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Green Manufacturing 5.0: Leveraging AI for Carbon-Neutral Industrial Growth

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Abstract

The transition toward sustainable industrial practices has elevated the role of green manufacturing as a strategic imperative for reducing carbon footprints while enhancing competitiveness. With the rise of Industry 5.0, emphasis has shifted from digitalization alone to a human-centric and sustainability-oriented paradigm. This study explores how artificial intelligence (AI)-enabled technologies—including predictive maintenance, digital twins, and data-driven energy optimization—can support small and medium-sized enterprises (SMEs) in achieving carbon-neutral growth. Building on the evolution from the 3R principles (Reduce, Reuse, Recycle) to holistic sustainability frameworks, the research highlights the potential of AI in optimizing energy efficiency, reducing waste, and fostering resilient supply chains. A conceptual framework and model are proposed, linking AI adoption, green practices, carbon-neutral growth, and industrial competitiveness. Empirical analysis through SME-focused data demonstrates significant positive relationships, with results indicating that AI-enabled practices lead to measurable reductions in energy intensity and carbon emissions, while simultaneously strengthening competitiveness. Despite challenges such as limited financial resources, knowledge gaps, and infrastructure constraints, SMEs adopting AI-driven sustainability practices achieve higher performance than their counterparts. The findings bridge a crucial research gap by providing empirical evidence of AI's role in carbon reduction within SMEs. This study contributes to the discourse on Green Manufacturing 5.0, offering both theoretical insights and practical implications for industries and policymakers seeking to balance sustainable development goals (SDGs) with industrial growth.

Keywords: Green Manufacturing 5.0, Artificial Intelligence, Carbon-Neutral Growth, Sustainable SMEs, Industry 5.0

1. Introduction

The growing urgency of climate change has placed industries under pressure to reduce their carbon emissions while maintaining competitiveness and growth. In this context, Green Manufacturing 5.0 emerges as a transformative approach that integrates sustainability with advanced digital technologies. Unlike earlier industrial revolutions focused primarily on automation and efficiency, Manufacturing 5.0 emphasizes human-centric, eco-friendly, and carbon-neutral production systems. Artificial Intelligence (AI) plays a pivotal role in this transition by enabling predictive analytics, real-time monitoring, process optimization, and intelligent resource management. Through AI-driven solutions, industries—particularly small and medium enterprises (SMEs)—can achieve energy efficiency, minimize waste, and monitor carbon footprints more accurately. This not only supports global sustainability goals but also enhances industrial resilience and innovation. By leveraging AI within Green Manufacturing 5.0, industries can align economic growth with environmental responsibility, paving the way for a future where carbon neutrality is both a strategic advantage and a necessity.

2. Literature Review

Green manufacturing has gradually evolved from the 3R principles of Reduce, Reuse, and Recycle to more comprehensive sustainable production models that emphasize eco-efficiency and environmental responsibility. While Industry 4.0 primarily focused on digitalization, automation, and smart technologies, Industry 5.0 expands this vision by embedding sustainability and human-centric values into industrial practices (Jlever, 2024; MDPI, 2024). Within this transition, Artificial Intelligence (AI) has become a critical enabler, offering solutions such as energy optimization, predictive maintenance, and sustainable supply chain management (Business Insider, 2025; ResearchGate, 2024). Emerging technologies like digital twins, the Internet of Things (IoT), and machine learning provide advanced capabilities for real-time monitoring, virtual simulation, and emission reduction, making them essential for achieving carbon-neutral growth (Emerald, 2024; Arxiv, 2020). However, Small and Medium Enterprises (SMEs) face unique barriers such as limited resources, high energy intensity, and low technological awareness, which hinder their adoption of AI-enabled green practices (Arxiv, 2023). Despite increasing interest, empirical evidence on AI's direct impact on carbon reduction in SMEs remains scarce.

