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Artificial Intelligence as a Catalyst for New Quality Productivity: Evidence from Chinese Companies

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ABSTRACT

This paper aims to explore the pathways through which artificial intelligence (hereinafter – AI) contributes to enhancing new quality productivity, based on empirical analysis of Chinese listed enterprises. The analysis covers panel data from 12,880 observations for 2013-2022, excluding companies from the financial and construction sectors. Based on the data of Chinese A-share listed enterprises, this study systematically explores the driving mechanism and practice path of AI technology on enterprises' new quality productivity. By constructing AI technology application indicators through machine learning and text analysis methods, combined with the heterogeneity perspective (enterprise attributes, industry characteristics, and regional policies), the empirical test finds that AI technology significantly enhances enterprises' new quality productivity. Its core paths include intelligent supply chain management, digital innovation efficacy enhancement, and information asymmetry alleviation. The results show that AI has a statistically significant positive effect on new quality productivity (coefficient = 1.18, $p < 0.01$). In addition, it was found that the key channels of impact are digital innovations (effect = 0.465, $p < 0.01$), supply chain efficiency (effect = 0.121, $p < 0.01$) and reduction of information asymmetry (effect = -0.053, $p < 0.01$). Heterogeneity analysis shows that the empowering effect of AI is particularly significant in SOEs, labor-intensive industries, high-tech manufacturing industries and regions with high government financial support. This study provides theoretical and empirical evidence for differentiated policy-making and emphasizes that AI technology needs to be combined with organizational characteristics and the external environment to accelerate the sustainable development of new quality productivity.

KEYWORDS: Artificial Intelligence, New Quality Productivity, Digital Economy, Digital Innovation, Production Strategy, China

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Искусственный интеллект как катализатор нового качественного роста производительности: на примере данных китайских компаний

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АННОТАЦИЯ

Целью данного исследования является выявление механизмов воздействия искусственного интеллекта (далее – ИИ) на формирование и рост новой качественной производительности на основе анализа данных китайских публичных компаний. Анализ охватывает панельные данные 12 880 наблюдений за период 2013–2022 гг., за исключением предприятий финансового и строительного секторов. На основе данных китайских компаний, зарегистрированных на рынке А-акций, в исследовании проводится системный анализ механизмов и практических траекторий влияния технологий искусственного интеллекта на формирование новой качественной производительности предприятий. На основе использования методов машинного обучения и текстового анализа были построены индикаторы применения ИИ, которые затем использовались в эмпирической проверке с учётом неоднородности по атрибутам предприятий, отраслевым особенностям и региональной политике. Полученные результаты свидетельствуют о значительном эффекте ИИ на новую качественную продуктивность предприятий (коэффициент = 1,18; $p < 0,01$). Кроме того, эмпирический анализ выявил, что ключевыми каналами влияния технологий искусственного интеллекта на производительность нового качества являются развитие цифровых инноваций (эффект = 0,121; $p < 0,01$), повышение эффективности цифровых инноваций (эффект = 0,465; $p < 0,01$), а также снижение информационной асимметрии (эффект = –0,053; $p < 0,01$). Анализ неоднородности демонстрирует, что усиливающий эффект ИИ особенно выражен в компаниях с государственной формой собственности, в трудоемких и высокотехнологичных отраслях, а также в регионах с высокой степенью бюджетной поддержки. Представленное исследование вносит вклад в развитие теоретических и прикладных основ формирования политики технологического развития, подчеркивая необходимость учета организационных характеристик и институциональной среды при внедрении ИИ для стимулирования устойчивого роста производительности нового качества.

КЛЮЧЕВЫЕ СЛОВА: искусственный интеллект, производительность нового качества, цифровая экономика, цифровые инновации, производственная стратегия, Китай

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1. INTRODUCTION

The concept of new quality productivity (hereinafter – NQP) consists of improving traditional productivity through the fundamental linkage of "new" and "quality" essential points. The combination effectively drives several changes, including the implementation of new technological elements and emerging industrial areas that push the forward momentum of productivity (Jiang & Qiao, 2024). The growth model under this concept promotes both high efficiency and multiple dimensions with high-quality dimensions (Ren & Dou, 2024). The growth of NQP advances because of scientific and technological innovation. The qualitative state of traditional productivity transforms into new productivity through technological innovation (Zhou & Xu, 2024).

As a modern digital technology, artificial intelligence (hereinafter – AI) promotes rapid changes alongside production methods and models alongside processing procedures, which results in radical changes to production factor conversions into productive capacity (Chen et al., 2019; Chai et al., 2024). The transformation leads the way for NQP to develop its potential for advancement. The analysis of AI's influence on NQP becomes essential due to its potential value because more detail must be studied about its mechanisms so enterprises can get theoretical guidance for advancing NQP growth.

