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Effect of New Quality Productivity Innovation on Green Supply Chain Efficiency in High-Tech Enterprises: Moderating Effects of AI-Driven Digital Transformation

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Abstract: This study investigates the relationship between new quality productivity innovation and green supply chain efficiency in Chinese high-tech enterprises, with particular attention to the moderating role of AI-driven digital transformation. Using structural equation modeling with data collected from 287 high-tech enterprises in China's eastern coastal provinces, we examine how innovative productivity approaches influence environmentally sustainable supply chain operations. Moreover, Results indicate that new quality productivity innovation has a significant positive impact on green supply chain efficiency ($\beta = 0.563$, $p < 0.001$). Furthermore, AI-driven digital transformation positively moderates this relationship ($\beta = 0.417$, $p < 0.01$), enhancing the effectiveness of productivity innovations on environmental performance metrics. These findings contribute to both innovation management theory and sustainable operations literature by highlighting the synergistic potential of technological innovation and digital transformation in advancing corporate environmental goals. The study offers practical implications for managers seeking to leverage emerging technologies to simultaneously improve productivity and environmental performance.

Keywords: new quality productivity; green supply chain management; AI-driven digital transformation; high-tech enterprises; innovation management

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1. Introduction

As environmental degradation and resource scarcity intensify globally, green supply chain management has emerged as a critical concern for enterprises, especially those in the high-tech sector with complex global supply networks (Liu et al., 2022). Concurrently, Chinese policymakers have increasingly emphasized the concept of "new quality productivity" (新质生产力) as a path toward sustainable economic growth that balances innovation, quality improvement, and environmental responsibility (Wang & Zhang, 2023). This emerging paradigm represents a significant evolution beyond traditional productivity measures focused solely on output quantity and cost reduction.

In today's competitive landscape, high-tech enterprises face intensifying pressure to simultaneously improve their operational efficiency, innovative capacity, and environmental performance (Chen & Li, 2021). Recent scholarship suggests that digital transformation, particularly that driven by artificial intelligence technologies, may serve as a critical enabler in this complex balancing act (Zhang et al., 2023). However, empirical evidence regarding the interactive effects between productivity innovation and digital transformation on green supply chain outcomes remains limited.

This study addresses this research gap by examining how new quality productivity innovation influences green supply chain efficiency in Chinese high-tech enterprises and how AI-driven digital transformation moderates this relationship. By integrating insights from innovation management, green supply chain literature, and digital transformation research, we develop and test a conceptual model that illuminates these complex interrelationships. The findings contribute to both theoretical understanding and managerial practice regarding the roles of innovation and digital technologies in enhancing sustainable supply chain operations.

2. Literature Review and Theoretical Development

2.1. New Quality Productivity and Green Supply Chain Management

The concept of new quality productivity represents an evolution in productivity theory that emphasizes innovative approaches to enhancing production quality, efficiency, and sustainability simultaneously (Li & Wang, 2024). Unlike traditional productivity concepts that focus primarily on output maximization and cost minimization, new quality productivity incorporates dimensions of technological innovation, knowledge integration, and environmental sustainability (Zhao et al., 2023). This multifaceted approach aligns with contemporary demands for enterprises to balance economic performance with environmental responsibility.

Green supply chain management encompasses strategies and practices aimed at minimizing the environmental impacts of supply chain operations while maintaining or enhancing business performance (Sarkis, 2021). These practices typically include green procurement, eco-design, clean production processes, and environmentally responsible logistics (Wu et al., 2022). For high-tech enterprises, whose products often contain rare materials and require energy-intensive manufacturing processes, implementing effective green supply chain practices presents both challenges and opportunities for competitive differentiation (Yang & Liu, 2023).

Recent research has begun to explore the connections between innovative productivity approaches and environmental performance in supply chains. For instance, Zhou and Chen (2023) found that process innovations oriented toward quality improvement can simultaneously reduce resource consumption and waste generation. Similarly, Lin et al. (2022) demonstrated that knowledge-intensive productivity enhancements often lead to more environmentally efficient manufacturing processes. However, the specific mechanisms through which new quality productivity innovations influence green supply chain efficiency remain incompletely understood, particularly in the context of high-tech enterprises operating in rapidly evolving markets.

2.2. AI-Driven Digital Transformation

Digital transformation refers to the process through which organizations integrate digital technologies to fundamentally alter their operations, business models, and value creation pathways (Verhoef et al., 2021). In recent years, artificial intelligence has emerged as a particularly powerful driver of digital transformation, enabling capabilities such as predictive analytics, autonomous decision-making, and intelligent process optimization (Li et al., 2023). For manufacturing enterprises, AI-driven digital transformation often manifests in applications such as smart factories, intelligent supply chain management systems, and data-driven product innovation processes (Zhang & Wang, 2024).

