

How Does Artificial Intelligence Empower the Upgrading of Enterprise Production Efficiency? — —Microscopic Inspection, Mechanism Deconstruction and Indicator Innovation Based on A-Share Listed Companies

Guanlin Guo, Yang Gao

How to cite: Guo G, Gao Y. How Does Artificial Intelligence Empower the Upgrading of Enterprise Production Efficiency? — —Microscopic Inspection, Mechanism Deconstruction and Indicator Innovation Based on A-Share Listed Companies. Textile & Leather Review. 2026; 9:6095-6110. <https://doi.org/10.31881/TLR.2026.6095>

How to link: <https://doi.org/10.31881/TLR.2026.6095>

Published: 15 June 2026



How Does Artificial Intelligence Empower the Upgrading of Enterprise Production Efficiency? — Microscopic Inspection, Mechanism Deconstruction and Indicator Innovation Based on A-Share Listed Companies

Guanlin Guo^{1*}, Yang Gao²

¹Business School, Central University of Finance and Economics, Beijing, 100081, China

²Tsinghua Shenzhen International Graduate School, Shenzhen, 518055, China

*g1374583757@163.com

Article

<https://doi.org/10.31881/TLR.2026.6095>

Published 15 June 2026

ABSTRACT

Using data of China's A-share listed firms from 2007 to 2023, this paper constructs an enterprise artificial intelligence (AI) level indicator via Python text analysis and empirically examines the impact of AI on enterprise production efficiency and its underlying mechanisms. The study finds that AI significantly improves enterprise production efficiency, and this conclusion remains robust after robustness checks and endogeneity treatments. Specifically, AI enhances production efficiency through two mediating channels: improving resource allocation efficiency (including capital investment efficiency and labor investment efficiency) and strengthening innovation capability; the degree of enterprise internationalization positively moderates these promotional effects. Heterogeneity analysis shows that AI boosts production efficiency more significantly in firms with high financing efficiency and labor-intensive firms. Further analysis reveals that the impact of AI on production efficiency exhibits a firm-size threshold effect and nonlinear characteristics. This paper provides comprehensive empirical evidence for understanding the efficiency effects of AI application at the micro-firm level and offers insights for enterprises to optimize AI strategies according to their characteristics and pursue high-quality development.

KEYWORDS

Artificial Intelligence, Enterprise Production Efficiency, Resource Allocation Efficiency

INTRODUCTION

The rapid advancement of artificial intelligence has become a core driver of global industrial transformation and technological progress, and its potential in optimizing resource allocation and improving production

efficiency has drawn wide attention. The report to the 20th National Congress of the Communist Party of China explicitly proposes promoting the integrated and clustered development of strategic emerging industries including artificial intelligence. The 14th Five-Year Plan for Digital Economy Development also emphasizes the coordination of technological innovation and industrial application, providing policy guidance for AI adoption at the micro-enterprise level. China's economy is shifting from high-speed growth to high-quality development, and the traditional factor-driven model faces challenges of diminishing marginal returns. The contribution of technological progress to production efficiency has become increasingly critical. As micro agents of the economy, enterprises' improvement in production efficiency is directly related to the achievement of high-quality development goals and serves as an important guarantee for China to cross the middle-income trap. Therefore, in-depth analysis of how AI affects enterprise production efficiency to provide a scientific basis for high-quality development is one of the key research directions.

Existing research on AI mostly focuses on the macro level: most studies find that AI alleviates the constraints of population aging on economic growth, improves labor productivity, or drives industrial upgrading, while a few studies argue that it may reduce economic growth. However, clear gaps remain in micro-level research: first, few direct studies focus on AI's impact on enterprise production efficiency, with existing micro research mostly centered on digital transformation and intelligent manufacturing; second, AI measurement indicators in existing studies are relatively one-sided, leading to limited generalizability of conclusions.

