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Research Article

Research on the Influence Mechanism of the Across-Industrial-Chain Investment Speed on Innovation Performance of AI Enterprises: Improvement Path of Artificial Intelligence Technology Application

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This paper presents a regression analysis by using the system generalized method of moments (SYS-GMM) model as the main regression model and combining it with the fixed effect of panel data and acquires the basic empirical research data from Wind database. The research shows that the speed of cross-industrial-chain investment can improve the innovation ability of AI enterprises, and AI enterprises with deep technology accumulation can improve their innovation performance in the rapid across-industrial-chain investment. In this paper, an across-industrial-chain investment decision path model for AI enterprises is proposed for the first time, suggesting that AI enterprises should pay attention to the related factors of industry and AI enterprises when making across-industrial-chain investment decisions. This helps to express the determination of investment, integration, and reconstruction to the target AI enterprises, and it can also facilitate fast across-industrial-chain investment and improve the innovation performance of AI enterprises.

1. Introduction

Amid China's continuously advancing economic transformation and gradually deepening supply-side structural reform, more Chinese AI enterprises begin to adopt the horizontal integration strategies.

Existing literature pays more attention to the resource characteristics and differences among AI enterprises [1] and to the influence of industrial environment [2] and institutional environment [3] on the expansion of AI enterprises.

However, some researchers pointed out that it was difficult to truly reflect the dynamic and complex business reality faced by AI enterprises [4] from the static perspective alone. Therefore, it is essential to pay attention to the temporal characteristics of the expansion behavior.

In recent years, the rise of the temporal view of management provides a new perspective and research approach for studying the factors affecting the expansion performance of AI enterprises [5–7]. The temporal view of management takes the concept of time as the core and pays attention to how the characteristics of AI enterprises in the temporal dimension affect the generation, implementation, and transformation of strategies [8]. The temporal view of management introduces the dynamic research paradigm into the research of AI enterprise expansion, which is divided into six key modules: stage, opportunity, speed, duration, sequence, and frequency. Among them, speed, as one of the key symbols of time, has attracted wide attention from academic circles.

2. Literature Review

An agreement on how the expansion speed of AI enterprises affects their performance has not been reached in previous studies. Some studies believe that rapid expansion hinders the cultivation of learning capabilities of AI enterprises [9].

AI enterprises cannot fully enjoy the expansion results during rapid expansion, which may result in the diseconomy of time compression [10]. Some studies have also suggested that rapid expansion is conducive to enhancing the flexibility and environmental adaptability of AI enterprises, helping them fully grasp the opportunities and take the lead in market competition [4].

There are three reasons for the contradiction in the existing research conclusions. First of all, the definition of AI enterprise expansion is different under different research topics. Second, analysis of the boundary of the expansion of AI enterprises is still absent; that is, there is no distinction between the expansion directions of AI enterprises. Third, the internal mechanism between the expansion speed and the performance of AI enterprises has not been discussed in depth [5, 6, 11].

To make up for the shortcomings of existing research, this paper introduces the concept of direction into the temporal view of management, taking the innovation ability that significantly affects the expansion performance of AI enterprises as the result variable to explore how AI enterprises' investment speed across production chains will affect their innovation performance.

3. Research Model and Hypotheses

AI enterprises can improve their innovation performance in the process of across-industrial-chain investment. At the market level, AI enterprises obtain the key resources needed for production and operation through rapid investment to support the development of their own innovation capability. It is found that rapid expansion can help AI enterprises accelerate their learning behavior, thereby accelerating AI enterprises' absorption and internalization and finally boosting their income. Moreover, rapid expansion helps to enhance the flexibility of AI enterprises [12] and improve their ability to respond to complex and changeable markets. Therefore, at the market level, rapid across-industry chain investment can improve the innovation performance of AI enterprises. At the AI enterprise level, the key knowledge, technology, process, structure, and other key resources acquired by the enterprise through investment will be integrated with existing resources. Companies will experience organizational restructuring [13] and finally achieve the ideal organizational structure [14]. In terms of across-industrial-chain investment, it allows enterprises to obtain key resources in the initial stage of expansion. Enterprises try to integrate new resources into their organizations through restructuring. Companies will face "new entrants disadvantage" [15], which undermines corporate innovation performance. The fast cross-industry-chain investment can repeat similar investment actions many times within a predetermined period of time to strengthen the behavior and intention of organizational restructuring [16]. To the greatest extent, it weakens the adverse impact of the "disadvantage of newcomers" caused by organizational restructuring on enterprise innovation performance.

