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Influencing Factors of the Digital Economy on the Green Development of China’s Manufacturing Industry

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Abstract

This research investigates the effects of IoT adoption along with AI integration in the digital economy on China's manufacturing industry's green development path. Statistics on secondary data show IoT implementation leads to dramatic reductions in both CO_2 emissions and energy usage, yet AI systems produce modest improvements in the same areas. Regression analysis results, together with Pearson correlation statistics, show digital technologies have fundamental transformative power for sustainable manufacturing. The study uses secondary data while recommending policy developments such as IoT infrastructure spending and technology efficiency promotion. The findings support China’s objective to reach net-zero carbon emissions by 2060 while creating an approach foutilisingng digital solutions for worldwide sustainability efforts. Subsequent studies need to analyze specific industrial effects.

Keywords: Digital Economy, Green Development, China's Manufacturing Industry, Influencing Factors

Introduction

Background of the Study

The connection between the digital economy and green development is highly significant for China's manufacturing industry due to technological innovation and sustainable development considerations. China is the largest manufacturing country in the world and occupies a very strategic position in the global value chain (Wang S & Wang, 2022). However, this role has been associated with high energy use, reserves, and significant CO_2 emissions throughout history. The transformation to IoT, AI, and significant data initiatives gives a pathway for improving productivity while decreasing energy consumption, consequently creating a more sustainable operation.

This transition is even more pressing, considering that China is committed to reaching a condition of zero carbon emission by 2060. The implementation strategy of the "Made in China 2025" strategy focuses on green manufacturing to implement intelligent manufacturing throughout various enterprises (Meng et al., 2020). China has the vision of tapping into the digital economy to overcome the environmental impacts without losing its competitive advantage in the manufacturing sector. Sustainability and digitalization are two significant areas that must always be prioritized to ensure a sustainable economic and environmental future.

Research Objectives and Questions

This research seeks to establish the effects of the digital economy on the green development of China's manufacturing industry. The primary research objectives are as follows:

Research Objectives

Analyze the factors characterizing the digital economy that have a bearing on green development.

Examine how these influence sustainable strategies in the manufacture of goods.

Research Questions

The following are the research questions,

- What digital economy factors influence green development in China's manufacturing sector?
- How can digital technologies be leveraged to improve green production processes in China's manufacturing industry?

Significance of the Study

This work can extend important implications for policies, business, and sustainability, especially China's strategy to net-zero carbon emissions by the year 2060. The findings can help policymakers develop policies that foster the use of technology in sustainable development.

Hence, for all industries, this study gives a clear perspective on how maximizing the initial use of technology such as AI, IoT, and big data can help overall operation efficiency, cutting down CO_2 emissions and enhancing competency levels. The study also benefits the global sustainable development goals by presenting approaches other countries and sectors can follow.

Literature Review

With artificial intelligence (AI), the Internet of Things (IoT), cloud computing and big data, the digital economy refers to advanced technologies which are transforming the economy across various industry sectors. Among other things, AI makes decisions, predicts, and controls processes, and IoT enables real-time interaction between objects through connected objects (Alahi et al., 2023). With the advantages of big data analytics and flexible and self-service computational resources, cloud computing offers (Al-Jumaili et al., 2023). These technologies working together increase efficiency, flexibilty, and production rates. In contrast, green development holds sustainable economic growth as its core and provides attention to energy sustainability, emissions reduction and waste management (Misztal & Dziekański, 2023).

Greenhouse gas control protects emission reduction targets, while waste minimization concentrates on recycling and waste generation management (Bhatia et al., 2023).

A strong link between the digital economy and green development is emphasized as a result of research. Together, AI works to support predictive maintenance and energy optimization, and IoT makes supply chain management more traceable and more efficient while minimizing waste by tracking resources (Ahmad et al., 2024). Big data analytics applies pattern mining to resource usage possibilities for sustainability. In integrating AI, IoT, and cloud technologies, China's "Made in China 2025" strategy has demonstrated that Huawei is reducing emissions and becoming even more competitive (Dongfang et al., 2022). Empirical studies, however, are still limited in their examination of AI's role in emission reduction and its utilization in the contexts of China's regulatory and cultural environments (Allioui & Mourdi, 2023).