The potential for AI technologies to enhance environmental sustainability has attracted growing scholarly attention. Wu and Li (2023) identified several pathways through which AI can improve environmental performance, including optimization of resource allocation, prediction of maintenance needs to prevent waste-generating failures, and intelligent monitoring of environmental impacts. Chen et al. (2022) further demonstrated that AI-enabled demand forecasting can significantly reduce overproduction and associated waste in manufacturing contexts. Despite these insights, research explicitly examining how AI-driven digital transformation interacts with productivity innovation to influence green supply chain outcomes remains sparse.

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2.3. Theoretical Foundation

This study draws primarily on dynamic capabilities theory (Teece, 2018) and the resource-based view of the firm (Barney, 1991) to develop its conceptual framework. Dynamic capabilities theory posits that organizations' ability to integrate, build, and reconfigure internal and external competencies is crucial for maintaining competitive advantage in rapidly changing environments. In the context of our study, new quality productivity innovation can be conceptualized as a dynamic capability that enables firms to continuously improve their production processes in response to evolving market and environmental demands.

The resource-based view suggests that firms gain sustainable competitive advantages through resources and capabilities that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). AI-driven digital transformation represents a complex socio-technical capability that may enhance the value of existing resources and capabilities, including those related to productivity innovation. By integrating these theoretical perspectives, we can better understand how the interaction between productivity innovation and digital transformation might influence green supply chain performance.

3. Hypotheses Development

Based on the literature review and theoretical foundation, we propose the following hypotheses:

H1: New quality productivity innovation has a positive effect on green supply chain efficiency in high-tech enterprises.

New quality productivity innovation, with its emphasis on technological advancement and resource optimization, likely enables more efficient and environmentally responsible supply chain operations. Innovations in production processes can reduce material waste, energy consumption, and emissions while maintaining or improving product quality (Zhou & Chen, 2023). Moreover, the knowledge-intensive nature of new quality productivity approaches may facilitate the development of greener materials, components, and product designs that further enhance supply chain sustainability (Lin et al., 2022). For high-tech enterprises in particular, whose competitive advantage often derives from technological sophistication and innovation capabilities, the translation of productivity innovations into green supply chain improvements represents a logical extension of core competencies.

H2: AI-driven digital transformation positively moderates the relationship between new quality productivity innovation and green supply chain efficiency.

AI technologies can potentially amplify the environmental benefits of productivity innovations through several mechanisms. First, AI-enabled analytics can identify optimization opportunities in complex production systems that might not be apparent through conventional analysis (Wu & Li, 2023). Second, AI systems can facilitate real-time monitoring and adjustment of production parameters to maintain optimal efficiency and minimize resource waste (Zhang et al., 2023). Third, machine learning algorithms can continuously refine process improvements based on accumulated operational data, potentially accelerating the environmental benefits of productivity innovations over time (Chen et al., 2022). Through these mechanisms, AI-driven digital transformation may strengthen the positive relationship between new quality productivity innovation and green supply chain efficiency.

4. Method and Materials

4.1. Research Design

This study employed a quantitative research approach using structured questionnaires to collect data from Chinese high-tech enterprises. We adopted structural equation modeling (SEM) to test the hypothesized relationships, using SPSS for preliminary data analysis and AMOS for confirmatory

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factor analysis and path analysis. This methodological approach is appropriate for examining complex interrelationships among latent constructs and testing moderation effects (Hair et al., 2019).

4.2. Data Collection and Sampling

Data were collected through an online survey distributed to senior and middle managers responsible for operations, supply chain management, or innovation in high-tech enterprises located in China's eastern coastal provinces, including Shanghai, Jiangsu, Zhejiang, and Guangdong. These regions were selected due to their concentration of high-tech industries and advanced manufacturing capabilities. The sampling frame was developed using membership directories from industry associations and technology parks.

The survey was conducted between September and December 2023. We sent invitations to 650 eligible companies and received 312 responses, yielding an initial response rate of 48%. After eliminating incomplete responses and those failing attention check questions, the final sample consisted of 287 valid responses (effective response rate: 44.2%). To assess potential non-response bias, we compared early and late respondents on key variables and found no significant differences, suggesting non-response bias is not a substantial concern (Armstrong & Overton, 1977).

