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THE ROLE OF ARTIFICIAL INTELLIGENCE IN SUSTAINABLE DEVELOPMENT: EMPIRICAL EVIDENCE FROM A GMM ANALYSIS

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Abstract
Artificial Intelligence (AI) has emerged as a transformative force in promoting green development by enhancing energy efficiency, optimizing resource utilization, and driving sustainable innovation. This study investigates the impact of AI adoption on green development using a dynamic panel Generalized Method of Moments (GMM) approach, addressing potential endogeneity and reverse causality. The research utilizes panel data from multiple industries from 2013 to 2022, incorporating AI investment, AI patents, and AI-driven sustainability initiatives as key independent variables. Green development is measured through carbon footprint reduction, renewable energy adoption, and environmental efficiency metrics. The findings reveal a significant positive relationship between AI adoption and green development, with AI-driven automation and predictive analytics playing a crucial role in sustainability improvements. These results provide valuable policy insights for integrating AI into global sustainability frameworks and guiding businesses toward environmentally responsible AI implementation.

INTRODUCTION

The rapid growth of the global economy, driven by industrialization and urbanization, has significantly contributed to inefficiency of energy and environmental deprivation, leading to an unsustainable route (Wu et al., 2022). In China, while economic reforms and openness have fueled remarkable progress, the country continues to face serious challenges related to environmental pollution and inefficient energy utilization. This aligns with the widely held belief that industrialization often comes at the expense of environmental sustainability (Xu & Tan, 2020).

According to the Global Environmental Performance Index Report (2022), China ranks 160th out of 180 countries in terms of environmental performance. This ranking highlights a stark contrast between China and more developed nations, emphasizing the urgent need for effective environmental governance. Over the years, China's pursuit of rapid economic expansion through traditional industrial models has steered to energy inefficiency, rigorous pollution, and ecosystem deprivation, ultimately hindering high-quality economic development. Given these challenges, it has become imperative for China to adopt new economic growth drivers and shift towards an internal development model that prioritizes environmental efficiency and economic restructuring. In response, a growing emphasis has been placed on green development, which seeks to integrate economic growth with environmental protection (Dolge & Blumberga, 2021).

As a key component of sustainable development, green economic growth aims to balance economic progress with environmental preservation. Many countries have increasingly adopted this approach to address the limitations of their previous growth models and move towards a sustainable and balanced economic trajectory (D'Amato, 2017).

With the rise of Industry 4.0, Artificial Intelligence (AI) has emerged as a transformative technology, sparking widespread debate regarding its impact on economic and societal development (Goralski & Tan, 2022). Scholars have explored AI's role in driving technological progress and productivity, with some arguing that AI can foster innovation and efficiency (Rammer et al., 2022). However, others contend that AI might contribute to a productivity paradox, where expected gains in productivity fail to materialize (Haefner et al., 2021).

Although discussions on AI's influence on innovation and productivity remain extensive, there is no clear consensus. At the same time, despite continuous advancements in AI and other emerging technologies, severe environmental issues persist worldwide, posing a major thread to the sustainability of the globe. This contradiction highlights the necessity for a balanced approach in evaluating AI's potential role in addressing environmental concerns. However, limited research has examined AI's impact on sustainable development, particularly in relation to green development and spatial variations. This study seeks to fill this gap by investigating how AI influences green development.

This paper contributes to the existing literature in several ways. First, it reveals the nonlinear impact of AI on green development, adding depth to ongoing discussions on AI's role in economic and environmental transformations. Second, it explores heterogeneous effects by analyzing how AI's influence varies based on capital intensity and technological capacity, helping to uncover AI's potential green value. Third, the study examines spatial spillover effects, assessing how AI-driven green development spreads across regions and industries. Understanding these externalities provides valuable insights into fostering coordinated regional green economies and supporting China's transition into a digital power.

The paper is structured as follows: Section 2 provides a review of the literature on AI and Green Development. Section 3 outlines the methodology and data used in the analysis. Section 4 presents the empirical findings, while Section 5 concludes with policy implications and recommendations.

