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Research on the Impact of Artificial Intelligence Technological Capability on New Quality Productive Forces

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Abstract: Drawing on data from Chinese A-share listed companies (2019-2023), this study investigates the impact of artificial intelligence (AI) technological capability on the development of new quality productive forces in enterprises and its underlying mechanisms. The empirical results demonstrate that: (1) AI technological capability exerts a significantly positive effect on new quality productive forces; (2) This positive effect is partially mediated through enhanced corporate innovation capacity; (3) Corporate data assets serve as a positive moderator that strengthens the relationship of AI and new quality productivity; (4) The productivity-enhancing effect is particularly pronounced in manufacturing firms and enterprises located in low marketization areas. These findings provide novel theoretical perspectives and empirical evidence for understanding how AI technologies empower the development of new quality productive forces.

Keywords: Artificial Intelligence Technology; New Quality Productive Forces; Innovation Capability; Data Assets

1. Introduction

In March 2024, China's Government Work Report officially proposed the implementation of the “artificial intelligence (AI) +” initiative, aiming to empower various industries and promote intelligent upgrading of traditional sectors through deep integration of AI technology with business entities. It not only facilitates industrial restructuring and productivity leaps, but also accelerates technological innovation and interdisciplinary integration, while reconstructing social governance models and public service systems to provide new momentum for high-quality development. As the core driver of the new round of technological revolution and industrial transformation, AI is profoundly changing production methods and lifestyles. With artificial intelligence being elevated as a national strategic priority, China has established a deep integration mechanism between AI and the real economy through top-level design and policy guidance, effectively fostering the vigorous development of intelligent economic ecosystems and accelerating the formation of new quality productive forces. In February 2025, the China Securities Regulatory Commission promulgated the “Implementation Opinions on Capital Markets Serving the Five Key Financial Tasks,” which established guiding principles for allocating resources to priority areas of new quality productive forces, with particular emphasis on supporting strategic emerging industries including technological innovation, advanced manufacturing, and green low-carbon development. Under this developmental context, new quality productive forces have become the pivotal enabler for achieving qualitative improvements, efficiency enhancements, and dynamic transformation in economic development. Characterized by innovation-driven growth, they provide innovative pathways for modernizing China's governance system and capabilities through industrial restructuring and systemic improvements in total factor productivity. According to data from People's Daily and the Ministry of Industry and Information Technology: In 2023, China's above-scale industrial enterprises achieved significant progress in adopting digital R&D tools, with a penetration rate exceeding 80%, while the numerical control rate of key production processes reached 62.9%. The new energy vehicle industry witnessed a major breakthrough in 2024, with both annual production and sales surpassing the 10 million unit mark, maintaining global leadership for ten consecutive years. In smart manufacturing, China accounts for over 50% of global industrial robot installations, with industrial internet infrastructure achieving comprehensive coverage across all 41 major industrial categories, and 421 national-level intelligent manufacturing demonstration factories being established. Xiaomi Corporation's innovative business division (including smart EVs) generated total revenue of 32.8 billion yuan in 2024 (32.1 billion from smart EVs, 0.7 billion from other businesses). Huawei's R&D expenditure reached 179.7 billion yuan in 2024 (20.8% of annual revenue), with cumulative R&D investment exceeding 1,249 billion yuan over the past decade. This demonstrates that new quality productive forces in enterprises exhibit significant advantages in promoting technological innovation, industrial upgrading, and fostering emerging industries. Despite continuous technological advancements in new quality productive forces, there remains substantial room for improvement. Consequently, enterprises must prioritize the development of new quality productive forces, increase R&D investment, and drive industrial upgrading, which has become a critical issue for future development trends.

Amidst the rapid development of contemporary new quality productive forces, artificial intelligence has emerged as the pivotal driver for qualitative leaps in productivity efficiency by virtue of its distinctive technological endowments. Under this context, the significance of corporate innovation capability has become increasingly prominent. As the primary entities of technological innovation, enterprises can effectively enhance production efficiency and product quality while fostering novel business models and industrial ecosystems through the adoption of AI and other emerging technologies. It empowers enterprises to achieve automated production, process optimization, and predictive maintenance, while fostering personalized customization and intelligent supply chain collaboration. This facilitates quality inspection, creative design, and knowledge sharing, comprehensively driving the development of new quality productivity. Notably, while propelling productivity advancement, artificial intelligence may concurrently engender multifaceted risks: structural employment imbalances induced by technological displacement, threats to personal data security, monopolistic concerns arising from heightened market concentration, and societal equity challenges stemming from algorithmic biases. These issues pose multidimensional constraints on the sustainable development of new quality productive forces, necessitating the establishment of robust policy frameworks and refined governance mechanisms to achieve dynamic equilibrium between fostering technological innovation and mitigating systemic risks.