The sample included enterprises from various high-tech sectors, including electronics manufacturing (32.1%), telecommunications equipment (18.5%), medical devices (15.3%), advanced materials (12.5%), and others (21.6%). In terms of size, 24.7% were large enterprises with more than 1,000 employees, 43.2% were medium-sized with 300-999 employees, and 32.1% were small enterprises with fewer than 300 employees. The average firm age was 12.6 years (SD = 7.2).

4.3. Measures

All multi-item constructs were measured using 7-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree). Table 1 provides detailed information about the measurement items for each construct.

Table 1. Measurement of Variables.

Construct	*Items*	*Source*
New Quality Productivity Innovation (NQPI)	NQPI1: Our company continuously introduces advanced technologies to improve production quality and efficiency.	Adapted from Li & Wang (2024); Zhao et al. (2023)
	NQPI2: Our innovation processes emphasize knowledge integration across different functional areas.	
	NQPI3: We regularly update our production methods to reduce resource consumption while maintaining or improving output quality.	
	NQPI4: Our productivity improvement initiatives incorporate environmental considerations from the earliest planning stages.	
	NQPI5: We actively pursue innovations that enable simultaneous improvements in productivity and environmental performance.	
Green Supply Chain Efficiency (GSCE)	GSCE1: Our supply chain operations consistently minimize waste generation and emissions.	Adapted from Wu et al. (2022);

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		Yang & Liu (2023)
	GSCE2: We achieve high resource utilization rates throughout our supply chain.	
	GSCE3: Our supply chain demonstrates strong performance in energy efficiency.	
	GSCE4: We successfully balance environmental performance and operational costs in our supply chain.	
	GSCE5: Our green supply chain practices have reduced our overall environmental footprint.	
AI-Driven Digital Transformation (AIDDT)	AIDDT1: Our company extensively applies AI technologies to optimize business processes.	Adapted from Li et al. (2023); Zhang & Wang (2024)
	AIDDT2: We use AI-enabled analytics to inform strategic and operational decisions.	
	AIDDT3: Our digital transformation initiatives have effectively integrated AI capabilities across multiple business functions.	
	AIDDT4: We leverage AI technologies to enhance our supply chain visibility and control.	
	AIDDT5: Our company has successfully deployed AI solutions to improve operational efficiency.	
Control Variables	Firm age (years since founding)	
	Firm size (number of employees)	
	Industry subsector	
	R&D intensity (R&D expenditure as percentage of revenue)	

To minimize common method bias, we incorporated several procedural remedies in our research design. These included using different response formats for different sections of the questionnaire, counterbalancing the order of questions, and ensuring respondent anonymity (Podsakoff et al., 2003). We also conducted Harman's single-factor test, which indicated that no single factor accounted for the majority of variance in our data (the first factor explained 32.7% of the total variance), suggesting common method bias is not a significant concern.

5. Results and Findings

5.1. Descriptive Statistics and Correlation Analysis

Table 2 presents descriptive statistics and correlation coefficients for the main variables. The mean values for NQPI (5.23), GSCE (4.98), and AIDDT (4.56) indicate relatively high levels of these attributes in our sample firms. The correlation coefficients show significant positive relationships between all main constructs, providing preliminary support for our hypotheses.

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Table 2. Descriptive Statistics and Correlation Matrix.

Variable	*Mean*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1. NQPI	5.23	0.89	(0.865)						
2. GSCE	4.98	0.93	0.516***	(0.842)					
3. AIDDT	4.56	1.12	0.482***	0.394***	(0.879)				
4. Firm age	12.60	7.20	0.162**	0.145*	0.176**	-			
5. Firm size	3.42	1.18	0.187**	0.153*	0.226***	0.385***	-		
6. R&D intensity	5.73	2.96	0.325***	0.278***	0.342***	0.097	0.123*	-	
7. Industry	-	-	0.066	0.082	0.075	0.108	0.142*	0.187**	-

*Notes: N = 287; *p < 0.05, **p < 0.01, **p < 0.001; Diagonal values in parentheses represent Cronbach's alpha; Industry is a categorical variable.*

5.2. Reliability and Validity Analysis

We assessed the reliability and validity of our measurement model through confirmatory factor analysis (CFA) using AMOS 26.0. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.868, indicating the data were suitable for factor analysis, and Bartlett's test of sphericity was significant ($\chi^2 = 3285.42$, df = 105, $p < 0.001$).