Against this background, this paper uses Python text analysis based on annual reports of A-share listed firms from 2007 to 2023 to build a more comprehensive enterprise AI level indicator and conducts empirical analysis. The core contributions of this paper are threefold: first, it fills the research gap from a micro perspective by exploring AI's impact on production efficiency using a latest long panel dataset of A-share listed firms; second, it optimizes AI measurement and introduces resource allocation efficiency (capital and labor investment efficiency) and innovation efficiency as mediators to systematically decompose the mechanism, enhancing the generalizability of findings; third, through firm-size threshold analysis, it reveals the nonlinear characteristics of AI's impact, providing theoretical support for enterprises to optimize AI application strategies.

LITERATURE REVIEW AND RESEARCH HYPOTHESES

Literature Review

In recent years, the rapid evolution of artificial intelligence (AI) technology has become a core driver of global industrial transformation. Existing literature has explored the economic effects of AI from multiple

perspectives. Building on these studies, this paper systematically reviews the existing literature from three dimensions: macroeconomic and overall performance impacts, micro-level optimization of production and operational scenarios, and cross-sectoral integration and theoretical mechanisms.

First, at the macro and overall performance level, AI is viewed as a key engine driving high-quality economic development and sustainable transformation. Based on data from Chinese listed companies, Zhu et al. provided micro-level evidence that AI promotes energy conservation and emissions reduction [1]. Regarding corporate overall performance, Wang et al. explored innovation pathways for intelligent management across the entire process and all factors [2]. Building on this, Jiaxin et al. further demonstrated that AI algorithm optimization can enhance production efficiency and supply chain stability in smart manufacturing processes [3]. Concurrently, Wang et al. utilized deep learning to achieve balancing optimization for wiring assembly lines [4]. Furthermore, the external environment cannot be overlooked; Lin et al. found that peer effects and the institutional environment are significant external factors driving productivity improvements in Chinese listed companies [5]. Regarding value chain reshaping, Mao focused on analyzing the role of generative AI in reshaping the content production value chain of the creative industry [6]. Li also explored digital pathways for AI-enabled rural revitalization from a broader societal perspective [7]. Wang et al. further explored how the integration of digital twins, the Internet of Things (IoT), and AI drives knowledge-driven innovation in cross-cultural fashion design and production [8]. Rose et al. found that AI not only optimizes physical production but also enhances the time efficiency of knowledge-production processes such as evidence synthesis [9]. Based on a mechanism analysis of firm efficiency and the external environment, Yu et al. confirmed that AI can significantly improve firms' ESG performance [10]. However, Qiao et al. point out that existing micro-level studies are largely confined to specific industries or individual production stages, lacking large-sample tests of firms' overall AI adoption levels and their systemic impact on total factor productivity (TFP) [11].

Second, at the micro-level of production and operations, a large body of research has confirmed the direct role of AI in enhancing efficiency within specific production stages. Through a comprehensive bibliometric review, Bitzenis et al. highlight that AI and machine learning hold immense potential for enhancing production efficiency and promoting sustainable development [12]. From a reverse perspective, Bai et al. found that AI can effectively curb corporate "greenwashing" practices [13]. Li et al. confirmed the positive role of AI in reducing energy intensity in the manufacturing sector [14]. Chen et al. validated the improvement in animation production efficiency brought about by AI through Data Envelopment Analysis (DEA) [15]. Ma et

al. confirmed that AI and machine learning can significantly improve quality control levels on electric vehicle production lines [16]. Sun et al. constructed a stochastic production frontier model to evaluate the performance efficiency of AI from a global investment perspective [17]. Hussein et al. demonstrated that intelligent process automation can effectively improve production efficiency in traditional industries such as cement [18]. Henrique et al. pointed out that hybrid AI solutions also provide methodological support for the efficiency optimization of production systems [19]. Looking at specific industries, Chemseddine et al. examined pathways for productivity improvement in the construction sector [20]. Meanwhile, the academic community has also noted various aspects of AI applications; for instance, Liu et al. explored practical challenges in applying AI to industries such as publishing [21].

