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The Mechanism of Digital Intelligence Transformation Empowering Enterprises' New Quality Productive Forces—Empirical Evidence from A-Share Listed Manufacturing Companies

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Abstract: *Confronted with a complex and challenging international environment alongside domestic reform and development imperatives, new quality productive forces have emerged as a pivotal driver for advancing Chinese modernisation and establishing a new development paradigm. Digital intelligence transformation, integrating digitalisation and intelligentisation, serves as a pivotal driver of technological revolution and industrial transformation. It reshapes corporate growth models and governance structures, acting as a crucial lever for fostering new quality productive forces within enterprises. This study empirically examines the impact and mechanisms of digital intelligence transformation on corporate new quality productive forces using a sample of A-share listed manufacturing companies from 2014 to 2022. Results show that digital intelligence transformation significantly enhances the development of new quality productive forces, a conclusion that holds across multiple robustness tests. This study offers insights for enabling China's manufacturing enterprises to leverage new quality productive forces through digital intelligence transformation, thereby contributing to high-quality economic development.*

Keywords: *Digital Intelligence Transformation; New Quality Productive Forces*

1. Introduction

Since the concept of new productive forces was proposed in 2023, it has become a vital economic development engine, with its application in promoting corporate transformation spreading across sectors. The 2025 National People's Congress emphasized developing these forces locally and building a modern industrial system. New-type productive forces, characterized by innovation, are high-tech, efficient, and quality-oriented, aligning with the new development philosophy[1]. Advancing their development is a major strategic task. Existing research shows digital intelligence transformation can affect total factor productivity[2], hinting it may drive new quality productive forces. Digital intelligence transformation, a higher-stage product of digital development, fuses digital and intelligent technologies. It enables innovation clustering, factor allocation, and productivity increase, supporting the essence of new quality productive forces—innovation-driven development. Studying their relationship is of great importance. However, current research on new quality productive forces focuses more on their role than driving factors, and digital intelligence transformation studies rarely consider its impact on corporate innovation. This paper takes a digital - intelligent integration perspective, analyzes how digital intelligence transformation affects enterprises' new - quality productivity, aiming to inform theory and practice.

2. Theoretical Analysis

The emergence of new quality productive forces not only disrupts traditional industries but also imposes novel demands on innovation capacity, intelligentisation, and sustainable development[3]. Corporate digital intelligence transformation, through digital-intelligent integration, consolidates factor and product markets, promotes production-distribution convergence, enhances worker quality-efficiency, achieves digital transformation of means of labour and efficient transformation of objects of labour, and optimises their combination, thereby empowering the leap in new quality productive forces.

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Regarding worker quality, digital intelligence transformation enhances workers' competence, efficiency, and collaborative innovation, thus supporting new quality productive forces. On one hand, the transformation demands workers master innovative skills; enterprises bolster this through training, cultivating an innovative talent pool to adapt to new production relations[4]. On the other hand, digital-intelligent technologies support workers in making efficient innovation decisions, elevating their capabilities and dynamism to propel new quality productive forces advancement[5]. In terms of means of labour, enterprises' digital and intelligent technologies replace traditional labour tools with more advanced and efficient production resources, boosting productivity and propelling new quality productive forces. Automated equipment and data analytics optimise production and factor allocation, ensuring operational stability while advancing technological, green, and digital productivity[1]. Simultaneously, it facilitates the digitisation and networking of production resources, enabling information sharing and collaboration. This enhances the integration of supply and demand experiences, elevates overall efficiency, and propels further leaps in new quality productive forces.Regarding objects of labour, digital intelligence transformation shifts traditional ones toward high-tech, green, precise, and personalised directions, boosting industrial progress and efficiency while fostering new quality productive forces. On one hand, it drives enterprises to adopt new energies and materials[6], improves energy and material efficiency via digital supply chains, and elevates green production. Additionally, by analysing demand preferences, it enables precise and personalised labour objects, cutting inventory and raising efficiency. Overall, digital-intelligent technologies advance workers, means and objects of labour, and their integration, thereby supporting new quality productive forces.Based on this, the following hypothesis is proposed:

H1: digital intelligence transformation exerts a positive promotional effect on enhancing enterprises' new quality productive forces.