Research related to AI focuses mainly on macroeconomic aspects, which study its economic growth effects, industrial structure developments, workforce allocation, and income distribution (Zhao & Gao, 2024). The present focus on understanding AI effects at the firm level has emerged because many enterprises now participate in intelligent transformation. Various academic research has analyzed AI's effects on production efficiency and organizational growth. The research conducted by Shen Kunrong et al. (2024) proves that smart manufacturing policies enhance production efficiency by boosting informatization systems, human capital resources, and financial channels. The research conducted by Xin Daleng and Qiu Yue (2023) showed how AI enables import expansion by using financial capabilities and labor skill improvements.

The research conducted by Li and Branstetter showed that smart manufacturing policies produce substantial productivity improvements for business operations (Li & Branstetter, 2024). The analysis by Feng investigated how national AI pilot zone policies influenced corporate financial resource decisions (Feng, 2024). The incorporation of industrial robot penetration rates for measuring AI adoption within companies exists in research alongside investigations about AI policy effects but few studies focus on generating AI indicator systems for enterprises using machine learning methods. The systems could supply extended analysis regarding AI technologies' effects on productivity development in companies.

This paper explores the pathways through which AI contributes to enhancing NQP based on empirical analysis of Chinese listed enterprises. The study focuses on heterogeneity across three dimensions: enterprises, industries, and regions. The key innovations of this paper are as follows:

(1) The evaluation targets the individual effects of AI on organizational advancement while maintaining its focus on enterprise development. The study introduces unique changes to research methodologies through machine learning techniques and text analysis to provide insights about AI adoption practices within organizations. In contrast, most previous studies have analyzed the macro-level effects on regional industries and labor markets.

(2) The research paper adds to studies about NQP. The paper presents a practical case analysis to show how AI affects NQP listed companies while also bringing attention to the field and emphasizing overlooked areas from earlier studies.

(3) The paper establishes theoretical concepts to advance NQP. The study reviews the enabling effects of AI technology through technological efficiency and informational frameworks with NQP growth, although the literature on this topic remains limited. The research targets delivering critical information that enables organizations to enhance their speed in NQP growth.

2. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

The economic drivers of NQP mainly depend on technological innovation because it focuses on emerging industries and developing sectors that show future growth potential. NQP represents a vital production method that facilitates excellence in development. Schumpeter's innovation and endogenous growth theory demonstrate that the concept of "creative destruction" enables technology to boost economic expansion (Aghion & Howitt, 1992). Intelligent artificial systems promote "creative destruction" through an environment which enables their operation. Allocation of AI systems throughout the economy presents enormous prospects for enhancing productive forces that lead to high-quality economic expansion.

NQP combines Marxist productivity theories with concrete data, which sustains and develops Marxist productivity theory according to political science principles. This new productivity system demonstrates its essence through optimal combinations between workers with their production subjects and tools. Marxist productivity theory receives theoretical support for Chinese modernization through the idea of new quality productive forces.

AI's integration with economic and social systems leads to the intelligent development of production factors and relations, which, in turn, enhances both the quality of labor and the technological sophistication of production materials. This fusion ultimately enables a leap in productive forces, paving the way for a new era of productivity enhancement. AI enables micro-enterprises to develop NQP through multiple mechanisms. The rapid acquisition of data through AI boosts information empowerment, which helps reduce information imbalances throughout the enterprise. Through this information, companies can choose improved options and achieve efficient daily management, which supports planned development strategies.

AI delivers efficiency improvements through its operations. Today's businesses apply AI since this technology provides the ability to analyze extensive datasets, predict market patterns, and support users' smarter choice-making. AI and simplified workflows enable smooth supply chain operations, resulting in enhanced overall company productivity. AI promotes enterprise technological advancement through digital innovation, enabling companies to use new technologies to boost their capabilities and market competitiveness.

To examine how AI enhances NQP, this study identifies three primary mechanisms through which AI exerts its influence. These include: (1) technological empowerment, reflecting AI's role in fostering digital innovation and knowledge creation; (2) efficiency improvement, emphasizing enhanced production processes and resource optimization; and (3) information empowerment, which reduces asymmetry and strengthens decision-making through improved data acquisition and analysis. Each of these pathways is discussed in detail below.

(1) Through technological innovation, AI provides numerous transformative possibilities to businesses, which operate like an exceptionally strong toolset that helps enterprises deliver improved digital transformations. The most significant characteristic of this toolbox lies in its ability to process extensive datasets and adapt to multiple-use contexts, thus enabling enterprises to become more influential in practical deployments. NQP develops at an accelerated speed because of this. Businesses benefit from various advantages that AI brings to their digital innovation efforts.

Businesses gain improved operations through AI, which is the core subject of this article. AI develops strong data processing capabilities to predict market changes and consumer preferences, enabling business organizations to understand market developments. Company data pattern analysis enables making reliable business decisions that improve operational efficiency. Through consumer behavior analysis, businesses expose invisible market possibilities for product development.