Methodology

Research Design

This research adopts secondary research analysis to determine the impact of the digital economy on China's green manufacturing industry. Secondary data analysis is selected based on time and cost considerations and also because the data collected are often standardized, reliable, and obtained from reputable sources(Wickham, 2019). In view of this, the study can take advantage of large and reliable datasets that are otherwise costly and time-consuming to develop exogenously. This approach will also ensure the experiments are replicated from previous research, hence enhancing the study's reliability and credibility.

Data Sources

One of the main strengths of the study is that several trustworthy databases have been employed to collect the data. The primary sources are the manufacturing and sustainable statistics generated from the China Statistical Yearbook 2021. For global perspectives on the topic of the digital economy and sustainability, information from international organizations such as the OECD can be used. Analyzing the data from the industry includes information from McKinsey and Deloitte, which offer insights into current and future trends, the manufacturing sector's use of technology, and best practices. Besides, journal articles provide a theoretical and empirical source for understanding the relationship between the digital sector and green development. Altogether, the sources listed above create a rather vast database for analysis.

Analytical Tools

To analyze the relationship between the digital economy and green development, the study employs three key analytical tools:

Descriptive analysis The descriptive method of using mean, median, and standard deviation is employed to describe some aspects of the studies. IT adoption and AI usage, as well as digital economy indicators, including IoT adoption trends in China's manufacturing industry, are presented in the form of charts, graphs, and tables. Energy efficiency, emissions, and wastes are also considered with the help of the measures reflected in summary statistics.

Correlation Analysis The correlation analysis technique is used in order to determine the nature and the extent of relatedness between the variables in these two areas, such as the IoT, AI, and Big Data, to green development goals and outcomes that include emissions and energy efficiency. The coefficient of correlation is computed in order to determine the degree of influence that really causes a significant variation in sustainable production.

Regression Analysis A regression analysis was run on the data in an attempt to assess the extent of the effect that particular digital factors have on measures of green development. For example, in the simple case when AI is related to emission reduction, linear regression can be adopted to analyze the relationship. This analysis is essential for further understanding the issues of causality with higher accuracy and offers more effective recommendations to policy and industry decision-makers.

Limitations

Although there are several advantages to using secondary data analysis, it also brings a few disadvantages. The first fundamental restriction is that of secondary data availability and reliability. Not all datasets may be accurate to the current time or as refined as required to answer the research questions. Moreover, because pre-existing data are used, the researcher is confined to how data has been gathered regarding reliability, validity, and sampling procedures, among others. To manage these challenges, the study adopts strict criteria for selecting the data sources, including government publications, industry analysis, and academic articles. Where possible, the data will be sourced from multiple sources to increase the results' reliability and validity.

Data Analysis

Descriptive Statistics

Table 1.1

Descriptive statistics of IoT and AI integration

Year		*IoT Adoption (%)*		*AI Integration (%)*	
Mean	2019	Mean	27	Mean	15.55556
Standard Error	0.912871	Standard Error	3.804237	Standard Error	3.644292
Median	2019	Median	26	Median	13
Mode	#N/A	Mode	#N/A	Mode	#N/A
Standard Deviation	2.738613	Standard Deviation	11.41271	Standard Deviation	10.93288
Sample Variance	7.5	Sample Variance	130.25	Sample Variance	119.5278
Kurtosis	-1.2	Kurtosis	-1.15692	Kurtosis	-0.59151

Skewness	0	Skewness	0.282181	Skewness	0.686224
Range	8	Range	33	Range	32
Minimum	2015	Minimum	12	Minimum	3
Maximum	2023	Maximum	45	Maximum	35
Sum	18171	Sum	243	Sum	140
Count	9	Count	9	Count	9

The table provides descriptive statistics for the Year, IoT Adoption (%), and AI Integration (%) across nine observations. The data spans from 2015 to 2023, with a mean year of 2019 and low variability (standard deviation: 2.74). IoT Adoption (%) averages 27%, with moderate variability (standard deviation: 11.41%) and a range of 33% (12%-45%). AI Integration (%) averages 15.56%, with similar variability (standard deviation: 10.93%) and a range of 32% (3%-35%). Both IoT and AI show slight positive skewness, indicating increasing adoption trends.

