systems. Moreover, GDP and population are commonly used control variables in technological adoption studies, as they shape both the capacity and scale of AI implementation. Patent counts are a widely accepted proxy for technological innovation and have been used to measure a country's readiness to adopt and diffuse AI technologies [31]. Additionally, to enhance clarity and critical synthesis, we have included Appendix A Table A2: Summary Table of Literature Supporting Key Variables, which outlines the theoretical and empirical foundations of each explanatory variable along with key supporting references.

2.1. AI and Energy Systems

A growing body of literature demonstrates that AI has the potential to revolutionize energy systems. Early studies [7] have shown that machine learning algorithms optimize renewable energy management, improve load forecasting, and enhance grid stability. The authors of [6] reported an "inverted U-shaped" relationship between AI deployment and carbon emissions in Chinese cities, indicating that while initial AI integration may increase emissions, further adoption ultimately enhances energy efficiency, leading to environmental benefits. However, most research has focused on isolated aspects such as energy efficiency or carbon emissions, without examining AI's broader role in transforming energy structures within emerging economies.

AI technologies have become pivotal in optimizing energy consumption, refining climate modeling, and accelerating transitions to low-carbon energy sources. Evidence

from previous studies suggests that AI-driven innovations significantly contribute to low-carbon energy transitions across various countries, underscoring AI's potential in fostering sustainable energy systems [32,33]. For example, in India, AI-powered solar forecasting has enhanced grid reliability [34], while Brazil's wind farms use AI-driven load-prediction models [35]. These insights emphasize AI's transformative role in reshaping energy frameworks and promoting environmental sustainability.

H1. *Renewable energy and economic growth have a significant and positive effect on AI adoption.*

2.2. AI and Infrastructure

Infrastructure modernization is a key area where AI is driving substantial changes. Research has highlighted AI's contributions to intelligent transportation systems, predictive maintenance of utilities, and the development of smart cities [36,37]. These AI-driven advancements enhance urban resilience, reduce operational costs, and improve infrastructure efficiency. However, the extent to which these improvements stimulate overall economic growth in developing nations remains unclear [2]. Moreover, much of the existing research focuses on developed economies, leaving a significant gap in understanding AI-induced infrastructure enhancements in E-7 countries.

AI plays a multifaceted role in improving infrastructure quality by optimizing resource allocation, facilitating predictive maintenance, and supporting the creation of smart urban environments [29]. These AI-driven solutions not only increase the efficiency and sustainability of infrastructure projects but also enhance public services, potentially driving economic expansion [38–40]. In Mexico, AI applications in traffic and waste systems have led to measurable urban efficiency gains [37]. Nevertheless, empirical studies examining AI-powered infrastructure improvements in E-7 nations are scarce, highlighting the need for further research into how AI interacts with local socioeconomic conditions in these emerging economies.

2.3. AI and Financial Inclusion

AI-driven digital finance solutions, including mobile banking, algorithmic credit scoring, and blockchain-based platforms, have become key drivers of financial inclusion. Empirical research [10,33] suggests that AI can lower transaction costs and expand financial service access, particularly in underbanked regions. However, gaps remain in the literature regarding how these innovations influence broader economic performance and technological advancements, particularly in the context of E-7 economies, where factors like GDP play a crucial role in financial growth.

AI-powered fintech solutions offer the potential to bridge financial disparities between urban and rural populations, thereby fostering inclusive and sustainable economic development. Recent study reviews suggest that AI-driven financial technologies not only enhance operational efficiency but also facilitate broader economic participation, contributing to financial sustainability [30]. Indonesia's expansion of AI-driven mobile banking is linked with a rise in financial account ownership in rural areas [16]. Many studies examining fintech innovations in E-7 nations indicate that AI integration improves financial efficiency and supports economic growth, underscoring the need for further research in this domain [41,42].

H2. *Poor Infrastructure and limited financial inclusion have a negative impact on AI adoption.*

2.4. AI and Environmental Sustainability

The environmental implications of AI, particularly its influence on carbon emissions (CE), have garnered significant academic attention. While some studies highlight AI's role

in reducing CE through enhanced energy efficiency [6,43], others caution that AI's high computational demands and energy-intensive data centers could increase emissions [44]. Rapid urbanization in many E-7 countries intensifies energy consumption and emissions, yet AI-driven smart urban planning and public service optimization offer viable solutions for mitigating these environmental pressures. However, the existing literature often isolates the environmental impacts from the demographic factors, overlooking an integrated perspective on AI's influence on both urban and environmental dynamics [45,46].

The relationship between AI adoption and environmental sustainability is complex. Although AI systems can elevate energy consumption and emissions, they also present opportunities for emission reduction through efficiency gains and carbon-neutral technologies. Research highlights the need to balance these competing forces to achieve net-zero emissions [47–49]. This nuanced understanding emphasizes the importance of integrated policy frameworks that incorporate technological innovations and demographic factors to maximize AI's role in sustainable development. Allam [50] highlights AI's dual role in smart city development, where optimized energy grids coexist with risks of digital exclusion if governance is inequitable [51–54]. This aligns with our findings on the nonlinear AI–emissions relationship in E-7 nations, where early AI adoption exacerbates disparities before yielding net benefits.

H3. *Carbon emissions have a positive and significant effect on AI adoption.*

2.5. AI and Innovation

Patent data (Tpatent) serve as a key indicator of a nation's innovation capacity. Prior research [55] demonstrates that AI drives technological breakthroughs, leading to increased patent outputs. However, most studies focus on high-income countries and fail to examine AI's influence on patent generation in emerging markets, where distinct regulatory, educational, and infrastructural conditions shape innovation pathways.

AI adoption stimulates innovation by fostering technological advancements and enhancing patent activity. Studies suggest that AI-driven innovations contribute to energy resilience and correlate positively with higher innovation outputs [56,57]. In China, patent applications in machine learning grew by 70% from 2015 to 2022, suggesting intensified innovation capacity through digital adoption [58]. Despite these promising findings, limited research explores this relationship within E-7 nations, underscoring the need for further empirical investigations to better understand AI's role in shaping technological progress in emerging economies.

2.6. Literature Gaps

Despite the expanding literature on AI's role in energy management, infrastructure, financial inclusion, environmental sustainability, and innovation, several critical gaps remain:

- Research on AI's environmental impacts is heavily skewed toward developed economies, with limited empirical work in the E-7 context. A recent study [59] demonstrates that in China's Yangtze River Delta, ICT usage exhibits an inverted U-shape relationship with SO_2 emissions, whereas ICT supply consistently reduces pollution. This highlights the need to extend analysis beyond Europe/North America to emerging regions with distinct infrastructural constraints.
- The moderating role of institutions remains underexplored in emerging economies. A recent research work [60] shows that better regulatory quality amplifies the negative impact of ICT service exports on CO_2 emissions in OECD settings. Incorporating similar institutional controls in the rule of law ensures policy coherence is essential to understand AI's sustainability pathways in the E-7 framework.

- Furthermore, most existing studies concentrate on AI adoption in advanced economies, paying insufficient attention to E-7 nations—an omission that obscures the sector and region-specific challenges and opportunities in these rapidly evolving emerging markets [4].
- While studies have explored AI's role in various sectors, comprehensive analyses addressing its cross-sectoral impacts in E7 nations are limited. There is a lack of integrated studies examining how AI affects infrastructure quality, financial inclusion, environmental sustainability, and innovation outputs within these countries [61].
- There is a notable gap in understanding the regulatory and policy implications of AI adoption specific to E7 nations. Detailed analyses tailored to the legislative and institutional contexts of these countries are lacking, hindering the development of effective governance structures for AI integration [62].
- While AI could advance SDG 9 (Industry and Innovation), its environmental costs remain under-addressed. For example, China's reliance on coal-powered data centers for AI training contradicts its climate goals [63]. Similarly, Brazil's AI-driven deforestation monitoring lacks integration with policies addressing ethical concerns, such as indigenous land rights [64].

This research contributes novel insights by integrating these diverse dimensions into a comprehensive empirical model. By focusing on the E-7 context and employing panel data techniques to simultaneously assess AI, ES, INFRA, FI, GDP, CE, TP, and Tpatent, the study offers a comprehensive and rigorous assessment of AI's diverse and far-reaching impacts. Moreover, it offers policy-relevant evidence to guide emerging economies in balancing rapid technological adoption with sustainable development goals.

2.7. Theoretical Framework

To strengthen the theoretical foundation of this study, we integrate concepts from the multi-level perspective (MLP) [65], disruptive innovation theory [66], and institutional co-evolution theory [67]. The multi-level perspective (MLP) framework positions AI within sustainability transitions by emphasizing its influence at the niche level through innovation, at the regime level through structural constraints, and at the landscape level through macro-environmental pressures including climate change and digitalization. Disruptive innovation theory further explains how AI can penetrate peripheral or underserved markets, gradually reshaping mainstream energy systems by offering novel, efficient alternatives to legacy structures. Additionally, institutional co-evolution theory explains how AI adoption and policy reforms mutually reinforce sustainability transitions. For example, India's 2023 National AI Strategy links renewable energy targets to data center subsidies, creating feedback loops between innovation and regulation.

