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Enterprise Artificial Intelligence Application and Digital-Industrial Technology Integration: Evidence from Chinese Listed Enterprises

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Abstract

Based on data from Chinese non-financial listed enterprises from 2010 to 2023, this paper systematically investigates the impact of enterprise artificial intelligence applications on digital-industrial technology integration. The results indicate that enterprise artificial intelligence applications can effectively promote digital-industrial technology integration, with enhancing corporate knowledge absorption capacity and elevating corporate digitalization level of business scenarios serving as effective mechanisms. Heterogeneity tests reveal that the integration-promoting effect of artificial intelligence applications is stronger for enterprises with less financing constraints, higher synergy between human capital and artificial intelligence applications, and stronger digital economy policy support in their cities. This study provides important policy implications for uncovering the economic value of artificial intelligence applications and accelerating digital-industrial integration.

Keywords

artificial intelligence application, digital-industrial technology integration, digital transformation

1. Introduction

The deep integration of the real economy and the digital economy is a crucial driving force for optimizing economic structure and achieving sustainable growth, becoming a common strategic choice for major global economies [1] Ideally, digital technological innovation should permeate and empower various aspects of real industries, thereby enhancing production efficiency and optimizing resource allocation [2]. However, in practice, a significant integration gap persists between digital technologies and real industries [3]. Many digital innovations tend to circulate internally within the digital domain or only affect non-core business operations, failing to effectively integrate into the core value chains of real industries. This limits the potential of digital technologies to fully empower real industries, posing a major challenge to digital-industrial technology integration.

Against this backdrop, the accelerating advancement of artificial intelligence (AI) acts as a pivotal catalyst for the current wave of technological innovation and industrial evolution, and is exerting a disruptive impact on enterprise operations and strategic decision-making. Existing literature has explored the empowering effects of AI on enterprises from multiple dimensions. For instance, some empirical evidence has confirmed that AI application demonstrates a positive correlation with elevated corporate total factor productivity [4-6], innovative production processes and products [7, 8], and optimized organizational governance and strategic decision [9]. Despite widespread recognition of AI's potential, systematic research on its role in promoting the deep integration of digital and industrial technologies remains scarce.

Theoretically, enterprise AI applications are expected to drive the digital-industrial technology deep integration. AI applications significantly enhance corporate knowledge absorption capacity, greatly expanding the breadth and depth of external knowledge searches, enabling more efficient identification, acquisition, and transformation of complex external knowledge related to real industries [10, 11]. This thereby facilitates the implementation of digital technologies within industrial ecosystems through knowledge-driven empowerment. Additionally, enterprise AI applications drive the deep digital transformation of core business scenarios by embedding intelligent decision-making capabilities into research, production, and supply chain management, achieving seamless integration of digital technologies with physical business operations rather than merely serving as peripheral tools.

To verify the above theoretical inferences, this paper uses Chinese listed enterprises from 2010 to 2023 as a sample and constructs proxy variables for enterprise AI applications through text analysis of annual reports to empirically test the promoting effect of enterprise AI applications on digital-industrial technology integration and the underlying mechanisms. The contributions of this paper are reflected as follows: First, we investigate the impact of enterprise AI applications on digital-industrial technology integration, enriching the understanding of the economic value of AI. Second, compared to existing studies that mainly use city-level or region-level digital-real integration indicators [12-14], this paper constructs enterprise-level digital-industrial technology integration indicators based on patent citation data, providing new micro-level evidence on how to effectively promote digital-real integration. Third, this paper reveals the "black box" of AI-driven digital-industrial integration from the perspectives of knowledge absorption capability and business scenario digitization, deepening the theoretical understanding of relevant impact mechanisms.

2. Theoretical Analysis and Research Hypothesis

Enterprise AI applications primarily promote digital-industrial technology integration through two core mechanisms: enhancing knowledge absorption capacity and driving digital transformation of business scenarios.