AI substantially boosts technology advancement through its capability to facilitate knowledge spread. AI enables the creation of new technologies and solutions across multiple industries, which produce unexpected advantages for companies (Huang et al., 2022). Businesses that incorporate AI technology into their research and development will develop intelligent products to enhance their digital innovation abilities (Wang et al., 2023).

AI acts as the essential force to enhance business operations at the conclusion. Intelligent production systems and supply chain management allow businesses to decrease expenses and build stronger market competitiveness (Zhang & Lin, 2024). The created environment provides a favorable setting for additional innovation development. This paper demonstrates that AI serves as an instrument that helps enterprises obtain better digital innovation results through its technical assistance combined with management support and data infrastructure capabilities to advance company productivity using higher-quality approaches.

(2) From the perspective of efficiency empowerment, AI plays a critical role in advancing NQP by enhancing production efficiency, supply chain performance, and resource allocation. AI achieves this through various mechanisms that optimize operations across different domains.

AI's most substantial benefit is its support for intelligent production and resource management (Wu et al., 2024). Integrating industrial robots with automated production brings about automation that enables a highly digitalized and efficient production process. Companies achieve better management of all production process details through this shift, bringing enhanced operational efficiency at every step. AI has acquired predictive functionalities from big data analytics alongside machine learning algorithms for companies to anticipate consumer preferences better, as detailed by Wan et al. (2020). Companies use personalized production techniques to serve market requirements with better results while improving their manufacturing efficiency.

Moreover, AI facilitates the creation of collaborative ecosystems through technologies like blockchain (W & Qian, 2024). Creating data-sharing and digital twin platforms allows organizations to monitor their supply chains with up-to-date information. The supply chain gains increased stability and enhanced flexibility through this ability to swiftly detect potential problems. Data-sharing enables supply chains to develop cooperative networks that increase their responsiveness and adaptability to achieve greater efficiency in the current fast business pace.

The main argument of this research paper is that supply chains and production efficiency improve because of AI. Artificial intelligence systems allow enterprises to control production operations, which leads to enhanced supply chain operations with increased speed and performance. AI has helped numerous enterprises achieve transformative intelligence that boosted their manufacturing efficiency at a practical level.

(3) From the perspective of information empowerment, AI enables enterprises to improve their ability to collect, integrate, and process both internal and external information. This reduces the risks and costs associated with information asymmetry, thus fostering the development of NQP.

Outside viewers can manage market changes through AI technology, creating transparent market information available to the public. AI uses intelligent digital platforms to analyze extensive market data and customer information, producing important insights through analysis. Businesses achieve better market performance and competitive advantage by accurately understanding market trend changes and customer requirements. By employing intelligent customer relationship management (CRM) systems and data mining technologies, AI delivers personalized services and accurate marketing, which boosts customer satisfaction and loyalty (Manser et al., 2021). AI systems enable businesses to acquire market information more easily, thus reducing considerable financial expenses. After applying AI tools, enterprises become better equipped for market changes because they achieve superior competitive positions. AI facilitates business market entry through its features while maintaining substantial stability against market competition.

Internally, AI supports enterprises in optimizing resource allocation by improving how they collect and analyze internal operational information (Dou et al., 2024). AI can mine vast internal datasets through intelligent data analysis and forecasting, providing valuable decision-making support and business insights. This helps enterprises allocate resources more efficiently, reduce operational costs, and increase production efficiency (Yin & Li, 2022).

In conclusion, AI empowers enterprises to gather and process information more effectively, mitigating information asymmetry in production and operations. This enhances overall business performance and accelerates the growth of NQP.

In conclusion, this paper proposes the following research hypothesis:

H1: AI significantly drives the advancement of NQP in enterprises, serving as a key enabler.

H2: AI can help companies do a better job of digital technology innovation, make supply chains run faster and smoother, and reduce problems in the information transmission process. In this way, companies can gain more advantages in improving product quality and productivity and drive NQP forward.

3. RESEARCH METHODS

The research draws data from A-share listed Chinese companies operating between 2013 and 2022 in Shanghai and Shenzhen stock exchanges to determine how AI affects NQP. The firms' annual reports were retrieved from Sina Finance, and fundamental financial information was obtained from the China Stock Market & Accounting Research Database (CSMAR) and the China Research Data Services Platform (CNRDS).

To ensure data reliability, several filtering steps were implemented. First, firms from the financial and real estate sectors were excluded due to their atypical balance sheet structures. Second, companies with ST or Special Treatment status, indicating sustained losses and potential delisting risks, were also removed. Third, firms with less than one year of listing history or those delisted during the period were excluded. Finally, observations with missing values were dropped, and all continuous variables were winsorized at the 1% level to reduce the influence of outliers. The final balanced panel comprises 12,880 firm-year observations from 2013 to 2022.

