

The Impact of AI Technology on the Green Development of Manufacturing Enterprises in Ghana

Abangbila Linda*, Xianmiao Li

School of Economics and Management, Anhui University of Science and Technology, Huainan, China

Email: *Sabangbila@gmail.com, lixm1122@163.com

How to cite this paper: Linda, A., & Li, X. M. (2025). The Impact of AI Technology on the Green Development of Manufacturing Enterprises in Ghana. *Low Carbon Economy*, 16, 94-109.

<https://doi.org/10.4236/lce.2025.163005>

Received: July 10, 2025

Accepted: September 9, 2025

Published: September 12, 2025

Copyright © 2025 by author(s) and Scientific Research Publishing Inc. This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

Artificial Intelligence (AI) is revolutionizing industries globally, with profound implications for manufacturing systems and environmental sustainability. In Sub-Saharan Africa, including Ghana, the push for industrialization presents environmental challenges, making it crucial to integrate green technologies. This study investigates the adoption of AI in Ghana's manufacturing sector, exploring its impact on green manufacturing practices and barriers to AI integration. Data was collected via an online survey with a 91.5% response rate (400 out of 455), yielding 400 valid responses. The survey revealed a predominantly male workforce (70%) aged 30 - 40 years (55%), with high education levels. Correlation analysis showed significant relationships between Corporate Green Innovation (0.723), Sustainable Manufacturing Practices (0.723), and Environmental Governance (0.547). AI technology had a moderate correlation with Environmental Governance (0.618). While Sustainable Manufacturing Practices achieved the highest mean score (4.133), Environmental Risk Factors scored the lowest (2.812), indicating challenges in addressing sustainability. The study used the PROCESS macro for mediation and moderation analysis. Findings revealed that Environmental Governance significantly influences Corporate Green Innovation (coefficient = 0.750, $p < 0.05$), whereas AI Technology's direct impact was not statistically significant (coefficient = -0.011 , $p = 0.707$). The interaction between AI and Environmental Governance was not significant (coefficient = -0.032 , $p = 0.503$), suggesting the moderating role of governance is minimal. The study concludes that AI alone does not directly drive green innovation in Ghana's manufacturing sector. Strong environmental governance is pivotal, offering a framework for policymakers to foster AI-driven, sustainable industrial practice.

Keywords

AI Technology, Green Development, Manufacturing Enterprises, Ghana, Sustainable Manufacturing

1. Introduction

Global manufacturing industries are undergoing a profound transformation driven by escalating concerns over resource depletion, environmental degradation, and the urgent need for sustainable economic growth (Moalla & Miçooğulları, 2023). As climate change and ecological pressures intensify, manufacturers worldwide must reexamine their production practices and adopt green development strategies that reduce waste, lower energy consumption, and mitigate environmental impacts (Zhang & Nakatani, 2024). This convergence of industrial modernization and sustainability imperatives has spurred widespread interest in integrating advanced digital technologies, most notably Artificial Intelligence (AI) and Internet of Things (IoT) systems into production processes (Tan et al., 2022). Such integrations promise to optimize production efficiency and enable manufacturing enterprises to transition toward greener, more resource-efficient models (Kracker & Sachs, 2024). For manufacturing sectors in emerging economies such as Ghana, where economic growth and environmental concerns are closely intertwined, adopting AI-driven solutions represents a critical pathway toward sustainable industrial development.

The manufacturing sector in Ghana, like in many Sub-Saharan African countries, is pivotal for economic diversification, job creation, and overall national development (Adediran, 2023). However, this industrial growth often comes with significant environmental costs, including increased pollution, resource depletion, and carbon emissions (Dong et al., 2020). The concept of “green development” in manufacturing thus emphasizes a paradigm shift towards production systems that are economically viable, environmentally sound, and socially responsible (Kalchschmid et al., 2023). AI technologies offer a suite of tools that can facilitate this transition by enabling predictive maintenance to reduce waste, optimizing energy consumption, improving supply chain logistics for lower emissions, and fostering innovation in green product design (Picaud-Bello et al., 2024). Despite the potential benefits, the adoption of AI in Ghanaian manufacturing enterprises faces several hurdles. These include the high initial investment costs, a shortage of skilled AI professionals, inadequate digital infrastructure, and a lack of awareness regarding AI’s potential for green development (Maghfirah & Eni, 2024). Furthermore, the existing environmental governance framework may not be sufficiently robust or adapted to guide and incentivize the integration of AI for sustainable outcomes (Anthuvan & Maheshwari, 2025). Understanding the interplay between AI technology adoption, corporate green innovation, sustainable manufacturing practices, and the overarching role of environmental governance is crucial for un-

locking the potential of AI in Ghana's green industrial transformation (Abbas & Mahmood, 2025).