Figure 2 presents the conceptual framework of this study, illustrating how the multi-level perspective (MLP), disruptive innovation theory, and institutional co-evolution theory link to the determinants of AI adoption in E-7 nations. It aligns each theoretical lens with the key explanatory variables and research hypotheses.

Complementing these perspectives, institutional co-evolution theory provides a dynamic lens to understand the mutual adaptation between AI technologies and policy environments. Although AI-enabled forecasting tools in renewable energy can drive regulatory reforms, which in turn facilitate wider AI deployment, highlighting a feedback loop between innovation and institutional change. This co-evolutionary approach positions AI not as a passive tool but as an active agent of systemic transformation, whose impact is shaped by the agility of governance, regulatory openness, and institutional learning. Furthermore, recent studies have applied the multi-level perspective (MLP) to analyze energy transitions in various contexts, including Saudi Arabia [68], Russia and Ghana [69],

and Western Australia [70]. Disruptive innovation theory has been explored through the duality of innovation in market dynamics [71], while institutional co-evolution frameworks have been utilized to understand development transitions in fossil fuel-producing low- and lower-middle-income countries [72].
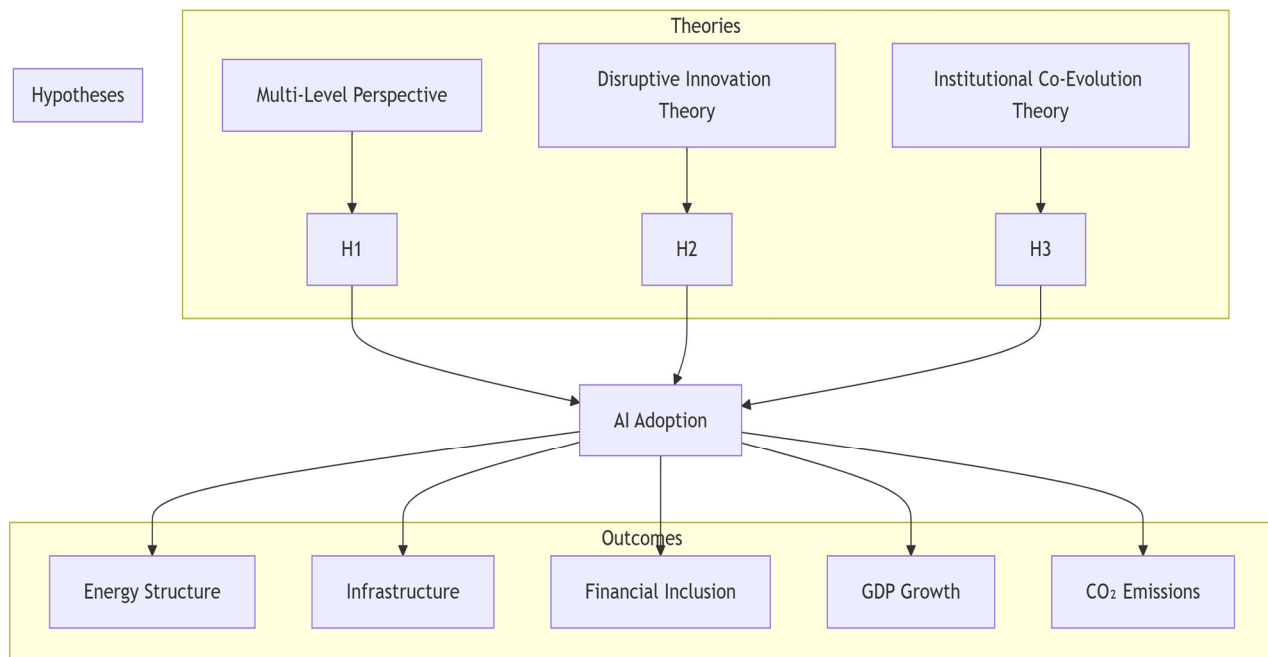

Figure 2. Conceptual framework linking theoretical perspectives to the determinants of AI adoption in E-7 nations.

3. Methodology

3.1. Study Area Map

Figure 3 illustrates the geographical distribution of the E-7 nations included in the analysis. This map provides a visual context for the regional diversity in AI adoption, infrastructure development, and environmental outcomes. Highlighting the study area supports comparative analysis across emerging economies with distinct demographic, economic, and technological characteristics. The E7 group, Brazil, China, India, Indonesia, Mexico, Russia, and Turkey, comprises dynamic economies that are rapidly embracing digital transformation and sustainable development. These nations actively invest in technologies such as artificial intelligence, automation, and renewable energy, each contributing uniquely to regional industrial upgrades and innovation. China and India stand out for their robust tech ecosystems and expansive digital infrastructures, while the other E7 countries play essential roles in advancing industrial modernization and economic resilience. This visual representation reinforces our analysis by clearly mapping the key players in emerging market innovation regions and highlighting the policy initiatives that support sustainable technological growth.

3.2. Empirical Framework

The integration of artificial intelligence (AI) is fundamentally altering industrial landscapes, driving economic evolution, and spurring technological innovation. This study delves into the primary factors influencing AI adoption within the E-7 nations, such as China, India, Brazil, Mexico, Russia, Indonesia, and Turkey, over the period from 2004 to 2024. Key variables under consideration include the AI adoption index (AI), energy structure (ES), infrastructure (INFRA), financial inclusion (FI), gross domestic product growth

(GDP), CO_2 emissions (CE), total population (TP), and the number of patents (Tpatent). The E-7 nations, comprising some of the world's largest emerging economies, play a crucial role in global GDP, population, and energy consumption, making them highly relevant for examining the developmental and environmental implications of AI adoption. These countries are rapidly integrating AI technologies, providing an ideal context to explore its transformative impact. Focusing on the E-7 group also minimizes cross-country heterogeneity, as their relatively similar institutional and economic contexts enhance the reliability of econometric analysis. Additionally, targeting this specific group yields more actionable policy insights for countries at comparable stages of development. Broadening the scope to include a wider set of countries could compromise analytical depth and introduce biases due to varied technological, institutional, and economic frameworks. The MMQREG model accounts for E-7 heterogeneity, but future work could integrate machine learning such as causal forests to unpack nonlinear threshold effects.
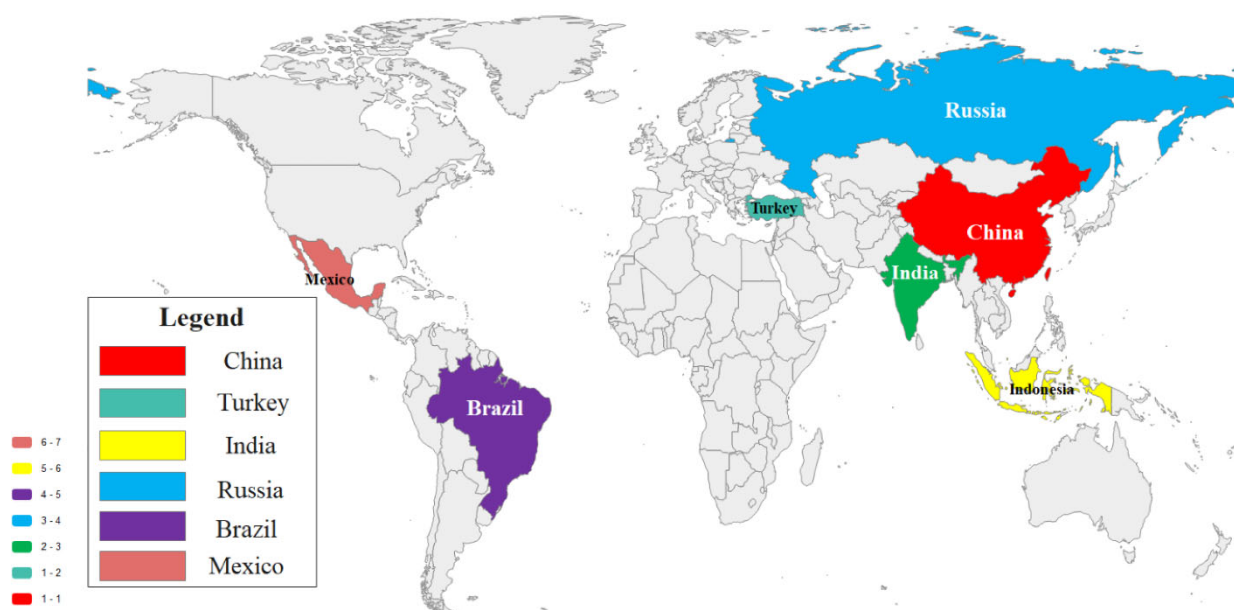

Figure 3. E-7 Study area map (authors' representation).

Given the diverse economic frameworks, policy landscapes, and digital infrastructures across these countries, a quantile-based econometric method is employed to capture the nuanced impacts of these determinants. Furthermore, details of study estimation steps are mentioned in Figure 4.