3. Research Design

3.1 Sample Selection and Data Sources

This study selects manufacturing companies listed on the A-share market as research samples. Given that the rapid development of digital and intelligent technologies can be traced back to 2014, the sample research period is set from 2014 to 2022. Enterprise-level data is sourced from the Guotai An database and WIND database. Annual reports required for textual analysis are obtained from the China Securities Regulatory Commission's website. The industry classification of listed companies is determined according to the industry codes and industry category codes specified in the CSRC's Guidelines for the Classification of Listed Companies by Industry (2012 Revision). Based on this, the sample undergoes the following cleaning procedures: (1) Exclusion of enterprises with financial data peculiarities during the sample period, including financial institutions, ST-listed companies, PT-listed companies, and delisted companies; (2) Firms with missing key variables were excluded; (3) Winsorisation tail trimming was applied within the intervals [0, 0.01] and [0.99, 1.00]. Following these procedures, 12,403 observations were ultimately obtained.

3.2 Variable Definitions

3.2.1 Dependent Variable

This study constructs an indicator system for new productive forces, examining the influence of laborers, means of labour, and objects of labour, based on Marx's three elements of productive forces. For new-type labourers, it emphasizes worker quality and efficiency, using indicators such as the share of R&D personnel, highly educated staff, and their remuneration to assess their role in driving innovation and technological breakthroughs. For means of labour, it focuses on advanced production tools, employing fixed asset ratios, industrial robot penetration, and AI adoption to analyse productivity gains. Concerning the new-quality labour object dimension, the study highlights enterprises' green productivity and environmental protection levels, underscoring the significance of green transformation for enhancing new-quality productivity. Resource utilisation efficiency is measured through the proportion of manufacturing overheads. Overall, the paper evaluates enterprises’ new productive forces through multi-dimensional indicator analysis.

In summary, this paper achieves a comprehensive characterization of new-type productive forces in manufacturing enterprises by defining their intrinsic nature, with the measurement indicator system detailed in Table 1. Furthermore, to ensure objectivity when synthesising the overall indicator,

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considering the strong substitutability among tertiary indicators and the need for balanced development of primary indicators, the entropy weighting method was first applied to assign weights to tertiary indicators, ultimately yielding the enterprise's comprehensive new-type productive forces score. The specific indicator system is presented in Table 1:

Table 1 Indicator System for New Quality Productive Forces

variate	factor	Primary indicator	Secondary indicator	Indicator description
New Quality Productive Forces	New quality laborers	New quality labor efficiency	R&D Personnel Compensation Ratio	Researchers' Salaries / R&D Expenses
			R&D Personnel Ratio	Number of R&D Personnel / Total Number of Employees
		New Quality labor Forces	Highly Educated Personnel Ratio	Number of Personnel with Bachelor's Degree or Above / Total Number of Employees
	New productive labor materials	New Quality Production tools	Fixed Assets Ratio	Fixed Assets / Total Assets
			Industrial Robot Penetration Rate	Reference Wang Yongqin and Dong Wen (2020)[7], data from IFR. Ln(Book Value of Machinery / Total Number of Employees)
			AI Adoption Level	
		New Quality technical level	Number of Invention Patent Applications	Ln(Number of Invention Patent Applications + 1)
			R&D Depreciation & Amortization expense Ratio	(R&D Expenses - Depreciation &Amortization) / Operating Revenue
			R&D Leasing Cost Ratio	(R&D Expenses - Leasing Costs) /Operating Revenue
	Newly created labor objects	Sustainable development capacity	Corporate Environmental Protection Level	Total Corporate Environmental Protection Investment/ Total Assets
			Green Transformation Level	Number of Green Patent Applications / Total Number of Patent Applications
		Resource utilization level	Manufacturing Overhead Ratio	• 1 - (Cash Paid for Goods and Services + Cash Paid to Employees) / (Cash Outflows from Operating Activities + Depreciation of Fixed Assets + Amortization of Intangible Assets + Impairment Losses)