The primary aim of this study is to investigate and analyze the core research questions central to understanding the interplay between AI technology and green development within Ghana's manufacturing sector. These objectives seek to systematically assess critical dimensions of AI adoption, including its technological feasibility, socio-economic implications, and environmental outcomes, within the context of sustainable industrialization. Through this research process, the study aims to achieve a nuanced understanding of how AI-driven innovations can address sustainability challenges while contributing novel insights to the existing body of knowledge on technology-enabled green transitions (Shirahase, 2023). Specifically, the research objectives are: 1) To assess the current level of AI technology adoption in Ghanaian manufacturing enterprises, and 2) To examine the relationship between AI technology adoption and corporate green innovation. The integration of Artificial Intelligence (AI) technology has become a pivotal factor in driving green development in manufacturing enterprises globally (Susithra & Vasantha, 2024). In the context of Ghana, the adoption of AI has the potential to revolutionize sustainable practices in the manufacturing sector by enhancing operational efficiency, reducing resource consumption, and promoting eco-friendly innovation (Ram et al., 2018). However, understanding the combined impact of AI technology, organizational culture, and managerial commitment to green manufacturing practices requires a more comprehensive and interconnected approach, considering their complexity and mutual effects (Lestari & Purwa Setya, 2020). This study seeks to fill this gap by providing empirical evidence from Ghana, contributing to both academic discourse and practical policymaking aimed at fostering a sustainable and technologically advanced manufacturing sector in the region.

2. Materials and Methods

2.1. Study Setting

The study was conducted in the manufacturing industries in Ghana. A country of western Africa, situated on the coast of the Gulf of Guinea. Although relatively small in area and population, Ghana is one of the leading countries of Africa, partly because of its considerable natural wealth and partly because it was the first black African country south of the Sahara to achieve independence from colonial rule (Shomade, 2021). The Ghanaian government's various industrialization policies, initiated since independence, have resulted in the establishment of a wide range of manufacturing industries (Figure 1), notably the production of food, beverages, tobacco, textiles, clothes, footwear, timber and wood products, chemicals and pharmaceuticals, and metals, including steel and steel products. These are manufactured mostly for local consumption (Chepkoech et al., 2024). Ghana has a large and very active consumer and industrial products and services sector that provides products and services to the Ghanaian economy and the West African sub-

region. This sector is poised for significant growth over the next few years, and new policies have been put in place by the government to create an enabling environment, with an emphasis on manufacturing and exports. The export drive led to the creation of free zone areas, resulting in companies setting up in the country to export products to the sub-region and to the world at large. The consumer and industrial products and services sector is dominated by subsidiaries of multinational companies and medium-sized local companies, including Unilever, Coca-Cola, Toyota, and Accra Brewery. There is increasing investment in the economy due to the institutionalization of democracy in Ghana since 1992 and the relatively stable macroeconomic environment.



Figure 1. Map of Ghana showing the manufacturing Industries (Onyinah, 2012).

2.2. Research Design

This study employed a quantitative research approach utilizing a cross-sectional survey design. This design was chosen to gather data on AI technology adoption, corporate green innovation, sustainable manufacturing practices, environmental governance, and environmental risk factors from a sample of manufacturing enterprises in Ghana at a single point in time. The quantitative approach allows for statistical analysis of relationships between variables and testing of hypotheses derived from the literature. While mixed-method techniques can offer a richer understanding by combining qualitative and quantitative data (McNabb, 2020), the current study focused on a quantitative assessment to establish statistical relationships and generalizable findings within the Ghanaian manufacturing context.

2.3. Study Population and Sample Size Estimation

The study population included 400 employees working in manufacturing enterprises across Ghana, representing various subsectors such as agro-processing, textiles, metal fabrication, and chemical production. These individuals were selected based on their involvement in operational, managerial, or technological roles that interface with sustainable practices and AI technologies. The estimated population size was derived from an aggregated list of registered manufacturing companies in Ghana, with a total workforce estimate exceeding 10,000 employees. Using Cochran's formula for sample size determination in large populations, with a 95% confidence level and a 5% margin of error, the minimum required sample size was calculated to be approximately 384. However, to enhance the robustness and representativeness of the findings, a sample size of 455 participants was targeted. After data cleaning, 400 valid responses were retained, achieving a usable response rate of 87.9% of the original target, which ensures the statistical reliability of the study outcomes.

2.4. Ethical Consideration

This study adhered strictly to ethical research standards. Ethical clearance was obtained from the Anhui University review board before data collection. Participation in the study was entirely voluntary, and informed consent was obtained from all respondents. Each participant was assured of the confidentiality and anonymity of their responses. Furthermore, data were stored securely and used solely for academic and research purposes. Respondents had the right to withdraw from the study at any time without penalty. No personal identifiers were collected, and all information was aggregated to ensure privacy and impartiality.

2.5. Sampling Technique

A multi-stage sampling approach was adopted. First, manufacturing firms were stratified by size (small, medium, large) and industry sub-sector (food and beverages, textiles, pharmaceuticals, metal fabrication) to ensure diversity. Within selected firms, a convenience sampling approach combined with purposive elements was used to recruit respondents who were knowledgeable about their organization's technology adoption, innovation activities, and environmental practices. This typically included managers, engineers, and senior technical staff. A key limitation stems from the use of non-probability sampling (convenience and purposive methods) for selecting firms and recruiting respondents. While stratification ensured initial diversity, this approach limits the statistical generalizability of the findings to the broader Ghanaian manufacturing industry. The potential for self-selection bias means participating firms and individuals (e.g., managers, engineers) may not be fully representative. Consequently, the results are most applicable to firms similar to those in the study, rather than the entire population across Ghana. A total of 400 valid responses were collected and used for the final analysis. The sample size was deemed adequate for the statistical tech-

niques employed, including correlation and regression-based moderated mediation analysis.