On the one hand, AI applications significantly enhance corporate knowledge absorption capacity, providing a knowledge foundation for digital-industrial technology integration. Against the backdrop of accelerated digital-industrial integration, the knowledge absorption ability is particularly crucial as it requires enterprises to efficiently internalize external digital technology knowledge and combine it with their accumulated industry-specific knowledge [15]. AI applications strengthen this process from multiple dimensions. In the knowledge identification and acquisition stage, AI-driven data analysis and natural language processing technologies help enterprises quickly and accurately identify potentially valuable frontier digital technologies from vast amounts of patents, scientific literature, and market information [16, 17]. At the stage of knowledge absorption and transformation, AI systems assist enterprises in deeply understanding the internal logic of complex digital technologies through simulation, data modeling, and knowledge graph construction, and integrating them with existing technological systems and production processes [18]. Ultimately, in the knowledge application stage, AI aids R&D decision-making, optimizes resource allocation, and accelerates the transformation of integrated new knowledge into market-competitive products or services [8]. Therefore, by empowering the entire knowledge absorption process, AI breaks down the knowledge barriers between digital technology and real industry, laying a solid cognitive and capability foundation for their integration.

On the other hand, AI applications create practical carriers for digital-industrial technology integration by driving the digitalization of business scenarios. It is important to note that, the digitalization of business scenarios extends beyond the superficial technological implementation but fundamentally reconstructs an enterprise's operational model, business processes, and value creation methods using digital technologies [19, 20], with AI functioning as the pivotal driver of the digital transformation [21]. Unlike traditional information technologies, AI can deeply embed into an enterprise's core business scenarios, enabling real-time perception, analysis, decision-making, and control of physical operations through digital logic [22, 23]. For example, in the manufacturing industry, intelligent quality inspection systems integrating machine vision and deep learning algorithms directly fuse digital analysis capabilities into physical production lines; in the logistics industry, AI-based dynamic path planning and warehouse robot scheduling achieve precise control of physical transport vehicles through digital algorithms. This process of deeply embedding AI into specific business scenarios is essentially a form of micro-level digital-industrial technology integration. By continuously creating and deepening such integrated scenarios in key links such as R&D, production, and supply chain, enterprises can systematically inject digital technology capabilities into the "capillaries" of real businesses, thereby achieving an overall leap in digital-industrial technology integration.

Therefore, the research hypothesis is proposed as follows:

Hypothesis 1: Enterprise AI applications can promote digital-industrial technology integration.

3. Research Design

3.1 Data Sources

This paper utilizes non-financial enterprises listed on China's A-share market from 2010 to 2023 as the research sample. To ensure data completeness and reliability, we processed the sample as follows: (1) excluding samples marked as ST, PT, and *ST; (2) retaining enterprises with continuous observation values for more than four years; (3) conducting bilateral 1% winsorization on continuous variables. Ultimately, 26,286 sample observations were obtained. The enterprise patent data used to construct the digital-industrial technology integration variable was sourced from the patent database of the CNRDS database, while enterprise characteristics and financial data were sourced from the CSMAR database.

3.2 Variable Definitions

3.2.1 Dependent Variable: Digital-Industrial Technology Integration

Drawing on Tianren and Sufeng [24] this paper measures digital-industrial technology integration based on patent citation information. Specifically, an enterprise is categorized as demonstrating digital-industrial technology integration innovation when its patent application, classified under non-digital industry codes, incorporates citations to digital technology patents. Aggregating these integration behaviors at the enterprise-year level and applying a logarithmic transformation of the aggregate value yields the measure of digital-industrial technology integration, denoted as *TI*.

3.2.2 Independent Variable: Enterprise AI Application

Following Chen et al. [25] and Xin [26], this paper compiles a keyword library related to AI applications from relevant academic literature, policy documents, and research reports, then uses Python to crawl AI-related words in annual reports and counts the total frequency. The logarithmic transformation of this frequency serves as the measure for enterprise AI application, denoted as *AIa*.

3.2.3 Control Variables

To reduce bias caused by omitted variables, this paper selects a series of enterprise-level control variables: enterprise size (*Size*), leverage ratio (*Lev*), return on total assets (*Roa*), largest shareholder's shareholding ratio (*Top*1), enterprise growth (*Growth*), enterprise age (*Age*), Tobin's Q (*Tobinq*), proportion of operational assets (*Tang*), and total asset turnover (*Tar*). Table 1 presents the descriptive statistics.