Specifically, the method of moments quantile regression (MMQR), developed by [73], is utilized in this model, AI adoption is the dependent variable, with energy structure, infrastructure, financial inclusion, GDP, carbon emissions, population, and patents serving as explanatory variables. Unlike traditional regression models that focus on average effects, MMQR enables the detection of heterogeneous impacts across different quantiles of AI adoption, offering a more detailed understanding of the relationships between economic, environmental, and technological factors. The foundational econometric model is articulated as follows:

$$AI_{it} = \alpha_i + X'_{it}\beta + (\delta_i + Z'_{it}\gamma)U_{it} \tag{1}$$

In this equation, AI_{it} denotes the AI adoption index for country i at time t; X'_{it} represents a vector of explanatory variables, including ES, INFRA, FI, GDP, CE, TP, and Tpatent; $(\delta_i + Z'_{it}\gamma)$ accounts for heterogeneous covariance effects; and U_{it} is the error term captur-

ing random disturbances. To address heteroskedasticity and enhance the robustness of estimations, all variables are log-transformed.

```
┌─────────────────────┐
│   Data Collection   │
└─────────────────────┘
           │
           ▼
┌─────────────────────┐
│ Panel Unit Root Tests│
└─────────────────────┘
           │
           ▼
┌─────────────────────┐
│    Cross-sectional  │
│    Dependence Test  │
└─────────────────────┘
           │
           ▼
┌─────────────────────┐
│  Cointegration Test │
└─────────────────────┘
           │
           ▼
┌─────────────────────┐
│   MMQR regression   │
└─────────────────────┘
           │
           ▼
┌─────────────────────┐
│   Driscoll–Kraay    │
└─────────────────────┘
           │
           ▼
┌─────────────────────┐
│   Interpretation    │
└─────────────────────┘
```
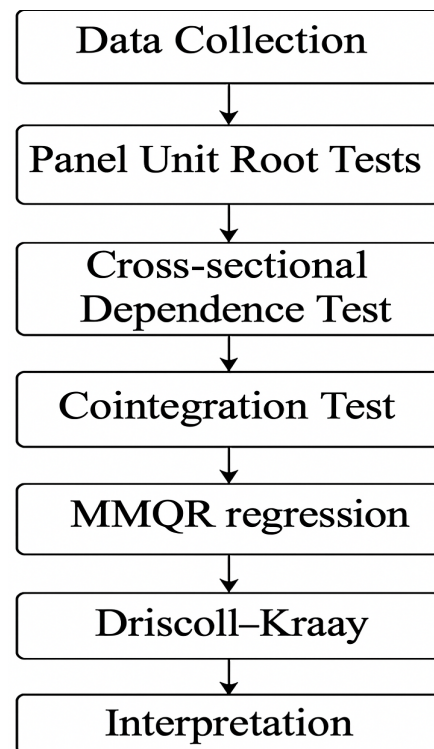
Figure 4. Study estimation steps.

Before model estimation, it is imperative to assess the stationarity of the panel dataset to avoid spurious regression outcomes. This assessment employs the cross-sectional dependence (CD) test by [74,75], the cross-sectionally augmented im, Pesaran, and Shi (CIPS) test, and the cross-sectionally augmented Dickey–Fuller (CADF) [76] test. The unit root testing equation is specified as the following:

$$\Delta Y_{it} = \mu_i + \gamma_i Y_{i,t-1} + \sum_{j=1}^{p} \rho_j \Delta Y_{i,t-j} + \varepsilon_{it} \tag{2}$$

Here, ΔY_{it} represents the variable under examination and μ_i is the country-specific intercept, while ε_{it} denotes the error term. If non-stationarity is detected, first-differencing is applied to achieve stationarity.

To examine cross-sectional dependence among the E-7 countries, Pesaran's CD test is employed, as formulated below:

$$the\ CD = \frac{\sqrt{2T}}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{3}$$

In this expression, $\hat{\rho}_{ij}$ signifies the correlation coefficient of residuals between countries i and j. Detecting significant cross-sectional dependence necessitates the application of panel quantile regression methods to account for these interdependencies.

To ascertain the existence of long-term relationships between AI adoption and its determinants, the [77] panel cointegration test is conducted, as represented by the following:

$$Y_{it} = \alpha_i + X'_{it}\beta + (\delta_i + Z_{it}\gamma)U_{it} \tag{4}$$

In this context, α_i and δ_i capture country-specific effects, while U_{it} accounts for short-term deviations. Confirming cointegration indicates that AI adoption and its determinants share a long-run equilibrium relationship, justifying the use of long-term estimation techniques.

Given the nonlinear and heterogeneous nature of AI adoption, the MMQR approach is implemented to estimate conditional quantiles while addressing outliers and asymmetric distributions. The MMQR model is specified as follows:

$$Q_y(\tau/X_{it}) = (\alpha_i + \delta_i(\tau)) + X_{it}\beta + Z_{it}\gamma q(\tau) \tag{5}$$

Here, $Q_y(\tau/X_{it})$ represents the conditional quantile function of AI adoption; $(\alpha_i + \delta_i(\tau))$ denotes the intercept capturing country-specific effects; and X_{it} includes the explanatory variables ES, INFRA, FI, GDP, CE, TP, and Tpatent. The MMQR model is estimated by minimizing the following objective function:

$$\min_q \Sigma_i\Sigma_t\rho_\tau(AI_{it} - (\delta_i + Z_{it}\gamma)q) \tag{6}$$

In this function, ρ_τ (A) is the quantile-specific loss function, ensuring robustness to heteroskedasticity. For validation of results, the Driscoll–Kraay method is employed to provide robust standard errors. The analysis encompasses eight estimator variables: AI, ES, INFRA, FI, GDP, CE, TP, and Tpatent, with AI serving as the dependent variable. The results and their implications are discussed in the subsequent section.

3.3. Data Sources and Description

Table 1 summarizes the key variables and data sources used to analyze the AI adoption across E-7 nations from 2004 to 2024. It includes the AI adoption index (AI) from Statista, which measures the percentage of AI adoption; the energy structure (ES) indicating the share of total energy derived from renewable sources from British petroleum; an infrastructure index (INFRA) based on PCA provided by the World Development Indicators; and a financial inclusion index (FI) from the World Bank. Additionally, the study incorporates macroeconomic and environmental variables GDP (% annual growth), CO_2 emissions (metric tons per capita), total population (TP), and number of patents (Tpatent) to comprehensively capture the interplay between technology, economic growth, environmental performance, and innovation in these emerging economies. In addtion, we measure technological innovation using patent counts, a widely accepted proxy in empirical literature [78–80], as patents represent concrete innovation outcomes rather than inputs like R&D. They offer standardized, comparable data across countries and time, particularly relevant for AI-related technologies where formal intellectual property signals both innovation and market readiness [31]. This choice also ensures data consistency across E-7 nations from 2004 to 2024.

This study utilizes the AI adoption index from Statista, which reflects the percentage interest level in AI technologies across countries, serving as a proxy for national-level digital transformation. The index aggregates data from industry surveys, policy disclosures, and digital engagement metrics, capturing macro-level trends in AI uptake. While we recognize the potential measurement bias in countries like China and India, where AI may be concentrated in select sectors, the index is intended to reflect overall national interest and diffusion, not sector-specific deployment. To address heterogeneity, we include country fixed effects and validate the index's consistency through correlations with complementary indicators such as ICT infrastructure and R&D intensity. Our approach aligns with prior empirical studies that use similar proxies to measure AI readiness or digital transition at the country level [81,82]. A transparent explanation of the index's structure, source,

and rationale has been added to the methodology section to clarify its use in our cross-country analysis.

Furthermore, our study employs a dual-faceted approach, distinguishing between ICT supply and demand dimensions. We construct a principal component analysis (PCA)-based infrastructure index (INFRA) to capture the supply-side strength of ICT, incorporating proxies such as internet penetration, mobile subscriptions, and broadband access. This index reflects a country's capacity to support AI infrastructure. On the demand side, we utilize a PCA-based financial inclusion (FI) index as a proxy for digital usage and engagement, encompassing indicators like digital banking adoption, mobile payments, and ATM accessibility. This reflects the extent of population interaction with AI-enabling platforms. This bifurcated modeling approach allows us to isolate the drivers of AI adoption and its transmission mechanisms on sustainability outcomes more effectively, thereby reducing endogeneity and omitted variable bias. Our methodology aligns with recent empirical frameworks that emphasize the co-evolution of digital infrastructure and institutional readiness in determining the environmental and innovation-related effects of AI and ICT [83]. By embedding institutional digital asymmetries into our analysis, we move beyond descriptive empiricism, offering a nuanced understanding of how AI diffusion and environmental impacts are shaped in emerging economies with uneven ICT maturity.

Table 1. Variables and source description.