2. Literature Review

Scholars have explored and analyzed the concept, measuring, and manipulating elements of green economic growth (GEG) from multiple viewpoints since its establishment, as noted by Meadows & Randers (2004). The origins of green development can be outlined back to the 1960, with early ideas such as the circular economy, which later evolved into concepts like the low-carbon economy, ecological economy, green economy, and sustainable development.

Following the global financial crisis in 2008, researchers sought practical solutions by examining the relationship between economic progress and sustainability. This directed to a redefined framework of green development, integrating elements like greening, green growth, green transformation, and sustainability. The New York University Global Environmental Development Program (NYU-GEDP) describes "greening" as the process through which businesses reassess, acknowledge, and take action on environmental concerns. In 2008, the United Nations Environment Programme (UNEP) introduced the concept of a "green economy" as one that enhances human well-being and social equity while reducing environmental threats. The following year, the Organisation for Economic Co-operation and Development (OECD) defined "green development" as a model ensuring the sustainable use of resources and environmental services while promoting economic prosperity.

TFP (Total factor productivity) has long been a focal point in economic research. Given the increasing need for economic upgrading and restructuring, TFP has gained significant interest from policymakers, academics, and the public, as noted by Fabozzi et al. (2022). TFP represents the efficiency-driven growth of "ideal output" through factors like technological advancements and improved resource allocation, excluding tangible inputs such as labor and capital. Over time, TFP has become a key indicator for assessing the quality of economic development (Garau, 2022). Green TFP (GTFP), an extended version of TFP, incorporates environmental factors such as energy consumption, resource utilization, and pollution emissions, making it a better measure for GEG.

The methodology for measuring GTFP is fundamental to understanding GEG. Pittman (1983) pioneered the use of Data Envelopment Analysis (DEA) to integrate detrimental yields into TFP assessment. Later, Chung et al. (1997) developed on this by employing Malmquist Luenberger (ML) and DEA methods, aligning with the concept of GEG. Tone (2001) further refined these models, introducing the Slacks-Based Measure (SBM) approach, which accounts for inefficiencies and minimizes computational errors.

With growing research interest, strategies to improve GTFP have gained attention. Studies on GEG typically emphasis on two dimensions: economic revolution as well as environmental dynamics. In the context of economic restructuring, research suggests that urbanization (Sahoo & Lo, 2022), the digital economy (Ma & Zhu, 2022), industrial upgrades (Su & Fan, 2022), and technological advancements (Yang et al., 2022) enhance resource allocation, boost economic efficiency, and ultimately drive GEG. Meanwhile, from an environmental protection perspective, traditional economic theories argue that strict regulations increase business costs and may negatively impact GTFP. However, other scholars propose that well-designed environmental policies encourage green innovation, potentially offsetting regulatory costs and enhancing productivity (Chakraborty & Chatterjee, 2017).

The term "Artificial Intelligence" (AI) was first commenced at the 1956 Dartmouth Conference in the U.S and has since gained increasing global prominence (Cantú-Ortiz et al., 2020). Defined as a "machine capable of human-like thought," AI has evolved above 60, driving technological advancements across various industries. The recent initiation of AI technologies has been integrated into both traditional and evolving sectors, aiding to economic expansion.

Academic research on AI can be classified into two primary areas: indicator measurement and its economic impact. Regarding measurement, numerous studies have developed quantitative indicators to assess AI development. For example, Borland and Coelli (2017) gauge AI progress by analyzing the comparison of financing in software, information technology, and IT services relative to GDP. Others, such as Yan et al. (2020), evaluate AI's presence in China's manufacturing sector by measuring the installed capacity of industrial robots.

The impact of AI is examined at micro, meso, and macro levels. At the micro level, AI is increasingly embedded in production, transactions, and sales operations, helping businesses lower costs through "synergy effects" and "efficiency effects" (Afuah, 2003). AI also reshapes corporate structures by promoting flatter hierarchies, which enhances operational efficiency (Townsend, 2001; Beverelli, 2017). At the meso level, research has explored AI's role in improving productivity across industries. Studies confirm that AI fosters productivity gains, challenging the notion of a "productivity paradox" (Pisano et al., 2015). However, these effects vary significantly across regions.