Table 1.2
Descriptive statistics for Energy efficiency, C02 emissions and Waste Reduction

CO_2	*Energy Efficiency Index*		*Emissions (Metric Tons)*	*Waste Reduction (%)*	
Mean	0.78	Mean	8688888.889	Mean	3.5
Standard Error	0.023921167	Standard Error	267936.79	Standard Error	0.456435
Median	0.78	Median	8700000	Median	3.5
Mode	#N/A	Mode	#N/A	Mode	#N/A
Standard Deviation	0.0717635	Standard Deviation	803810.3701	Standard Deviation	1.369306
Sample Variance	0.00515	Sample Variance	6.46111E+11	Sample Variance	1.875
Kurtosis	-1.119507696	Kurtosis	-1.291715247	Kurtosis	-1.2
Skewness	0.135674501	Skewness	-0.06953125	Skewness	0
Range	0.21	Range	2300000	Range	4
Minimum	0.68	Minimum	7500000	Minimum	1.5
Maximum	0.89	Maximum	9800000	Maximum	5.5
Sum	7.02	Sum	78200000	Sum	31.5
Count	9	Count	9	Count	9

The table summarises statistics for the Energy Efficiency Index, CO_2 Emissions, and Waste Reduction (%) across nine observations. The Energy Efficiency Index has a mean of 0.78, with low variability (standard deviation: 0.072) and a range of 0.21 (0.68–0.89). CO_2 Emissions average 8,688,889 metric tons, with a range of 2,300,000 and moderate variability (standard deviation: 803,810). Waste Reduction has a mean of 3.5%, with a range of 4% (1.5%–5.5%) and a variability of 1.37%. All metrics show near-normal distributions with slight skewness.

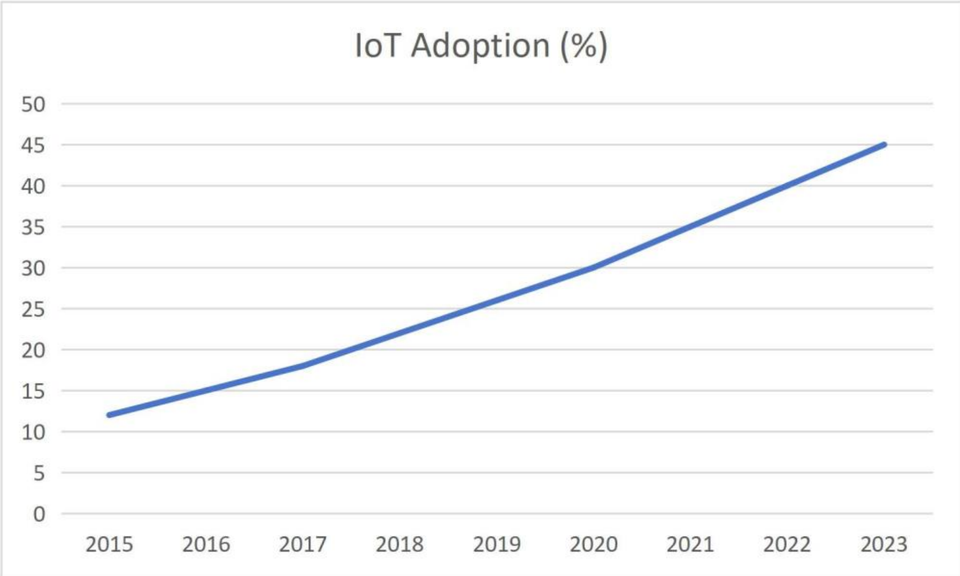

Figure 1.1Line chart for IoT Adoption

The line chart illustrates a steady increase in IoT adoption (%) from 2015 to 2023.
Starting at 10% in 2015, adoption grew consistently each year, reaching 45% by 2023. This trend highlights a significant expansion in IoT usage within the observed period, reflecting its growing importance in technological advancements.