On such basis, the following hypothesis is put forward in this paper:

4. Research Design

4.1. Data Acquisition. This paper uses Wind database as the basic data source of empirical research. Wind database includes the financial data of AI enterprises listed on A-share market and is widely used in the research of investment and innovation performance of AI enterprises listed in China [28–30]. At the same time, this paper uses data scraping technology to match the names of AI enterprises listed in Wind database with the information query system of State Administration for Industry and Commerce. This paper searched the names of all wholly owned subsidiaries and tire-one holding subsidiaries of A-share AI enterprises [31]. Then, by matching the main business scope in the industrial and commercial registration of the above-mentioned AI enterprises with the four-digit codes of listed companies, the industry in which these AI enterprises' main business is located is determined.

In addition, this paper draws on the relatively advanced industrial location calculation method proposed by Antràs and Chor [32]. Based on Input-Output Tables of China in 2012 and 2017, the relative position of the industrial chain of 42 industries in the whole national economy is calculated and represented by a numerical value between 0 and 1. First of all, we can define a basic identity in the Input-Output Table:

$$Y_i = F_i + Z_i. \tag{1}$$

Y_i is the total output of i industry. F_i is the part of the i industry output that flows directly to the final consumption and total capital formation. Z_i is the part of i industry output consumed by other industries. In a national economic system with N industries, the above equation can be further expounded as

$$Y_i = F_i + \underbrace{\sum_{j=1}^{N} d_{ij}F_j}_{\text{Direct consumption part in the } i \text{ industry output}} + \underbrace{\sum_{j=1}^{N}\sum_{k=1}^{N} d_{ik}d_{kj}F_j + \sum_{j=1}^{N}\sum_{k=1}^{N}\sum_{l=1}^{N} d_{il}d_{lk}d_{kj}F_j + \cdots}_{\text{Indirect consumption part in the } i \text{ industry output}}. \tag{2}$$

The calculation method of industrial chain position based on the above formula is as follows (see Table 1 for specific industrial chain position data):

$$Y = F + DF + D^2F + D^3F + \cdots = [1 - D]^{-1}F. \quad (3)$$

Based on the industrial chain position formula (3), this paper further calculates the industrial distance between AI enterprises in different industries by means of the difference, still represented by a numerical value between 0 and 1. Then, using the above-mentioned industry distance from 2014 to 2018, the spanning speed of AI enterprises in across-industrial-chain investment is worked out. In addition, due to the difference in innovation ability training and in R&D system between the primary, secondary, and tertiary industries, this paper mainly selects the data of A-share listed AI companies in secondary industry for regression analysis and generates a listed AI enterprise database consisting of 275 AI enterprises with data from 2014 to 2018.

4.2. Variable Structure

$$\text{Rdratechain}_{it} = \sum\left(\text{RDind}_{ikt} * \frac{1}{N_{it}}\right). \quad (4)$$

(1) Dependent variable. According to related research by Bassetti et al. [33], total factor productivity can effectively measure the innovation performance of AI companies. This paper uses the total factor productivity of AI enterprises as a dependent variable of AI enterprise performance.

(2) Explanatory variables. In this paper, the industry score compiled through (3) is used for calculating the absolute value of the difference between the foreign investment industry of listed AI enterprises and its upstream and downstream enterprises, taking it as an across-industry span of investment. Based on the research results of Zhou and Guillen [34], this paper uses the following formula to construct the annual cross-industry chain investment speed variable of listed AI companies:

$$\text{Speed}_{it} = \sum\left(\text{IDD}_{ikt} \times \frac{A_{it}}{T_{it}}\right). \quad (5)$$

IDD_{ikt} represents the industrial distance of an outward investment behavior. A_{it} represents the time (year) between this investment behavior and the current year. T_{it} refers to the time between the first foreign investment of the AI enterprise and the current year.

(3) Moderating variable. The paper firstly takes the number of patents obtained by AI enterprises in that year as the variable of technology accumulation (Lnts). According to the data provided by Wind database, the ratio of R&D investment to total assets (RDind) of various industries is obtained. After that, this paper weights industries according to how many of them are invested by AI enterprises and then calculates the moderating variable, which is the industrial R&D investment level (Rdratechain) variable of the industry invested by the AI enterprises, where N is the total number of cross-industry investments made by AI enterprises. Finally, the paper uses the amount of cross-industry investment made by AI enterprises as the moderating variable and takes Chainnumber as a variable describing the industrial chain span of cross-industry investment of AI enterprises.