This study examines the impact of AI on corporate new quality productivity using financial and operational data from Chinese A-share listed companies during 2019-2023, with particular focus on the mediating roles of innovation capability and the moderating effect of digital assets. The paper makes two primary marginal contributions: First, it enriches existing literature by expanding research on AI's influence on corporate new quality productivity. Second, this study innovatively proposes that data assets play a moderating role in the process of AI technology driving corporate new quality productivity, revealing the nonlinear transformation mechanism of the “data-technology-productivity” pathway.

2. Literature Review

2.1 The Direct Mechanistic Effects of Artificial Intelligence Technology on New Quality Productivity Development of Enterprise

AI as a technological system emulating human cognitive behaviors, fundamentally operates through the synergistic integration of algorithms, data, and computing power to achieve autonomous perception, learning, and decision-making. Its core paradigm lies in endowing machines with human-like cognitive and executive capabilities [1]. From a technological evolution perspective, artificial intelligence has transitioned from early rule-driven approaches to data-driven deep learning, progressively overcoming human cognitive limitations in complex environments [2]. From an application logic perspective, it drives a qualitative leap in productivity by optimizing resource allocation (e.g., cost control in smart manufacturing) and reconstructing management paradigms (e.g., shifting decision-making from satisfactory to optimal) [3]. From an application logic perspective, it drives a qualitative leap in productivity by optimizing resource allocation (e.g., cost control in smart manufacturing) and reconstructing management paradigms (e.g., shifting decision-making from satisfactory to optimal) [4]. New Quality Productive Forces represent a novel form of productivity development in the new era, with technological innovation as the core driving force, emphasizing breakthroughs in critical disruptive technologies [5]. It transcends traditional productive forces by integrating new technologies, new economic models, and emerging business formats, thereby achieving both high efficiency and high-quality development, breaking away from conventional growth trajectories to meet the demands of the digital era [6]. AI technology serves as a pivotal driver in advancing New Quality Productive Forces for enterprises, with its direct operational mechanisms permeating multiple dimensions including production process optimization, market responsiveness enhancement, and supply chain management reinforcement, thereby establishing an organically synergistic empowerment framework. Within production operations, AI's precision automation substantially reduces human-induced errors, simultaneously elevating production efficiency and product quality, which directly translates into measurable economic benefits for enterprises [7, 8]. In the sales domain, artificial intelligence enables enterprises to accurately capture market dynamics through in-depth data analysis and precise forecasting, thereby facilitating proactive resource allocation, marketing strategy formulation, and inventory management. This sophisticated market rhythm mastery not only accelerates corporate response velocity but also significantly enhances competitive resilience in highly contested markets [9]. However, this highly efficient operation fundamentally relies on robust supply chain support. The application of AI enables real-time monitoring and optimization across all supply chain segments, effectively mitigating risks associated with information asymmetry while significantly enhancing both transparency and operational efficiency [10]. Such optimization not only mitigates the risk of supply chain disruptions but also reduces operational costs, thereby significantly enhancing corporate economic performance. This synergistic effect endows enterprises with greater competitive advantages in market competition, enabling superior adaptation to market fluctuations and sustainable development, which directly accelerates the advancement of New Quality Productive Forces [11, 12]. Therefore, we propose Hypothesis 1:

H1: The enhancement of corporate AI technological capabilities can significantly facilitate the development of New Quality Productive Forces.