Table 1: Descriptive Statistics of Variables

VarName	Obs	Mean	Median	SD	Min	Max
TI	26286	1.508	1.099	1.438	0.000	5.762
AIa	26286	1.168	0.693	1.344	0.000	4.836
Size	26286	22.402	22.186	1.359	20.070	26.538
Lev	26286	0.429	0.423	0.202	0.060	0.918
Roa	26286	0.034	0.037	0.066	-0.288	0.192
*Top*1	26286	33.395	30.905	14.906	8.020	73.670
Growth	26286	0.157	0.106	0.347	-0.509	1.978

Age	26286	2.106	2.303	0.873	0.000	3.367
Tobinq	26286	1.978	1.605	1.180	0.826	7.666
Tang	26286	0.332	0.320	0.160	0.026	0.741
Tar	26286	0.602	0.521	0.372	0.093	2.242

3.3 Model Construction

The baseline regression model in this paper is specified as follows:

$$TI_{it}=\beta_0+\beta_1 AIa_{it}+\sum\beta_n Controls_{it}+EE_i+YE_t+\varepsilon_{it} \tag{1}$$

In mode (1), AIa_{it} is the AI technology application variable; TI_{it} is the digital-industrial technology integration variable; $Controls_{it}$ *represents* a set of control variables; EE_i and YE_t are enterprise and year fixed effects, respectively.

4. Empirical Analysis

4.1 Baseline Regression Results

Table 2 presents the baseline regression results. In column (1), the regression model only incorporates enterprise and year fixed effects, and the regression coefficient of the enterprise AI application variable (*AIa*) is significantly positive at the 1% level. After adding a series of control variables in column (2), the coefficient of *AIa* remains significantly positive, indicating that enterprise AI technology applications have a significant promoting effect on digital-industrial technology integration, thus verifying Hypothesis 1.

Table 2: Baseline Regression Results

	(1)	(2)
	Techconv	Techconv
AIa	0.126***	0.085***
	(10.18)	(7.16)
Controls	No	Yes
Enterprise FE	Yes	Yes
Year FE	Yes	Yes
N	26286	26286
Adj. R^2	0.71	0.72

*Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The explanations were not repeat ed in the following.*

4.2 Endogeneity Analysis

Omitted variable bias or reverse causality may undermine the reliability of baseline regression results. To address potential endogeneity, a Bartik-type instrumental variable is employed. Specifically, the interaction term of the number of fixed telephones in cities in 1999 and the national growth rate of AI enterprises serves as the instrumental variable (*IV*). The growth rate of the number of AI enterprises nationwide represents the overall development trend of the AI industry, which naturally affects the intensity of AI applications in individual enterprises. Moreover, the historical digital infrastructure as share weight and AI industry development as global shock both lack direct causal pathways to influence contemporaneous digital-industrial technology integration at the enterprise level. Therefore, the instrumental variable (*IV*) satisfies the criteria of relevance and exogeneity.

As shown in Table 3, the estimation coefficients in the two-stage regression are all are all in line with expectations, and the F statistic confirms the non-existence of weak instrument issues, demonstrating that after controlling for endogeneity, AI applications still significantly promote digital-industrial technology integration.

Table 3: Instrumental variable method test results

	(1)	(2)
	AIa	*Techconv*
AIa		1.603**

		(2.11)
IV	0.088**	
	(2.54)	
Controls	Yes	Yes
Enterprise FE	Yes	Yes
Year FE	Yes	Yes
N	25644	25644
Adj. R^2	0.79	-1.38

4.3 Robustness Tests

This paper conducts the following robustness checks: (1) Replacing the independent variable. Following Zhai and Liu[5], we screen out AI-related patents from enterprise patent applications, and use the logarithmic transformation of the number of patents related to AI as an alternative indication for AI applications (*AIp*) to re-conduct the test; (2) Replacing the estimation model. Given the presence of many zeros in our constructed digital-industrial technology integration variable (TechConv), which may bias OLS estimates, we re-estimate using a Tobit model; (3) Excluding special samples. Since enterprises in the information technology and computer service industries may have advantages in absorbing AI technologies due to their established digital foundations, we exclude these industries from the sample and conduct robustness checks; (4) More stringent fixed effects. To exclude the interference of time-varying confounding factors at the industry and city levels, this paper further controls for "Industry×Year" and "City×Year" fixed effects in the regression. The results of a series of robustness tests in Table 4 further validate the robustness of the baseline findings.