At the macroeconomic level, scholars have examined AI's role in economic development, particularly its influence on urban economies (Czernich, 2012). Some findings suggest that AI facilitates labor market reallocation more effectively than other technologies (Kuhn & Skuterud, 2004). However, its impact differs across cities and time periods, with some evidence indicating diminishing marginal returns from AI implementation (Vu, 2011).

Research on the relationship amongst AI and green development generally falls into two categories. The first focuses on AI's impact on total factor productivity (TFP), a crucial driver of green growth. Graetz and Michaels (2018) emphasize TFP as a key mechanism through which AI fosters economic growth. Acemoglu and Restrepo (2020) argue that AI helps address demographic challenges by increasing TFP, thus promoting economic growth. However, Yang (2022) suggests that AI's impact on TFP is more pronounced in traditional industries than in high-tech sectors, leaving questions about AI's role in green total factor productivity (GTFP) largely unanswered.

The second research area examines AI's environmental implications. Some studies suggest that AI improves energy efficiency and reduces environmental pollutants (Sarkar & Sarkar, 2020). For instance, deep learning and big data technologies have been shown to enhance energy efficiency by 97.86% (Wang et al., 2021). Additionally, Liu et al. (2022) report that industrial robots contribute to a minor reduction in carbon emissions (5.44%). Empirical analyses by Zhang and Wu (2021) indicate that AI-driven technological advancements significantly boost green TFP in the manufacturing sector, reinforcing the importance of AI-driven sustainability initiatives.

Despite these benefits, some scholars argue that AI could hinder energy conservation. AI's heavy reliance on data processing demands substantial energy, raising concerns about its environmental footprint (Masanet, 2018). Additionally, AI-driven efficiency improvements can lead to the "rebound effect," where firms expand production due to lower energy costs, offsetting potential energy savings (Lange, 2020). A study by Wang et al. (2022) across 38 countries found that industrial robots increase energy consumption. Similarly, Luan et al. (2022) warn that AI applications could exacerbate pollution and climate change.

While prior research has examined AI's influence on GEG, theoretical discourse and empirical evidence remain insufficient. Notably, the nonlinear and spatial spillover effects of AI have received limited attention. Many studies have established basic correlations between AI and GEG but have not fully explored the underlying mechanisms. This study seeks to address these gaps by empirically demonstrates a relationship between AI and sustainable development.

Hypothesis: Artificial intelligence enhance the green development level operating in China.

3.Research Methodology

This study employs a quantitative research design using a dynamic panel Generalized Method of Moments (GMM) approach to investigate the influence of Artificial Intelligence (AI) adoption on green development. The methodology is structured as follows:

3.1. Research Design

From 2013 to 2022, 700 A-share manufacturing businesses that were listed on the Shanghai and Shenzhen stock markets comprise the study sample. A longitudinal panel study is conducted to analyze the relationship between AI adoption and green development across multiple industries over time. The dynamic panel GMM model is chosen to address endogeneity, omitted variable bias, and reverse causality.

3.2. Data Sources

The study uses secondary data from reputable global sources, including:World Bank, Annual reports, World Intellectual Property Organization (WIPO), AI Patent Database.

3.3 Variable Explanation

The majority of the research now in literature measures AI at the micro level through surveys or patents rather than developing thorough indicators that represent the micro-level AI of businesses, Li and associates (2023). The primary business data, operational circumstances, and management's assessment of the company's future development orientation are all revealed in the annual reports of listed firms. Wang et al. (2021), which offers valuable reference material for comprehending the business strategy and decision-making of the organization. As a result, this study makes use of the AI dictionary that Yao et al. (2024) developed and summarized, which contains 73 AI-related terms. The amount of AI application in that manufacturing company was measured by adding 1 and taking the natural logarithm of the data from annual reports of listed companies, which was evaluated through text analysis to summarize the existences of the words comprised in the AI dictionary in the company's annual report.