2.2 The Indirect Mechanism of Artificial Intelligence Technology in Promoting the Development of New Quality Productive Forces in Enterprises

AI can provide enterprises with precise market forecasting and consumer profiling through its data analysis and mining capabilities, thereby assisting in developing more competitive products and services and enhancing corporate innovation capacity [13, 14]. It optimizes R&D processes, improves research efficiency, and facilitates technological innovation and product upgrading [15, 16]. Furthermore, by strengthening organizational knowledge absorption and learning capabilities, AI can further drive corporate innovation activities [17, 18]. Consequently, AI technology exhibits a significant facilitative effect on corporate innovation. Corporate innovation serves as a pivotal driver for developing new quality productive forces. Innovation activities, through technological upgrading, product innovation, and service optimization, directly enhance production efficiency and market competitiveness. By leveraging AI-powered innovation applications, enterprises can more accurately identify market demands and accelerate technological iteration and product optimization, thereby gaining competitive advantages in intense market competition. Through R&D investments and technological innovation, enterprises optimize production processes and resource allocation, develop more competitive products and services, reduce production costs, consequently improving economic performance and further advancing the development of new quality productive forces [19, 20]. Therefore, we propose Hypothesis 2:

H2: The enhancement of corporate AI technological capabilities can significantly boost enterprise innovation capacity, thereby advancing the development of new quality productive forces.

2.3 The Moderating Effect of Data Assets on the Relationship between AI Technology and Enterprise New Quality Productive Forces

During the iterative advancement of artificial intelligence technologies, the value of raw corpora as core data assets has become increasingly prominent. These corpora not only serve as fundamental elements for large-scale model training but also emerge as critical variables influencing technological breakthroughs. Currently, Chinese linguistic resources face practical challenges of insufficient volume and inconsistent quality when compared with English corpus resources [21]. As fundamental input elements for models, the quality and volume of data directly determine the precision of algorithmic training and the reliability of predictions. Higher-quality and larger-scale corporate data assets can significantly accelerate the transformation efficiency of AI technologies in business operations, create greater enterprise value, and facilitate the formation of new quality productive forces [22]. Specifically, enterprises establish structured data warehouses and real-time data cleansing systems to perform deep semantic parsing and knowledge graph construction on massive unstructured raw corpora [23, 24]. This process not only significantly enhances the usability of corpus resources but also optimizes model training parameters through feature engineering, enabling AI algorithms to more accurately capture subtle fluctuations in market demand and technological evolution trends [22]. Simultaneously, leveraging AI's cross-modal learning capabilities, enterprises achieve multimodal integration of supply chain data, user behavior data, and R&D data. The synergistic innovation mechanism among data elements significantly enhances the construction and iteration of corporate innovation ecosystems [25-27]. However, the value transformation of data elements is not a linear process. It requires agile organizational restructuring and systematic cultivation of digital talent. With AI-enabled capabilities, enterprises can achieve qualitative leaps from data resources to innovation capacity, thereby promoting the formation and development of new quality productive forces [21, 23]. In summary, we propose Hypothesis 3:

H3: The accumulation of corporate data assets can significantly enhance the positive impact of AI technologies on new quality productive forces.

3. Research Method

3.1 Sample Selection and Data Sources

To examine the impact of AI technological capabilities on corporate new quality productivity development, this paper employs Chinese A-share listed companies the research sample in period of 2019-2023. To ensure the reliability and accuracy of research findings, the following sample screening procedures were implemented: (1) exclusion of financial sector firms; (2) removal of financially distressed PT, ST, and *ST listed companies; (3) elimination of observations with missing variables. After applying these selection criteria, the final sample comprises 18,073 observations. The financial data and AI-related term frequency data were obtained from the China Stock Market & Accounting Research database (CSMAR), while patent data were sourced from the Chinese Research Data Service Platform (CNRDS). Continuous variables were winsorized at the top and bottom 1% to mitigate the influence of extreme outliers.

3.2 Variable Description

3.2.1 Dependent variable

The measurement of corporate new quality productive forces (Npro) is grounded in the two-factor theory of productivity [28], decomposing it into two core dimensions: labor and production tools. Within the labor dimension, we further distinguish between living labor and materialized labor (objects of labor): living labor is measured by three indicators - the proportion of R&D personnel salaries, the percentage of R&D personnel, and the share of highly educated employees; materialized labor is characterized by two indicators - the fixed assets ratio and manufacturing expenses ratio. The “hard technology” and “soft technology” sub-dimensions of the "production tools" dimension are separated into four indicators: the percentage of direct R&D investment, the depreciation and amortization ratio, the leasing expenses ratio, and intangible assets. The "soft technology" sub-dimension uses two proxy variables: total asset turnover and the inverse of the equity multiplier (since the equity multiplier is a negative indicator). Table 1 lists the precise measuring techniques for every indication. In the end, a thorough measurement index for corporate new quality producing forces is constructed using the entropy approach to establish indicator weights.