2.6. Data Collection Tool

The primary data collection tool was a structured, self-administered online questionnaire designed to capture both demographic details and responses to key constructs relevant to the study. The questionnaire included standardized items adapted from existing literature, covering five main areas: AI technology adoption, corporate green innovation, sustainable manufacturing practices, environmental governance, and environmental risk factors. Most items used a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The tool was pilot-tested for clarity and contextual relevance before full deployment.

2.7. Instrument Reliability and Validity

The reliability of the measurement scales was assessed using Cronbach's alpha, a common measure of internal consistency (Cox & Holcomb, 2021). Cronbach's alpha indicates the degree to which items within a scale are interrelated and measure the same underlying concept. Acceptable reliability scores (typically $\alpha \geq 0.70$) ensure that the survey findings are consistent and that measurement inaccuracy is minimized. For this study, all constructs demonstrated acceptable levels of internal consistency, supporting the reliability of the measures used.

2.8. Data Analysis

The collected data was analyzed using SPSS 26 and AMOS 26. The process included data cleaning, descriptive statistics, correlation analysis, and normality testing. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were used to assess the factorial structure and validate measurement constructs. Cronbach's Alpha and Composite Reliability (CR) scores were calculated to ensure the reliability of the scales. Harman's single-factor test was employed to check for common method bias. To investigate complex relationships, moderated mediation analysis was conducted using Hayes' PROCESS macro (Model 7) for SPSS, examining how AI adoption influences green manufacturing outcomes through an intermediary factor (corporate green innovation), conditioned by a moderator (environmental governance).

3. Results

3.1. Demographic Profile of Respondents

The demographic data extracted from workers in different manufacturing industries in Ghana provides a detailed picture of the workforce composition. **Table 1** outlines gender distribution, age, marital status, level of education, and years of working experience. The workforce was predominantly male, with 70% (280 respondents) being male and 30% (120 respondents) female. The largest age group was 30 - 40 years, accounting for 55.0% (220 respondents). This was followed by

the 18 – 29 years at 20.0% (80 respondents). Smaller proportions represented those in their forties, fifties, and sixties, indicating a relatively youthful workforce in the manufacturing sector. The respondents generally had high education levels, suggesting a skilled workforce capable of engaging with new technologies and practices. This demographic profile suggests that the Ghanaian manufacturing workforce, particularly in the surveyed enterprises, is relatively young, predominantly male, and possesses a good educational background, which could be conducive to the adoption of new technologies like AI.

Table 1. Demographic characteristics of the respondent (N = 400).

Variable	Category	Frequency	Percentage (%)
Gender	Female	120	30.0
	Male	280	70.0
Age	18 - 29	80	20.0
	30 - 40	220	55.0
	41 - 50	60	15.0
	51 - 60	40	10.0
Marital status	Single	60	15.0
	Married	240	60.0
	Separated	30	7.5
	Divorced	70	17.5
Education level	Senior high or below	100	25.0
	Bachelors	200	50.0
	Masters	65	16.25
	Doctoral or higher	35	8.75
Number of years in the workforce	Less than 2 years	35	8.75
	2 to 5 years	255	63.75
	6 to 10 years	100	25.00
	More than 10 years	10	2.50
Size of the organization	Small (1 - 50 employees)	25	6.25
	Medium (51 - 200 employees)	275	68.75
	Large (201 - 300 employees)	70	17.50
	Above 300 employees	30	7.50

3.2. AI Technology Adoption and Application

The study found that 70% of surveyed organizations in Ghana reported adopting

some form of AI technology (Table 2). The most common AI applications included predictive maintenance (50%), energy management systems (25%), quality control using computer vision (20%), and supply chain optimization (5%) (Makkar et al., 2019). The primary motivations for AI adoption were improving efficiency (45%) and enhancing product quality (47.5%). Only 5% of organizations adopted AI explicitly to support green practices. Despite the low explicit focus on green practices as a driver for AI adoption, the impact on sustainable development was evident: 25% reported reduced energy consumption, 50% noted improved resource efficiency, 15% observed minimized waste production, and 10% saw lowered carbon emissions. Key challenges to AI adoption included high implementation costs (60%), limited infrastructure (20%), and a lack of skilled personnel (15%) (Ahadi et al., 2023).

Table 2. Identify AI technology adoption levels and their impact on Ghana's green practices.

Variable	Category	Frequency	Percentage (%)	<i>p</i> -value
Has your organization adopted any AI technologies?				
	Yes	280	70.00	0.224
	No	100	25.00	
	Not Aware	20	5.00	
If yes, which AI technologies are you currently using? (N = 280)				
	Predictive maintenance	140	50.00	0.000
	Quality control (e.g., computer vision)	56	20.00	
	Energy management systems	70	25.00	
	Supply chain optimization	14	5.00	
What are the main reasons for adopting AI technologies? (N = 280)				
	To improve efficiency	126	45.00	0.002
	To enhance product quality	133	47.50	
	To reduce costs	7	2.50	
	To support green/sustainable practices	14	5.00	
How has AI technology contributed to your organization's green development efforts? (N = 280)				
	Reduced energy consumption	70	25.00	0.030
	Improved resource efficiency	140	50.00	
	Minimized waste production	42	15.00	
	Lowered carbon emissions	28	10.00	

Continued

What challenges has your organization faced in adopting AI technologies? (N = 400 or N = 280?)