Table 4: Robustness tests

	(1)	(2)	(3)	(4)	(5)
	Techconv	*Techconv*	*Techconv*	*Techconv*	*Techconv*
AIa		*0.512****	*0.083****	*0.074****	*0.078****
		(29.09)	*(5.94)*	*(6.22)*	*(6.01)*
AIp	*0.340****				
	(15.45)				
Controls	Yes	Yes	Yes	Yes	Yes
Enterprise FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	No	No	No	Yes	No
City×Year FE	No	No	No	No	Yes
N	26286	26286	20114	26165	24787
Adj. R^2	0.73		0.67	0.73	0.72

4.4 Mechanism Tests

According to previous theoretical analysis, this paper primarily tests whether enterprise AI applications promote digital-industrial technology integration by enhancing knowledge absorption capacity and elevating business scenario digitalization. Drawing on Kim et al. [27] and Luo and Zor [28], we use the average number of patents cited by an enterprise's patent applications to reflect the knowledge absorption capacity (*Absorb*). The results in Column (1) of Table 5 show that AI applications can help enterprises enhance their knowledge absorption capacity. Using CSMAR database data, we constructed a segmented business scenario digitization indicator (*Digitization*) by counting word frequencies related to mobile internet, mobile payment, smart healthcare, digital marketing, etc. The results in Column (2) of Table 5 show that the impact of AI applications on business scenario digitization is also significantly positive. Therefore, the results of Table 5 verify the mechanisms of enhancing corporate knowledge absorption capacity and elevating business scenario digitalization.

Table 5: Mechanism test results

	(1)	(2)
	Absorb	*Digitization*
AIa	0.055*	0.256***
	(1.70)	(23.79)
Controls	Yes	Yes
Enterprise FE	Yes	Yes
Year FE	Yes	Yes
N	17220	24113
Adj. R^2	0.22	0.67

4.5 Heterogeneity Analysis

This paper introduces interaction terms between group dummy variables and AI applications variable to examine heterogeneity on enterprise financing constraint, synergy between human capital and AI applications, and government digital economy policy support. First, drawing on Hadlock and Pierce[29], we use the FC index to measure enterprise financing constraints and construct a group dummy variable (*FCdummy*) based on the mean of the FC index. If *FCdummy*=1, the sample is classified into the more financing constraint group; otherwise, it belongs to the less financial constraints group (*FCdummy*=0). Second, the proportion of employees holding bachelor's degrees or higher serves as a measurement for human capital [30] and we quantify the synergy between human capital and AI applications based on coupling coordination degree model. The group dummy variable (*Sydummy*) is constructed based on the mean of synergy. If *Sydummy*=1, the sample is classified into the higher synergy group; otherwise, it belongs to the lower synergy group (*Sydummy*=0). Third, we measure the intensity of government digital economy policy support by counting the word frequency related to digital technology and application in city government work reports [31, 32]. The group dummy variable (*Govdummy*) is constructed based on the mean of digital policy support intensity. If *Govdummy*=1, the sample is classified into the stronger policy support group; otherwise, it belongs to the weaker policy support group (*Govdummy*=0). The results of Table 6 show that the estimated coefficients of all interaction terms are statistically significant, revealing that the integration-promoting effect of artificial intelligence applications is stronger for enterprises with less financing constraints, higher synergy between human capital and artificial intelligence applications, and stronger digital economy policy support in their cities.

Table 6: Heterogeneity test results

	(1)	(2)	(3)
	Techconv	Techconv	Techconv
AIa	0.114***	-0.006	0.072***
	(8.10)	(-0.12)	(5.59)
FCdummy	0.088***		
	(3.25)		
AIa×FCdummy	-0.060***		
	(-4.46)		
Sydummy		-0.010	
		(-0.34)	
AIa×Sydummy		0.089*	
		(1.77)	
Govdummy			-0.025
			(-1.34)
AIa×Govdummy			0.021**
			(1.97)
Controls	Yes	Yes	Yes
Enterprise FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	26286	24187	25262

Adj. R^2	0.72	0.73	0.73

5. Conclusion and Policy Implications

Based on data from Chinese non-financial listed enterprises from 2010 to 2023, this paper investigates the impact of enterprise AI applications on digital-industrial technology integration. The results show that enterprise AI applications can promote digital-industrial technology integration, with enhancing corporate knowledge absorption capacity and elevating business scenario digitalization serving as effective mechanisms. Finally, for enterprises with less financing constraints, higher synergy between human capital and AI applications, and stronger digital economy policy support in their cities, the integrative promotion effect of AI applications is even stronger.

The policy implications are as follows. First, policymakers need to strengthen top-level design, incentivizing broader and deeper AI application in enterprises to leverage its significant potential in driving digital-real economy integration. Second, to smooth the transmission mechanism of AI applications, it is necessary to build an open knowledge-sharing network and inclusive digital infrastructure. These measures can effectively enhance enterprises' technology absorption capability and significantly reduce transition costs associated with data integration and business process transformation, facilitating smoother transmission of AI applications to digital-industrial integration. Third, besides technological development, policymakers should improve corporate financing accessibility and enterprise managers should strive to vigorously cultivate new types of human capital that can efficiently collaborate with AI, creating more favorable conditions for deeper digital-industrial integration.