Table 1. Enterprise New Quality Productive Forces Index

Factor	Subfactors	Indicator	Explanation of Indicator Values	Secondary index weight	First-order index weight
Means of production	Living labor	Percentage of R&D staff salary	R&D expenses-Salary/total revenue	13.5855	20.3822
		The percentage of R&D personnel	Number of R&D personnel/Total number of employees	4.0098	
		The percentage of high-quality talents	Number of bachelor degree or above/Number of employees	2.7869	
	Materialized labor (labor objects)	Percentage of fixed assets	Fixed assets/total assets	3.1030	3.2764
		Percentage of overhead	(Cash outflow from operating activities+ depreciation of fixed assets +amortization of intangible assets +impairment reserve - Purchase of goods and services worth cash - wages paid to employees) / (Cash outflow from operating activities + depreciation of fixed assets + amortization of intangible assets + impairment reserve)	0.1734	
Means of production	Hard technology	R&D depreciation and amortization ratio	R&D expenses - Depreciation and amortization/operating income	7.8755	74.0865
		Percentage of R&D leasing costs	R&D expenses - Lease fees/operating income	35.1110	
		Percentage of direct investment in R&D	R&D expenses - Direct input/operating income	25.4900	
		Percentage of intangible assets	Intangible assets/total assets	5.6100	
	Soft technology	Total assets turnover	Operating income/Average assets	2.1561	2.2550
		The inverse of the equity multiplier	Total owner's equity/assets	0.0989	
New quality productive forces				100	100

3.2.2 Explanatory variable

Artificial intelligence technological capability (AI) represents a relatively abstract concept, with no dedicated disclosure of relevant information in listed companies' annual reports. Existing studies predominantly employ industrial robot adoption as a proxy for measuring corporate AI technological capability [29]. However, industrial robot penetration cannot comprehensively reflect a firm's artificial intelligence technological capability, rendering this approach methodologically limited. Accordingly, this study employs the AI-related term frequency from the 'Artificial Intelligence' sub-database of the CSMAR database, applying natural logarithm transformation after adding one as the proxy variable for corporate AI technological capability.

3.2.3 Mediating variable

Corporate innovation capability (Pat). This study measures corporate innovation capability using the annual number of patent applications. we apply the natural logarithm transformation to the annual patent application count after adding one.

3.2.4 Control variables

Based on research [7,23], this study chooses as control variables the following: return on total assets (ROA), asset-liability ratio (Lev), age at company listing (Age), cash flow ratio (CFrate), the largest shareholder's shareholding ratio (Top1), enterprise size (Size), and the percentage of independent directors (Indep).

3.3 Model Specification

To examine the impact of AI technological capability on corporate new quality productive forces, this study establishes the following baseline regression model.

$$Npro_{it} = \alpha_0 + \alpha_1 AI_{it} + \sum Controls + \sum Industry + \sum Year + \varepsilon_{it} \quad (1)$$

In Model (1), Npro serves as the dependent variable representing corporate new quality productive forces development level, while AI functions as the independent variable denoting AI technological capability.With subscripts i and t standing for individual companies and time periods, respectively, controls represent a collection of control variables, Ind for industry fixed effects, Year for year fixed effects, and ε for the random disturbance term.

We build the following mediation effect models using the three-step mediation analysis approach based on the aforementioned model in order to investigate the mediating function of corporate innovation capability in the link between AI technological competence and Npro development level.

$$AI_{it} = \beta_0 + \beta_1 Pat_{it} + \sum Controls_{it} + \sum Industry + \sum Year + \varepsilon_{it} \quad (2)$$

$$Npro_{it} = \alpha_0 + \theta_1 Pat_{it} + \theta_1 AI_{it} + \sum Controls + \sum Industry + \sum Year + \varepsilon_{it} \quad (3)$$

Where Pat denotes corporate innovation capability, with all other variables identical to those in Equation (1).