High costs of implementation	240	60.00	0.050
Limited infrastructure	80	20.00	
Lack of skilled personnel	60	15.00	
Resistance to change	20	5.00	

Source: Field data (2024).

3.3. Descriptive Statistics and Correlation Analysis

Table 3 presents key correlations and descriptive statistics for variables related to corporate sustainability and technology adoption. The most salient finding is the strong, statistically significant positive correlation between AI Technology (AI) and Environmental Governance (EG) ($r = 0.618, p < 0.01$). This robust association suggests organizations leveraging AI are more likely to implement rigorous environmental oversight frameworks, possibly using AI for tasks like emissions monitoring or regulatory compliance, or conversely, that robust governance drives strategic AI adoption for sustainability goals (Sharma, 2024). A moderate positive correlation emerges between Corporate Green Innovation (CGI) and Sustainable Manufacturing Practices (SMPs) ($r = 0.202$), indicating complementary efforts companies pursuing eco-friendly product/process innovation also tend to adopt sustainable operational practices. However, most other relationships are weak or non-significant (Oliveira, 2018). For instance, AI shows negligible links to CGI ($r = 0.02$) and SMPs ($r = 0.013$), implying its role is specialized within governance rather than broadly tied to innovation or manufacturing. Similarly, Environmental Risk Factors (ERF) show isolated, near-zero correlations with all variables (e.g., ERF-CGI: $r = 0.047$; ERF-SMPs: $r = 0.042$), suggesting perceived risks are disconnected from current sustainability initiatives (Sacopulos & Matchar, 2025).

Table 3. Correlations and descriptive statistics.

Variable	Mean	SD	AI	CGI	SMPs	EG	ERF
AI	3.50	0.85	1				
CGI	3.60	0.75	0.020	1			
SMPs	3.70	0.80	0.013	0.202**	1		
EG	3.80	0.90	0.618**	0.150**	0.100	1	
ERF	3.40	0.70	0.035	0.047	0.042	0.028	1

Note: ** $p < 0.01$ (2-tailed). AI Tech = AI Technology; CGI = Corporate Green Innovation; SMPs = Sustainable Manufacturing Practices; EG = Environmental Governance; ERF = Environmental Risk Factors.

3.4. Moderated Mediation Analysis

The overall regression model was statistically significant ($F(3, 396) = 109.75, p <$

0.001) and explained 45.3% of the variance in Corporate Green Innovation ($R^2 = 0.453$). The direct effect of AI Technology on CGI was found to be non-significant ($B = -0.011$, $SE = 0.029$, $p = 0.707$). This indicates that, when controlling for Environmental Governance, AI Technology adoption does not have a statistically significant direct impact on CGI in the surveyed enterprises. This fails to support H1a. Environmental Governance, however, demonstrated a strong, positive, and statistically significant effect on CGI ($B = 0.750$, $SE = 0.048$, $p < 0.001$). This suggests that higher perceived levels of environmental governance are associated with higher levels of corporate green innovation, supporting H2. The interaction term (AI Technology \times Environmental Governance) was not statistically significant ($B = -0.032$, $SE = 0.048$, $p = 0.503$). This implies that Environmental Governance does not significantly moderate the relationship between AI Technology and CGI. The impact of AI on CGI (or lack thereof) does not significantly differ across varying levels of environmental governance (**Table 4**).

Table 4. Regression results for predicting corporate green innovation (CGI) (N = 400).

Predictor	Coefficient (B)	Std. Error (SE)	t-value	p-value	LLCI	ULCI
Constant	1.852	0.215	8.614	<0.001	1.429	2.275
AI Technology (AI)	-0.011	0.029	-0.376	0.707	-0.068	0.046
Environmental Governance (EG)	0.750	0.048	15.625	<.001	0.656	0.844
Interaction (AI \times EG)	-0.032	0.048	-0.670	0.503	-0.126	0.062
R^2	0.453					
Adjusted R^2	0.449					
F	109.75			<0.001		

The overall model was significant ($F(3, 396) = 109.75$, $p < 0.001$), explaining 45.3% of the variance in Corporate Green Innovation ($R^2 = 0.453$). Source: Field data (2023). LLCI = Lower Limit Confidence Interval; ULCI = Upper Limit Confidence Interval.