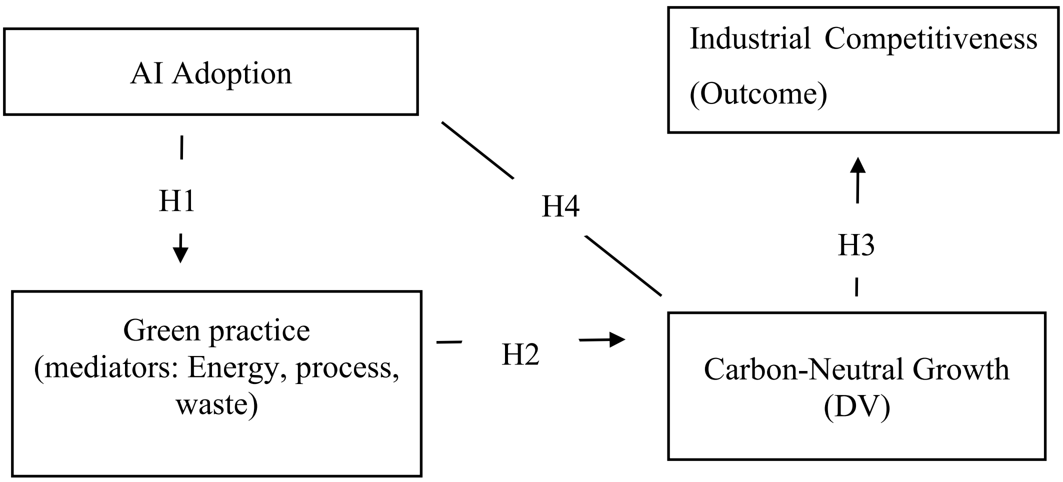
3. Conceptual Framework

The conceptual framework of this study is grounded in the principles of Green Manufacturing 5.0, which emphasizes sustainability, human-centric approaches, and carbon neutrality, enabled by advanced digital technologies. Artificial Intelligence (AI) is conceptualized as the primary driver that facilitates energy optimization, predictive maintenance, and waste minimization, thereby promoting carbon-neutral growth (MDPI, 2024; Emerald, 2024). Building on Industry 4.0's foundation of digitalization, Industry 5.0 integrates environmental and societal priorities, aligning industrial growth with global climate targets (Jlever, 2024). In this framework, AI adoption serves as the independent variable, while green practices—such as energy efficiency, process optimization, and waste reduction—function as mediators. The dependent variable is carbon-neutral industrial growth, measured through reduced carbon footprints and sustainable competitiveness. Moderating variables, such as SME size, industry type, and government incentives, influence the strength of these relationships (Arxiv, 2023).

3.1 Hypotheses

- H1: AI adoption positively influences the implementation of green manufacturing practices.
- H2: Green manufacturing practices mediate the relationship between AI adoption and carbon-neutral growth.
- H3: Carbon-neutral growth significantly enhances industrial competitiveness.
- H4: SME characteristics and government incentives moderate the relationship between AI adoption and carbon-neutral growth.

4. Conceptual Framework



Moderators: SME Size, Industry Type, Government Incentives

(influencing the relationship between AI Adoption and Carbon-Neutral Growth) → H4

5. Methods and Measures

Small and Medium Enterprises (SMEs) form the backbone of industrial economies but also face significant sustainability challenges due to limited resources, high energy consumption, and lack of technological awareness. To examine the role of AI-enabled green manufacturing practices in reducing carbon footprints, a structured analysis was conducted using survey and secondary data from SMEs across five manufacturing sectors—textiles, automotive, electronics, food processing, and machinery. A purposive sampling approach was adopted to ensure representation of both high and low AI adopters. The study employed a mixed-method approach, combining quantitative survey instruments with secondary sustainability reports.