Furthermore, this study constructs a moderating effect model (Model 4) by incorporating corporate data assets (Data_Asset) as the moderating variable to examine its influence on the baseline regression. The interaction term between the moderating variable and explanatory variable is employed in this model to test the moderating effect of Data_Asset on Npro.

$$Npro_{it} = \gamma_0 + \gamma_1 AI_{it} + \gamma_2 (AI_{it} \times Data\_Asset) + \sum Controls_{it} \sum Industry + \sum Year + \varepsilon_{it} \quad (4)$$

4. Empirical Analysis

4.1 Descriptive Statistics

The descriptive statistics for each variable are shown in Table 2. The highest and lowest values of Npro, 8.331 and 0.840, respectively, show notable variations in new quality productive forces among Chinese A-share listed companies. Npro's mean value of 2.835, which is consistent with the previous study, shows that it is still at a low level and has a great deal of room to develop [28]. Though they are all very low, listed firms' degrees of AI development vary, with a mean score of 1.267 and maximum and minimum values of 4.898 and 0.000, respectively.

4.2 Baseline Regression

Table 3 displays the results of the baseline regression. Column (1) shows that the AI coefficient is 0.248 and statistically significant at the 1% level when control variables and industry/year fixed effects are not present. Column (2) demonstrates that the AI coefficient is 0.125, which is still statistically significant at the 1% level even after controlling for year and industry fixed effects and eliminating control variables. Column (3) demonstrates that the AI coefficient, which is 0.218, retains statistical significance at the 1% level when control variables are included but no fixed effects are present. The coefficient of AI, 0.116 in Column 4, is still statistically significant at the 1% level after adjusting for both industry/year fixed effects and control factors. By repeatedly demonstrating that AI technical proficiency favorably supports the production of new, high-quality productive forces across a range of specifications, these findings support study hypothesis H1.

Table 2. Descriptive Statistics of Variables

	N	Mean	Median	SD	Min	Max
Npro	18073	2.835	2.500	1.341	0.840	8.331
AI	18073	1.267	0.693	1.332	0.000	4.898
ROA	18073	0.032	0.036	0.070	-0.284	0.205
Lev	18073	0.409	0.402	0.195	0.060	0.888
Age	18073	1.974	2.197	0.993	0.000	3.367
CFRate	18073	0.053	0.051	0.066	-0.142	0.250
Top1	18073	0.323	0.299	0.144	0.081	0.724

Size	18073	22.310	22.111	1.270	19.994	26.290
Indep	18073	0.379	0.364	0.053	0.333	0.571

Table 3. The Baseline Regression Estimates of AI on New Quality Productive Forces

	(1)	(2)	(3)	(4)
	Npro	Npro	Npro	Npro
AI	0.248^{***}	0.125^{***}	0.218^{***}	0.116^{***}
	(34.11)	(13.48)	(29.49)	(12.37)
ROA			-1.746^{***}	-1.634^{***}
			(-10.32)	(-10.04)
Lev			-0.854^{***}	-0.466^{***}
			(-14.13)	(-7.78)
Age			-0.125^{***}	-0.091^{***}
			(-11.08)	(-8.33)
CFRate			0.332^{**}	0.473^{***}
			(2.00)	(2.96)
Top1			-0.647^{***}	-0.319^{***}
			(-9.31)	(-4.70)
Size			0.076^{***}	0.059^{***}
			(7.85)	(6.04)
Indep			0.040	0.071
			(0.22)	(0.42)
_cons	2.522^{***}	2.676^{***}	1.687^{***}	1.854^{***}
	(189.04)	(180.65)	(8.16)	(8.94)
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES
N	18073	18073	18073	18073
adj. R^2	0.060	0.188	0.083	0.196

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3 Robustness Test

4.3.1 Incorporating province fixed effects

Considering the heterogeneity in policy implementation across Chinese provinces and its time-varying effects on regional enterprises' new quality productive forces [30, 31], we augment Model (1) by incorporating province fixed effects. As presented in Column (1) of Table 4, the coefficient of AI is 0.111 and statistically significant at the 1% level. This result demonstrates that the productivity-enhancing effect of AI remains robust even after controlling for industry, year, and province fixed effects, thereby providing stronger empirical support for our findings.

4.3.2 Replacing explanatory variable

In order to assess corporate AI technological capacity, this study uses the natural logarithm transformation of the artificial intelligence keyword count (plus one) taken from the MD&A portions of listed firms' annual reports as a novel explanatory variable (AI_MDA). After the explanatory variable is substituted, the AI_MDA coefficient, as shown in column (2) of Table 4, demonstrates positive directionality and statistical significance at the 1% level, showing that AI technical skill continues to have a favorable impact on new quality productive forces.