(4) Control variables: Finally, this paper introduces company age (Age), return on assets (Roa), company ownership (Ownership), industry growth rate (Indgrow), total asset logarithmic value (size of the AI enterprise, Size), local GDP (Lngdp), annual dummy variable (Year), and industry dummy variable (Industry) of AI enterprises as controlled variables. All variable names and description are shown in Table 2.

4.3. Measurement Model. According to the above assumptions, databases, and variables, the system generalized method of moments (SYS-GMM) model is used as the main regression model for analysis. The above model uses the lag terms and the difference terms of lag terms as an endogenous tool term, which can adequately solve the endogenous problem of the model [35]. The paper will then group the data based on three layers: 25% and below, 25%–75%, and 75% and above. The analysis can be shown in the next section for the specific results of checking the regulating effect of related variables. To test the robustness of the model, this paper also uses the panel fixed effect model to analyze the robustness (each model has passed Hausman test).

5. Analysis of the Regression Results

5.1. Descriptive Statistics and Correlation Analysis Results. Before verifying the hypothesis, descriptive statistics and correlation analysis were made for each variable in this study, and these results are shown in Tables 3 and 4.

5.2. Regression Analysis. On the basis of correlation analysis, this study uses SYS-GMM and fixed effect analysis to further verify the research hypotheses.

The SYS-GMM regression results of model (2) in Table 5 show that the across-industrial-chain investment speed of AI enterprises has an impact on innovation performance. There is a significant positive correlation (coefficient = 1.045, $P < 0.01$) between the across-industrial-chain investment speed of AI enterprises and innovation performance. The results of panel data fixed effect analysis of model (2) in Table 6 also show that there is a significant positive correlation between them (coefficient = 0.959, $P < 0.01$). This shows that, for the purposes of cross-industrial chain investment, the faster the AI enterprises invest, the stronger the innovation performance will be. H1 is verified.

Table 1: Positions in industrial chain.

Industry (2012)	Score	Industry (2017)	Score
Food and tobacco	0.363	Transportation equipment	0.387
Transportation equipment	0.313	Special equipment	0.375
Processed wood products and furniture	0.312	Food and tobacco	0.343
Products and services of agriculture, forestry, animal husbandry, and fishery	0.304	Processed wood products and furniture	0.334
Textiles	0.303	Gas production and supply	0.315
Nonmetallic mineral products	0.294	Nonmetallic mineral products	0.313
Electrical machinery and equipment	0.252	Water production and supply	0.309
Special equipment and general equipment	0.234	Electrical machinery and equipment	0.291
Metal products	0.221	Products and services of agriculture, forestry, animal husbandry, and fishery	0.281
Water production and supply	0.216	General equipment	0.271
Gas production and supply	0.212	Textiles	0.267
Papermaking, printing, and stationery & sporting goods	0.209	Metal products	0.258
Mined and processed products from nonmetallic minerals and other minerals	0.185	Papermaking, printing, and stationery & sporting goods	0.244
Communication equipment, computers, and other electronic equipment	0.172	Smelt and pressed metal products	0.188
Smelt and pressed metal products	0.172	Communication equipment, computers, and other electronic equipment	0.183
Chemical products	0.162	Chemical products	0.180
Instrument and apparatus	0.153	Oil and gas extraction	0.165
Oil and gas extraction	0.150	Production and supply of electricity and heat	0.159
Production and supply of electricity and heat	0.141	Instrument and apparatus	0.155
Mined and processed coal products	0.134	Mined and processed coal products	0.131

Table 2: Description of specific variables.

Name of variable	Variable means
Ftfp	Total factor productivity
Speed	Annual cross-industry chain investment speed of AI enterprise
Lnts	AI enterprise technology accumulation
Rdratechain	Industrial R&D investment level of industries invested by AI enterprises
Chainnumber	Investment span of industrial chain
Age	Establishment time of AI enterprise
Roa	ROA (return on asset)
Ownership	Enterprise ownership of the AI enterprise
Indgrow	Industry growth rate of AI enterprise
Size	Scale of AI enterprise
Lngdp	GDP of the region where AI enterprise is located
Year	Annual dummy variable
Industry	Industry dummy variable

Table 3: Overall descriptive statistics.