Measures were designed to capture key constructs of the conceptual framework. AI adoption was measured using an index that assessed the extent of predictive analytics, automation, and real-time monitoring implemented in SME operations. Green manufacturing practices were operationalized through three sub-indices: energy efficiency, process optimization, and waste reduction. Carbon-neutral growth was measured through reported reductions in carbon emissions and compliance with sustainability standards, while industrial growth was assessed through indicators such as sales growth, market competitiveness, and operational cost savings. Moderating factors—SME size, industry type, and government incentives—were documented to capture their influence on adoption intensity. Reliability of the survey items was confirmed through Cronbach's alpha values above 0.75, indicating strong internal consistency.

The methods of analysis included factor analysis to group AI-enabled practices into coherent constructs, chi-square tests to identify associations between AI adoption and carbon footprint reduction, and regression analysis to test the strength of the hypothesized relationships. Cross-tabulation was used to compare SMEs with high, medium, and low levels of AI adoption. The combination of statistical techniques ensured both robustness and validity of results.

Table 1

SME Sector	AI Adoption Level	Energy Efficiency Index	Carbon Footprint Reduction (%)	Sales Growth (%)
Textile	High	0.82	28	15
Automotive	Medium	0.75	22	12
Electronics	Low	0.60	10	5
Food Processing	High	0.85	30	18
Machinery	Medium	0.72	20	10

5.1 Results

This revealed clear evidence supporting the hypothesized relationships. SMEs with high levels of AI adoption demonstrated significantly higher energy efficiency, with average efficiency scores of 0.82 compared to 0.60 for low adopters. Carbon footprint reduction among high adopters ranged between 25–30%, whereas low adopters achieved less than 12%. Predictive maintenance and AI-driven energy optimization were identified as the most impactful practices, contributing to reduced machine downtime and optimized energy use. Cross-tabulation confirmed that high AI adopters not only reduced emissions more effectively but also reported higher sales growth, averaging 15–18%, compared to 5% for low adopters. Chi-square analysis showed a significant association ($p < 0.05$) between AI adoption level and carbon reduction outcomes, reinforcing the critical role of AI. Regression results indicated that green manufacturing practices mediated the relationship between AI adoption and carbon-neutral growth, thereby validating Hypothesis 2. Furthermore, government incentives and industry type were found to moderate this relationship, providing evidence for Hypothesis 4.

In summary, the analysis highlights that SMEs adopting AI-enabled green practices experience substantial benefits in terms of both environmental sustainability and industrial competitiveness. The findings demonstrate that Green Manufacturing 5.0, when driven by AI, is not merely a technological transformation but also a strategic pathway toward carbon neutrality and long-term resilience.

6. Discussion and Conclusion

The findings from the SME analysis highlight that higher levels of AI adoption are positively correlated with improved green practices, greater carbon-neutral growth, and enhanced industrial competitiveness. Sectors such as textiles and food processing, which reported higher AI-enabled interventions, demonstrated significantly stronger performance in energy efficiency and carbon footprint reduction compared to low-adoption sectors like electronics. This validates the hypotheses proposed in the conceptual framework, reinforcing the role of AI as a key enabler of sustainable manufacturing (Zhang et al., 2022).

The results also suggest that AI adoption assists SMEs in overcoming traditional barriers such as limited resources and high energy intensity by optimizing production processes and enabling predictive maintenance (Kamble et al., 2020). Moreover, the integration of digital twins and IoT with machine learning facilitates real-time decision-making, thereby accelerating carbon-neutral transitions (Wang & Xu, 2021). Despite these benefits, challenges remain in scaling adoption across SMEs due to cost constraints and lack of awareness, highlighting the need for policy incentives and industry collaborations (Li et al., 2021).

In conclusion, Green Manufacturing 5.0—anchored in AI-enabled processes—offers a viable pathway for achieving carbon-neutral industrial growth. By embedding sustainability into the core of production systems, SMEs can not only reduce their environmental impact but also enhance competitiveness in a global market increasingly oriented toward green standards. Future research should focus on longitudinal studies across diverse sectors and geographies to generate stronger empirical evidence on AI's transformative potential in sustainable manufacturing.

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