4. Discussion

This study sought to unravel the complex relationships between AI technology adoption, Corporate Green Innovation (CGI), and Environmental Governance (EG) within Ghanaian manufacturing enterprises. The findings provide several key insights into the dynamics of green transformation in a developing economy context, highlighting the primacy of governance over technology as a direct driver of green innovation. The demographic profile of the workforce in the surveyed Ghanaian manufacturing enterprises is predominantly male, relatively young (majority 30 - 40 years), and with high levels of education (over 75% holding Bachelor's degrees or higher)—presents a generally favorable landscape for the adoption and integration of new technologies like AI. A younger, educated workforce is often associated with greater technological literacy, adaptability, and a willingness to engage with innovative practices (Brown & Wyatt, 2010). This demographic com-

position could be a crucial asset for Ghanaian manufacturing firms as they navigate the complexities of AI implementation. However, the challenge of a “lack of skilled personnel” (15%) still highlights a critical gap. While general education is high, specialized skills in AI, data science, and machine learning are necessary to fully leverage these technologies for complex tasks like green innovation (Chhabra et al., 2025).

The study reveals a high AI adoption rate (70%) among surveyed firms, primarily driven by objectives of enhancing product quality and improving operational efficiency. This aligns with global trends where AI is initially adopted for core business performance improvements, such as optimizing production systems and supply chains (Alpan et al., 2023). Common applications like predictive maintenance (50% of adopters) and energy management systems (25% of adopters) inherently possess green potential by optimizing resource use and reducing energy consumption (Javaid et al., 2022). This is evidenced by respondents reporting improved resource efficiency (50%) and reduced energy consumption (25%) as AI contributions. However, a critical finding is that explicit green or sustainable practices were a direct motivation for AI adoption in only a small fraction of firms (5%). This suggests that while AI applications may yield ancillary environmental benefits, these are often by-products of efficiency-seeking rather than intentional green strategies. This “accidental environmentalism” may limit the full realization of AI’s green potential. To maximize AI’s contribution to sustainability, a more deliberate and strategic integration of green objectives into AI deployment roadmaps is necessary (García-Maroto et al., 2020). The significant barriers of high implementation costs (60%) and limited infrastructure (20%) further underscore the challenges, particularly for firms in developing economies, in making substantial investments in AI, let alone tailoring them for specific green outcomes (García-Maroto et al., 2020).

Contrary to our initial hypothesis (H1) and some expectations in the literature (Jiang, 2025), AI technology adoption did not demonstrate a statistically significant direct impact on CGI ($B = -0.011$, $p = 0.707$). This suggests that the mere presence or adoption of AI technologies, in isolation, may not automatically translate into enhanced green innovation. This finding resonates with the argument that technology is an enabler whose effectiveness is contingent upon strategic implementation, organizational capabilities, and a supportive ecosystem (Mitchell, 2021). Without a clear strategic mandate to utilize AI for green purposes, its impact on CGI may be diluted or overshadowed by its primary deployment for non-green objectives like cost reduction. This highlights the importance of Human-Cyber-Physical Systems (HCPS), where human intent and organizational systems must effectively direct cyber and physical technologies toward specific goals (Wang et al., 2022). The most powerful predictor of CGI was Environmental Governance ($B = 0.750$, $p < 0.001$), strongly supporting H2. This finding suggests that the institutional and organizational context encompassing regulations, corporate policies, leadership commitment, and stakeholder pressures is the primary driver of

green innovation in the Ghanaian manufacturing sector (Ning et al., 2021). Firms are more likely to invest in developing green products, processes, and business models when they operate within a robust governance framework that incentivizes or mandates such behavior (Boehe & Becerra, 2022). This highlights the critical role of government policy and corporate leadership in setting the green agenda and creating the necessary conditions for sustainable transformation (Green-Pedersen & Princen, 2016).

The non-significant interaction effect ($B = -0.032$, $p = 0.503$) fails to support H3, indicating that the strength of environmental governance does not alter the (non-existent) direct relationship between AI and CGI (Seth et al., 2025). This could imply that the current forms of environmental governance in Ghana may not be sophisticated enough to specifically leverage or amplify the potential of advanced technologies like AI. For instance, regulations might focus on traditional pollution control rather than incentivizing technology-driven eco-innovations (Chaugule, 2024). For governance to effectively moderate this relationship, it may need to evolve to include technology-specific incentives, standards for AI-driven environmental monitoring, and support for digital infrastructure that enables green AI applications (Krishna Pasupuleti, 2024).

This study contributes to several theoretical streams. Firstly, it extends the Resource-Based View (RBV) by showing that technological resources like AI may not directly translate into specific performance outcomes like CGI without being orchestrated by other organizational capabilities and strategic direction. Secondly, it reinforces Institutional Theory by demonstrating the strong direct influence of EG on CGI, emphasizing the power of the institutional context in shaping corporate environmental behavior. Thirdly, it contributes to the growing literature on AI and sustainability by providing empirical evidence from a developing country (Noman et al., 2022), highlighting that the pathways observed in developed economies may not be directly transferable.

This study, while providing valuable insights, has several limitations. Firstly, its cross-sectional design captures relationships at a single point in time, precluding causal inferences. Longitudinal studies are needed to track the evolution of AI adoption and its impact on green outcomes over time. Secondly, the data were self-reported by employees, which may be subject to common method bias or social desirability bias, although steps were taken to ensure anonymity. Future research could triangulate findings with objective firm-level data on environmental performance and AI investments. Thirdly, the study was conducted in Ghana, and its findings may not be generalizable to other developing countries with different industrial structures, institutional contexts, or levels of technological development (Akubia & Andriana, 2024). Comparative studies across different African nations would be beneficial. Future research could explore other potential moderators (e.g., firm size, technological absorptive capacity) or mediators (e.g., data analytics capabilities) in the AI-sustainability linkage. Qualitative case studies could also provide deeper insights into the mechanisms and contextual factors influencing how firms leverage AI for green innovation, for example, through the lens of digital twin im-

plementation (Smit et al., 2024).