Variable Description

(1) The dependent variable – NQP.

Following the framework proposed by Song Jia et al. (2024), this study adopts a two-factor theory of productivity to evaluate enterprise-level NQP. The evaluation focuses on two primary components: labor input and production tools. Labor input is further divided into two subcomponents: (i) active labor, referring to human capital directly involved in production processes, and (ii) labour objects, representing intermediate inputs or materials processed during production. Production tools are also classified into two categories: (i) hard technologies, such as machinery and physical equipment, and (ii) soft technologies, including digital infrastructure, software systems, and intellectual property assets.

(2) Explanatory variable – AI.

While industrial robot penetration rates are commonly used in existing research to measure corporate AI, they do not provide a comprehensive view of AI technologies within enterprises. Drawing on the measurement approach developed by Yao et al. (2024), this paper collects text data from the annual reports of listed companies. A machine learning-generated AI dictionary is then applied, and the number of AI-related keywords in the annual reports is increased by one. The natural logarithm of this adjusted count is used as the indicator for measuring corporate AI.

(3) Control variables.

Using logarithmic calculations, the study implements several essential control variables during analysis, with the company age measured in the present-day years since its inception. Another variable is the size of the company, which is measured by the company's total asset logarithm; return on equity (roe), calculated as net profit divided by net assets; cash flow ratio (cashflow), determined by the ratio of net operating cash flow to total assets; ownership concentration (top), measured by the proportion of shares held by the largest shareholder; audit opinion (opinion), coded as 1 for unqualified opinions and 0 for others; and the independent director ratio (indep), defined as the proportion of independent directors in the total number of board members.

Model Design

To examine the impact of AI on NQP, the following regression model is constructed by formula (1):

$$NQP_{ct}= a_0 +a_1 AI_{ct}+a_2 Controls_{ct}+ year+ind+pro+R_{ct} \quad (1)$$

where:

NQP_{ct} – new quality productivity of firm c in year t;

AI_{ct} – AI intensity indicator for firm c in year t;

c and *t* – denote individual firms and time;

$Controls_{ct}$ – vector of control variables for firm *c* in year *t*;

year, ind and *pro* – represent time, industry, and province fixed effects;

R_{ct} – the random error term.

Clustered standard errors are applied to regression coefficients to address heteroscedasticity across industries.

Building on the methodology proposed by Jiang Ting (2022), this study constructs a mediation model to investigate the mechanisms through which AI influences NQP. The model is specified in formula (2):

$$MV_{ct}+\beta_0+\beta_1 AI_{ct}\beta_2 Controls_{ct}+year+ind+pro+R_{ct} \quad (2)$$

where:

MV_{ct} – the mediating variable for firm *c* in year *t*, representing one of the intermediate mechanisms (i.e., digital innovation, production efficiency, or information empowerment);

AI_{ct} – artificial intelligence intensity;

$Controls_{ct}$ – vector of control variables;

year, ind and *pro* – represent time, industry, and province fixed effects;

R_{ct} – the random error term.

These factors together explain how AI can help improve productivity and improve what is produced. These mediating channels are intended to capture the underlying pathways through which AI adoption enhances NQP. This model framework allows for a comprehensive empirical test of AI's direct and indirect effects on firm-level productivity transformation.

4. EMPIRICAL ANALYSIS

4.1 DESCRIPTIVE STATISTICS AND CORRELATION ANALYSIS

The relevant variable statistics appear in Table 1. Specifically, the range of NQP spans from 1.068 to 13.932, with an average value of 5.230. Listed companies display significant differences in the development of NQP because their minimum NQP value stands much lower than their average. The available data shows that many organizations operating in this sector have ample potential to expand their Non-Quantitative Performance (NQP) systems. The analyzed companies demonstrate minimal use of AI technologies since their AI values are distributed between 0 and 1.415 and average 0.133.

The data in Table 1 demonstrates that the statistical relationship between AI, AI and NQP amounts to 0.254 while maintaining a significant value of 1%. Data indicates that AI positively affects enterprise NQP, thus strengthening the production quality capabilities of the company. The correlations between all control variables and NQP of the corporation confirm the suitable nature of their use in statistical modeling. The statistical relationship between most control variables remains under 0.4, indicating their proper representation for the analysis. The Key variables demonstrate minimal Vulnerability through VIF values that fall between 1.00 and 1.54. This indicates the absence of Multicollinearity problems.

Descriptive statistics and correlation analysis results in Appendix 1.

The second column presents results from regression analysis with fixed effects control only, and the third column displays explicitly the control variable effects. A complete analysis appears in the fourth column because control variables and fixed effects, including year, industry and province inclusion, exist in this data. All data points to a positive regression coefficient of AI both with and without the introduction of control variables or fixed effects. Our assumptions proved valid.