Finally, at the level of theoretical mechanism exploration, J. S. D. constructed a simple efficiency-allocation model incorporating robots to theoretically examine the productivity effects of technological shocks [22]. Long et al. empirically demonstrated that the development of an AI management system improved product quality and production efficiency in the furniture manufacturing sector [23]. Overall, the existing literature has laid the groundwork for understanding the efficiency dividends of AI; however, few studies have systematically deconstructed the underlying mechanisms through which AI enhances productivity (such as resource allocation and innovation capabilities) from a micro-firm perspective, and there is a particular lack of boundary condition analysis based on firm heterogeneity.

Research Hypotheses

From the perspective of technological economics, artificial intelligence, as a new type of general-purpose technology, can be deeply embedded in a firm's production, management, and decision-making processes. On the one hand, AI directly replaces or assists traditional manual operations through technologies such as machine vision, natural language processing, and deep learning, thereby reducing error rates and marginal costs in the production process; for instance, it has been demonstrated that intelligent algorithm optimization can significantly enhance production line stability and output efficiency [2,3,16]; on the other hand, AI breaks the input-output constraints of traditional production factors and, through data-driven approaches, enables intelligent management of all factors and optimization of assembly line balancing [2,4], thereby maximizing output given fixed inputs. Furthermore, both theoretical models and cutting-edge evaluation models indicate that AI investment and technological application have a positive impact on the production frontier [17,22]. Therefore, the application of AI technology by enterprises can effectively break through traditional produc-

tivity bottlenecks and achieve a leap in total factor productivity. Based on this, this paper proposes Hypothesis 1:

Hypothesis 1: Artificial intelligence positively improves enterprise production efficiency.

Improvements in production efficiency fundamentally depend on the optimization of factor combinations. Traditional enterprises often face information asymmetry and agency costs in capital investment and labor hiring, leading to underinvestment or overinvestment [11]. The introduction of artificial intelligence can significantly improve this situation: in terms of capital allocation, AI's powerful data mining and predictive capabilities can accurately identify market trends and project risks, optimize investment decision-making models, and reduce inefficient capital expenditures; Regarding labor allocation, AI enables dynamic, optimal matching of human resources through intelligent scheduling, human-machine collaboration, and precise performance evaluations, thereby reducing efficiency losses caused by excess hiring or labor shortages [18,19]. Comprehensive, all-factor intelligent management systems further integrate underlying data across the production chain, making the coordinated scheduling of capital and labor possible [2]. By correcting resource misallocations, AI redirects idle or misallocated factors to high-return segments, thereby driving growth in total factor productivity. Based on this, this paper proposes Hypothesis 2:

Hypothesis 2: Artificial intelligence positively improves total factor productivity by enhancing enterprise resource allocation efficiency.

Innovation is the core driving force behind the leapfrog development of corporate total factor productivity. The application of AI technology has significantly expanded the boundaries of corporate innovation and enhanced R&D efficiency. First, AI accelerates the production and retrieval of knowledge, improving information processing efficiency in the early stages of R&D [9]. Second, in product R&D and design, AI—combined with digital twin and IoT technologies—enables cross-regional and cross-cultural collaborative design and knowledge-driven innovation, significantly shortening R&D cycles and reducing trial-and-error costs [8]. Third, the integration of cutting-edge technologies such as generative AI is reshaping the value chains in content-producing sectors like the creative industries, endowing enterprises with stronger capabilities for creating product differentiation [6]. Finally, the continuous optimization of AI algorithms not only facilitates the commercialization of smart manufacturing outcomes [3] but also, by enhancing overall corporate efficiency, provides more abundant resource support and room for trial and error in innovation activities [10]. This AI-driven leap in innovation capacity helps enterprises build core technological barriers, capture monopoly rents

and excess profits, and ultimately leads to an increase in total factor productivity. Based on this, this paper proposes Hypothesis 3:

Hypothesis 3: Artificial intelligence positively improves total factor productivity by enhancing enterprise innovation capability.