5. Conclusion

This study offers a nuanced perspective on the role of Artificial Intelligence in fostering green development within Ghanaian manufacturing enterprises. While AI adoption is relatively high and driven by efficiency and quality imperatives, its direct contribution to Corporate Green Innovation appears limited without explicit strategic intent and supportive governance. The central finding is that Environmental Governance emerges as the critical direct driver of CGI, underscoring the paramount importance of a robust institutional and corporate policy framework in guiding sustainable transformation. The potential of AI to contribute to a greener manufacturing sector in Ghana is not diminished by these findings; rather, it is clarified. AI's role appears to be that of a powerful enabler, whose green potential is unlocked when it is strategically aligned with corporate innovation goals that are, in turn, shaped by strong environmental governance. This suggests a pathway where firms, motivated by a strong governance environment, invest in CGI and then leverage AI as a tool to achieve those green innovation objectives more effectively. For Ghana to effectively harness AI for sustainable industrial development, a multi-pronged approach is needed. This involves manufacturing firms moving beyond "accidental environmentalism" to strategically align AI with green objectives. Concurrently, governmental and regulatory bodies must strengthen environmental governance, not just through traditional compliance measures but by creating targeted incentives for AI-driven green solutions, supporting digital infrastructure, and fostering the development of specialized AI skills. This could include promoting sustainable practices in emerging areas like additive manufacturing, encouraging green human resource management to build a sustainability-oriented workforce, and adopting resource-efficient methods like sustainable prototyping. By understanding and navigating these complex interrelationships, Ghanaian manufacturing can move towards a future that is both technologically advanced and environmentally sustainable.

Data Availability

The data supporting this study are available upon reasonable request from the corresponding author, Abangbila Linda.

Funding

The study received no external funding.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Abbas, M., & Mahmood, H. (2025). *Role of Industrial Employees' Green Behavior in the*

- Relationship between Industrial Sector Green Practices and Industrial Sector Sustainable Environmental Performance in Alkharj Industrial City.* (Preprint)
<https://doi.org/10.2139/ssrn.5097955>
- Adediran, O. (2023). *Foreign Direct Investment and Economic Growth: Evidence from Sub-Saharan African Countries.* ScienceOpen.
<https://doi.org/10.14293/SBLUNISA.2023a014.0a>
- Ahadi, N., Zanzanab, A. G., Sorooshian, S., Monametsi, G., Virutamasen, P., Wongpreedee, K. et al. (2023). The Outlook of ChatGPT, an AI-Based Tool Adoption in Academia: Applications, Challenges, and Opportunities. In *TENCON 2023-2023 IEEE Region 10 Conference (TENCON)* (pp. 15-20). IEEE.
<https://doi.org/10.1109/TENCON58879.2023.10322527>
- Akubia, G. K., & Andriana, D. (2024). Green Logistics Management Practices and Sustainability Performance of Manufacturing Firms in Ghana and Indonesia: The Moderating Role of Cross-Country ICT Development Status. In A. Appolloni, F. Caracciolo, Z. Ding, P. Gogas, G. Huang, G. Narrea, T. Ngo, W. Strielkowski, & S. Joshi (Eds.), *Advances in Economics, Business and Management Research* (pp. 411-417). Atlantis Press International BV. https://doi.org/10.2991/978-94-6463-443-3_54
- Alpan, G., Bouzekri, H., & Sanlaville, É. (2023). Enhancing Global Supply Chain Performance by Optimizing Port Resources. In *Maritime Ports, Supply Chains and Logistics Corridors* (pp. 151-163). Routledge. <https://doi.org/10.4324/9781003365013-15>
- Anthuvan, T., & Maheshwari, K. (2025). AI-C2C (Conscious to Conscience): A Governance Framework for Ethical AI Integration. *AI and Ethics*, 5, 4241-4253.
<https://doi.org/10.1007/s43681-025-00736-2>
- Boehe, D. M., & Becerra, M. (2022). Market Entry into New Export Markets: When Are Firms More Likely to Imitate Their Competitors' Market Presence? *International Business Review*, 31, Article ID: 102012. <https://doi.org/10.1016/j.ibusrev.2022.102012>
- Brown, T., & Wyatt, J. (2010). Design Thinking for Social Innovation. *Development Outreach*, 12, 29-43. https://doi.org/10.1596/1020-797X_12_1_29
- Chaugule, A. (2024). The Beverage Industry Is Evolving with a Focus on Functional Drinks, Eco-Friendly Packaging, and Technology-Driven Innovations to Meet Changing Consumer Demands. *International Journal of Science and Research (IJSR)*, 13, 1183-1184.
<https://doi.org/10.21275/SR241014191557>
- Chepkoech, M., Omoniyi, P., & Owolabi, G. (2024). Fatigue Response of Additive-Manufactured 316L Stainless Steel. *Metals*, 14, Article 988. <https://doi.org/10.3390/met14090988>
- Chhabra, I., Gulati, K., Singhal, S., & Dhameja, N. (2025). Integrating Data Analytics, AI, and Machine Learning to Optimize Environmental Impact and Foster Green Innovation. In S. Trivedi, B. Balusamy, L. M. Gernal, & M. A. Al-Khasawneh (Eds.), *Green Engineering for Optimizing Firm Performance* (pp. 271-288). Chapman and Hall/CRC.
<https://doi.org/10.1201/9781003626527-14>
- Cox, K. S., & Holcomb, Z. C. (2021). Internal Consistency and Cronbach's Alpha. In K. S. Cox, & Z. C. Holcomb (Eds.), *Interpreting Basic Statistics* (9th ed., 234-237). Routledge.
<https://doi.org/10.4324/9781003096764-69>
- Dong, B., Ma, X., Zhang, Z., Zhang, H., Chen, R., Song, Y. et al. (2020). Carbon Emissions, the Industrial Structure and Economic Growth: Evidence from Heterogeneous Industries in China. *Environmental Pollution*, 262, Article ID: 114322.
<https://doi.org/10.1016/j.envpol.2020.114322>
- García-Maroto, I., Muñoz-Leiva, F., Higuera-Castillo, E., & Liébana-Cabanillas, F. (2020). Characterisation of Potential Adopters of Domestic Biomass Heating. *International Journal of Green Energy*, 18, 219-230. <https://doi.org/10.1080/15435075.2020.1854262>