3.2.2 Explanatory Variables

Enterprise digital intelligence transformation level (Dt). This study refines its measurement by integrating the Word2Vec neural network with text analysis. Drawing on Wang Yong et al. (2024)[8], six seed keyword categories were designed based on the underlying technologies required for digital intelligence transformation: "digitalisation", "artificial intelligence", "big data", "cloud computing", "blockchain", and "Internet of Things".Subsequently, the Word2Vec model was trained using Python, employing management discussion and analysis (MD&A) texts from annual reports spanning 2014 to 2022 as the training corpus. The continuous bag-of-words (CBOW) model within the WordEmbedding methodology was utilised to extract vocabulary highly correlated with the seed keywords, thereby forming a digital intelligence transformation keyword library. Finally, the annual report text was processed using jieba word segmentation, and the frequency of digital intelligence transformation keywords was counted to measure the extent of corporate digital intelligence transformation.Given right-skewed data, values were logarithmically transformed. The CBOW model expression is shown in the following formula:

$$max\sum_{W=C}\log_{p}\,[w|\,Content(w)] \tag{1}$$

3.3 Control Variables

To control for the influence of other variables on enterprises' New Quality Productive Forces, this study selected the following variables: enterprise scale (Size), enterprise age (Age), debt-to-asset ratio (Lev), operating revenue growth rate (Grow), equity concentration (Sc), dual roles (Duality), management shareholding ratio (Ms), board size (Bs), and independent director ratio (Pid). The

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meanings of each variable are shown in Table 2:

Table 2 Variable Selection and Definitions

Variable Type	Variable Name	Symbol	Measurement Method
Explained Variable	New Quality Productive Forces	Nqp	Sum of entropy weights of New Quality Laborers, New Quality Objects of Labor, and New Quality Means of Labor
Explanatory Va riable	Digital intelligence transformation	Dt	Ln(Digital-Intelligent related word frequency +1)
Control Variables	Firm Size	Size	Ln(Total Assets)
	Firm Age	Age	Number of years since the firm's establishment
	Debt-to-Asset Ratio	Lev	Total Liabilities / Total Assets
	Operating Revenue Growth Rate	Grow	(Current Year's Operating Revenue - Previous Year's Operating Revenue) / Previous Year's Operating Revenue
	Ownership Concentration	Sc	Percentage of shares held by the largest shareholder
	CEO Duality	Duality	A value of 1 if the Chairman and General Manager are the same person, otherwise 0
	Management Shareholding Ratio	Ms	Number of shares held by management / Total number of shares
	Board Size	Bs	Ln(Number of directors + 1)
	Proportion of Independent Directors	Pid	Number of independent directors at year-end / Total number of board members

3.4 Model Specification

To test the impact of digital intelligence transformation on enterprises' New Quality Productive Forces as posited in Hypothesis 1, the following model is designed:

$$NQP_{it}=\alpha_0+\alpha_1 Dt_{it}+\alpha_2 Controls_{it}+\lambda_i+\gamma_t+\vartheta_d+\varepsilon_{it} \tag{2}$$

Where NQP represents the dependent variable, denoting the level of a firm's new-type productive capacity; Dt serves as the core explanatory variable, indicating the level of a firm's digital intelligence transformation; Controls constitutes the control variables, comprising a series of firm and industry characteristic variables that may influence the status of new-type productive capacity.ε_{it} denotes the random disturbance term. To enhance the reliability of regression results and mitigate the impact of unobservable factors at the firm, year, and region levels, individual fixed effects λ_i, year fixed effects γ_t, and region fixed effects ϑ_d are incorporated.