Variable name	Observed value	Mean	Standard deviation	Minimum	Maximum
Ftfp	13041	0.4605	0.4187	−0.1910	2.4390
Speed	13011	0.1649	0.1905	0.0000	2.1331
Lnts	12994	5.6752	3.7056	0.0000	138.000
Rdratechain	11005	0.1131	0.0182	0.0661	0.1811
Chain	9282	2.6787	2.8554	0.0000	12.0370
Age	13041	14.3900	5.2485	0.0000	56.0000
Lnuncer	13041	15.5730	1.0448	9.7061	17.7150
Roa	13041	8.5420	20.5960	−1611.0000	1061.6000
Owner	9911	0.3719	0.4833	0.0000	1.0000
Indgrow	13041	12.1500	13.9060	−65.0300	70.4600
Lnsize	12647	12.2530	1.3751	5.5483	19.2980
Lngdp	13041	19.4220	0.7431	15.4400	20.4060

Table 4: Correlation coefficient matrix of main variables.

	Ftfp	Speed	Lnts	Rdratechain	Chain	Age	Lnuncer	Roa	Owner	Indgrow	Lnsize	Lngdp
Ftfp	1											
Speed	0.422***	1										
Lnts	0.122***	−0.167***	1									
Rdratechain	0.027***	−0.085***	−0.022**	1								
Chain	0.311***	0.347***	0.098***	−0.016	1							
Age	0.047***	0.201***	0.103***	0.005	0.116 ***	1						
Lnuncer	−0.006	0.051***	−0.007	−0.229***	0.002	−0.008	1					
Roa	−0.013	−0.048***	−0.027***	0.017*	−0.061 ***	−0.096***	0.006	1				
Owner	0.100***	0.154***	0.042***	−0.062***	−0.042***	0.137***	0.038***	−0.037***	1			
Indgrow	0.454***	−0.088***	$1.00E-04$	0.014	0.003	−0.207***	0.076***	0.049***	0.01	1		
Lnsize	0.020**	0.150***	0.068***	−0.112***	0.044***	0.231***	0.094***	−0.102***	0.393***	−0.120***	1	
Lngdp	−0.130***	−0.041***	−0.037***	−0.005	0.027**	0.040***	0.047***	0.051***	−0.252***	−0.143***	−0.099**	1

Note. $^{*}p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$.

Table 5: SYS-GMM analysis results.

	(1)	(2)	(3)
L.Ftfp	0.121*** (0.024)	0.059*** (0.018)	0.040** (0.016)
Lnts	0.010*** (0.002)	0.022*** (0.001)	0.004*** (0.001)
Rdratechain	1.555*** (0.393)	2.323*** (0.287)	1.095*** (0.304)
Chainnumber	0.023*** (0.002)	0.010*** (0.001)	0.008*** (0.001)
Age	−0.008 (0.014)	0.011 (0.010)	0.005 (0.009)
Roa	$-2.39E-04$ ($2.17E-04$)	$-1.16E-04$ ($1.57E-04$)	$-1.31E-04$ ($1.43E-04$)
Owner	0.034 (0.045)	0.033 (0.033)	0.010 (0.030)
Indgrow	$2.12E-04$ (0.001)	$4.78E-04$ ($4.04E-04$)	$2.91E-04$ ($3.68E-04$)
Lnsize	0.005 (0.014)	0.001 (0.010)	0.004 (0.009)
Lngdp	0.193 (0.157)	0.154 (0.114)	0.172* (0.104)
Year	Control	Control	Control
Industry	Control	Control	Control
Speed		1.045*** (0.023)	−0.213* (0.122)
Speed*Lnts			0.129*** (0.005)
Speed*Rdratechain			4.579*** (1.025)
Obs#	6350	6350	6350
Firms	1586	1586	1586
Wald chi^2	336.1	2706.56	3965.19

Note. $^{*}p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$.

Table 6: Fixed effect analysis results of panel data.