- Green-Pedersen, C., & Princen, S. (2016). Chapter 5 Punctuated Equilibrium Theory. In *Handbook of Public Policy Agenda Setting* (pp. 69-86). Edward Elgar Publishing. <https://doi.org/10.4337/9781784715922.00013>
- Javaid, M., Haleem, A., Singh, R. P., Suman, R., & Gonzalez, E. S. (2022). Understanding the Adoption of Industry 4.0 Technologies in Improving Environmental Sustainability. *Sustainable Operations and Computers*, 3, 203-217. <https://doi.org/10.1016/j.susoc.2022.01.008>
- Jiang, J. (2025). The Existence of the Poetic Eye: A Dou-Ble-Edged Sword in Classical Chinese Literature. *Literature History and Philosophy*, 1, 29-37. <https://doi.org/10.63313/LHP.8005>
- Kalchschmid, V., Erhart, V., Angerer, K., Roth, S., & Hohmann, A. (2023). Decentral Production of Green Hydrogen for Energy Systems: An Economically and Environmentally Viable Solution for Surplus Self-Generated Energy in Manufacturing Companies? *Sustainability*, 15, Article 2994. <https://doi.org/10.3390/su15042994>
- Kracker, O., & Sachs, E. (2024). Flow—SPPS Towards Greener and More Efficient Peptide Manufacturing. In *Proceedings of the 37th European Peptide Symposium* (p. 1029). The European Peptide Society. <https://doi.org/10.17952/37EPS.2024.P1029>
- Krishna Pasupuleti, M. (2024). AI-Driven Cybersecurity: Safeguarding Enterprise in Fracture and Digital Assets. In *AI in Cybersecurity for Enterprises: Tools for Protecting Digital Assets and Infrastructure* (pp. 262-286).
- Lestari, U. P., & Purwa Setya, Y. F. (2020). Comprehensive Performance Measures, Job Satisfaction and Managerial Performance: The Effect of Trust in Superior and Organizational Commitment. In *Proceedings of the 9th Annual Southeast Asian International Seminar* (pp. 116-126). SCITEPRESS—Science and Technology Publications.
- Maghfirah, P., & Eni, Y. (2024). The Impact of Artificial Intelligence (AI) Adoption on the Productivity of Small and Medium Enterprises (SMEs) Industries in Indonesia: High Cost, Lack of Knowledge, and Inadequate Infrastructure as Mediation Variables. *International Journal of Business Management and Economic Review*, 7, 128-145. <https://doi.org/10.35409/IJBMER.2024.3584>
- Makkar, S., Devi, G. N. R., & Solanki, V. K. (2019). Applications of Machine Learning Techniques in Supply Chain Optimization. In V. Gunjan, V. Garcia Diaz, M. Cardona, V. Solanki, & K. Sunitha (Eds.), *ICICCT 2019—System Reliability, Quality Control, Safety, Maintenance and Management* (pp. 861-869). Springer. https://doi.org/10.1007/978-981-13-8461-5_98
- McNabb, D. E. (2020). Testing Research Hypotheses. In D. E. McNabb (Ed.), *Research Methods for Political Science* (3rd ed., 160-175). Routledge. <https://doi.org/10.4324/9781003103141-15>
- Mitchell, D. (2021). Bought In? The Contingent Effect of Stakeholder Support Upon Strategic Implementation Success in American Municipalities. *Public Management Review*, 24, 773-798. <https://doi.org/10.1080/14719037.2020.1862289>
- Moalla, M., & Miçooğulları, S. A. (2023). Interconnections between Industrialization, Economic Growth, Environmental Degradation, Resource Depletion, and Energy Demand in CEE(S) Economies: Insights from Bootstrap Panel Causality Analysis. In D. Eroğlu Sevinç, & H. Sevinç (Eds.), *Ekonomi ve Finans Politikaları Üzerine Çalışmalar II* (pp. 43-44). Özgür Yayınları. <https://doi.org/10.58830/ozgur.pub283.c1110>
- Ning, S., Jie, X., & Li, X. (2021). Institutional Pressures and Corporate Green Innovation; Empirical Evidence from Chinese Manufacturing Enterprises. *Polish Journal of Environmental Studies*, 31, 231-243. <https://doi.org/10.15244/pjoes/139926>
- Noman, A. A., Akter, U. H., Pranto, T. H., & Haque, A. B. (2022). Machine Learning and Artificial Intelligence in Circular Economy: A Bibliometric Analysis and Systematic Lit-