Variable	Acronym	Measurement	Data Source
Artificial intelligence adoption	AI	AI adoption index (%)	Statista [20]
Energy structure	ES	% of total energy from renewable sources	British Petroleum (BP) [84]
Infrastructure	INFRA	Infrastructure index (PCA-based)	World Development Index (WDI) [85]
Financial inclusion	FI	Financial Inclusion Index (PCA-based)	World Bank [86]
Gross domestic product	GDP	GDP (% annual growth)	-
CO_2 emissions	CE	Metric tons per capita	-
Total population	TP	Total population	-
Number of patents	Tpatent	Total patent applications	-

4. Results and Discussion

Table 2 summarizes the descriptive statistics test results, revealing significant variability across key variables in E-7 nations. AI adoption averages 15.721, with a wide spread of 19.956, indicating diverse technological advancements across countries. GDP per capita shows notable economic variability, ranging from -8.655 to 13.636, reflecting both economic downturns and growth phases. Energy structure (ES) varies from 3.18% to 50.05%, suggesting that some E-7 nations heavily depend on fossil fuels, while others have made substantial progress in adopting renewable energy. Infrastructure development (INFRA) and financial inclusion (FI) also exhibit broad heterogeneity, with FI displaying the highest dispersion (Std. Dev. 38.879), highlighting differences in financial accessibility. Total population (TP) shows relatively moderate variation, whereas technology patents (Tpatent) reveal stark contrasts (160 to 159,019), indicating disparities in innovation and research intensity. Carbon emissions (CE) fluctuate from 0.897 to 11.880, pointing to diverse environmental policies and industrial activities across nations. In addition, we also provide

a temporal breakdown of key variables in Appendix A Table A3. This table summarizes AI adoption, GDP, and energy structure (ES) across three subperiods: 2004–2010, 2011–2020, and 2021–2024. The results show a substantial increase in AI adoption and ES improvement in the latter periods, reflecting both technological advancement and policy shifts

Table 2. Descriptive statistics test.

Variable	Obs	Mean	Std. Dev.	Min	Max	JB Test
AI	159	15.721	19.956	1.00	95.00	70.21 ***
GDP	159	3.639	3.853	−8.655	13.636	10.23 **
ES	159	22.534	15.334	3.18	50.05	109.87 ***
INFRA	159	16.040	8.513	1.436	31.790	11.97 **
FI	159	53.715	38.879	12.794	185.364	39.42 ***
TP	159	0.890	0.540	−0.460	1.986	8.54 *
Tpatent	159	22,890.11	39,570.74	160.00	159,019.00	56.36 ***
CE	159	4.411	3.298	0.897	11.880	19.10 ***

The significance at 1%, 5%, and 10% is denoted by ***, **, and *, respectively.

The results of the Jarque–Bera (JB) test indicate significant deviations from normality across all variables, highlighting substantial heterogeneity in economic, technological, and environmental conditions among E-7 nations. This lack of normal distribution suggests the presence of skewness and kurtosis, reinforcing the need for advanced econometric techniques that account for such distributional irregularities. Given the diverse structural characteristics of these economies, a one-size-fits-all policy approach may not be effective. While common objectives, such as fostering AI adoption and sustainable economic growth, remain central, the pathways to achieving these goals must be tailored to each nation's unique context. The JB test outcomes further validate the applicability of MMQREG, which accommodates non-normality and allows for a more precise examination of the heterogeneous impacts of key determinants across different quantiles.

The results of the cross-sectional dependence (CD) test in Table 3 confirm significant interdependence between variables across the panel. The highly significant coefficients and *p*-values (all at 0.000) indicate the presence of cross-sectional dependence in AI, GDP, energy structure (ES), infrastructure (INFRA), financial inclusion (FI), total population (TP), technology patents (Tpatent), and carbon emissions (CE). These findings suggest that economic and environmental dynamics in one country are strongly influenced by those in others, reinforcing the necessity for coordinated policy measures among nations. Ignoring cross-sectional dependence could lead to biased estimates, underscoring the importance of employing econometric models that account for such interdependencies. Employing methodologies like the method of moments quantile regression (MMQR) can effectively address these interdependencies, leading to more robust and reliable results in analyzing AI adoption determinants among the E-7 countries.

To ensure the robustness of our econometric analyses, we conducted both the CIPS and CADF panel of unit root tests to assess the stationarity of our dataset. The CIPS and CADF unit root test results, presented in Tables 4 and 5, indicate the stationarity properties of the variables. The CIPS test shows that most variables are non-stationary at level I(0) but become stationary after first differencing I(1), confirming the presence of unit roots in AI, GDP, ES, INFRA, FI, TP, Tpatent, and CE. The CADF test results further validate these findings, as several variables fail to reject the null hypothesis of non-stationarity at level I(0) but become significant at first difference I(1). These findings suggest that the variables exhibit long-run equilibrium properties and require first-differenced

transformations for robust econometric analysis. The presence of unit roots emphasizes the necessity of employing techniques such as cointegration analysis or error-correction models to capture the dynamic relationships among variables effectively.

Table 3. CD test results.

Variable	Coffecient CD	*p*-Value
AI	19.95 ***	0.000
Gdp	10.26 ***	0.000
ES	6.73 ***	0.000
INFRA	7.85 ***	0.000
FI	17.92 ***	0.000
TP	11.36 ***	0.000
Tpatent	6.37 ***	0.000
CE	7.06 ***	0.000

The significance at 1%, 5%, and 10% is denoted by ***, **, and *, respectively.

Table 4. CIPS Test.

Variable	CIPS I(0)	CIPS I(1)
AI	−2.784 *	−5.376 ***
Gdp	−2.893 **	−5.044 ***
ES	−2.880 **	−4.116 ***
INFRA	−2.009	−3.787 ***
FI	−2.011	−3.344 ***
TP	−2.669	−3.640 ***
Tpatent	−2.936 **	−4.930 ***
CE	−2.013	−4.058 ***

Critical values are −2.74 (10%), −2.88 (5%), and −3.15 (1%). The significance at 1%, 5%, and 10% is denoted by ***, **, and *, respectively.

The Westerlund cointegration test in Table 6 evaluates whether the variables maintain a long-run relationship despite being non-stationary at the level. The results show that Gt (0.493, $p = 0.000$) and Pt (0.452, $p = 0.000$) are statistically significant, confirming the existence of cointegration. However, Ga (−0.160, $p = 1.000$) and Pa (0.265, $p = 0.997$) are insignificant, suggesting inconsistencies in panel-wide cointegration. Since at least two key statistics indicate cointegration, we reject the null hypothesis of no cointegration and conclude that the variables share a stable long-term relationship.

Table 7 reports the MMQREG results examining the heterogeneous determinants of AI adoption in E-7 nations across different quantiles. The results indicate that GDP consistently exerts a positive effect on AI adoption, with the coefficient increasing from 0.028 in the base (location) model to 0.085 at the highest quantile 9, implying that stronger economic growth is associated with higher AI uptake among countries already advanced in AI integration. These findings are aligned with [87], although these results did not support the results of [88]. In contrast, INFRA yields robust negative coefficients across all quantiles, −0.604 in the location model and −0.720 at quantile_9, suggesting that infrastructure inhibits the diffusion of cutting-edge AI technologies [89]. The negative coefficient for infrastructure (INFRA: −0.604) reflects a critical E-7 paradox: legacy systems, such as Indonesia's 35% broadband gap, hinder AI adoption despite nominal digital readiness. For instance, Brazil's AI-driven energy projects in São Paulo are throttled by outdated grid

infrastructure, corroborating the INFRA-AI inverse relationship observed here. Moreover, financial inclusion also shows a consistent negative effect on AI adoption. The results reveal that both infrastructure quality and financial inclusion exhibit negative and significant impacts on AI adoption at lower and median quantiles, suggesting that weak infrastructure and limited financial access constrain the diffusion of AI technologies across E-7 nations. This evidence supports our second hypothesis (H2), confirming that poor infrastructure and limited financial inclusion negatively affect AI adoption.

Table 5. CADF test.

Variable	CADF I(0)	CADF I(1)
AI	−1.019	−3.247 ***
Gdp	−2.986 **	−4.051 ***
ES	−2.500 **	−3.395 ***
INFRA	−2.879 **	−3.746 ***
FI	−2.339 **	−2.609 ***
TP	−3.680 ***	−3.997 ***
Tpatent	−2.992 **	−3.697 ***
CE	−2.024 *	−3.560 ***

The significance at 1%, 5%, and 10% is denoted by ***, **, and *, respectively.

Table 6. Cointegration test.

Statistic	Value	Z-Value	*p*-Value
Gt	0.493 ***	6.259	0.000
Ga	−0.160	3.985	1.000
Pt	0.452 ***	4.443	0.000
Pa	0.265	2.760	0.997

The significance at 1%, 5%, and 10% is denoted by ***, **, and *, respectively.

Table 7. MMQREG test.