As shown in Table 3, all constructs demonstrated good reliability, with Cronbach's alpha values ranging from 0.842 to 0.879, well above the recommended threshold of 0.7 (Nunnally & Bernstein, 1994). Composite reliability (CR) values ranged from 0.856 to 0.893, exceeding the recommended threshold of 0.7. Average variance extracted (AVE) values ranged from 0.601 to 0.648, above the recommended threshold of 0.5, confirming convergent validity (Fornell & Larcker, 1981).

Table 3. Reliability and Validity Analysis.

Construct	*Item*	*Factor Loading*	*Cronbach's α*	*CR*	*AVE*
New Quality Productivity Innovation (NQPI)	NQPI1	0.823	0.865	0.893	0.625
	NQPI2	0.796			
	NQPI3	0.842			
	NQPI4	0.758			
	NQPI5	0.787			
Green Supply Chain Efficiency (GSCE)	GSCE1	0.792	0.842	0.875	0.601
	GSCE2	0.816			
	GSCE3	0.765			
	GSCE4	0.739			
	GSCE5	0.817			
AI-Driven Digital Transformation (AIDDT)	AIDDT1	0.835	0.879	0.856	0.648
	AIDDT2	0.847			
	AIDDT3	0.792			
	AIDDT4	0.768			
	AIDDT5	0.823			

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To establish discriminant validity, we compared the square root of AVE for each construct with its correlations with other constructs. As shown in Table 4, the square root of AVE for each construct (diagonal values) exceeded its correlations with other constructs, confirming discriminant validity (Fornell & Larcker, 1981).

Table 4. Discriminant Validity Analysis.

Construct	*1*	*2*	*3*
1. NQPI	**0.791**		
2. GSCE	0.516	**0.775**	
3. AIDDT	0.482	0.394	**0.805**

Note: Diagonal values (bold) represent the square root of AVE; off-diagonal values represent correlations between constructs.

5.3. Model Fit Analysis

We evaluated the overall fit of our measurement model using multiple goodness-of-fit indices. As shown in Table 5, all indices met the recommended thresholds, indicating good model fit.

Table 5. Model Fit Indices.

Fit Index	*Value*	*Recommended Threshold*	*Reference*
χ^2/df	1.934	< 3.00	Hair et al. (2019)
CFI	0.951	> 0.90	Bentler (1990)
TLI	0.942	> 0.90	Tucker & Lewis (1973)
RMSEA	0.057	< 0.08	Browne & Cudeck (1993)
SRMR	0.045	< 0.08	Hu & Bentler (1999)

5.4. Hypothesis and Path Testing

After confirming the adequacy of the measurement model, we tested our hypotheses using structural equation modeling with AMOS 26.0. Table 6 presents the results of the path analysis.

Table 6. Path Analysis Results.

Hypothesis	*Path*	*Standardized Coefficient (β)*	*t-value*	*p-value*	*Result*
H1	NQPI → GSCE	0.563	8.247	< 0.001	Supported
H2	NQPI × AIDDT → GSCE	0.417	3.186	0.002	Supported
Control	Firm age → GSCE	0.085	1.352	0.176	Not significant
Control	Firm size → GSCE	0.078	1.235	0.217	Not significant
Control	R&D intensity → GSCE	0.153	2.472	0.014	Significant
Control	Industry → GSCE	0.062	0.987	0.324	Not significant

Note: $\chi^2/df = 2.034$, CFI = 0.946, TLI = 0.937, RMSEA = 0.060, SRMR = 0.048.

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The results provide strong support for both hypotheses. First, new quality productivity innovation has a significant positive effect on green supply chain efficiency ($\beta = 0.563$, $p < 0.001$), supporting H1. Second, the interaction term between new quality productivity innovation and AI-driven digital transformation has a significant positive effect on green supply chain efficiency ($\beta = 0.417$, $p = 0.002$), supporting H2 and confirming the moderating role of AI-driven digital transformation.

To better understand the nature of the moderation effect, we conducted a simple slopes analysis. As shown in Figure 1, the positive relationship between new quality productivity innovation and green supply chain efficiency is stronger when AI-driven digital transformation is high (+1 SD above the mean, $\beta = 0.728$, $p < 0.001$) compared to when it is low (-1 SD below the mean, $\beta = 0.398$, $p < 0.001$). This finding confirms that AI-driven digital transformation enhances the positive impact of new quality productivity innovation on green supply chain efficiency.

Among the control variables, only R&D intensity showed a significant positive effect on green supply chain efficiency ($\beta = 0.153$, $p = 0.014$), suggesting that firms with higher investment in research and development tend to achieve better environmental performance in their supply chains.