To ensure the robustness of the empirical results, several additional tests were conducted using alternative variable specifications, sample modifications, and estimation strategies.

First, the explained variable was replaced. In particular, total factor productivity (TFP) was used as an alternative indicator for NQP, calculated using the Levinsohn-Petrin (LP) method. As shown in Column (1) of Table 1, the application of AI continues to exert a statistically significant and positive impact on enterprise-level productivity, confirming the consistency of the findings.

Table 1. Benchmark regression results

Variable	NQP			
	(1)	(2)	(3)	(4)
AI	1.964 ###(0.373)	1.211 ###(0.296)	1.757 ###(0.373)	1.180 ###(0.280)
asset	—	—	0.206 ###(0.079)	0.063(0.079)
age	—	—	0.377 ###(0.082)	0.184 # (0.107)
lev	—	—	-0.881 ##(0.425)	-0.141(0.349)
roe	—	—	-0.870 ###(0.167)	-0.472 ###(0.139)
cash flow	—	—	2.701###(0.631)	2.356 ###(0.527)
top	—	—	-0.560(0.448)	0.010 (0.405)
opinion	—	—	0.089 (0.173)	0.029(0.158)
indep	—	—	1.406 # (0.779)	1.487 ##(0.687)
Cons	4. 969 ### (0.102)	6.132 ###(0.342)	-0.627(1.605)	3.848 ### (1.440)
N	12 880	12 880	12 880	12 880
Fixed Effects	No Control	Control	No Control	Control
Adi. R^2	0.065	0.250	0.094	0.257
* Figures in parentheses represent industry-clustered standard errors				

Note: compiled by authors

Next, the explanatory variable was modified. In line with the approach of Wang and Dong (2020), the industrial robot penetration rate (AI-ROB) was employed as a proxy for AI. The regression results reported in Column (2) of Table 2 support the stability of the main conclusions.

Table 2. Robustness test results (variable replacement, sample adjustment, PSM regression)

Variable	TFP	NQP				
	(1) Replace the dependent variable	(2) Replace the explanatory variable		(3) Exclude abnormal years	(4) Exclude abnormal cities	(5) PSM regression
AI	0.122#(0.067)			1.319 ### (0.317)	1.098 ### (0.286)	0.922 ### (0.275)
AI-ROB		1.179 ### (0.092)				
AI-MDA			1.248 ### (0.232)			
Cons	-5.645 ###(0.316)	3.847 ### (0.566)	3.438 ##(1.568)	4. 485 ### (1.425)	3.978 ##(1.614)	2.447 (2.033)
N	12 880	12 880	12 880	9016	11 093	5 570
Fixed effects	Control	Control	Control	Control	Control	Control
Adj. R^2	0.726	0.264	0.252	0.250	0.243	0.257

Note: compiled by authors

Fair presentation of corporate development plans, critical business choices, and AI technology updates exist in MD&A (Management Discussion and Analysis) sections found in listed companies' annual reports. This paper focuses on AI-MDA in enterprise AI by recording and calculating the natural logarithm of AI-related keyword occurrences in annual report MD&A sections. However, it adds one to each occurrence for statistical accuracy. Table 3 shows that AI-MDA has a positive relationship which reaches statistical significance at level 1% based on data in column two.

To account for the effects of external shocks and regional heterogeneity, the sample was adjusted in two ways. First, data from 2020 to 2022 were excluded to mitigate potential distortions caused by the COVID-19 pandemic. Second, firms located in the four centrally administered municipalities (Beijing, Shanghai, Tianjin, and Chongqing) and surrounding provinces were removed to control for geographical bias. Results presented in Columns (3) and (4) of Table 3 show that the AI variable remains significantly and positively associated with NQP, demonstrating that the baseline findings are not driven by exceptional years or regional anomalies.

The Propensity Score Matching (PSM) method was applied to address potential sample selection bias. Firms were divided into treatment and control groups based on the presence of AI-related terminology in their annual reports. Nearest neighbor matching without replacement was employed using all control variables as covariates. Balance tests indicate that standardized biases for all covariates fell below the 5% threshold, confirming successful matching. The subsequent regression analysis using the matched sample, presented in Column (5) of Table 3, reveals that the positive effect of AI on NQP remains robust and statistically significant, thereby validating the stability of the baseline regression model.

To further address potential endogeneity concerns, an instrumental variable (IV) approach was implemented using the lagged value of the AI variable as the instrument, following the methodology of Dai Xiang and Wang Ruxue (2023). The estimation results for the two-stage least squares (2SLS) are presented in Table 3.