4. Empirical Results Analysis

4.1 Descriptive Statistics

Table 3 Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)
Variable	Observation	Mean	Standard deviation	Minimum	Maximum
Nqp	12,403	0.141	0.0707	0.00145	0.466
Dt	12,403	0.977	0.532	0	2.663
Chain	12,403	0.0875	0.0459	0.0156	0.297
Size	12,403	22.32	1.165	19.53	27.62
Age	12,403	10.94	6.878	0	30
Lev	12,403	0.401	0.178	0.00910	0.990
Grow	12,403	0.314	7.865	-2.624	865.9
Sc	12,403	32.64	13.72	1.840	89.99
Duality	12,403	0.296	0.457	0	1
Ms	12,403	14.16	18.81	0	89.18
Bs	12,403	2.107	0.191	0	2.890
indep	12,403	37.66	5.583	0	80

Table 3 reports descriptive statistics for key variables. The mean value of corporate new-quality productivity (Nqp) is 0.141, with standard deviation of 0.0707. This indicates overall low levels of new-quality productivity among sample enterprises with a relatively concentrated distribution,

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suggesting considerable room for improvement. The mean value for digital intelligence transformation level (Dt) was 0.977, with a minimum of 0 and a maximum of 2.663, and a standard deviation of 0.532. The maximum value was several times the minimum, reflecting significant disparities among enterprises in their digital intelligence transformation processes. Furthermore, the extremes, means, and standard deviations for all control variables fell within reasonable ranges.

4.2 Baseline regression analysis

To exclude potential multicollinearity interference, variance inflation factor (VIF) diagnostics were conducted for each variable. All VIF values are below 2, suggesting no severe multicollinearity issues exist between variables. Table 4 presents the benchmark regression analysis results for Model 1. To mitigate extreme value interference, trimming at the 1% and 99% percentiles was applied to all variables except the dummy variable for dual roles (Dual). Model (1) presents the direct regression of the dependent variable (Nqp) on the explanatory variable (Dt). Model (2) incorporates individual, year, and city fixed effects on top of Model (1). Model (3) includes control variables but omits fixed effects, while Model (4) simultaneously includes both control variables and fixed effects. Analysis of the benchmark regression results reveals that the coefficients for the explanatory variable (Dt) in all four models are statistically significant at the 1% level. This indicates that digital intelligence transformation significantly promotes the development of enterprises' new-type productive forces. Specifically, by integrating digital and intelligent technologies, it enables the optimization of labourers, means of labour, and objects of labour, thereby enhancing new-type productive forces. Hypothesis 1 is thus validated.

Table 4 Benchmark Regression Analysis

Variable	(1) Nqp	(2) Nqp	(3) Nqp	(4) Nqp
Dt	0.039***	0.011***	0.035***	0.010***
	(19.303)	(6.273)	(18.003)	(6.043)
Size			0.018***	0.011***
			(12.137)	(4.885)
Age			-0.002***	-0.002
			(-7.525)	(-0.566)
Lev			0.014**	0.003
			(1.981)	(0.376)
Grow			0.004	-0.001
			(1.626)	(-0.760)
Sc			-0.000***	-0.000*
			(-3.209)	(-1.805)
Duality			0.001	-0.002
			(0.325)	(-1.006)
Ms			-0.000	-0.000
			(-0.146)	(-0.204)
Bs			0.017**	0.002
			(2.034)	(0.351)
indep			0.000*	0.000
			(1.852)	(0.595)
Constant term	0.102***	0.130***	-0.334***	-0.098
	(44.307)	(79.464)	(-9.235)	(-1.521)
N	12,403	12,403	12,403	12,403
adjR^2	0.090	0.666	0.176	0.668
Individual fixed	No	Yes	No	Yes
Year fixed	No	Yes	No	Yes
City fixed	No	Yes	No	Yes

Notes: Values in parentheses denote t-values; ***, ** and * denote significance at the 1%, 5% and 10% levels respectively. The same applies below.

4.3 Robustity Test

4.3.1 Lagged Variable Method

Considering the potential time lag effect of digital transformation on enterprises' new productive

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forces, this study applies a one-period lag to the core explanatory variable. The regression results in Column (1) of Table 5 indicate that L.Dt is significantly positive at the 1% significance level, consistent with the benchmark regression results, thereby validating the robustness of the model.