Log_AI	Coefficient	Std.eror	*p*-Value
Location			
log_Gdp	0.028 **	0.074	0.009
log_ES	0.102 **	0.038	0.020
log_INFRA	−0.604 ***	0.066	0.000
log_FI	−0.125 ***	0.019	0.004
log_TP	−0.133 ***	0.058	0.000
log_Tpatent	−0.368 ***	0.067	0.000
log_CE	0.629 **	0.026	0.015
_cons	3.735 ***	1.266	0.003
Scale			
log_Gdp	0.039 **	0.049	0.021
log_ES	−0.237 ***	0.087	0.009
log_INFRA	−0.079 **	0.109	0.065

Table 7. *Cont.*

Log_AI	Coefficient	Std.eror	*p*-Value
log_FI	0.240 *	0.044	0.095
log_TP	−0.295 *	0.069	0.081
log_Tpatent	−0.039 *	0.044	0.081
log_CE	−0.412 **	0.010	0.015
_cons	1.224	0.830	0.140
qtile__1			
log_Gdp	−0.029 *	0.089	0.045
log_ES	0.136 **	0.030	0.010
log_INFRA	−0.489**	0.020	0.015
log_FI	−0.574 **	0.068	0.032
log_TP	−0.903 ***	0.017	0.004
log_Tpatent	−0.312 ***	0.081	0.000
log_CE	1.228 ***	0.058	0.005
_cons	1.957 ***	1.546	0.000
qtile__25			
log_Gdp	−0.006 ***	0.076	0.003
log_ES	0.122 ***	0.048	0.006
log_INFRA	−0.536 ***	0.069	0.002
log_FI	−0.430 ***	0.024	0.005
log_TP	−1.080 ***	0.063	0.000
log_Tpatent	−0.335 ***	0.069	0.000
log_CE	0.980 **	0.039	0.025
_cons	2.692 ***	1.293	0.000
qtile__5			
log_Gdp	0.028 *	0.074	0.074
log_ES	0.101 **	0.040	0.021
log_INFRA	−0.605 ***	0.066	0.000
log_FI	−0.221 **	0.021	0.016
log_TP	−1.336 ***	0.060	0.000
log_Tpatent	−0.368 ***	0.067	0.000
log_CE	0.622 *	0.029	0.023
_cons	3.755 ***	1.275	0.003
qtile__75			
log_Gdp	0.062 ***	0.094	0.007
log_ES	0.806 ***	0.057	0.008
log_INFRA	−0.675 ***	0.011	0.001
log_FI	−0.012 ***	0.078	0.006
log_TP	−1.594 ***	0.024	0.000
log_Tpatent	−0.402 ***	0.085	0.000

Table 7. *Cont.*

Log_AI	Coefficient	Std.eror	*p*-Value
log_CE	0.262 *	0.095	0.042
_cons	4.824 ***	1.604	0.003
qtile__9			
log_Gdp	0.085 **	0.014	0.013
log_ES	0.672 ***	0.074	0.009
log_INFRA	−0.720 ***	0.055	0.005
log_FI	−0.125 **	0.036	0.011
log_TP	−1.761 ***	0.092	0.000
log_Tpatent	−0.424 ***	0.003	0.000
log_CE	0.028 *	0.062	0.077
_cons	5.519 ***	1.941	0.000

The significance at 1%, 5%, and 10% is denoted by ***, **, and *, respectively.

Energy structure shows a markedly positive and significant impact that grows substantially at higher quantiles, from 0.102 in the location model to 0.806 at quantile_75, indicating that a greater reliance on renewable energy sources is strongly related to higher levels of AI adoption. These findings support our first hypothesis (H1), confirming that renewable energy has a positive and significant effect on AI adoption. These results align with [9,90]. Additionally, TP consistently demonstrates negative impacts on AI adoption, while the effect of Tpatent remains negative and significant across quantiles, highlighting that higher patent activity does not necessarily correspond with increased AI diffusion. This is also conceptually linked to the institutional co-evolution framework, which acknowledges the lag between innovation output and institutional readiness. Finally, CE exhibits a positive effect at lower quantiles that diminishes at higher quantiles, suggesting a more complex interplay between environmental conditions and AI uptake. This pattern supports our third hypothesis (H3), confirming that carbon emissions are positively and significantly associated with AI adoption in E-7 nations. For improved visualization and a more intuitive understanding of the heterogeneous effects captured in our empirical analysis, we include a graphical representation of the method of moments quantile regression (MMQREG) coefficients in Figure 5.
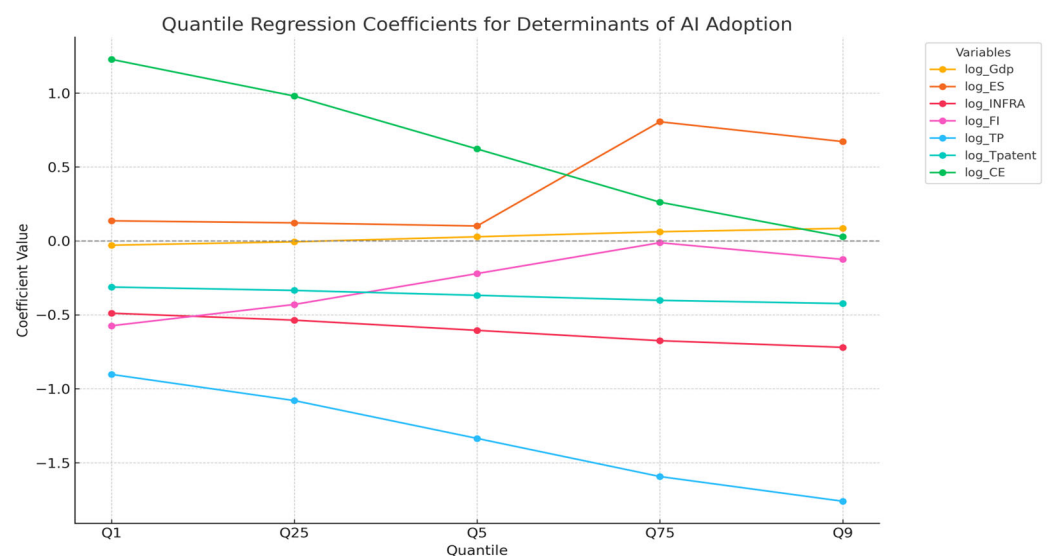

Figure 5. MMQREG results showing key variables influencing AI adoption in E-7.

To enhance AI adoption, policymakers should focus on improving infrastructure, expanding financial accessibility, and ensuring the smooth integration of technological advancements. Additionally, as AI adoption shifts from industrial use to broader applications, strategies should emphasize sustainability and efficiency to support long-term AI growth.

The robustness check using the Driscoll–Kraay method in Table 8 confirms the stability of our estimates in the AI adoption model for E-7 nations. The results indicate that a 1% increase in GDP is associated with a 0.032% increase in AI adoption ($p = 0.011$), suggesting a positive effect of economic growth on technology uptake. In contrast, the energy structure (ES) variable has a large and highly significant coefficient of 1.117 ($p = 0.008$), implying that a higher share of renewable energy substantially drives AI adoption. Meanwhile, both infrastructure (INFRA) and financial inclusion (FI) exhibit robust negative impacts, with coefficients of -0.433 ($p = 0.003$) and -0.228 ($p = 0.004$), respectively, indicating that conventional infrastructure limitations and challenges in financial inclusion are associated with lower levels of AI diffusion. Total population (TP) shows a strong negative effect of -1.670 ($p = 0.000$), and the number of patents (Tpatent) also has a significant negative relationship value of -0.320 ($p = 0.002$), suggesting that higher population and patent activity do not necessarily promote broader AI adoption in these economies. Finally, CO_2 emissions (CE) have a positive effect of 0.750 ($p = 0.013$), highlighting a complex link between environmental pressures and AI uptake. Figure 6 represents a detailed illustration of the key variables influencing AI adoption, summarizing the direction of relationships identified in the empirical analysis. Overall, the Driscoll–Kraay robust standard errors ensure the consistency and reliability of our findings about the factors influencing AI adoption in the E-7 nations.

These results align with the multi-level perspective (MLP) framework, in which AI adoption is influenced by niche-level innovations such as renewable energy integration, constrained by regime-level barriers including weak infrastructure and limited financial inclusion, and accelerated by landscape-level forces such as economic growth and environmental pressures. This layered interpretation emphasizes the need for coordinated policy interventions at all levels to support sustainable AI transitions in E-7 nations.
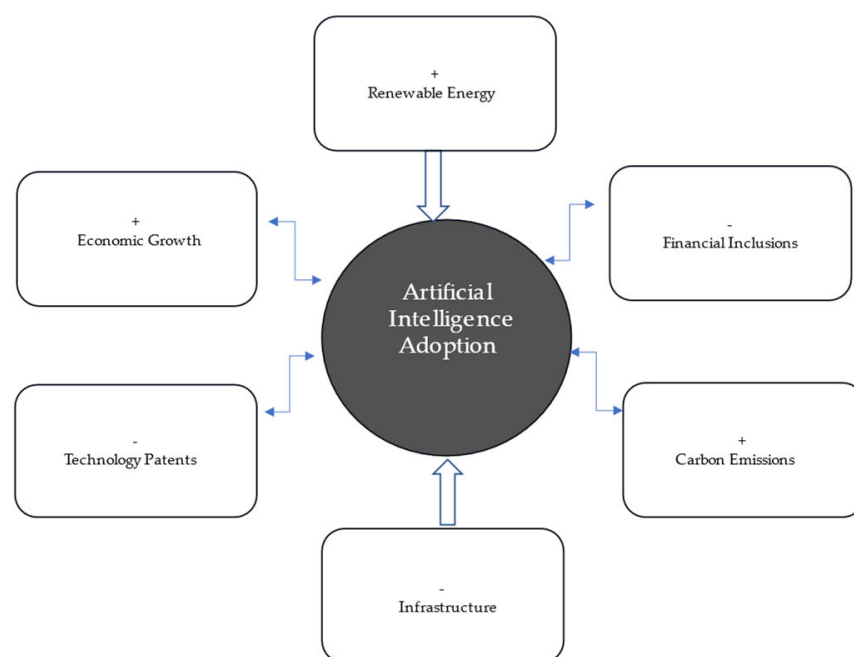

Figure 6. Graphical representation of results.

Table 8. Driscoll–Kraay method.

