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IMPACT OF ARTIFICIAL INTELLIGENCE INVESTMENT ON ENTERPRISE TALENT RESERVE: EVIDENCE FROM CHINESE ENTERPRISES

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Abstract. *This research aims to explore the impact mechanism and role of artificial intelligence (AI) investment on corporate talent reserves, ensuring that enterprises maintain a competitive advantage during AI transformation. Using StataMP 17 analysis software, this paper analyzes corporate data from Chinese listed companies from 2014 to 2023, and conducts an empirical study on the promotion of corporate talent reserves by AI investment from a new perspective of technological transformation. The results show that AI investment has a significant promoting effect on corporate talent reserves; for every unit increase in AI investment, the talent reserve ratio increases by 0.378%. AI investment promotes corporate talent reserves by increasing the proportion of technical personnel. The study also found that regional AI subsidy policies can enhance the impact of AI investment on talent reserves, and the promoting effect of AI investment on talent reserves is more significant in private enterprises.*

Keywords: *artificial intelligence, talent reserve, investment, empirical analysis, technological transformation.*

Main provisions. This study uses the proportion of technical personnel in enterprises as a mediating variable to analyze the transmission mechanism of AI's impact on enterprise talent reserves. Using regional AI subsidy policies as moderating variables, analyze the moderating mechanism of AI's impact on enterprise talent reserves. Analyze the types of enterprises that are more suitable for this model through heterogeneity analysis. Based on multidimensional empirical results, policy recommendations and enterprise talent strategic planning have been proposed. These measures are aimed at supporting enterprises in building competitive advantages during the AI transformation process.

Based on the above theory, this research proposes the following hypotheses:

Hypothesis 1: AI investment can enhance a company's talent reserve.

Hypothesis 2: Technological transition can promote the talent reserve of enterprises.

Hypothesis 3: Government subsidies can strengthen the impact of corporate AI investment on talent reserve.

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Introduction. Artificial intelligence (AI) represents a major technological leap in human development. The development and application of AI have sparked numerous social transformations. Countries around the world are accelerating the introduction of relevant policies to promote the advancement of their own AI technologies, ensuring a competitive edge in the new round of AI technology competition. The core advantage of AI lies in its data processing capability. When AI technology is applied to enterprises, it can improve the efficiency of various departments within the enterprise. It can also be used to analyze historical data and empower corporate strategic decision-making. As a universal technology, AI is gradually breaking down the boundaries between disciplines and industries, promoting cross-disciplinary and interdisciplinary integration. Building a professional talent reserve that matches AI is the key to unleashing the practical value of AI. By reserving relevant talents, enterprises will not only be able to master AI technology, but also occupy an advantageous position in the future technological competition landscape.

The application data of AI in enterprises can enhance the effectiveness of research. Rammer et al. [1] collected enterprise AI application data through a questionnaire survey, analyzed the AI technology and talent matching status of companies using job advertisements [2]. The application of AI technology in enterprises has promoted research on AI and human resources. AI technology is reshaping work methods and skill requirements, and improving employment standards for enterprises [3, 4]. Jaiswal et al. [5] pointed out that multinational corporations use AI technology to train employees to match job positions. In Europe and the United States, many companies have launched digital academies to train employees in data analysis, interpreting AI-generated reports, and other skills [6]. In China, government emphasis on AI education has permeated into enterprises [7]. The deepening application of AI by enterprises has led to a sustained increase in their demand for professional talents. The mechanism between enterprise AI investment and talent reserve has become an important theoretical research topic. In depth exploration of the dynamic relationship between the two provides decision-making basis for enterprises to achieve effective matching of technology investment and talent strategy in the process of AI transformation.

Literature review. AI drives enterprise technological upgrading and the pursuit of technical talents. Building a solid talent reserve is a crucial foundation for future enterprise growth. The penetration of AI technology has created a demand for individuals with AI and data analysis skills. Choi & Leigh [8] found through empirical analysis of the Greater Metropolitan Area in the United States that investment in AI significantly increased the demand for AI-skilled personnel, while the demand for non-AI-related labor decreased. Li et al. [9] argues that AI must work in tandem with human cognitive skills in production, thus increasing the demand for skilled personnel with cognitive and interpersonal interaction abilities. Wang [10] studied manufacturing and found that investment in AI reduces total employment but increases reliance on high-skilled positions and their compensation. This indicates that AI investment has upgraded the structure of labor demand, emphasizing high-level professional skills. AI investment has significant human substitution effects while promoting industrial upgrading. The application of industrial robots in the United States is closely related to the decline in industry labor share [11]. AI technology has not created new jobs of corresponding scale while replacing human labor. Therefore, enterprise AI investment needs to be synchronized with talent planning.