RESEARCH DESIGN

Data Source and Sample Processing

This paper takes A-share listed firms as research objects. Data sources are as follows: annual report text data are from CNINFO (2007–2023), and financial data are from the CSMAR database. To ensure accuracy, samples are processed as follows:

Exclude ST and *ST firms;

Exclude financial firms;

Exclude AI-related core industries such as information transmission, software, and information technology services to avoid data bias; the purpose is to distinguish the ‘providers’ of AI technology from its ‘users,’ thereby more accurately identifying the empowering effect of AI on traditional physical industries. Winsorize continuous variables at the 1% level.

The final sample includes 31,698 firm-year observations.

Variable Definition

Dependent Variable

Enterprise production efficiency is measured by total factor productivity (TFP_LP). The LP method is used to calculate TFP, as the OP method has strict investment requirements and easily causes sample attrition.

Independent Variable

AI level (L.LnAI). Existing measures such as industrial robot stock and penetration rate only reflect AI in specific links, cannot cover management and organization, and are limited to manufacturing. To solve this, we build an AI dictionary combining WIPO AI terminology and CAICT Artificial Intelligence Development Report (2024), count AI word frequency in annual reports via Python text mining, and take the logarithm of (frequency + 1). To address lag effects and endogeneity, we use the one-period lagged value (denoted L.LnAI). Considering the potential for ‘tech-washing’ in annual reports, we use the one-period lagged value (L.LnAI). This not

only addresses the time lag of AI implementation but also reduces the interference of managers' short-term rhetorical adoption driven by investor sentiment.

Mediating Variables

Resource allocation efficiency: measured by capital investment efficiency (Capital) and labor investment efficiency (Labor).

Capital investment efficiency: predicted ideal investment is estimated from Model (1); the absolute value of the residual (actual minus predicted investment) measures inefficiency—larger absolute value means lower efficiency (positive = overinvestment, negative = underinvestment).

Labor investment efficiency: expected net hiring is estimated from Model (2); the absolute value of the residual measures inefficiency—larger absolute value means lower efficiency (positive = excess hiring, negative = insufficient hiring).

Innovation capability (Inv): measured as the natural logarithm of (total patent applications + 1), weighted 3:2:1 for invention, utility model, and design patents.

$$Invest_{i,t} = \alpha_0 + \alpha_1 Lev_{i,t-1} + \alpha_2 Roa_{i,t-1} + \alpha_3 Growth_{i,t-1} + \alpha_4 Size_{i,t-1} + \alpha_5 Age_{i,t-1} + \alpha_6 Invest_{i,t-1} + \sum Industry_i + \sum Year_t + \varepsilon_{i,t} \tag{1}$$

$$NetHire_{i,t} = \alpha_0 + \alpha_1 Growth_{i,t-1} + \alpha_2 Growth_{i,t} + \alpha_3 Roa_{i,t-1} + \alpha_4 Roa_{i,t} + \alpha_5 \Delta Roa_{i,t} + \alpha_6 Size_{i,t-1} + \alpha_7 Quick_{i,t-1} + \alpha_8 Quick_{i,t} + \alpha_9 \Delta Quick_{i,t} + \alpha_{10} Lev_{i,t-1} + \alpha_{11} Lossbin1_{i,t-1} + \alpha_{12} Lossbin2_{i,t-1} + \alpha_{13} Lossbin3_{i,t-1} + \alpha_{14} Lossbin4_{i,t-1} + \alpha_{15} Lossbin_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

Moderating Variable

Degree of internationalization (Inter): measured by the ratio of overseas operating income to total operating income.

Control Variables

Log of total assets (Asset), log of firm age (Age), return on equity (ROE), operating profit margin (Profit), CEO-Chairman duality (Dual), largest shareholder ownership (Top1), Tobin's Q (TBQ), log of board size (Board).

Model Specification

A two-way fixed-effects model is used:

$$TFP_LP_{i,t} = \beta_0 + \beta_1 L.LnAI_{i,t} + \gamma \sum X_{i,t} + \sum Year_t + \sum Company_i + \varepsilon_{i,t} \quad (3)$$

Where:

L.LnAI = AI level;

TFP_LP = production efficiency; To address the potential circular logic where AI optimizes intermediate inputs (used as a proxy in the LP method), we further utilize the GMM method (TFP_GMM) in the robustness check to ensure that the findings are not driven by mechanical correlation.