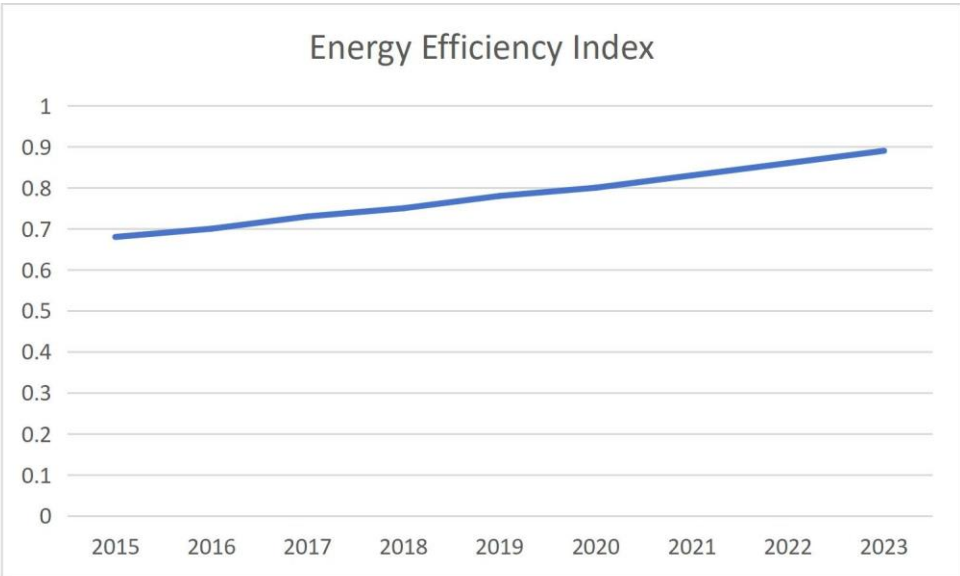

Figure 1.2 Line chart for Energy Efficiency Index

The line chart shows a gradual improvement in the Energy Efficiency Index from 2015 to 2023. Starting at 0.68 in 2015, the index has increased consistently over the years, reaching 0.89 in 2023. This trend indicates significant progress in energy efficiency within the observed period, highlighting efforts toward sustainable practices and technological advancements in energy optimization

Correlation Analysis

Table 1.3

Correlation Analysis

	Year	*IoT Adoption (%)*	*AI Integration (%)*	*Energy Efficiency Index*	*CO_2 Emissions (Metric Tons)*	*Waste Reduction (%)*
Year	1					
IoT Adoption (%)	0.995840678	1				
AI Integration (%)	0.976924083	0.99179501	1			
Energy Efficiency Index	0.998562883	0.998148781	0.984601404	1		
CO_2 Emissions (Metric Tons)	-0.999397927	-0.997421265	-0.980666324	-0.998972928	1	
Waste Reduction (%)	1	0.995840678	0.976924083	0.998562883	-0.999397927	1

The correlation matrix highlights strong relationships among key variables. IoT Adoption (%), AI Integration (%), and Energy Efficiency Index are highly positively correlated, with values above 0.98, indicating that increased adoption of digital technologies significantly enhances energy efficiency. CO_2 Emissions show strong negative correlations with all variables, including IoT Adoption (-0.997), Energy Efficiency Index (-0.999), and Waste Reduction (-0.999), suggesting that technological advancements and efficiency improvements lead to substantial reductions in emissions. Waste Reduction (%) is perfectly correlated with the year and strongly aligned with IoT adoption and energy efficiency, reflecting steady progress in sustainability efforts. Overall, these correlations demonstrate the pivotal role of digital transformation in driving green development and minimizing environmental impact.