4.3.3 Lagged explanatory variable

To examine the dynamic effects of AI technology on new quality productive forces, this study incorporates one-period lagged (L.AI) and two-period lagged (L2.AI) measures of AI technological capability for robustness analysis. As evidenced in columns (3) and (4) of Table 4, both L.AI and L2.AI coefficients demonstrate statistically significant positive effects at the 1% significance level, confirming the robustness of our findings.

Table 4. Robustness Test

	(1)	(2)	(3)	(4)
	Npro	Npro	Npro	Npro
AI	0.111^{***}			

	(11.82)			
AI_MD&A		0.121^{***}		
		(12.3)		
L.AI			0.104^{***}	
			(9.49)	
L2.AI				0.093^{***}
				(7.09)
ROA	-1.571^{***}	-1.635^{***}	-1.357^{***}	-1.175^{***}
	(-9.63)	(-10.04)	(-6.91)	(-4.89)
Lev	-0.417^{***}	-0.454^{***}	-0.434^{***}	-0.429^{***}
	(-6.92)	(-7.57)	(-6.20)	(-5.15)
Age	-0.079^{***}	-0.092^{***}	-0.134^{***}	-0.177^{***}
	(-7.15)	(-8.39)	(-8.76)	(-8.44)
CFRate	0.446^{***}	0.487^{***}	0.385^{**}	0.167
	(2.80)	(3.06)	(2.05)	(0.74)
Top1	-0.322^{***}	-0.330^{***}	-0.288^{***}	-0.215^{**}
	(-4.74)	(-4.86)	(-3.64)	(-2.28)
Size	0.048^{***}	0.059^{***}	0.055^{***}	0.061^{***}
	(4.88)	(6.12)	(4.87)	(4.63)
Indep	0.044	0.071	0.295	0.262
	(0.26)	(0.42)	(1.48)	(1.11)
_cons	2.070^{***}	1.853^{***}	1.958^{***}	1.943^{***}
	(9.91)	(8.94)	(8.17)	(6.92)
Province FE	YES	NO	NO	NO
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	18073	18079	13105	9130
adj. R^2	0.204	0.196	0.193	0.195

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.4 Endogeneity Analysis

We use an instrumental variable (IV) technique to resolve endogeneity issues brought on by omitted variables and reverse causality. After applying two-stage least squares (2SLS) regression and using the industry-average AI technology level as the IV, Column (1) of Table 5 demonstrates that the IV coefficient of 0.990 is statistically significant at the 1% level, indicating a strong positive association between the IV and AI. The instrument is both exogenous and strong, as evidenced by the Cragg-Donald Wald F-statistic of 15,046.92, which significantly surpasses the threshold value of 16.38. At the 1% significance level, the null hypothesis of "underidentification" is rejected using the Anderson LM test. When taken as a whole, these diagnostic tests confirm that our IV choice was suitable. The regression analysis reveals a statistically significant positive coefficient of 0.346 for the AI variable at the 1% significance level, as indicated in Column (2) of Table 5, indicating AI's strong productivity-boosting impact. After resolving endogeneity issues, our primary conclusions remain consistent.

Table 5. Endogeneity Analysis

	(1)	(2)
	AI	Npro
AI		0.346^{***}
		(0.01)
ROA	-0.538^{***}	-1.526^{***}
	(0.13)	(0.17)
Lev	-0.232^{***}	-0.766^{***}
	(0.05)	(0.06)
Age	-0.085^{***}	-0.097^{***}
	(0.01)	(0.01)
CFRate	-0.318^{**}	0.482^{***}
	(0.12)	(0.17)
Top1	-0.377^{***}	-0.474^{***}
	(0.05)	(0.07)
Size	0.148^{***}	0.060^{***}
	(0.01)	(0.01)
Indep	0.159	-0.147
	(0.14)	(0.18)
IV	0.990^{***}	
	(0.01)	
Anderson canon. corr. LM statistic	8214.08^{***}	

Cragg-Donald Wald F statistic	15046.92	
Year FE	YES	YES
N	18,073	18,073
R^2		0.066

t statistics in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

5. Mechanism Analysis

5.1 Mediation Effect Test

To test the mediating effect of corporate innovation capability in the relationship between AI technological level and new quality productivity, this study employs the natural logarithm transformation after adding one to patent applications as the innovation capability metric. As presented in Column (1) of Table 6, the regression of AI on Pat yields a coefficient of 0.173 for AI, which is significantly positive at the 1% level, indicating that AI advancement enhances corporate innovation capability. Column (2) demonstrates that after incorporating innovation capability (Pat), the AI coefficient of 0.102 remains significantly positive at the 1% level, confirming that higher AI levels promote innovation capability, thereby fostering new quality productivity development. Consequently, research hypothesis H2 is empirically validated.