X = controls;

Company = firm fixed effect;

Year = time fixed effect;

ε = error term.

EMPIRICAL RESULTS

Baseline Regression

Table 1 reports baseline results. Column (1) (no controls) shows L.LnAI is positive and significant at the 1% level (coefficient = 0.0752). Column (2) (with controls) shows L.LnAI = 0.0193, still significant at 1%. Results indicate AI significantly improves production efficiency: a 1% increase in AI raises efficiency by about 0.02%. Hypothesis 1 is supported.

Table 1 Baseline Regression Results

Table 1. Baseline Regression Results

Variable	(1) TFP_LP	(2) TFP_LP
L.LnAI	0.0752*** (0.0098)	0.0193*** (0.0062)
Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	31698	31698
R ²	0.3084	0.5863

Note: *, **, ***= 10%, 5%, 1% significance; clustered robust standard errors in parentheses.

Robustness Checks

Replace Dependent Variable

TFP is recalculated using the GMM method (TFP_GMM). Regression results (Table 2) confirm consistent sign and significance, supporting robustness.

Table 2 Regression with Replaced Dependent Variable

Table 2. Regression with Replaced Dependent Variable

Variable	(1) TFP_GMM	(2) TFP_GMM
L.LnAI	0.0463*** (0.0083)	0.0152*** (0.0066)
Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	31698	31698
R ²	0.2329	0.3901

Double Machine Learning

A double machine-learning partially linear model is estimated using 5-fold cross-fitting and random forest. Results (Table 3) show L.LnAI = 0.0475***, consistent with baseline.

Table 3 Double Machine Learning Results

Table 3. Double Machine Learning Results

Variable	(1) TFP_LP
L.LnAI	0.0475*** (0.0018)
Controls	Yes
Firm FE	Yes
Year FE	Yes
N	31698
R ²	0.5454

$$Y_{i,t} = \theta_0 D_{i,t} + g(X_{i,t}) + U_{i,t} \tag{4}$$

$$E(U_{i,t} | D_{i,t}, X_{i,t}) = 0 \tag{5}$$

$$D_{i,t} = m(X_{i,t}) + V_{i,t} \tag{6}$$

$$E(V_{i,t} | X_{i,t}) = 0 \tag{7}$$

Endogeneity Test: Instrumental Variable Method

To address reverse causality, two instrumental variables (IVs) are used:

IV1: interaction between whether the firm’s city was a treaty port (1840–1911) and log national AI patent applications;

IV2: average AI level of other firms in the same industry.

The logic of IV1 lies in path dependence: historical treaty ports established long-term advantages in technological openness and information infrastructure, which significantly enhanced these cities’ capacity to absorb and diffuse modern AI technologies during the sample period.

These IVs satisfy relevance and exogeneity. First-stage coefficients are significantly positive. Cragg-Donald Wald F = 1026.618 (passes weak IV test); Kleibergen-Paap rk LM = 175.49*** (passes underidentification test); Hansen J = 1.677 (passes overidentification test). Second-stage L.LnAI = 0.1071***, confirming robustness (Table 4).

Table 4 Instrumental Variable Regression

Table 4. Instrumental Variable Regression

Variable	First Stage (1) L.LnAI	Second Stage (2) TFP_LP
IV1	0.0056** (0.0024)	–
IV2	0.6541*** (0.0432)	–
L.LnAI	–	0.1071*** (0.0321)
Tests	F = 1026.618; LM = 175.49***	Hansen J = 1.677
Controls	Yes	Yes
FE	Yes	Yes
N	25470	25470

MECHANISM TESTS

Following Jiang Ting (2022), the mediating model is:

$$Mediator_{i,t} = \alpha_0 + \alpha_1 LnAI_{i,t} + \sum \beta X_{i,t} + \sum Year_t + \sum Company_i + \varepsilon_{i,t} \tag{8}$$

Resource Allocation Efficiency

Columns (1)–(2) of Table 5 show L.LnAI is significantly negative (at least 5% level) for Capital and Labor, meaning AI reduces inefficient capital and labor investment, improving resource allocation efficiency. Hypothesis 2 is supported.