Log_AI	Coefficient	Std. Error	*p*-Value
log_Gdp	0.032 **	0.090	0.011
log_ES	1.117 ***	0.028	0.008
log_INFRA	−0.433 ***	0.040	0.003
log_FI	−0.228 ***	0.097	0.004
log_TP	−1.670 ***	0.046	0.000
log_Tpatent	−0.320 ***	0.016	0.002
log_CE	0.750 **	0.098	0.013
_cons	2.466 ***	3.480	0.000

The significance at 1%, 5%, and 10% is denoted by ***, **, and *, respectively.

5. Conclusions

The E-7 nations, representing the world's most dynamic emerging economies, stand at a critical juncture where the adoption of artificial intelligence (AI) could either catalyze sustainable development or exacerbate existing environmental and economic disparities. Despite the potential of AI to optimize renewable energy systems, enhance infrastructure efficiency, and expand financial access, the path to its integration is fraught with systemic obstacles. This study analyzes the main enablers of AI adoption across E-7 nations, focusing on the roles of energy structure, infrastructure, financial inclusion, economic growth, carbon emissions, population, and innovation. Our goal is to unravel the complex interplay between these factors and AI adoption to inform strategies that align technological progress with sustainability.

Our MMQREG analysis identifies renewable energy (energy structure) and economic growth (GDP) as pivotal catalysts for AI diffusion across E-7 nations. A 1% increase in renewable energy share (ES) boosts AI adoption by 0.806%. Conversely, infrastructure deficiencies and financial constraints consistently impede progress, where each 1% infrastructure improvement correlates with a 0.720% decline in adoption, while a 1% expansion in financial inclusion reduces uptake by 0.228%. Carbon emissions exhibit a J-curve relationship; a 1% emission increase accelerates adoption by 1.228% during initial deployment phases, though this effect reverses as efficiency gains materialize. Furthermore, patent activity demonstrates a negative relationship with adoption, indicating significant innovation–commercialization disconnects. This quantile-based perspective advances theoretical understanding of AI-sustainability transitions in emerging economies.

E-7 nations leverage AI for sustainable development, yet face trade-offs between technological advancement and environmental costs. AI adoption exacerbates carbon emissions due to energy-intensive infrastructure, but sustained integration enables efficiency gains that mitigate environmental harm. However, systemic barriers, such as weak institutional linkages between patent output and commercialization, prevent innovation from translating into scalable AI solutions. These insights highlight the urgency of policies that address infrastructural gaps, accelerate renewable energy transitions, and bridge innovation-to-adoption pathways to align AI adoption with the Sustainable Development Goals (SDGs).

5.1. Policy Implications

To address the pressing environmental challenges, E-7 nations should consider the following policy recommendations:

1. Expanding renewable energy projects, such as solar and wind, will reduce dependence on fossil fuels. AI technologies can optimize energy consumption, enhance grid efficiency, and support the transition to sustainable energy.
2. Modernizing smart energy grids, expanding high-speed internet access, and developing AI-friendly ecosystems are crucial for seamless AI integration across industries, particularly in the energy and financial sectors.
3. Governments should promote financial instruments such as green bonds and climate funds to attract investment in AI-powered sustainability projects, mobilizing capital for smart grids, emissions monitoring, and energy-efficient industries.
4. Fiscal incentives, including carbon taxes and subsidies for AI-driven clean energy solutions, can drive industries toward sustainable practices while promoting economic and environmental resilience.
5. Develop sectoral AI hubs like Java–Sumatra to commercialize patents and overcome adoption barriers. Launch training programs to certify workers in AI-for-sustainability by 2030.
6. Establish an E-7 AI Sustainability Consortium to share best practices in green AI deployment and policy design

5.2. Study Limitations

Endogeneity risks, such as bidirectional GDP–AI links, may persist despite MMQREG's robustness. Future studies could employ instrumental variables, including lagged policy shocks, or apply dynamic panel models to better isolate causality.

5.3. Future Research Directions

Future studies should explore the evolving regulatory landscape of AI in E-7 nations, ensuring a more tailored policy framework for sustainable development. Expanding the dataset to include real-time AI-driven innovations and sector-specific case studies would enhance the findings. Moreover, integrating advanced econometric techniques, such as machine learning models, could provide deeper insights into AI's long-term effects on economic and environmental sustainability.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be made available on request from the corresponding authors.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. E-7 vs. BRICS comparative metrics (2024).

Metric	E-7 Average	BRICS Average	Source
GDP growth rate (%)	3.6	2.8	World Bank (2025)
Renewable energy share (%)	22.5	18.7	BP Statistical Review

Table A1. *Cont.*

Metric	E-7 Average	BRICS Average	Source
AI adoption index (%)	15.7	12.3	Statista (2025)
Population (bn)	0.89	1.12	UN DESA (2025)

Table A2. Summary table of literature supporting key variables.

Variable	Supported By	Key Insight
Renewable energy (ES)	[13,28,32]	AI enables clean energy forecasting and grid optimization.
Infrastructure (INFRA)	[37]	Infrastructure quality influences AI integration across sectors.
Financial inclusion (FI)	[16,33]	AI-based fintech improves service delivery but faces rural access barriers.
GDP (growth)	[88,91]	Economic scale supports AI investment and digital transition.
Carbon emissions (CE)	[17,50]	AI may raise emissions initially; green integration is key to long-term gains.
Patent activity (Tpatent)	[87,91]	High patent output may not convert to AI adoption without commercialization.
Population (TP)	[88]	Population size drives digital service needs, affecting AI scale potential.

Table A3. Subperiod comparison of key variables (2004–2024).

Variable	2004–2010 (Mean $\pm$ SD)	2011–2020 (Mean $\pm$ SD)	2021–2024 (Mean $\pm$ SD)
AI	8.21 $\pm$ 6.32	16.54 $\pm$ 12.45	28.76 $\pm$ 18.21
GDP	4.12 $\pm$ 3.21	3.58 $\pm$ 3.45	3.01 $\pm$ 2.98
ES	18.22 $\pm$ 10.11	24.67 $\pm$ 14.32	29.01 $\pm$ 16.54

References

1. Li, D.; Wang, H.; Wang, J. Artificial Intelligence and Technological Innovation: Evidence from China's Strategic Emerging Industries. *Sustainability* **2024**, *16*, 7226. [CrossRef]
2. Robbins, S.; van Wynsberghe, A. Our New Artificial Intelligence Infrastructure: Becoming Locked into an Unsustainable Future. *Sustainability* **2022**, *14*, 4829. [CrossRef]
3. Zhao, C.; Dong, K.; Wang, K.; Nepal, R. How does artificial intelligence promote renewable energy development? The role of climate finance. *Energy Econ.* **2024**, *133*, 107493. [CrossRef]
4. Khan, M.S.; Umer, H.; Faruqe, F. Artificial intelligence for low-income countries. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 1422. [CrossRef]
5. Han, P.; He, T.; Feng, C.; Wang, Y. Research on Whether Artificial Intelligence Affects Industrial Carbon Emission Intensity Based on the Perspective of Industrial Structure and Government Intervention. *Sustainability* **2024**, *16*, 9368. [CrossRef]
6. Liu, J.; Shen, H.; Chen, J.; Jiang, X.; Siyal, A.W. Artificial Intelligence and Carbon Emissions: Mediating Role of Energy Efficiency, Factor Market Allocation and Industrial Structure. *Energies* **2025**, *18*, 1102. [CrossRef]
7. Rolnick, D.; Donti, P.L.; Kaack, L.H.; Kochanski, K.; Lacoste, A.; Sankaran, K.; Ross, A.S.; Milojevic-Dupont, N.; Jaques, N.; Waldman-Brown, A.; et al. Tackling Climate Change with Machine Learning. *ACM Comput. Surv.* **2023**, *55*, 1–96. [CrossRef]
8. Liu, J.; Qian, Y.; Yang, Y.; Yang, Z. Can Artificial Intelligence Improve the Energy Efficiency of Manufacturing Companies? Evidence from China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 2091. [CrossRef]
9. Fang, Y.; Lee, C.C.; Li, X. Assessing the impact of artificial intelligence on the transition to renewable energy? Analysis of U.S. states under policy uncertainty. *Renew. Energy* **2025**, *246*, 122969. [CrossRef]
10. Ozili, K. Impact of digital finance on financial inclusion and stability. *Borsa Istanb. Rev.* **2018**, *18*, 329–340. [CrossRef]
11. Iqbal, A.; Zhang, W.; Jahangir, S. Building a Sustainable Future: The Nexus Between Artificial Intelligence, Renewable Energy, Green Human Capital, Geopolitical Risk, and Carbon Emissions Through the Moderating Role of Institutional Quality. *Sustainability* **2025**, *17*, 990. [CrossRef]

12.   Adegbite, A.O.; Barrie, I.; Osholake, S.F.; Alesinloye, T.; Bello, A.B. Corresponding author: Ibrahim Barrie Artificial Intelligence in Climate Change Mitigation: A Review of Predictive Modeling and Data-Driven Solutions for Reducing Greenhouse Gas Emissions. *World J. Adv. Res. Rev.* **2024**, *24*, 408–414. [CrossRef]