Technological changes correspond to changes in the human relations of enterprises. Technological innovation will increase the demand for new talents, which prompts enterprises to actively reserve talents in related fields [12]. From the perspective of macro level skill structure changes, technological changes exhibit skill preference characteristics. Digital technology has increased the demand for skilled labor while reducing reliance on ordinary operational positions [13]. Technological changes are driving enterprises to actively reserve talents with new skills. Technological change requires enterprises to cultivate or introduce high skilled talents to maintain competitiveness by utilizing emerging technologies.

Government subsidies have a significant impact on the relationship between AI investment and talent demand. The government's support for enterprise AI research and application can incentivize enterprises to increase technology investment and amplify their demand for professional talents. Government subsidies can also be seen as a positive signal, guiding resources to tilt towards AI technology and corporate talent. Professional talents and advanced technology are the most important strategic resources for enterprises, as well as key targets for government funding support. Reasonable financial subsidies not only enhance the innovation momentum of enterprises, but also help motivate them to retain specialized talents.

Materials and methods. The empirical analysis data in this research comes from the China Stock Market & Accounting Research (CSMAR) database [14]. The article uses data from Chinese listed companies between 2014 and 2023. This article selects China as the research context, based on three logical points: firstly, China provides national strategic and financial support for AI, creating cross enterprise variability in AI investment; Secondly, there is a large shortage of AI talents, and the competition for high skilled talents is fierce; Thirdly, the dual ownership structure of state-owned and private enterprises allows for the examination of the moderating effect of ownership nature. These institutional features make China an ideal laboratory for testing the relationship between AI investment and corporate talent reserves.

The sample data obtained are processed as follows: removing data from companies with abnormal operations; removing financial company data; removing missing samples; removing single observation data for corporate entities; applying 1-99% truncation to continuous variables in the company data. After data processing, a total of 23,196 sample observations from 4,252 listed companies were obtained [15]. This study used a bidirectional fixed effects regression model. Therefore, the R^2 and R^2_a shown in the table refer to within R-squared and its adjusted versions within the group. The empirical analysis software is StataMP 17.

The dependent variable of this article is talent reserve. Talent reserve uses the proportion of personnel with bachelor's degrees or above (BDR) in listed companies as a measure. The explanatory variable in this research is AI investment. AI investment refers to the total amount of annual investment in AI hardware and software by listed companies. This numerical value is statistics and provided by the commercial database CSMAR. To eliminate heteroscedasticity, improve normality, and reduce the impact of extreme values, this study uses the logarithm of AI investment (AITR) to measure the explanatory variable. The control variables in this research are shown in Table 1.

Table 1 - Variable definition table

Type of variable	Variable name	Variable symbol
CONTROLS	Company scale	Size
	Asset-liability ratio	Lev
	Inventory ratio	INV
	Increase rate of business revenue	Growth
	Total asset growth rate	TGROW
	Accounts receivable ratio	REC
	Age of company	FirmAge
	Management shareholding ratio	Mshare
	Large shareholders' capital occupation	Occupy
	Long-term capital debt ratio	LTPR
	The proportion of intangible assets	IAR

Model construction. Based on the content of this research, the empirical analysis model is constructed as follows:

Benchmark regression model

$$BDR_{i,t} = \alpha_0 + \alpha_1 AITR_{i,t} + \beta X + \lambda_i + year_t + \varepsilon_{i,t} \quad (1)$$

In the formula, i and t are the data of the i-th enterprise in the year, α_0 is intercept, BDR is the talent reserve, X is the control variable, λ_i is the individual fixed effect, $year_t$ is the time fixed effect, $\varepsilon_{i,t}$ is the random disturbance term.

Mediation regression model. Theoretical analysis has found that investing in AI can increase the proportion of technical personnel in enterprises. The increase in the proportion of technical personnel can promote the talent reserve of enterprises. This research selected the proportion of technical personnel (TPR) in enterprises as the mediating variable. The model transmission formula is Formula 2 and 3.

$$TPR_{i,t} = \gamma_0 + \gamma_1 AITR_{i,t} + \gamma' X + \lambda_i + year_t + \eta_{i,t} \quad (2)$$

$$BDR_{i,t} = \delta_0 + \delta_1 AITR_{i,t} + \delta_2 TPR_{i,t} + \delta' X + \lambda_i + year_t + \theta_{i,t} \quad (3)$$

In the formula, is the $TPR_{i,t}$ transmission variable, which is the proportion of technical personnel in enterprises every year.

Moderating effect model. This research constructed a moderating effect model and conducted a moderating effect analysis. The ratio of regional AI subsidy funds to GDP (AIVG) was used as a moderating variable. The model transmission formula is Formula 4.

$$\mathrm{BDR}_{i,t} = \varphi_0 + \varphi_1 \mathrm{AITR}_{i,t} + \varphi_2 \mathrm{AIVG} * \mathrm{AITR}_{i,t} + \varphi_3 \mathrm{AIVG}_{i,t} + \varphi' V + \lambda_i + year_t + \mu_{i,t} \quad (4)$$

In the formula, the interaction $\mathrm{AIVG} * \mathrm{AITR}_{i,t}$ term of explanatory variable and moderator variable is explained, and the other symbols have the same meaning as model 1.