Table 5 Mechanism Test Results

Table 5. Mechanism Test Results

Variable	(1) Capital	(2) Labor	(3) Inv
L.LnAI	-0.0123*** (0.0043)	-0.0075** (0.003)	0.0388*** (0.0149)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
N	31698	31698	31698
R ²	0.0238	0.0738	0.2935

Innovation Capability

Column (3) of Table 5 shows L.LnAI is significantly positive at 1% for Inv, meaning AI enhances innovation capability. Hypothesis 3 is supported.

HETEROGENEITY ANALYSIS

Firm Heterogeneity

Financing Efficiency

Firms are split at the median of financing efficiency. Table 6 shows AI’s effect is stronger and significant in high-financing-efficiency firms.

Table 6 Financing Efficiency Heterogeneity

Table 6. Financing Efficiency Heterogeneity

Variable	(1) TFP_LP (High FE)	(2) TFP_LP (Low FE)
L.LnAI	0.0218** (0.0096)	0.0091 (0.0068)
Controls	Yes	Yes
FE	Yes	Yes
N	15889	15809
R ²	0.5586	0.6003

Factor Endowment

Firms are divided into labor-intensive and non-labor-intensive. Table 7 shows AI’s efficiency gain is much larger and significant in labor-intensive firms.

Table 7 Factor Endowment Heterogeneity

Table 7. Factor Endowment Heterogeneity

Variable	(1) TFP_LP (Labor-intensive)	(2) TFP_LP (Non-labor-intensive)
L.LnAI	0.0389*** (0.0133)	0.0096 (0.006)
Controls	Yes	Yes
FE	Yes	Yes
N	10787	20911
R ²	0.4904	0.6389

FURTHER ANALYSIS: THRESHOLD EFFECT

To test nonlinearity, a panel threshold model is estimated with firm size (log total employees, Lnsize) as the threshold variable:

$$TFP_{i,t} = \lambda_0 + \lambda_1 L.LnAI_{i,t} I(Lnsize_{i,t} \leq \gamma_1) + \lambda_2 L.LnAI_{i,t} I(\gamma_1 < Lnsize_{i,t} \leq \gamma_2) + \dots + \mu \sum X_{i,t} + \sum Year_t + \sum Company_i + \varepsilon_{i,t} \tag{9}$$

Tests confirm a double threshold at 7.4271 and 8.2561 (Table 8). Threshold regression (Table 9) shows:

Table 8 Threshold Effect Test

Table 8. Threshold Effect Test

Model	F-value	P-value	Bootstrap	Threshold	10% CV	5% CV	1% CV
Single	772.31	0.074*	500	7.4271	706.46	836.40	1195.34
Double	643.79	0.038**	500	8.2561	524.02	607.54	801.15
Triple	250.30	0.886	500	9.5291	966.14	1131.85	1611.23

Table 9 Threshold Regression Results

Table 9. Threshold Regression Results

Variable	TFP ($Lsize \leq \gamma_1$)	TFP ($\gamma_1 < Lsize \leq \gamma_2$)	TFP ($Lsize > \gamma_2$)
L.LnAI	0.0095 (0.0094)	0.0262*** (0.0073)	0.0204** (0.0081)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
N	31698	31698	31698
R ²	0.5865	0.5865	0.5865

When $Lsize \leq 7.4271$: L.LnAI = 0.0095 (insignificant);

When $7.4271 < Lsize \leq 8.2561$: L.LnAI = 0.0262*** (strongest effect);

When $Lsize > 8.2561$: L.LnAI = 0.0204** (positive but weaker).

Thus, AI's effect is insignificant for very small firms, strongest for medium-sized firms, and slightly weaker for very large firms. This marginal decline in large firms can be attributed to 'organizational inertia' and bureaucracy. Although large firms possess superior resources, their complex hierarchical structures and longer decision chains increase the coordination costs of integrating AI, which may partially offset the efficiency gains from their resource advantages.