13.   Tiwari, S.; Khan, S.; Mohammed, K.S.; Bilan, Y. Connectedness between artificial intelligence, clean energy, and conventional energy markets: Fresh findings from CQ and WLMC techniques. *Gondwana Res.* **2024**, *136*, 92–103. [CrossRef]

14.   Samour, A.; Ali, M.; Tursoy, T.; Radulescu, M.; Balsalobre-Lorente, D. The nexus between technological innovation, human capital and energy efficiency: Evidence from E7 countries. *Gondwana Res.* **2024**, *135*, 89–102. [CrossRef]

15.   Kshetri, N. The Role of Artificial Intelligence in Promoting Financial Inclusion in Developing Countries. *J. Glob. Inf. Technol. Manag.* **2021**, *24*, 1–6. [CrossRef]

16.   Sun, Y.; Li, T. Mehmood, Balancing acts: Assessing the roles of renewable energy, economic complexity, Fintech, green finance, green growth, and economic performance in G-20 countries amidst sustainability efforts. *Appl. Energy* **2025**, *378*, 124846. [CrossRef]

17.   Shan, T.; Feng, S.; Li, K.; Chang, R.; Huang, R. Unveiling the effects of artificial intelligence and green technology convergence on carbon emissions: An explainable machine learning-based approach. *J. Environ. Manag.* **2025**, *373*, 123657. [CrossRef]

18.   Kirikkaleli, D.; Sofuoğlu, E.; Ojekemi, O. Does patents on environmental technologies matter for the ecological footprint in the USA? Evidence from the novel Fourier ARDL approach. *Geosci. Front.* **2023**, *14*, 101564. [CrossRef]

19.   Oyebanji, M.O.; Castanho, R.A.; Genc, S.Y.; Kirikkaleli, D. Patents on Environmental Technologies and Environmental Sustainability in Spain. *Sustainability* **2022**, *14*, 6670. [CrossRef]

20.   Statista. AI Adoption Rate Selected Countries 2023. Available online: https://www.statista.com/statistics/1462656/ai-adoption-rate-numerous-countries/ (accessed on 18 March 2025).

21.   Nahar, S. Modeling the effects of artificial intelligence (AI)-based innovation on sustainable development goals (SDGs): Applying a system dynamics perspective in a cross-country setting. *Technol. Forecast. Soc. Change* **2024**, *201*, 123203. [CrossRef]

22.   Saba, C.S.; Monkam, N. Artificial intelligence's (AI's) role in enhancing tax revenue, institutional quality, and economic growth in selected BRICS-plus countries. *J. Soc. Econ. Dev.* **2025**, *2025*, 1–31. [CrossRef]

23.   Kalai, M.; Becha, H.; Helali, K. Effect of artificial intelligence on economic growth in European countries: A symmetric and asymmetric cointegration based on linear and non-linear ARDL approach. *J. Econ. Struct.* **2024**, *13*, 22. [CrossRef]

24.   Mehmood, U.; Aslam, M.U.; Javed, M.A. Associating Economic Growth and Ecological Footprints through Human Capital and Biocapacity in South Asia. *World* **2023**, *4*, 598–611. [CrossRef]

25.   Li, Y.; Li, T.; Javed, M.A.; Nassani, A.A. Examining the contribution of globalization, renewable energy, and economic growth towards CO_2 emissions in the G-7 countries. *Nat. Resour. Forum* **2024**, *2024*, 1–17. [CrossRef]

26.   Javed, M.A.; Mehmood, U.; Tariq, S.; Haq, Z.U. Long-term spatio-temporal trends in atmospheric aerosols and trace gases over Pakistan using remote sensing. *Acta Geophys.* **2023**, *72*, 489–508. [CrossRef]

27.   Javed, M.A.; Shamas, T. Sustainable Approaches for Developing Nations Through Education, Renewable Energy, and Foreign Direct Investment. *Int. J. Energy Environ. Res.* **2024**, *12*, 40–58. [CrossRef]

28.   Ukoba, K.; Olatunji, K.O.; Adeoye, E.; Jen, T.C.; Madyira, D.M. Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy Environ.* **2024**, *35*, 3833–3879. [CrossRef]

29.   McMillan, L.; Varga, L. A review of the use of artificial intelligence methods in infrastructure systems. *Eng. Appl. Artif. Intell.* **2022**, *116*, 105472. [CrossRef]

30.   Vasile, V.; Manta, O. FinTech and AI as Opportunities for a Sustainable Economy. *FinTech* **2025**, *4*, 10. [CrossRef]

31.   Grashof, N.; Kopka, A. Artificial intelligence and radical innovation: An opportunity for all companies? *Small Bus. Econ.* **2023**, *61*, 771–797. [CrossRef]

32.   Tao, W.; Weng, S.; Chen, X.; ALHussan, F.B.; Song, M. Artificial intelligence-driven transformations in low-carbon energy structure: Evidence from China. *Energy Econ.* **2024**, *136*, 107719. [CrossRef]

33.   Yang, S.; Wang, J.; Dong, K.; Dong, X.; Wang, K.; Fu, X. Is artificial intelligence technology innovation a recipe for low-carbon energy transition? A global perspective. *Energy* **2024**, *300*, 131539. [CrossRef]

34.   Earth5R. Artificial Intelligence on Renewable Energy in India ans It's Impact. Available online: https://earth5r.org/assessing-the-impact-of-artificial-intelligence-on-renewable-energy-in-india (accessed on 15 June 2025).

35.   Paula, M.; Casaca, W.; Colnago, M.; da Silva, J.R.; Oliveira, K.; Dias, M.A.; Negri, R. Predicting Energy Generation in Large Wind Farms: A Data-Driven Study with Open Data and Machine Learning. *Inventions* **2023**, *8*, 126. [CrossRef]

36.   Efthymiou, I.; Egleton, T.E. Artificial Intelligence for Sustainable Smart Cities. In *Handbook of Research on Applications of AI, Digital Twin, and Internet of Things for Sustainable Development*; IGI Global: Hershey, PA, USA, 2023. [CrossRef]

37.   Elassy, M.; Al-Hattab, M.; Takruri, M.; Badawi, S. Intelligent transportation systems for sustainable smart cities. *TransEng.* **2024**, *16*, 100252. [CrossRef]

38. Vinuesa, R.; Azizpour, H.; Leite, I.; Balaam, M.; Dignum, V.; Domisch, S.; Felländer, A.; Langhans, S.D.; Tegmark, M.; Fuso Nerini, F. The role of artificial intelligence in achieving the Sustainable Development Goals. *Nat. Commun.* **2020**, *11*, 233. [CrossRef]

39. Chen, M.; Wang, S.; Wang, X. How Does Artificial Intelligence Impact Green Development? Evidence from China. *Sustainability* **2024**, *16*, 1260. [CrossRef]

40. Regona, M.; Yigitcanlar, T.; Hon, C.; Teo, M. Artificial intelligence and sustainable development goals: Systematic literature review of the construction industry. *Sustain. Cities Soc.* **2024**, *108*, 105499. [CrossRef]

41. Wang, S.; Li, J.; Zhao, E. Exploring the role of financial technologies and digital trade in shaping trade-adjusted resource consumption in E7 countries. *Resour. Policy* **2024**, *88*, 104495. [CrossRef]

42. Ghouse, G.; Bhatti, M.I.; Nasrullah, M.J. The impact of financial inclusion, Fintech, HDI, and green finance on environmental sustainability in E-7 countries. *Financ. Res. Lett.* **2025**, *72*, 106617. [CrossRef]

43. Wang, Q.; Li, Y.; Li, R. Ecological footprints, carbon emissions, and energy transitions: The impact of artificial intelligence (AI). *Humanit. Soc. Sci. Commun.* **2024**, *11*, 1043. [CrossRef]

44. Taddeo, M.; Tsamados, A.; Cowls, J.; Floridi, L. Artificial intelligence and the climate emergency: Opportunities, challenges, and recommendations. *One Earth* **2021**, *4*, 776–779. [CrossRef]

45. Luo, Q.; Feng, P. Exploring artificial intelligence and urban pollution emissions: 'Speed bump' or 'accelerator' for sustainable development? *J. Clean. Prod.* **2024**, *463*, 142739. [CrossRef]

46. Zheng, X.; Ma, Z.; Yuang, Z. Urban design and pollution using AI: Implications for urban development in China. *Heliyon* **2024**, *10*, e37735. [CrossRef]

47. Olawade, D.B.; Wada, O.Z.; David-Olawade, A.C.; Fapohunda, O.; Ige, A.O.; Ling, J. Artificial intelligence potential for net zero sustainability: Current evidence and prospects. *Next Sustain.* **2024**, *4*, 100041. [CrossRef]

48. Ding, C.; Ke, J.; Levine, M.; Zhou, N. Potential of artificial intelligence in reducing energy and carbon emissions of commercial buildings at scale. *Nat. Commun.* **2024**, *15*, 5916. [CrossRef]

49. Naseem, S.; Ji, T.G.; Kashif, U. Exploring the Impact of Energy Consumption, Food Security on CO_2 Emissions: A Piece of New Evidence from Pakistan. *Int. Energy J.* **2020**, *20*, 115–128.