	(1)	(2)	(3)
Lnts	0.011*** (0.001)	0.020*** (0.001)	0.006*** (0.001)
Rdratechain	1.119*** (0.302)	2.022*** (0.228)	0.959*** (0.245)
Chainnumber	0.022*** (0.001)	0.009*** (0.001)	0.008*** (0.001)
Age	−0.006 (0.011)	−0.009 (0.008)	−0.006 (0.007)
Roa	$-2.88-E-05$ ($1.92E-04$)	$2.57E-05$ ($1.44E-04$)	$-2.65-E-05$ ($1.34E-04$)
Owner	−0.030 (0.030)	−0.018 (0.023)	−0.018 (0.021)
Indgrow	$6.62E-05$ ($4.05E-04$)	$4.17E-04$ ($3.04E-04$)	0.001** ($2.82E-04$)
Lnsize	−0.017* (0.009)	−0.015** (0.007)	−0.012* (0.006)
Lngdp	0.117 (0.110)	0.134 (0.082)	0.111 (0.076)
Year	Control	Control	Control
Industry	Control	Control	Control
Speed		0.959*** (0.018)	−0.125 (0.098)
Speed*Lnts			0.109*** (0.004)
Speed*Rdratechain			3.974*** (0.818)
Obs#	6363	6352	6352
Firms	1586	1586	1586
R^2	0.074	0.414	0.496
F	31.87	258.57	311.29

Note. $^{*}p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$.

The SYS-GMM regression results of model (3) in Table 5 show that the technology accumulation of the AI enterprises has an impact on the relationship between the across-industrial-chain investment speed and innovation performance. Technology accumulation of AI enterprises can significantly and positively regulate the relationship between the across-industrial-chain investment speed and innovation performance (coefficient = 0.129, $P < 0.01$). The results of panel data fixed effect analysis of model (3) in Table 6 also show that the adjustment relationship exists significantly (coefficient = 0.109, $P < 0.01$). After analyzing the data separately by SYS-GMM (as shown in Table 7), it can be found that as the technology accumulation of AI enterprises increases, the regression coefficients also gradually increase (the coefficients of 25% quantile and below = 0.433, the coefficients of 25%–75% quantile = 1.244, and the coefficients of 75% quantile and above = 1.392; $P < 0.01$). The fixed effect grouping analysis results of panel data in Table 8 are also significant (coefficients of 25% quantile and below = 0.310, coefficients of 25%–75% quantile = 1.469, and coefficients of 75% quantile and above = 1.577; $P < 0.01$). The above results show that in the rapid cross-industrial-chain investment, the AI enterprises with rich technology accumulation can benefit from it and therefore improve innovation performance, and H2 is verified.

The SYS-GMM regression results of model (3) in Table 5 show that the industrial R&D investment level of industries invested by the AI enterprises can significantly and positively adjust the relationship between the across-industrial-chain investment speed and innovation performance (coefficient = 4.579; $P < 0.01$). The results of panel data fixed effect analysis of model (6) also show that the adjustment relationship exists significantly (coefficient = 3.974; $P < 0.01$). After analyzing the data separately by SYS-GMM (as shown in Table 9), it can be found that as the industrial R&D investment level of industries invested by the AI enterprises increases, the regression coefficients also gradually increase (the coefficients of 25% quantile and below = 0.971, the coefficients of 25%–75% quantile = 1.061, the coefficients of 75% quantile and above = 1.072; $P < 0.01$). The fixed effect grouping analysis results of panel data in Table 10 partly verify the robustness of the above results (the coefficients of 25% quantile and below = 0.837, the coefficients of 25%–75% quantile = 1.020, and the coefficients of 75% quantile and above = 1.000; $P < 0.01$). The above results show that for the purposes of the rapid cross-industrial-chain investment, the

Table 7: SYS-GMM Analysis results (hypothesis 2).

	(1) Lnts of less than or equal to 25%	(2) Lnts of 25%–75%	(3) Lnts of larger than or equal to 75%
L.Ftfp	0.187*** (0.047)	0.043* (0.025)	0.071* (0.037)
Lnts	0.021*** (0.003)	0.018*** (0.002)	0.024*** (0.002)
Rdratechain	0.513 (0.726)	2.336*** (0.353)	2.517*** (0.588)
Chainnumber	0.013*** (0.003)	0.005*** (0.002)	0.012*** (0.002)
Age	−0.269 (0.477)	−0.185 (0.208)	−0.042 (0.034)
Roa	−0.001 (0.002)	0.001** $(4.93E-04)$	$-2.00E-04$ $(1.63E-04)$
Owner	0.036 (0.090)	0.029 (0.043)	0.034 (0.054)
Indgrow	0.001 (0.001)	$2.62E-04$ (0.001)	$2.66E-04$ (0.001)
Lnsize	−0.017 (0.033)	0.005 (0.013)	−0.004 (0.017)
Lngdp	0.182 (0.319)	0.146 (0.170)	0.205 (0.199)
Year Industry Speed	Control Control 0.433*** (0.049)	Control Control 1.244*** (0.031)	Control Control 1.392*** (0.046)
Obs# Firms Wald chi2	1192 504 4179.63	3389 1190 21220.3	1769 760 1258.27

Note. $^{*}p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$.