Table 6. Mediation Effect Test Results

	(1)	(2)
	Pat	Npro
AI	0.173^{***}	0.102^{***}
	(16.08)	(10.87)
ROA	1.470^{***}	-1.751^{***}
	(7.89)	(-10.78)
Lev	0.018	-0.468^{***}
	(0.27)	(-7.83)
Age	-0.286^{***}	-0.068^{***}
	(-22.86)	(-6.19)
CFRate	0.897^{***}	0.401^{**}
	(4.91)	(2.53)
Top1	0.068	-0.325^{***}
	(0.87)	(-4.80)
Size	0.307^{***}	0.034^{***}
	(27.63)	(3.47)
Indep	-0.093	0.079
	(-0.47)	(0.46)
Pat		0.079^{***}
		(12.24)
_cons	-4.790^{***}	2.235^{***}
	(-20.19)	(10.70)
Industry FE	YES	YES
Year FE	YES	YES
N	18073	18073
adj. R^2	0.307	0.203

t statistics in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

5.2 Moderating Effect Test

In order to examine its impact on the link between AI technical competence and new quality productive forces, this study uses corporate data assets (Data_Asset) as the moderating variable [32]. The interaction term coefficient between AI and Data_Asset is 0.010, which is statistically positive at the 10% level, as seen in Column (1) of Table 7. These findings suggest that when businesses have more intangible assets, such data resources, the beneficial impact of AI technology on new, high-quality productive forces is more noticeable. Table 7 displays the findings of the moderating effect.

Table 7. Moderating Effect Test Results

	(1)
	Npro
AI	-0.126
	(-0.90)
AI×Data_Asset	0.010^{*}
	(1.70)
Data_Asset	0.270^{***}
	(11.92)
ROA	-2.050^{***}
	(-12.43)
Lev	-0.620^{***}
	(-10.20)
Age	-0.074^{***}
	(-6.76)
CFRate	0.342^{**}
	(2.15)
Top1	-0.313^{***}
	(-4.62)
Size	-0.179^{***}
	(-8.89)
Indep	-0.031
	(-0.18)
_cons	1.039^{***}
	(3.59)
Industry FE	YES
Year FE	YES
N	18073
adj. R^2	0.204

t statistics in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

6. Further Analysis

6.1 Heterogeneity Analysis

6.1.1 Industry heterogeneity

This study separates the sample into manufacturing and non-manufacturing subsamples based on whether the businesses are part of the manufacturing sector. The AI coefficients for manufacturing and non-manufacturing businesses are 0.007 and 0.004, respectively, as indicated in Table 8's columns (1) and (2). These findings suggest that manufacturing firms are more affected by AI's influence on new quality productive forces than non-manufacturing ones. To determine if there was a significant difference between the two sets of coefficients and zero, we performed the Fisher's permutation test with 1,000 replications. The null hypothesis that the AI coefficients of the groups were identical was rejected by the data, which showed a p-value of 0.000.

6.1.2 Heterogeneity in marketization levels

To examine the various effects of corporate AI technological levels on new quality productive forces across provinces with varying marketization levels, we divide the sample into high-marketization and low-marketization groups for regression analysis [33]. As shown in Columns (3) and (4) of Table 8, the AI coefficients for high- and low-marketization provinces were 0.087 and 0.151, respectively, indicating that the influence of AI on increasing productivity is more pronounced in less marketized regions. We confirmed the disparities in the coefficients using 1,000 bootstrap replications of Fisher's permutation test, which yielded a p-value of 0.000, rejecting the null hypothesis of equal coefficients.