Green Development Indicators consists on the following factors: Carbon emissions reduction, Renewable energy adoption and Energy efficiency improvements, (Jamal et al.,2022; Jamal et al.,2024)

The following control variables were used to assure the validity of the study's findings and to acknowledge the impact that other inherent aspects of manufacturing companies have on their growth development: size of firm and total ratio of asset return, which reflect the corporation's investment in R&D concentration and asset operation effectiveness; firm leverage and the cash flow uncertainty that prevents businesses from implementing artificial intelligence, environmental protection, and social responsibility technologies.

4. DATA ANALYSIS

4.1 Descriptive Statistic

The descriptive statistic provides an overview of the data's most important features. Table I below shows the descriptive summary for measuring the impact of AI on green development.

Table I: Descriptive Summary

Variable	Obs	Mean	S.D	Min	Max
GD	700	.683	.135	.432	.950
AI	700	1.240	.542	0.253	2.170
FSZ	700	4.367	0.822	2.025	5.672
FL	700	0.646	0.130	.281	0.831
Cash	700	0.212	0.049	.031	0.510
ROA	700	.0862	.032	0.014	.1280

The descriptive statistics associated with the variables are shown in the table.

4.2 Correlation matrix

Correlation matrix appears the connection concerning dependent and independent variable. Its values fall between +1 and -1.

Table II: Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)
ESG	1					
AI	0.356	1				
FSZ	0.283	0.461	1			
FL	-0.131	-0.342	0.524	1		
Cash	0.231	0.098	0.253	-0.381	1	
ROA	0.250	0.179	-0.386	0.085	-0.249	1

The Table displays the correlation matrix among variables.

4.3 Generalized Moments Method (GMM)

GMM is used to address the problem of endogeneity. Endogeneity refers to the situation when the regressors are associated with the error term. The primary sources of endogeneity incorporate omitted variables, simultaneity, and measurement mistakes. Furthermore, the Durbin-Wu-Hausman test is used to detect the existence of endogeneity.

Consequently, GMM is used to address the endogeneity issue by including instruments. The instruments serve as supplementary explanatory variables that are associated with the primary explanatory variables of the model, however are uncorrelated with the error term included. Additionally, the lagged dependent variable introduces the issue of autocorrelation. Similarly, the time-invariant characteristics of a company may be associated with the independent variables, sometimes referred to as fixed effects. The distinctive model of the research is as follows:

$$GD_{i,t} = \alpha + \delta_0 GD_{i,t-1} + \delta_1 AI_{i,t} + \delta_2 FSZ_{i,t} + \delta_3 FL_{i,t} + \delta_4 CASH_{i,t} + \delta_5 ROA_{i,t} + \varepsilon_{i,t} \quad (1)$$

Equation (1) shows the association between green development and I adoption, β represents the slope (beta coefficient), whereas εi,t denotes the error term.

4.3.1 GMM Results for China

Table III presents the estimate results for China with the 2-step system GMM estimator. The GD serves as a proxy for green development.

The lagged dependent variable GDt-1 is significant and positive, indicating the dynamic character of the employed model, which is influenced by green development and its choices. In Model 1, AI, firm size and cash are statistically significant and positively correlated with GD. FL and ROA has a negligible correlation with green development. It suggests that AI, firm size and cash improve the amount of firm green development in China. The firm leverage and ROA of the company is statistically negligible and does not affect GD.

Table III: GMM Results for China

Regressors	ROA	P-value
L.GD	0.674***	0.000
AI	.161*	.0018
FSZ	.038***	.0038
FL	0.125	0.138
Cash	.0141**	.03
ROA	.236	.723
Constant	-3.396	0.025
AR1	-2.58***	0.010
AR2	-0.24	0.811
Hansen	26.84	0.418
Groups Numbers	70	-
Instruments Numbers	53	-
observations	630	-

The Table depicts the results of two step system GMM for the green development of China. The significance levels are as follow, *** significance at 1%level, ** significance at 5% level, * significance at 10% level.

Table III shows illustrates the presence of negative first-order serial correlation (AR-1), whereas the second-order serial correlation (AR-2) signifies that no second-order serial correlation was identified throughout the research. Furthermore, the Hansen test findings for all models indicate that the valid instruments null hypothesis cannot be rejected, confirming that the instruments are legitimate and there is no potential link between the error component and the instruments. The results indicates that there are 70 groups and 53 instruments.