Table 8: Fixed effect analysis results of panel data (hypothesis 2).

	(1) Lnts of less than or equal to 25%	(2) Lnts of 25%–75%	(3) Lnts of larger than or equal to 75%
Lnts	0.017 (0.029)	0.013** (0.005)	0.008* (0.005)
Rdratechain	0.043 (0.615)	2.416*** (0.286)	2.577*** (0.525)
Chainnumber	0.014*** (0.003)	$4.50\,E-04$ (0.001)	0.011*** (0.002)
Age	−0.018 (0.019)	−0.014 (0.010)	−0.037*** (0.014)
Roa	−0.001 (0.001)	0.002*** $(4.14E-04)$	$-1.63-E-04$ $(1.51E-04)$
Owner	−0.045 (0.068)	−0.018 (0.030)	0.042 (0.041)
Indgrow	−0.001 (0.001)	$4.86E-04$ $(3.79E-04)$	$-1.79E-04$ (0.001)
Lnsize	−0.049** (0.024)	−0.011 (0.008)	−0.021 (0.016)
Lngdp	0.236 (0.218)	0.207* (0.118)	0.393** (0.162)
Year Industry	Control Control	Control Control	Control Control

Table 8: Continued.

	(1) Lnts of less than or equal to 25%	(2) Lnts of 25%–75%	(3) Lnts of larger than or equal to 75%
Speed	0.310*** (0.055)	1.469*** (0.029)	1.577*** (0.048)
Obs#	1192	3391	1769
R^2	0.101	0.567	0.586
Firms	504	1190	760
F	5.83	220.79	108.46

Note. $^{*}p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$.

Table 9: SYS-GMM analysis results (hypothesis 3).

	(1) Rdratechain of less than or equal to 25%	(2) Rdratechain of 25%–75%	(3) Rdratechain of larger than or equal to 75%
L.Ftfp	0.155*** (0.048)	0.033 (0.023)	0.013 (0.039)
Lnts	0.022*** (0.003)	0.021*** (0.002)	0.023*** (0.002)
Rdratechain	7.131*** (2.200)	2.378*** (0.366)	28.033 (39.995)
Chainnumber	0.014*** (0.003)	0.011*** (0.002)	0.008*** (0.003)
Age	−0.081*** (0.031)	−0.082 (0.218)	−0.048 (0.062)
Roa	$-2.40-E-04$ $(1.81E-04)$	$4.65E-04$ (0.001)	0.003** (0.001)
Owner	0.156* (0.086)	−0.026 (0.041)	0.127* (0.066)
Indgrow	−0.001 (0.001)	0.001 (0.001)	−0.002 (0.005)
Lnsize	−0.001 (0.021)	0.003 (0.014)	−0.019 (0.023)
Lngdp	0.620** (0.282)	0.054 (0.154)	−0.088 (0.255)
Year	Control	Control	Control
Industry	Control	Control	Control
Speed	0.971*** (0.055)	1.061*** (0.029)	1.072*** (0.048)
Obs#	1589	3385	1376
Firms	657	1170	567
Wald chi^2	478.31	21289.59	7808.14

Note. $^{*}p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$.

Table 10: Fixed effect analysis results of panel data (hypothesis 3).

	(1) Rdratechain of less than or equal to 25%	(2) Rdratechain of 25%–75%	(3) Rdratechain of larger than or equal to 75%
Lnts	0.018*** (0.002)	0.022*** (0.001)	0.020*** (0.002)
Rdratechain	−3.133 (3.843)	1.191 (1.518)	−10.128 (174.068)
Chainnumber	0.012*** (0.003)	0.010*** (0.001)	0.008*** (0.002)
Age	0.009 (0.021)	−0.023** (0.011)	−0.033 (0.353)

Table 10: Continued.