In summary, the empirical results consistently demonstrate that AI acts as a potent catalyst for enterprise production efficiency. By deconstructing the mechanisms and exploring the boundary conditions through threshold effects and machine learning methods, this study provides a multi-dimensional understanding of the digital transformation landscape in China's A-share firms. These findings lay the groundwork for the following conclusions and targeted policy recommendations.

CONCLUSION

Using a sample of China's A-share listed firms from 2007 to 2023, this paper systematically examines how AI affects enterprise production efficiency and its boundary conditions. The main findings are:

AI significantly improves production efficiency, robust to various checks;

Mechanisms: improving resource allocation efficiency (capital + labor) and strengthening innovation capability;

Heterogeneity: effects are stronger in labor-intensive and high-financing-efficiency firms;

Nonlinearity: double firm-size threshold—insignificant for small firms, strongest for medium firms, slightly weaker for large firms.

Policy Implications

Strengthen AI infrastructure: The government should expand cloud computing, IoT, 5G, and industrial internet, open public data platforms, and set up special funds to support smart data centers and edge computing.

Optimize innovation environment: Support industry-university-research cooperation, build joint labs, and improve intellectual property protection.

Differentiated support by firm size:

Medium firms: subsidize AI application in intelligent manufacturing and decision-making;

Small firms: lower inclusive loan barriers, provide free AI training and consulting;

Large firms: offer organizational consulting to streamline structure and avoid bureaucracy weakening AI effects.

Author Contributions

Conceptualization – Guo G; methodology – Guo G and Gao Y; formal analysis – Guo G; investigation – Gao Y; resources – Gao Y; writing-original draft preparation – Guo G and Gao Y; writing-review and editing – Guo G and Gao Y; visualization – Gao Y; supervision – Guo G. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Funding

This research received no external funding.

Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Acknowledgements

Not applicable.

REFERENCES

- [1] Zhu Q, Zhang Z. The Impact of Artificial Intelligence on Energy Conservation and Emission Reduction: Evidence From China's Listed Firms. *International Studies of Economics*. 2025;20(4):410-430. doi:10.1002/ISE3.70026
- [2] Wang D, Zhang R, Chai Y. Innovative Path to Intelligent Management of the Entire Production Lines Full Process and Full Element. *Innovation Series: Advanced Science*. 2025;2(6):511-516. doi:10.66521/2938-9933-2025121902