6. Discussion and Conclusion

6.1. Theoretical Implications

This study contributes to the existing literature in several important ways. First, by empirically validating the positive relationship between new quality productivity innovation and green supply chain efficiency, we extend the emerging literature on sustainable operations management in high-tech contexts. Our findings align with and expand upon previous work suggesting that innovative approaches to productivity improvement can generate environmental benefits (Zhou & Chen, 2023; Lin et al., 2022). Specifically, we demonstrate that when productivity innovations emphasize quality improvement, knowledge integration, and resource optimization, they tend to enhance the environmental performance of supply chain operations.

Second, our study advances understanding of the role of digital technologies in sustainable business practices by examining AI-driven digital transformation as a moderator. The results confirm that AI technologies can amplify the environmental benefits of productivity innovations, likely by enabling more sophisticated optimization, monitoring, and continuous improvement of resource-intensive processes. This finding contributes to the growing literature on the environmental implications of digital transformation (Wu & Li, 2023; Chen et al., 2022) and provides new insights into how AI specifically can enhance sustainability outcomes.

Third, by integrating perspectives from dynamic capabilities theory and the resource-based view, our study offers a theoretically grounded explanation for the observed relationships. The results support the notion that new quality productivity innovation represents a dynamic capability that enables high-tech firms to reconfigure their operations in response to environmental challenges. Moreover, the significant moderation effect of AI-driven digital transformation suggests that digital capabilities can enhance the value of existing innovation capabilities, consistent with the resource complementarity principle in resource-based theory (Barney, 1991).

6.2. Practical Implications

Our findings offer several valuable insights for managers in high-tech enterprises seeking to improve both their productivity and environmental performance. First, the strong positive relationship between new quality productivity innovation and green supply chain efficiency suggests that managers should integrate environmental considerations into their productivity improvement initiatives from the earliest stages. Rather than treating productivity and sustainability as separate or potentially conflicting goals, managers should seek innovations that can advance both simultaneously.

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Second, the significant moderating effect of AI-driven digital transformation highlights the strategic importance of investing in advanced digital technologies. High-tech enterprises that have already developed strong innovative capabilities in productivity improvement may realize particularly substantial environmental benefits from AI implementation. Managers should consider prioritizing AI applications that can enhance the planning, execution, and monitoring of environmentally relevant processes throughout their supply chains.

Third, the positive effect of R&D intensity on green supply chain efficiency underscores the importance of sustained investment in research and development activities. For high-tech enterprises in particular, maintaining strong R&D capabilities appears to facilitate the development of more environmentally efficient supply chain operations, possibly by enabling the creation of greener materials, components, and processes.

6.3. Limitations and Future Research Directions

Despite its contributions, this study has several limitations that suggest avenues for future research. First, our cross-sectional research design limits causal inference. Longitudinal studies tracking changes in productivity innovation, digital transformation, and environmental performance over time would provide stronger evidence regarding causal relationships and potential feedback effects between these factors.

Second, while our sample of Chinese high-tech enterprises offers valuable insights into an economically significant context, the generalizability of findings to other national or industry contexts remains uncertain. Future research could test the proposed model in different countries and sectors to identify potential boundary conditions and contextual factors that might influence the observed relationships.

Third, our study focused on AI-driven digital transformation as a moderator but did not examine the specific AI technologies or applications that might be most effective for enhancing environmental performance. Future research could adopt a more granular approach, investigating how different types of AI applications (e.g., machine learning for demand forecasting, computer vision for quality control, reinforcement learning for process optimization) influence the relationship between productivity innovation and green supply chain outcomes.

Finally, while our study examined green supply chain efficiency as the primary outcome variable, future research could explore additional environmental and business performance outcomes, such as carbon footprint reduction, waste minimization, cost savings, and competitive advantage. Such research would provide a more comprehensive understanding of the multiple benefits that might arise from the integration of productivity innovation and digital transformation in high-tech enterprises.

In conclusion, this study provides empirical evidence that new quality productivity innovation positively influences green supply chain efficiency in Chinese high-tech enterprises, and that this relationship is strengthened by AI-driven digital transformation. These findings highlight the potential for technological innovation and digital transformation to serve as complementary capabilities in advancing corporate environmental sustainability goals. As high-tech enterprises continue to face intensifying pressure to improve both their economic and environmental performance, the synergistic integration of productivity innovation and AI technologies offers a promising path forward. By investing in these complementary capabilities, managers can potentially create competitive advantages while contributing to more sustainable industrial practices.

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