Table 3. Robustness tests: instrumental variable method and PSM-DID

Variable	**2SLS (Two-Stage Least Squares)**		**NQP**	
	(1) First stage AI	**(2) Second stage NQP**	**(3) DID (Difference-in-Differences)**	**(4) PSM-DID (Propensity Score Matching-Difference-in-Differences)**
AI		1.355 ### (0.133)		
Instrumental variable	0.768 ### (0.010)			
treat X post			0.279 ###(0.104)	0.299 ##(0.134)
Constant	-0.228 ### (0.049)	5.055 ### (0.614)	3.019 ##(1,313)	2.776 ##(1.388)
N	11 592	11 592	12 880	10 686
Fixed effects	Control	Control	Control	Control
Adj. R^2	0.685	0.246	0.242	0.223
F-test	132. 900 ###			

Note: compiled by authors

In the first stage, the instrumental variable is significantly correlated with the endogenous regressor, and the Cragg-Donald Wald F-statistic exceeds the conventional threshold of 10, indicating the strength and relevance of the instrument. In the second stage, the coefficient of the AI variable remains significantly positive at the 1% level, which confirms the robustness of Hypothesis 1.

Finally, this paper uses the intelligent transformation of key industries outlined in "Made in China 2025" as a quasi-experiment. The PSM-DID method is employed to address endogeneity concerns within the model. A DID model is then constructed by formula (3):

$$NQP_{ct}=\lambda_0+\lambda_1 treat\times post+\lambda_2 Controls_{ct}+year+ind+pro+R_{ct} \quad (3)$$

In this model, “treat” indicates whether the company’s industry falls under the ten key sectors identified in “Made in China 2025” (assigned a value of 1 if yes, zero otherwise). Suppose the year is 2015 or later, post=1 (since “Made in China 2025” was issued by the State Council in 2015). Otherwise, it is 0. The sample is divided into treatment and control groups, with all control variables used as covariates. Columns (3) and (4) in Table 4 present the regression results before and after matching. The interaction term “treat×post” coefficient remains significantly positive in both cases, indicating that, even after addressing endogeneity, AI continues to drive the development of NQP in enterprises.

4.2 TECHNOLOGY EMPOWERMENT MECHANISM TEST

Enterprises’ digital technology innovation capabilities improve through AI implementations of adaptive systems combined with intelligent algorithm optimization and smart assistive tools. Continuous innovation of digital technologies allows businesses to decrease information search costs alongside transmission and verification costs while tracking activities, ultimately resulting in NQP development.

The research team determined the number of digital patents filed by listed companies by applying the main patent categories contained in the “Statistical Classification of Digital Economy and Its Core Industries (2021)” from the National Bureau of Statistics. The digital technology innovation capability (Dig) is determined by the natural logarithm of digital patent applications plus one (Huang et al., 2023). The Sobel test results demonstrate a digital technology innovation mediation effect because they produce values below 0.05. Table 4 shows that NQP fueled by AI achieves its results through digital innovation methods in Column 1.

Table 4. Mechanisms test results

Variable	Technology Empowerment	Efficiency Empowerment	Information Empowerment
	(1) Dig	(2) Effi	(3) Asy
AI	0.465 ###(0.077)	0.121 ###(0.036)	-0.053 ###(0.013)
Cons	-5.538 ###(1.171)	6.598 ###(0.264)	3.818 ###(0.202)
N	12 880	12 880	12 880
Fixed Effects	Control	Control	Control
Adj. R^2	0.391	0.353	0.570
Sobel Test	17.320 ###	3.962 ###	7.867 ###

Note: compiled by authors

Every operational element of enterprises now benefits from AI technologies, which transform their business processes. These new technologies digitize each part of the supply chain, creating networked assets and flexible partnership dynamics that help manage resources appropriately. Such technologies dramatically boost the operational effectiveness of supply chain management (Tan Yongsheng, 2024).

This paper investigates corporate supply chain efficiency (Effi) through inventory turnover based on the research by Zhang Qianxiao and Duan Yixue (2023). Column 2 of Table 5 results show that AI has a strongly positive relationship with supply chain efficiency, a vital connecting factor between AI and corporate NQP at the 1% significance level. The Sobel test validated this mediating role by producing a P value below 0.05. The research validates that AI raises supply chain performance, escalating NQP incorporates.

Information Empowerment Mechanism Test

Quickly analysing and collecting enterprise operational data through AI technologies aids information processing capability and internal information symmetry reduction (Shen et al., 2024). The paper discusses how AI technology enhances work efficiency while increasing information transparency for better cooperation between organizations and companies, enabling improved product quality. Through AI, enterprises gain streamlined daily work operations and improve their productivity through stronger external partnerships to achieve better enterprise development quality.

The research adopts the methodology of Yu Wei et al. (2012) to measure information asymmetry (Asy) through the first principal component analysis of the liquidity ratio and illiquidity ratio with reversal indicators. Companies show more information asymmetry when the Asy value becomes elevated.

The information in Table 5 shows that AI effectively decreases asymmetry, which helps enterprises accelerate NQP developments.