4.3.2 Alternative Approach to Measuring digital intelligence transformation Level

Due to potential measurement errors in digital intelligence transformation levels affecting conclusions on its impact on new quality productive forces, this study replaces the measurement method for digital intelligence transformation to examine its effect on corporate new quality productive forces. Following Wu Fei et al. (2021)[9], a keyword corpus for digital transformation was constructed from AI, big data, cloud computing, and blockchain dimensions. Using Python text analysis, semantic density of keywords was quantified from A-share listed manufacturing companies' annual reports. After standardizing and log-transforming word frequency data, a composite digital-intelligence transformation index was built. Regression results in Table 5, Column (2) indicate a statistically significant coefficient at the 1% level, consistent with the primary test findings.

4.3.3 Replacement of the New Quality Productive Forces Measurement Method

Given potential measurement errors in the dependent variable (enterprise new-type productivity levels), this study replaces the measurement method for enterprise new-type productivity levels to conduct a robustness test on the influence of digital intelligence transformation. As new-type productivity is fundamentally characterized by total factor productivity (TFP) improvements, drawing on Song et al. (2024)[5], we employ the LP method to calculate TFP as a proxy. Regression results in Column (3) of Table 5 show the digital intelligence transformation coefficient is positively significant at the 1% level, thereby reaffirming Hypothesis 1.

4.3.4 Exclusion of Time Samples

To mitigate the effects of the 2015 Chinese stock market crash and the 2018 Asian financial crisis, and to avoid observational errors arising from uncontrollable factors, this study conducts a robustness check by excluding corporate samples from 2015 and 2018. As shown in Column (4) of Table 5, the coefficient remains positive and significant at the 1% level, with its magnitude largely consistent with that from the main regression, further confirming the model's robustness.

4.3.5 Exclusion of spatial samples

Central municipalities exhibit significant economic, political, and locational advantages. To assess robustness, the regression was rerun excluding Beijing, Tianjin, Shanghai, and Chongqing. As shown in Column (5) of Table 5, the coefficient remains significantly positive at the 1% level, with magnitude largely consistent with the main regression, confirming robustness.

Table 5 Robustness Test Results

	(1)	(2)	(3)	(4)	(5)
Variable	Nqp	Nqp	TFP_LP	Nqp	Nqp
Dt			0.031**	0.011***	0.010***
			(2.380)	(5.445)	(5.215)
L.Dt	0.005***				
	(2.842)				
Dt_2		0.012***			
		(15.338)			
Constant term	-0.086	-0.074	-5.032***	-0.130*	0.130***
	(-1.189)	(-1.166)	(-8.683)	(-1.870)	(73.083)
N	10,172	12,403	12,403	8,342	10,550
adjR^2	0.674	0.677	0.936	0.643	0.652
Control variables	Yes	Yes	Yes	Yes	Yes
Individual fixed	Yes	Yes	Yes	Yes	Yes
Fixed year	Yes	Yes	Yes	Yes	Yes
Urban fixed	10,172	Yes	Yes	Yes	Yes

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5. Conclusion

5.1 Research Findings

This paper establishes an indicator system for new quality productive forces, examining dimensions of labourers, means of labour, and objects of labour. Utilising data from Chinese manufacturing A-share listed companies between 2014 and 2022, it empirically analyses the impact mechanism. Research findings indicate that digital and intelligent transformation has significantly elevated the level of new productivity within enterprises. This conclusion remains robust after undergoing multiple stability tests.

5.2 Policy Implications and Recommendations

Based on the findings, this paper proposes countermeasures to enhance the enabling effects of digital intelligence transformation on new quality productive forces by addressing key issues such as transformation disparities.

To enhance new quality productive forces, firms must accelerate digital-intelligence transformation to elevate new-quality productive forces. Low overall levels remain concentrated, so corporate R&D in digital and intelligent technologies and systematic talent cultivation must expand, while government should offset SME costs via tax credits, subsidies, regional industrial-internet and data-centre build-out to deliver inclusive support.

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