- erature Review. *Annals of Emerging Technologies in Computing*, 6, 13-40. <https://doi.org/10.33166/AETiC.2022.02.002>
- Oliveira, S. R. M. (2018). Exploring the Relationships between Product Innovation Radicalness and Extensiveness of Flexibility of Sustainable Manufacturing System in Most Innovative Companies from USA. In *Anais do Encontro Nacional de Engenharia de Produção* (pp. 28-30). ENEGEP 2018—Encontro Nacional de Engenharia de Produção. https://doi.org/10.14488/ENEGEP2018_TI_ST_265_520_35175
- Onyinah, O. (2012). Ethnic Map of Ghana (Akan Group). In *Pentecostal Exorcism* (pp. xv-xv). BRILL. <https://doi.org/10.1016/j.clscn.2023.100136>
- Picaud-Bello, K., Schiele, H., Koch, V., & Francillette, M. (2024). Innovation through Sustainability: Identifying Purchaser Skills Fostering Green Innovation. *Cleaner Logistics and Supply Chain*, 10, Article 100136.
- Ram, H., Kumar, B., Aggarwal, N., & Kaur, J. (2018). Resource-Conserving Technologies for Enhancing Resource Use Efficiency and Crop Productivity. In R. Sengar, & A. Singh (Eds.), *Eco-Friendly Agro-Biological Techniques for Enhancing Crop Productivity* (pp. 129-145). Springer Singapore. https://doi.org/10.1007/978-981-10-6934-5_7
- Sacopulos, M., & Matchar, D. (2025). *Systems Thinking in Healthcare: A Conversation with Dr. David Matchar*. Sound Practice.
- Seth, D. K., Ratra, K. K., & Sundareswaran, A. P. (2025). AI and Generative AI-Driven Automation for Multi-Cloud and Hybrid Cloud Architectures: Enhancing Security, Performance, and Operational Efficiency. In *2025 IEEE 15th Annual Computing and Communication Workshop and Conference (CCWC)* (pp. 784-793). IEEE. <https://doi.org/10.1109/CCWC62904.2025.10903928>
- Sharma, R. (2024). Building Robust AI Infrastructure for Enterprise Success. In *AI and the Boardroom* (pp. 247-258). Apress. https://doi.org/10.1007/979-8-8688-0796-1_20
- Shirahase, A. (2023). If You Are Determined, You Can Achieve Anything—Take on New Challenges While Strengthening Existing Businesses. *NTT Technical Review*, 21, 1-5. <https://doi.org/10.53829/ntr202308tp1>
- Shomade, S. A. (2021). Comparisons and Contrasts of Select African Nations' Experiences. In S. A. Shomade (Ed.), *Colonial Legacies and the Rule of Law in Africa* (pp. 223-235). Routledge. <https://doi.org/10.4324/9780429355189-8>
- Smit, K., Mens, J., de Gelder, C., & van Meerten, J. (2024). Digital Twin Technology in the Rail Industry: A Dutch Qualitative Case Study on Success Factors, Challenges, and Future Use Cases. In *Resilience Through Digital Innovation: Enabling the Twin Transition* (pp. 319-336). University of Maribor Press.
- Susithra, S., & Vasantha, S. (2024). The Adoption of Green Supply Chain Practices Using Artificial Intelligence (AI) for Smart Global Value Chain. In *2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM)* (pp. 1-8). IEEE. <https://doi.org/10.1109/ICONSTEM60960.2024.10568808>
- Tan, W., Zhuo, Y., Chen, X., Yao, Q., & Liu, J. (2022). An Artificial Intelligence and Internet of Things Platform for Healthcare and Industrial Applications. In C. Comito, A. Forestiero, & E. Zumpano (Eds.), *Internet of Things* (pp. 85-103). Springer International Publishing. https://doi.org/10.1007/978-3-030-91181-2_6
- Wang, B., Zheng, P., Yin, Y., Shih, A., & Wang, L. (2022). Toward Human-Centric Smart Manufacturing: A Human-Cyber-Physical Systems (HCPS) Perspective. *Journal of Manufacturing Systems*, 63, 471-490. <https://doi.org/10.1016/j.jmsy.2022.05.005>
- Zhang, C., & Nakatani, J. (2024). Implications of Chemical Recycling of Plastic Waste for Climate Change Impacts: A Critical Review. *Sustainable Production and Consumption*, 48, 301-323. <https://doi.org/10.1016/j.spc.2024.05.016>