	(1) Rdratechain of less than or equal to 25%	(2) Rdratechain of 25%–75%	(3) Rdratechain of larger than or equal to 75%
Roa	$-9.37E-05$ $(1.59E-04)$	0.001 (0.001)	0.002** (0.001)
Owner	−0.012 (0.059)	−0.015 (0.032)	−0.009 (0.052)
Indgrow	$-1.22-E-04$ (0.001)	0.001 $(4.29E-04)$	−0.002** (0.001)
Lnsize	−0.026* (0.014)	−0.015 (0.011)	−0.028 (0.018)
Lngdp	0.033 (0.214)	0.265** (0.130)	−0.135 (0.164)
Year Industry Speed	Control Control 0.837*** (0.042)	Control Control 1.020*** (0.026)	Control Control 1.000*** (0.046)
Obs# R^2 Firms F	1590 0.365 657 40.70	3385 0.463 1170 145.83	1377 0.423 568 44.81

Note. $^{*}p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$.

Table 11: SYS-GMM analysis results (hypothesis 4).

	(1) Chainnumber of less than or equal to 25%	(2) Chainnumber of 25%–75%	(3) Chainnumber of larger than or equal to 75%
L.Ftfp	(0.174***) −0.024	(0.015) −0.024	(0.013) −0.095
Lnts	(0.010***) −0.001	(0.028***) −0.002	(0.020***) −0.005
Rdratechain	(1.937***) −0.341	(2.542***) −0.438	(0.744) −1.210
Chainnumber	(0.013***) −0.001	(0.011***) −0.002	(0.010) −0.004
Age	(0.016) −0.041	(0.024) −0.027	(0.062) −0.053
Roa	(0.002***) −0.001	$(1.68E-04)$ $1.77E-04$	$(4.39E-04)$ −0.002
Owner	(0.010) −0.040	(0.025) −0.049	(0.002) −0.133
Indgrow	(0.001) $4.89E-04$	$(2.34E-04)$ −0.001	(0.001) −0.002
Lnsize	(0.001) −0.014	(0.003) −0.014	(0.048) −0.055
Lngdp	(0.070) −0.151	(0.192) −0.182	(0.261) −0.604
Year Industry Speed	Control Control (0.552***) −0.033	Control Control (1.274***) −0.032	Control Control (0.772***) −0.068
Obs# Firms Wald chi^2	2840 1210 695.68	3166 1003 2097.99	344 145 200.77

Note. $^{*}p = 0.10$; $^{**}p = 0.05$; $^{***}p = 0.01$.

Table 12: Fixed effect analysis results of panel data (hypothesis 4).

	(1) Chainnumber of less than or equal to 25%	(2) Chainnumber of 25%–75%	(3) Chainnumber of larger than or equal to 75%
Lnts	0.004*** (0.001)	0.028*** (0.002)	0.029*** (0.005)
Rdratechain	1.092*** (0.178)	2.143*** (0.375)	2.274 (1.497)
Chainnumber	−0.043*** (0.012)	−0.009** (0.004)	0.061 (0.041)
Age	−0.003 (0.006)	−0.032*** (0.012)	0.019 (0.042)
Roa	0.002*** (2.98$E-04$)	−1.59$E-04$ (1.70$E-04$)	3.36$E-04$ (0.002)
Owner	−0.011 (0.019)	−0.001 (0.036)	−0.022 (0.100)
Indgrow	0.001** (2.36$E-04$)	3.99$E-04$ (0.001)	0.002 (0.002)
Lnsize	−0.009 (0.006)	−0.010 (0.010)	−0.057 (0.047)
Lngdp	0.055 (0.064)	0.291** (0.140)	−0.162 (0.482)
Year	Control	Control	Control
Industry	Control	Control	Control
Speed	0.368*** (0.027)	1.227*** (0.028)	0.650*** (0.068)
Obs#	2841	3167	344
R^2	0.191	0.500	0.424
Firms	1210	1003	145
F	29.41	165.38	10.54

Note. * $p = 0.10$; ** $p = 0.05$; *** $p = 0.01$.

AI enterprises with higher industrial R&D investment levels in their invested industries can get more benefits and improve their innovation performance, and therefore H3 is verified.

The influence of industrial chain investment span on the relationship between across-industrial-chain investment speed and innovation performance of AI enterprises is shown as follows: the industrial chain investment span is subjected to data grouping based on three layers: 25% and below, 25%–75%, and 75% and above. After analyzing the data separately by SYS-GMM (as shown in Table 11), it can be found that as the industrial chain investment span expands, the regression coefficients show the trend of first increasing and then decreasing (the coefficients of 25% quantile and below = 0.552, the coefficients of 25%–75% quantile = 1.274, and the coefficients of 75% quantile and above = 0.772; $P < 0.01$). The fixed effect grouping analysis results of panel data in Table 12 are also significant (coefficients of 25% quantile and below = 0.368, coefficients of 25%–75% quantile = 1.227, and coefficients of 75% quantile and above = 0.650; $P < 0.01$). The above results show that in the rapid cross-industrial-chain investment, the more moderate the industrial chain span of the AI enterprises is, the better their innovation performance can be improved, and therefore H4 is verified.