4.3 THE IMPACT OF ENTERPRISE CHARACTERISTICS ON AI-ENABLED NQP

State-owned Enterprises maintain an intensely close connection to governmental entities, enabling them to act immediately during policy adjustments. State-owned enterprises, along with government departments, maintain multiple contacts, which enables them to recognize policy changes before making prompt adjustments. SOEs benefit from their access to plentiful resources and robust risk-bearing competencies that give them an advantageous market standing. Through an ownership type assessment, the research divides its survey population into two separate groups, which represent state-owned enterprises and non-state-owned enterprises.

Table 5 shows that the two variables in the first columns demonstrate a positive correlation with each other through their high numbers. An analysis shows that SOEs demonstrate a greater coefficient value.

Table 5. Impact of enterprise characteristics on AI empowering NQP

Variable	**(1) State-owned enterprises**	**(2) Non-state-owned enterprises**	**(3) High labor intensity**	**(4) Low labor intensity**
AI	1.754 ###(0.386)	1.023 ###(0.232)	1.425 ###(0.247)	0.886 ###(0.284)
Cons	7.790 ##(3.129)	4. 358 ### (1.460)	2.483 (2.124)	6.466 ###(1.535)
N	3 801	9 079	6 442	6 438
Fixed effects	Control	Control	Control	Control
Adj. R^2	0.285	0.282	0.307	0.252
Coefficient difference P-value	0.007		0.040	

Note: compiled by authors

The Chow test verifies significant statistical significance at the 0.007 level between the coefficient values of the two groups. The research indicates that AI produces dissimilar variations of NQP between Chinese state-owned enterprises and non-state-owned enterprises. The study shows that AI improves NQP in both organizations but produces stronger effects within state-owned enterprises.

Businesses with higher labor costs typically maintain lower automation levels, thus needing additional staff. Introducing smart equipment alongside human capital restructuring helps these businesses reach better operational performance and innovation results. The research findings indicate that AI impacts businesses that use large numbers of human workers to a greater extent. Labor intensity calculations adhered to the methodology introduced by Huang Bo et al. (2023) track the total employee-to-total fixed asset relation. The sample groups receive their categorization according to the ratio median. Table 6 demonstrates positive values in Columns 3 and 4, which confirm that AI significantly enhances NQP across enterprises regardless of their labor intensity levels. The results from the Chow test demonstrate that AI has a more substantial enabling impact on NQP in enterprises which are labor-intensive than those that are not labor-intensive.

Research by Peng Hongxing and Mao Xinshu (2017) coupled with the "Guidelines for Industry Classification of Listed Companies" (2012 revision) provided by the China Securities Regulatory Commission allows this paper to separate the sample into high-tech industry enterprises and non-high-tech industry enterprises. The evaluation results have been presented in Table 6.

Table 6. Impact of industrial and regional characteristics on AI empowering NQP

Variable	Industry Heterogeneity		Regional Heterogeneity	
	(1) High-Tech Industries	(2) Non-High-Tech Industries	(3) High Fiscal Support	(4) Low Fiscal Support
AI	1.215 ###(0.285)	0.363(0.262)	1.497 ##(0,284)	0.900 ##(0.353)
Cons	1.951 (1.795)	7.176 ###(1.686)	4. 153 ##(1. 976)	1.738 (2.256)
N	8 496	4 384	6 401	6 479
Fixed Effects	Control	Control	Control	Control
Adj. R^2	0.252 0.320		0.271 0.248	
Coefficient Difference P-Value	0.029		0.063	

Note: compiled by authors

AI technology primarily affects NQP through empowering effects within high-tech industry organizations (Table 7 columns 1 and 2).

The research defines two groups of regions based on the median value of fiscal budget expenditure as a percentage of regional GDP to measure support levels. Table 7 displays the results in columns 3 and 4. The study reveals that AI provides more substantial empowering advantages to enterprise NQP in regions with stronger financial government backing. The research outcomes support government investments in infrastructure and digital technology adoption by enterprises, which will boost the advancement of new quality productive forces.

5. CONCLUSION

This paper analyzes the data of listed companies from 2013 to 2022 to explore the effect of AI technology on NQP of enterprises. The following key conclusions are drawn from the analysis:

(1) The development of China's listed companies in terms of new quality and productivity is not the same, and there is a clear gap between different companies. This paper shows that the progress shown by these companies in the process of improving production efficiency and quality level is very different. The overall level of NQP remains relatively low, suggesting that there is significant potential for growth and improvement.

(2) AI plays a crucial role in empowering enterprises, significantly enhancing their NQP.

(3) The mechanism analysis shows that AI boosts NQP in enterprises by improving supply chain efficiency, enhancing digital technology innovation capabilities, and reducing information asymmetry.

(4) The heterogeneity analysis reveals that, at the enterprise characteristics level, AI has a more significant enabling effect on state-owned enterprises and labor-intensive firms. Meanwhile, at the industry and regional levels, AI's impact is stronger in high-tech industries and regions with more substantial fiscal support.