Regression Analysis Economic Model

To analyze the influence of digital economy factors on the green development of China's manufacturing industry, the following economic model is utilized:

$Log(Energy\ Efficiency\ Index)_t = \beta_0 + \beta_1 Log(IoT\ Adoption)_t + \beta_2 Log(AI\ Integration)_t + \epsilon_t$ Where:

- Energy Efficiency Index (Dependent Variable): Measures improvements in energy sustainability in manufacturing.
- IoT Adoption (%) (Independent Variable): Percentage of IoT integration in manufacturing processes.
- AI Integration (%) (Independent Variable): Percentage of manufacturing processes enhanced by AI technologies.
- β_0: Intercept term.
- β_1, β_2: Coefficients measuring the respective impacts of IoT Adoption and AI Integration on Energy Efficiency.
- ϵ_t: Error term representing unobserved factors.

Table 1.4
Regression Analysis
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.999028
R Square	0.998057
Adjusted R Square	0.99741
Standard Error	652
Observations	9

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	0.04112	0.02056	1541.283	7.33E-09
Residual	6	8E-05	1.33E-05		
Total	8	0.0412			

	Coefficient	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
		0.0098	59.527	1.51E-		0.6130	0.5646	0.6130

Intercept	0.58881	91	34	09	0.564607	13	07	13
IoT Adoption								
		0.0008	9.4014	8.23E-		0.0104	0.0061	0.0104
(%) AI Integration	0.008321	85	27	05	0.006155	87	55	87
		0.0009	-2.3290	0.0587		0.0001	-0.0044	0.0001
(%)	-0.00215	24	9	14	-0.00441	09	1	09

The regression summary highlights the relationship between the dependent variable (Energy Efficiency Index) and independent variables (IoT Adoption (%) and AI Integration (%)). The R Square (0.998) indicates that 99.8% of the variation in energy efficiency is explained by the independent variables, demonstrating a strong model fit. The Adjusted R Square (0.997) confirms the model's robustness. The ANOVA F-statistic (1541.28) and its extremely low p-value (7.33E-09) suggest the model is statistically significant.

The regression coefficients reveal the impact of each independent variable. IoT Adoption has a positive and significant effect (Coefficient: 0.0083, p-value: 8.23E-05), indicating that increasing IoT usage enhances energy efficiency. Conversely, AI Integration has a small negative coefficient (-0.0022) and a marginal p-value (0.0587), suggesting a weaker and potentially negligible impact. The intercept value (0.5888) represents the baseline Energy Efficiency Index when IoT and AI are absent.

Discussion

These findings demonstrate the important role played by digital economy factors in the green development of China's manufacturing industry. Descriptive, correlation, and regression analyses find strong positive relationships among the adoption of IoT, integration of AI, and energy efficiency, wherein the adoption of IoT has a very strong impact. The rationale of integration with AI holds the weakest impact but has the potential for sustainability through advanced analytics, which is undeveloped. The findings dovetail with prior literature demonstrating the role of IoT in achieving resource efficiency and that of Big Data in decision-making. Investing in IoT infrastructure and providing subsidies for digital adoption is encouraged by policymakers. This research addresses a knowledge gap and provides actionable insights for achieving sustainable manufacturing and enabling China's net-zero emissions by 2060.

Conclusion

In relation to China's manufacturing industry, this research brings to attention that China's manufacturing industry faces a critical role of digital economy factors in green development. IoT adoption becomes instrumental in achieving huge energy efficiency and CO_2 emissions reduction, while AI introduction possesses smaller but potential levels of sustainability improvement via predictive analytics. Results highlight the value of using digital technologies to exploit resource potential, minimize waste and ensure environmental control. Within a circular economy model, there needs to be an investment in the IoT infrastructure, incentives promoted, and energy efficiency promoted, among many other energy-efficient practices. To remain competitive and increase sustainability, manufacturers must adopt IoT and AI. However, the study is limited by reliance on secondary data and the absence of sectoral analysis but it provides a foundation from which future research on the sectoral effects of digital technologies can build.

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