References

[1] Zhao, M., Liu, R. and Dai, D. Synergistic effect between China's digital transformation and economic development: A study based on sustainable development. Sustainability. 2021, 13(24), p. 13773. https://doi.org/10.3390/su132413773.

[2] Jin, C., Xu, A., Zhu, Y. and Li, J. Technology growth in the digital age: Evidence from China. Technological Forecasting and Social Change. 2023, 187, p. 122221. https://doi.org/10.1016/j.techfore.2022.122221.

[3] Prytkov, N. and Zamorev, A. Barriers to the integration of digital twin technology in manufacturing. Philosophical Problems of IT & Cyberspace (PhilIT&C). 2023, 1, pp. 53-64. https://doi.org/10.17726/philit.2023.1.5.

[4] Marioni, L. d. S., Rincon-Aznar, A. and Venturini, F. Productivity performance, distance to frontier and AI innovation: Firm-level evidence from Europe. Journal of Economic Behavior & Organization. 2024, 228, p. 106762. https://doi.org/10.1016/j.jebo.2024.106762.

[5] Zhai, S. and Liu, Z. Artificial intelligence technology innovation and firm productivity: Evidence from China. Finance Research Letters. 2023, 58, p. 104437. https://doi.org/10.1016/j.frl.2023.104437.

[6] Zhang, B. and Peng, B. Artificial Intelligence and the Development of "Specialized, Refined, Unique, and Innovative" Small- and Medium-Sized Enterprises. Managerial and Decision Economics. 2025, 46(2), pp. 843-861. https://doi.org/10.1002/mde.4407.

[7] Bahoo, S., Cucculelli, M. and Qamar, D. Artificial intelligence and corporate innovation: A review and research agenda. Technological Forecasting and Social Change. 2023, 188, p. 122264. https://doi.org/10.1016/j.techfore.2022.122264.

[8] Wang, S., Huang, X., Xia, M. and Shi, X. Does Artificial Intelligence Promote Firms' Innovation Efficiency: Evidence from the Robot Application. Journal of the Knowledge Economy. 2024, 15(4), pp. 16373-16394. https://doi.org/10.1007/s13132-023-01707-w.

[9] Shen, L., Jin, Y. and Xue, Q. Artificial intelligence and corporate investment efficiency. Finance Research Letters. 2025, 85, p. 108050. https://doi.org/10.1016/j.frl.2025.108050.

[10] Broekhuizen, T., Dekker, H., de Faria, P., Firk, S., Nguyen, D. K. and Sofka, W. AI for managing open innovation: Opportunities, challenges, and a research agenda. Journal of Business Research. 2023, 167, p. 114196. https://doi.org/10.1016/j.jbusres.2023.114196.

[11] Kuzior, A., Sira, M. and Brożek, P. Use of artificial intelligence in terms of open innovation process and management. Sustainability. 2023, 15(9), p. 7205. https://doi.org/10.3390/su15097205.

[12] An, Q., Wang, Y., Liu, F. and Wang, R. Does the integration of digital and real economies enhance corporate supply chain resilience? Evidence from China's listed firms. Finance Research Letters. 2025, 85, p. 107953. https://doi.org/10.1016/j.frl.2025.107953.

[13] Sun, G., Fang, J., Li, J. and Wang, X. Research on the impact of the integration of digital economy and real economy on enterprise green innovation. Technological Forecasting and Social Change. 2024, 200, p. 123097. https://doi.org/10.1016/j.techfore.2023.123097.

[14] Sun, G., Yin, D., Kong, T. and Yin, L. The impact of the integration of the digital economy and the real economy on the risk of stock price collapse. Pacific-Basin Finance Journal. 2024, 85, p. 102373. https://doi.org/10.1016/j.pacfin.2024.102373.

[15] Wang, F. and Ye, L. Digital transformation and export quality of Chinese products: An analysis based on innovation efficiency and total factor productivity. Sustainability. 2023, 15(6), p. 5395. https://doi.org/10.3390/su15065395.