7. Conclusions and Implications

7.1 Research Findings

This paper investigates the impact of AI technological capability on corporate new quality productive forces and its underlying mechanisms, using financial data, patent data, and AI-related term frequency data from China's A-share listed companies during 2019-2023. The findings reveal: (1) AI technological capability demonstrates a significantly positive effect on new quality productive forces, which remains robust after endogeneity treatment and robustness tests. (2) The enhancement of AI capability positively stimulates corporate innovation capacity, thereby promoting new quality productive forces development. This positive correlation strengthens with greater accumulation of intangible assets such as enterprise data. (3) The technological level of AI demonstrates a more pronounced enhancement effect on new quality productive forces for manufacturing enterprises and firms in regions with lower marketization degrees.

However, this study has certain limitations. First, the sample selected consists of China's A-share listed companies and does not include companies listed on the Hong Kong Stock Exchange, which may constrain the generalizability of the research findings. Second, regarding data sources, this study primarily relies on publicly available data, where missing information and incomplete datasets may compromise data integrity, consequently affecting the comprehensiveness and accuracy of research findings to some extent.

Table 8. Heterogeneity Analysis

	(1)	(2)	(3)	(4)
	Manufacturing Industry	Non- manufacturing Industry	High Degree of Marketization	Low Degree of Marketization
	Npro	Npro	Npro	Npro
AI1	0.139***	0.061***	0.087***	0.151***
	(12.26)	(3.70)	(6.51)	(11.46)
ROA	-1.766***	-1.210***	-1.992***	-1.249***
	(-8.42)	(-4.83)	(-8.09)	(-5.85)
Lev	-0.227***	-0.949***	-0.487***	-0.455***
	(-2.96)	(-10.17)	(-5.31)	(-5.74)
Age	-0.099***	-0.062***	-0.101***	-0.064***
	(-7.36)	(-3.32)	(-6.04)	(-4.36)
CFRate	0.320	1.166***	0.177	0.691***
	(1.62)	(4.37)	(0.75)	(3.22)
Top1	-0.472***	-0.061	-0.356***	-0.265***
	(-5.61)	(-0.54)	(-3.47)	(-2.94)

Size	0.016	0.138***	0.032**	0.082***
	(1.28)	(9.03)	(2.04)	(6.65)
Indep	0.401*	-0.956***	-0.278	0.213
	(1.91)	(-3.24)	(-1.07)	(0.94)
_cons	2.622***	0.596*	2.698***	1.123***
	(9.95)	(1.82)	(8.14)	(4.27)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	12532	5535	9022	9051
adj. R^2	0.100	0.393	0.185	0.228
Empirical p-value	0.000		0.000	

Note: The empirical p-value was calculated to test the significance of between-group coefficient differences in AI, obtained through 1000 bootstrap resampling iterations.

7.2 Policy Recommendations

7.2.1 Government aspects

First, in order to lower corporate R&D expenses and promote innovative vigor, national policies ought to support the creation of AI-specific funding and tax incentives. Second, in order to improve data privacy protection, standardize technology applications, and preserve market order, national regulation should create a thorough regulatory framework. Thirdly, in order to support AI technology applications, encourage deep industry and technology integration, and assist businesses in cutting costs and improving efficiency, the rollout of new infrastructure, such as 5G networks and data centers, should be expedited in the building of national infrastructure. Lastly, by policy support and regulatory reforms, the government should encourage the development of corporate new quality productive forces and reinforce guidelines for businesses using AI technology.

7.2.2 Corporate perspective

Firstly, enterprises should increase R&D investment, establish professional teams or conduct industry-academia-research collaboration, keep abreast of AI frontier developments, promote technology transfer and application, and actively explore innovative AI applications in multiple scenarios to enhance technological innovation. Secondly, regarding data management, enterprises should establish efficient data collection systems, improve data quality, strengthen data analysis capabilities, and mine data value to support decision-making. Thirdly, in talent development, enterprises should formulate internal training programs and incentive mechanisms to enhance employees' AI skills and actively recruit external high-end talents. In terms of cooperation and exchange, enterprises should strengthen collaboration with peers and upstream/downstream partners in the industrial chain to share resources and reduce R&D risks, while actively pursuing international cooperation to introduce advanced experience and technologies. Finally, enterprises should emphasize the management and application of intangible data assets, fully leverage their value in the process of AI technology empowering new quality productive forces. Through technological innovation and data management, enterprises can improve production efficiency and service quality, enhance competitiveness, and thereby achieve sustainable long-term development of neo-quality productivity.

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