- [3] Jiaxin C, Lu L, Meiyan C, et al. Optimization of Artificial Intelligence Algorithms for Intelligent Manufacturing: Enhancing Production Efficiency and Supply Chain Stability. *Journal of Organizational and End User Computing (JOEUC)*. 2025;37(1):1-28. doi:10.4018/JOEUC.392071
- [4] Wang X, Lin C, Yang S, et al. A deep learning approach for balance optimisation of patch panel assembly line. *Journal of Engineering Design*. 2025;36(7-9):1302-1320. doi:10.1080/09544828.2024.2309861
- [5] Lin S, Chen X, Huang R. UNLOCKING THE POWER OF AI: HOW PEER EFFECTS AND INSTITUTIONAL ENVIRONMENT DRIVE PRODUCTION EFFICIENCY IN CHINA'S PUBLIC LISTED FIRMS. *Trends in Social Sciences and Humanities Research*. 2025;3(5). doi:10.61784/TSSHR3170
- [6] Mao Y. The Reshaping of the Creative Industry Value Chain by Generative Artificial Intelligence: A Study Based on the Content Production Segment. *Industry Science and Engineering*. 2025;2(8). doi:10.62381/I255803
- [7] Li F. Research on the path of digital empowering rural revitalization under the background of artificial intelligence. *Journal of Sociology and Ethnology*. 2025;7(3). doi:10.23977/JSOCE.2025.070314
- [8] Wang Y, Chen H, Feng X, et al. Knowledge-Driven Innovation: Leveraging Digital Twins, Internet of Things, and AI for Cross-Cultural Fashion Design and Production between China and South Africa. *International Journal of High Speed Electronics and Systems*. 2025;35(04). doi:10.1142/S012915642540645X
- [9] Rose J C, Echavez M F J, Muller E A, et al. Artificial Intelligence and Machine Learning to Improve Evidence Synthesis Production Efficiency: An Observational Study of Resource Use and Time-to-Completion. *Cochrane Evidence Synthesis and Methods*. 2025;3(3):e70030-e70030. doi:10.1002/CESM.70030
- [10] Yu X, Fan L, Yu Y. Artificial Intelligence and Corporate ESG Performance: A Mechanism Analysis Based on Corporate Efficiency and External Environment. *Sustainability*. 2025;17(9):3819-3819. doi:10.3390/SU17093819
- [11] Qiao Z. Research on the Impact of Artificial Intelligence, Enterprise Production Efficiency and Enterprise Innovation Performance. *Advances in Social Science and Culture*. 2025;7(1). doi:10.22158/ASSC.V7N1P140
- [12] Bitzenis A, Koutsoupas N, Nosios M. Artificial intelligence and machine learning in production efficiency enhancement and sustainable development: a comprehensive bibliometric review. *Frontiers in Sustainability*. 2025;51508647-1508647. doi:10.3389/FRSUS.2024.1508647
- [13] Bai C, Yao D, Xue Q. Does artificial intelligence suppress firms' greenwashing behavior? Evidence from robot adoption in China. *Energy Economics*. 2025;142108168-108168. doi:10.1016/J.ENERCO.2024.108168
- [14] Li H, Lu Z, Zhang Z, et al. How does artificial intelligence affect manufacturing firms' energy intensity? *Energy Economics*. 2025;141108109-108109. doi:10.1016/J.ENERCO.2024.108109

- [15] Chen Y, Wang Y, Yu T, et al. The Effect of AI on Animation Production Efficiency: An Empirical Investigation Through the Network Data Envelopment Analysis. *Electronics*. 2024;13(24):5001-5001. doi:10.3390/ELECTRONICS13245001
- [16] Ma Z, Wang Y. Optimizing Quality Control on Electric Vehicle Production Lines with AI and Machine Learning. *Journal of Research in Science and Engineering*. 2024;6(9):8-13. doi:10.53469/JRSE.2024.06(09).02
- [17] Sun C Y, Cosgun O, Sharman R, et al. A stochastic production frontier model for evaluating the performance efficiency of artificial intelligence investment worldwide. *Decision Analytics Journal*. 2024;12:100504-100504. doi:10.1016/J.DAJOUR.2024.100504
- [18] Hussein M I M, Sharif M S. The role of intelligent process automation in raising production efficiency: A field study in the Tasluja cement factory. *Review of Socio-Economic Perspectives*. 2024;9(1):149-157. doi:10.19275/RSEP182
- [19] Henrique J C, Tibor K, Andrea K, et al. Production system efficiency optimization through application of a hybrid artificial intelligence solution. *International Journal of Computer Integrated Manufacturing*. 2024;37(6):790-807. doi:10.1080/0951192X.2023.2257661
- [20] Chemseddine D, Khaled B, Mohamed B. Improvement of Productivity in Buildings Construction. *Selected Scientific Papers - Journal of Civil Engineering*. 2023;18(1). doi:10.2478/SSPJCE-2023-0005
- [21] Liu L. The applications and challenges of artificial intelligence in the publishing industry. *Geographical Research Bulletin*. 2023;2124-127. doi:10.50908/GRB.2.0_124
- [22] J. S D. Simple efficiency-distribution models of production, with an application to robotics. *SN Business & Economics*. 2022;2(8). doi:10.1007/S43546-022-00260-Z
- [23] Long J G, Lin H B, Cai X H, et al. Developing an Artificial Intelligence (AI) Management System to Improve Product Quality and Production Efficiency in Furniture Manufacture. *Procedia Computer Science*. 2020;166(C):486-490. doi:10.1016/j.procs.2020.02.060