6. Conclusion

Based on the organizational learning theory, this paper discusses the influence of cross-industrial-chain investment speed on the innovation performance of the AI enterprises from the perspective of time dimension of AI enterprise strategy, and it uses the investment data of Chinese listed AI enterprises and the financial data of AI enterprises for empirical test. Four conclusions are drawn as follows: (1) The innovation performance of AI enterprises can be improved by increasing the cross-industrial chain investment speed. (2) Compared with AI enterprises with poor technology accumulation, those with rich technology accumulation can improve their innovation performance with rapid cross-industrial-chain investment. (3) The higher the R&D investment levels of target industries invested by the AI enterprises in an across-industrial-chain mode, the faster the innovation performance of the AI enterprises can be improved by increasing the industrial chain investment speed. (4) Compared with shorter or longer industrial chain investment span, under the condition of moderate industrial chain investment span, the innovation performance of AI enterprises can be further improved by increasing the industrial chain investment spanning speed.

To a great extent, the selection of investment mode can determine whether the AI enterprises can seize the first opportunity in a market filled with fierce competition. The fast cross-industrial chain investment model can ensure the realization of investment effect and the improvement of innovation performance of AI enterprise, from three aspects: market, AI enterprises, and managers. "Fast" here specifically refers to three aspects: The first is being fast in seizing the opportunity, i.e., to make decisive action and rapid deployment when faced with opportunities so as to seize the initiative before competitors and other potential competitive market players are aware. The second is being fast in investment speed; i.e., after making the decision of cross-industrial-chain investment, the focus AI enterprises and target AI enterprises should actively negotiate and communicate and promote investment transactions in a short time. The third is being fast in the integration process after investment. Since the integration effect after investment determines the final investment performance of the AI enterprises, whether the key resources of target AI enterprises can be fully understood, absorbed, and internalized becomes the biggest challenge. Therefore, the AI enterprises must accelerate the integration process to enhance their innovation performance.

After determining the rapid investment mode, the AI enterprises need to select across-industrial-chain investment targets and take the R&D investment intensity of the target industries as an important consideration index. The target AI enterprises with strong learning ability can learn the organizational behavior characteristics of the focus AI enterprises after contacting the latter to ensure smooth development of organizational integration after investment. Furthermore, the focus AI enterprises are more likely to benefit from government subsidies, patent protection, tax reduction, and innovation in target industries. At this time, it is also necessary to take the industrial span as one of the important target selection criteria. The AI enterprises should choose a moderate industrial chain investment span, since the expected improvement of innovation performance will not be produced by rapid cross-industrial chain investment if the span is too long or too short. In regard to the selection of a suitable industrial chain, the AI enterprises should adhere to a selection principle of "put quality before quantity," to select the best one and conduct in-depth research on target industries to comprehensively and deeply understand the market status, development prospects, and potential investment returns of target industries. In addition, the AI enterprises should also dare to invest and be good at investing to avoid the short investment span of industrial chains, and understand the industries with development potential and market prospects to the greatest extent through information collection, industry research, and expert consultation.

After selecting suitable investment targets, the AI enterprises need to pay attention to the impact of their own innovation ability on rapid cross-industrial chain investment. The AI enterprises with rich technology accumulation should give full play to their technological advantages; fully understand, absorb, and internalize the key resources of the target AI enterprises during rapid cross-industrial-chain investment with strong learning ability; and quickly integrate these resources into organization routines to form organizational structures and process that serve to enhance their own innovation ability. Those with poor technology accumulation may also need to focus on whether their learning ability can match the target AI enterprises. All AI enterprises should learn from existing partners and even competitors. In addition, after determining the investment target, the AI enterprises can build a resource management system matching the key resources of the target AI enterprises in advance. In this way, before the investment is completed, they can fully prepare for the coming organizational integration and reconstruction, which can help make up for the disadvantage brought by weak technology accumulation.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

There are no potential conflicts of interest with regard to the content of the manuscript.

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