[16] Li, C., Xu, Y., Zheng, H., Wang, Z., Han, H. and Zeng, L. Artificial intelligence, resource reallocation, and corporate innovation efficiency: Evidence from China's listed companies. Resources Policy. 2023, 81, p. 103324. https://doi.org/10.1016/j.resourpol.2023.103324.

[17] Wang, Z., Li, M., Lu, J. and Cheng, X. Business Innovation based on artificial intelligence and Blockchain technology. Information Processing & Management. 2022, 59(1), p. 102759. https://doi.org/10.1016/j.ipm.2021.102759.

[18] Guo, L., Pei, H. and Liu, Y. Artificial intelligence and corporate green innovation: Evidence from China. Research in International Business and Finance. 2025, 79, p. 103039. https://doi.org/10.1016/j.ribaf.2025.103039.

[19] Liu, L., Cui, L., Han, Q. and Zhang, C. The impact of digital capabilities and dynamic capabilities on business model innovation: the moderating effect of organizational inertia. Humanities and Social Sciences Communications. 2024, 11(1), p. 420. https://doi.org/10.1057/s41599-024-02910-z.

[20] Wang, Y. and Han, P. Digital transformation, service-oriented manufacturing, and total factor productivity: Evidence from a-share listed companies in China. Sustainability. 2023, 15(13), p. 9974. https://doi.org/10.3390/su15139974.

[21] Zhang, Q., Wang, A. and Li, R. Enterprise value creation effects of artificial intelligence technology from the perspective of digital agility: evidence from China. Technology Analysis & Strategic Management. 2025, 37(12), pp. 2874-2888. https://doi.org/10.1080/09537325.2024.2383605.

[22] Hui, L., Xie, H. and Chen, X. Digital technology, the industrial internet, and cost stickiness. China Journal of Accounting Research. 2024, 17(1), p. 100339. https://doi.org/10.1016/j.cjar.2023.100339.

[23] Jalil, M. F., Lynch, P., Marikan, D. A. B. A. and Isa, A. H. B. M. The influential role of artificial intelligence (AI) adoption in digital value creation for small and medium enterprises (SMEs): does

technological orientation mediate this relationship? AI & SOCIETY. 2025, 40(3), pp. 1875-1896. https://doi.org/10.1007/s00146-024-01969-1.

[24] Tianren, L. and Sufeng, H. Does digital-industrial technology integration reduce corporate carbon emissions? Environmental Research. 2024, 257, p. 119313. https://doi.org/10.1016/j.envres.2024.119313.

[25] Chen, L., Li, S. and She, Z. A study on the impact of artificial intelligence applications on corporate green technological innovation: A mechanism analysis from multiple perspectives. International Review of Economics & Finance. 2025, 103, p. 104490. https://doi.org/10.1016/j.iref.2025.104490.

[26] Xin, W. The impact of corporate artificial intelligence on financial risk: Evidence from China. Finance Research Letters. 2025, 81, p. 107435. https://doi.org/10.1016/j.frl.2025.107435.

[27] Kim, S., Kim, H. and Kim, E. How knowledge flow affects Korean ICT manufacturing firm performance: a focus on open innovation strategy. Technology Analysis & Strategic Management. 2016, 28(10), pp. 1167-1181. https://doi.org/10.1080/09537325.2016.1182150.

[28] Luo, K. and Zor, S. How does social network in patent provide changes in the Chinese manufacturing firm market value? Heliyon. 2023, 9(3), p. e14358. https://doi.org/10.1016/j.heliyon.2023.e14358.

[29] Hadlock, C. J. and Pierce, J. R. New evidence on measuring financial constraints: Moving beyond the KZ index. The Review of Financial Studies. 2010, 23(5), pp. 1909-1940. https://doi.org/10.1093/rfs/hhq009.

[30] Jin, Y., Li, X., Tian, G., Shi, J. and Wang, Y. Employee education level and efficiency of corporate investment. Journal of Accounting Literature. 2023, 47(2), pp. 277-297. https://doi.org/10.1108/JAL-08-2023-0150.

[31] Hong, S., Wang, T., Fu, X. and Li, G. Research on quantitative evaluation of digital economy policy in China based on the PMC index model. PLOS ONE. 2024, 19(2), p. e0298312. https://doi.org/10.1371/journal.pone.0298312.

[32] Zhao, W., Yang, X. and Sun, N. Do digital city policies promote corporate ESG performance? Evidence from research on textual analysis of China. Emerging Markets Finance and Trade. 2024, 60(13), pp. 2960-2979. https://doi.org/10.1080/1540496X.2024.2331013.

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