The paper provides the following policy recommendations:

(1) The acceleration of NQP development requires proper guidance and technological support for businesses transitioning into intelligent technologies. An urgent need exists to help businesses through their "inability to transform" and "lack of transformation capacity" barriers because most listed Chinese companies have not yet adopted AI. First, a financial support system should be established, including creating industry-specific development funds or special funds to encourage greater investment in the R&D and application of intelligent technologies. Promoting deep integration between industry players with universities and research institutions is the second crucial strategy. The effective advancement of AI technology development alongside its applications requires enterprise relationships with universities and research institutions, enabling accelerated technological commercialisation development phases. Third, demonstration projects should be expanded. Governments can collaborate with leading enterprises to launch pilot intelligent production projects, using successful examples to motivate other companies to follow suit.

(2) Implementing AI technology should transform corporate production systems and operations to develop new quality productive forces faster. The mechanisms of AI generate new quality productive forces through stronger digital technology innovation, more efficient supply chains, and more trans-

parent information systems. Businesses must utilize AI technology to transform their business models to achieve NQP growth. First, companies should strengthen their digital technology innovation capabilities through AI by pursuing active R&D initiatives. This includes exploring new digital technology applications, such as developing advanced software, hardware, algorithms, and platforms to meet market demands and improve competitive edge. AI and data analytics allow businesses to boost supply chain efficiency through their implementation. Businesses using AI have the ability to achieve precise market demand forecasts and complete supply chain transparency, as well as effective management. Supply chain optimization through AI brings better efficiency to different supply chain components, such as inventory control, logistics path planning, and delivery strategies alongside supplier management, generating new quality productive forces. Businesses must use digital platforms to develop collaborative innovation networks that help share data and resources while combating information gaps. Lastly, firms must integrate AI into their development strategies, enhancing internal management systems and organizational resilience. By doing so, companies can foster business innovation and sustain long-term growth.

(3) The government needs to enhance financial backing alongside making new quality productive forces their core development priority. The government should create innovation vouchers and funding programs to motivate organizations toward increased research spending, which would drive enterprise adoption of new technology methods, leading to the natural development of industry innovation capabilities. All eligible high-tech enterprises receive special tax benefits that lower their innovation expenses to drive the development of modern quality productive forces. The government should establish science and technology parks and provide support through venue rental subsidies as well as equipment facility and technology service subsidies to develop new enterprise quality productive forces.

LIMITATIONS AND PROSPECTS

Additional research in this area should assess the impact of artificial intelligence (AI) on new quality productive forces within specific industries, including manufacturing and services as well as high-pollution industries. Artificial intelligence warrants further exploration through multiple angles because it needs to be evaluated in terms of reasonable resource distribution and improved resource organization schemes.

AUTHOR CONTRIBUTIONS

Conceptualization and theory: XL; research design: XL and GA; data collection: XL and JJ; analysis and interpretation: XL; writing draft preparation: XL and JJ; supervision: GA; correction of article: XL, GA and JJ; proofread and final approval of article: XL, GA and JJ. All authors have read and agreed to the published version of the manuscript.

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Appendix 1

Descriptive statistics and correlation analysis

Variable	Sample Size	Mean	Standard Deviation	Min	Max	NQP	AI	asset	age	lev	roe	cash flow	top	opinion	indep
NQP	12 880	5.230	2.292	1.068	13.932	1									
AI	12 880	0.133	0.297	0.000	1.415	0.254###	1								
asset	12 880	22.182	1.101	19.940	25.387	0.126###	0.101###	1							
age	12 880	2.368	0.566	1.099	3.332	0.136 ###	0.085###	0.427 ###	1						
lev	12 880	0.412	0.200	0.054	0.913	-0.010	-0.023###	0.414 ###	0.327 ###	1					
roe	12 880	0.044	0.158	-0.802	0.426	-0.025###	-0.056 ###	0.146###	-0.050###	-0.238###	1				
cash flow	12 880	0.046	0.065	-0.154	0.237	0.072###	-0.045 ##	0.119###	0.039###	-0.155###	0.308###	1			
top	12 880	0.305	0.138	0.078	0.688	-0.059###	-0.151 ###	0.123###	-0.033###	0.008	0.143 ###	0.104 ##	1		
opinion	12 880	0.959	0.198	0.000	1.000	0.009	-0.006	0.075###	-0.062###	-0.166###	0.272 ###	0.095 ###	0.085###	1	
indep	12 880	0.377	0.056	0.333	0.600	0.045 ###	0.061###	-0.029###	-0.016###	-0.007	-0.031###	0.011	0.007	-0.006	1

Note: #, ##, and ### indicate significance at the 10%, 5%, and 1% levels, respectively. The same applies below.compiled by author