50. Allam, Z.; Dhunny, Z.A. On big data, artificial intelligence and smart cities. *Cities* **2019**, *89*, 80–91. [CrossRef]

51. Jobin, A.; Ienca, M.; Vayena, E. The global landscape of AI ethics guidelines. *Nat. Mach. Intell.* **2019**, *1*, 389–399. [CrossRef]

52. Floridi, L.; Cowls, J.; Beltrametti, M.; Chatila, R.; Chazerand, P.; Dignum, V.; Luetge, C.; Madelin, R.; Pagallo, U.; Rossi, F.; et al. AI4People—An Ethical Framework for a Good AI Society: Opportunities, Risks, Principles, and Recommendations. *Minds Mach.* **2018**, *28*, 689–707. [CrossRef]

53. Taddeo, M.; McNeish, D.; Blanchard, A.; Edgar, E. Ethical Principles for Artificial Intelligence in National Defence. *Philos. Technol.* **2021**, *34*, 1707–1729. [CrossRef]

54. Naseem, S.; Kashif, U.; Rasool, Y.; Akhtar, M. The impact of financial innovation, green energy, and economic growth on transport-based CO_2 emissions in India: Insights from QARDL approach. *Environ. Dev. Sustain.* **2023**, *26*, 28823–28842. [CrossRef]

55. Zhao, X.; Wu, W.; Wu, D. How does AI perform in industry chain? A patent claims analysis approach. *Technol. Soc.* **2024**, *79*, 102720. [CrossRef]

56. Nepal, R.; Zhao, X.; Dong, K.; Wang, J.; Sharif, A. Can artificial intelligence technology innovation boost energy resilience? The role of green finance. *Energy Econ.* **2025**, *142*, 108159. [CrossRef]

57. Jiang, M.; Yu, X. Enhancing the resilience of urban energy systems: The role of artificial intelligence. *Energy Econ.* **2025**, *144*, 108313. [CrossRef]

58. PatentPC, AI Patent Boom: The Latest Stats on Global AI Patent Filings. Available online: https://patentpc.com/blog/ai-patent-boom-the-latest-stats-on-global-ai-patent-filings (accessed on 15 June 2025).

59. Kashif, U.; Shi, J.; Li, S.; Wu, Q.; Song, Q.; Dou, S.; Wei, M.; Naseem, S. Navigating the digital divide: Unraveling the impact of ICT usage and supply on SO_2 emissions in China's Yangtze River Delta. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 777. [CrossRef]

60. Kashif, U.; Shi, J.; Naseem, S.; Dou, S.; Zahid, Z. ICT service exports and CO_2 emissions in OECD countries: The moderating effect of regulatory quality. *Econ. Change Restruct.* **2024**, *57*, 1–17. [CrossRef]

61. Filho, M.G.; de Almeida, S.V.Q.; Junior, M.L.; Osiro, L.; Lima, B.; Callefi, M.H. A path to follow to overcome foundational barriers to the adoption of artificial intelligence within the manufacturing industry: A conceptual framework. *EnterInf. Syst.* **2025**, *19*, 2458685. [CrossRef]

62. Borines, A.; Teckle, P.; Turi, A.N. Exploring the Current AI Landscape in Global South Economies: A Systematic Literature Review and Research Agenda. In *Tech Transformation and AI Readiness. Future of Business and Finance*; Springer: Cham, Switzerland, 2025; pp. 1–30. [CrossRef]

63. Li, G.; Sun, Z.; Wang, Q.; Wang, S.; Huang, K.; Zhao, N.; Di, Y.; Zhao, X.; Zhu, Z. China's green data center development: Policies and carbon reduction technology path. *Environ. Res.* **2023**, *231*, 116248. [CrossRef]

64. BenYishay, A.; Heuser, S.; Runfola, D.; Trichler, R. Indigenous land rights and deforestation: Evidence from the Brazilian Amazon. *J. Environ. Econ. Manag.* **2017**, *86*, 29–47. [CrossRef]

65. Geels, F.W. Technological transitions as evolutionary reconfiguration processes: A multi-level perspective and a case-study. *Res. Policy* **2002**, *31*, 1257–1274. [CrossRef]

66. Terry, O.; Terry, O. Disruption Innovation and Theory. *J. Serv. Sci. Manag.* **2020**, *13*, 449–458. [CrossRef]

67. Nelson, R.R.; Sampat, B.N. Making sense of institutions as a factor shaping economic performance. *J. Econ. Behav. Organ.* **2001**, *44*, 31–54. [CrossRef]

68. Belaïd, F.; Al-Sarihi, A. Saudi Arabia energy transition in a post-paris agreement era: An analysis with a multi-level perspective approach. *Res. Int. Bus. Financ.* **2024**, *67*, 102086. [CrossRef]

69. Siakwah, P.; Ermolaeva, Y.V.; Ermolaeva, P.O.; Agyekum, B. Sustainable Energy Transition in Russia and Ghana Within a Multi-Level Perspective. *Chang. Soc. Personal.* **2023**, *7*, 165–185. [CrossRef]

70. Jayaraj, N.; Klarin, A.; Ananthram, S. The transition towards solar energy storage: A multi-level perspective. *Energy Policy* **2024**, *192*, 114209. [CrossRef]

71. Zeng, Y.; Shi, Y.; Wei, Z.; Zafar, M.W. Exploring the duality of disruptive innovation: A technology-utility model analysis of market encroachment. *Manag. Syst. Eng.* **2023**, *2*, 13. [CrossRef]

72. Foster, V.; Trotter, P.A.; Werner, S.; Niedermayer, M.; Mulugetta, Y.; Achakulwisut, P.; Brophy, A.; Dubash, N.K.; Fankhauser, S.; Hawkes, A.; et al. Development transitions for fossil fuel-producing low and lower–middle income countries in a carbon-constrained world. *Nat. Energy* **2024**, *9*, 242–250. [CrossRef]

73. Machado, J.A.F.; Silva, J.M.C.S. Quantiles via moments. *J. Econom.* **2019**, *213*, 145–173. [CrossRef]

74. Pesaran, M.H. General Diagnostic Tests for Cross Section Dependence in Panels 2004. *Economics* **2004**, *1240*, 1.

75. Pesaran, M.H. A simple panel unit root test in the presence of cross-section dependence. *J. Appl. Econom.* **2007**, *22*, 265–312. [CrossRef]

76. Levin, A.; Lin, C.-F.; Chu, C.-S.J. Unit root tests in panel data: Asymptotic and finite-sample properties. *J. Econom.* **2002**, *108*, 1–24. [CrossRef]

77. Westerlund, J.; Edgerton, D.L. A Simple Test for Cointegration in Dependent Panels with Structural Breaks. *Oxf. Bull. Econ. Stat.* **2008**, *70*, 665–704. [CrossRef]

78. Griliches, Z. Patent Statistics as Economic Indicators. In *R&D and Productivity: The Econometric Evidence*; University of Chicago Press: Chicago, IL, USA, 1998; pp. 1–14.

79. Hall, B.H.; Jaffe, A.; Trajtenberg, M. Market Value and Patent Citations. Available online: http://www.nber.org/patents/ (accessed on 13 May 2025).

80. World Intellectual Property Report 2022—The Direction of Innovation. Available online: https://www.wipo.int/en/web/world-ip-report/2022/index (accessed on 13 May 2025).

81. Stanford HAI. The Global AI Vibrancy Tool 2024. Available online: https://hai.stanford.edu/research/the-global-ai-vibrancy-tool-2024 (accessed on 12 May 2025).

82. Government AI Readiness Index—Oxford Insights. Available online: https://oxfordinsights.com/ai-readiness/ai-readiness-index/ (accessed on 12 May 2025).

83. Pingali, S.R.; Singha, S.; Arunachalam, S.; Pedada, K. Digital readiness of small and medium enterprises in emerging markets: The construct, propositions, measurement, and implications. *J. Bus. Res.* **2023**, *164*, 113973. [CrossRef]

84. Energy Economics | Home. Available online: https://www.bp.com/en/global/corporate/energy-economics.html (accessed on 30 March 2025).

85. WDI—Home. Available online: https://datatopics.worldbank.org/world-development-indicators/ (accessed on 23 September 2024).

86. World Bank Open Data | Data. Available online: https://data.worldbank.org/ (accessed on 19 March 2025).

87. Gonzales, J.T. Implications of AI innovation on economic growth: A panel data study. *J. Econ. Struct.* **2023**, *12*, 1–37. [CrossRef]

88. Selten, F.; Klievink, B. Organizing public sector AI adoption: Navigating between separation and integration. *Gov. Inf. Q.* **2024**, *41*, 101885. [CrossRef]

89. Zhang, L.; Ling, J.; Lin, M. Artificial intelligence in renewable energy: A comprehensive bibliometric analysis. *Energy Rep.* **2022**, *8*, 14072–14088. [CrossRef]

90. Siddik, A.B.; Forid, M.S.; Yong, L.; Du, A.M.; Goodell, J.W. Artificial intelligence as a catalyst for sustainable tourism growth and economic cycles. *Technol. Forecast. Soc. Change* **2025**, *210*, 123875. [CrossRef]

91. Hossin, M.A.; Alemzero, D.; Wang, R.; Kamruzzaman, M.M.; Mhlanga, M.N. Examining artificial intelligence and energy efficiency in the MENA region: The dual approach of DEA and SFA. *Energy Rep.* **2023**, *9*, 4984–4994. [CrossRef]