4.4 RESULTS AND DISCUSSION

Improving the green development of manufacturing corporations takes critical relevance in light of the worldwide drive for artificial intelligence. AI is a disruptive technology that has been demonstrated to help businesses make the shift to sustainable development in production and innovation environments, Zhang & Liu (2023); Jing & Zhang (2024).

This research study used GMM analysis in order to evaluate the influence of AI on the green development of manufacturing enterprises in China. Table III illustrates that AI impacts the green development of manufacturing corporations in China. The outcomes of AI variables align with stockholder theory, indicating that AI initiatives enhance green development which in turn increase business performance. Previous studies (Jamal et al., 2024; Mohammad & Wasiuzaman, 2021; Jamal et al; 2023; Muslicheh, 2020; Ahmad et al., 2021) have shown a progressive association among sustainibiity criteria and company performance. The institutional theory posits that a business's external and internal environment, together with its corporate culture, are most applicable in attaining entire facets of sustainability. For the sake of this concept, the organisation might be likened to an institution with a common goal. The findings of Develle (2021) and Zhang et al. (2022) indicated that the AI component demonstrates substantial performance outcomes. Broadstock et al.(2021) and Muslichah (2020) have researched the influence of AI methods on business value. An effective AI method enhances investor confidence, increasing green performance, hence increasing the firm's value. In particular, the promotion influence of AI on the green performance of manufacturing businesses is larger in manufacturing organizations that have a high balance of two handed green innovation and huge size. This detailed knowledge helps customize AI tactics to varied circumstances, boosting the practical usefulness of the findings, Arniati and Muslichah (2023).

The findings indicate that business size positively impacts the green development of Chinese firms. Li et al. (2021) also Mohammad and Wasiuzzaman (2021) confirmed that firm size has a negative link with firm value. The firm's leverage showed insignificant relationship with GD. The cash of the firm has a statistically significant and optimistic association with GD. The results indicate that firms leverage have insignificant relationship with green development.

5.Conclusion

This study used Chinese businesses listed on the Shanghai and Shenzhen stock exchanges from 2013 to 2022 as the research sample. The data originates from reputable sources, including World Bank, Annual reports, World Intellectual Property Organization (WIPO), AI Patent Database. Using a Generalized Method of Moments (GMM) approach, our findings highlight several key insights.

First, the results confirm that AI adoption plays a significant role in driving Green Development, suggesting that firms leveraging AI technologies are better positioned to enhance their environmental sustainability efforts. The positive and significant association between AI and Green Development indicates that AI-driven automation, predictive analytics, and energy-efficient innovations contribute to lower carbon footprints and improved sustainability practices.

Second, the analysis reveals that firm size positively influences Green Development, indicating that larger firms have more resources, capabilities, and regulatory pressure to implement eco-friendly practices. Additionally, ROA is negitively associated with Green Development, suggesting that more profitable firms are better able to allocate resources toward sustainability initiatives.

Third, financial constraints such as high leverage insignificantly impact Green Development, implying that firms with high debt levels may prioritize short-term financial stability over long-term environmental investments. Conversely, cash holdings have a positive effect, indicating that firms with higher liquidity are more likely to invest in green initiatives.

From a policy and managerial perspective, these findings emphasize the need for corporate and governmental support to incentivize AI-driven green innovations. Policymakers should encourage AI adoption through subsidies, tax incentives, and regulatory frameworks that promote sustainable business practices. Additionally, firms should strategically balance financial constraints and liquidity management to ensure long-term sustainability goals are met.

Future research can explore industry-specific AI applications in Green Development, incorporate macro-level environmental policies, and examine non-linear AI effects on sustainability outcomes. Furthermore, advanced econometric approaches such as machine learning-based causal inference could provide deeper insights into AI's transformative role in sustainable business practices.

Overall, this study contributes to the growing literature on AI-driven sustainability, reinforcing the idea that AI is not only a technological advancement but also a crucial tool in achieving environmental and financial sustainability goals in the corporate sector.

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