Results and discussion. Table 2 presents the results of the benchmark regression. Column (1) shows the regression results without control variables and fixed effects. The results show that the AITR regression coefficient is significantly positive, proving that AI investment can improve corporate talent reserves. Column (2) shows the results of adding company and year fixed effects to the model. Column (3) included all control variables and fixed effects. The regression results are all significant. AITR is a logarithmic structure. BDR is a percentage structure. Therefore, the coefficients indicate that a 1% rise in AITR raises the proportion of BDR by approximately 0.00378 percentage points. The mean of BDR is 0.321. A 1% increase in AI investment raises the proportion of highly educated workers by approximately 0.0118% relative to its mean. This proves that Hypothesis 1 is valid.

Table 2 – Regression analysis results

Type of variable	(1)	(2)	(3)
	BDR	BDR	BDR
AITR	0.0251***	0.00416***	0.00378***
	(33.9)	(8.28)	(7.03)
CONTROLS	No	No	Yes
_cons	-0.078***	0.255***	0.311***
	(-6.61)	(31.78)	(7.04)
Firm		Yes	Yes
Year		Yes	Yes
N	23196	23196	23145
F	1149***	69***	31***
r2	0.0472	0.949	0.950
r2_a	0.0472	0.938	0.939
Notes: * p < 0.1, ** p < 0.05, *** p < 0.01			

Model robustness test. This research conducted robustness tests from four aspects. As shown in Table 3, the first column shows the robust standard error results. The second column shows the regression results after removing the 2019 sample. The third column shows the regression results after adjusting the sample period to 2018-2023, because high-quality literature using AI as a tool was published after 2018. The fourth column shows the regression results after adding industry fixed effects. The above robustness tests are all significant, indicating that the results of this model are robust.

Table 3 – Robustness test results

Variable	(1) Robust standard error BDR	(2) Excluding data from 2019 BDR	(3) Samples after 2018 BDR	(4) Fixed effects industries BDR
AITR	0.00378***	0.00387***	0.00264***	0.00344***
	(5.15)	(6.75)	(3.86)	(6.45)
CONTROLS	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	No	No	No	Yes
N	23145	20626	15593	23143
F	16***	30***	9***	27***
r2	0.950	0.950	0.971	0.952
r2_a	0.939	0.938	0.962	0.941
Notes: * p < 0.1, ** p < 0.05, *** p < 0.01				

Endogeneity test of the model. Instrumental variable method. This research uses instrumental variable regression to address endogeneity issues caused by reverse causality, omitted variables, and selection bias, thereby improving the credibility of benchmark conclusions. The frequency of appearance of AI terms in annual reports of listed companies (MDAIWT) as an instrumental variable (IV). This instrumental variable is highly correlated with investment in AI technology, but not with residual terms. The regression results of two-stage least squares are shown in columns (1) and (2) of Table 4. The regression coefficients are significantly correlated at the 1% level of significance. The Kleibergen-Paap rk LM test value is 36.83. The Cragg Donald Wald F statistic value is 30.416. Confirm that there are no recognition issues with the model and that the instrumental variables have been tested. This once again confirms hypothesis 1, that AI technology investment promotes talent reserves in enterprises.

System Generalized Method of Moments. The intensity of R&D expenditure (RDEI) and its lagged values are used as instrumental variables, with RDEI having no direct impact on BDR. The R&D expenditure intensity of listed companies is the ratio of R&D expenses to revenue. In Table 5, column (3) presents the SYS-GMM analysis, and the regression results show that Arellano-Bond test for AR(1) P equals 0.000, indicating first-order autocorrelation in the first-difference residual. Arellano-Bond test for AR(2) P equals 0.110, suggesting that the difference-in-differences error term is reasonable and the instrumental variables are acceptable. In the Hansen test, P equals 0.634, within an ideal range. Additionally, the regression coefficient of AITR is significantly positive at the 1% level, further confirming that AI technology investment promotes corporate talent reserves.

Table 4 - Endogeneity Analysis result

Variable	(1)	(2)	(3)
	2SLS first stage	2SLS second stage	SYS-GMM
	AITR	BDR	BDR
AITR		0.0838***	
		4.23	
IV	0.155***		
	6.44		
Anderson canon. corr. LM		36.83	
Cragg-Donald Wald F statistic		30.416	
L.BDR			0.878***
			0.046
AITR			0.018***
			0.007
Arellano-Bond test for AR(1)			0
Arellano-Bond test for AR(2)			0.11
Hansen			0.634
CONTROLS	Yes	Yes	Yes
Firm	Yes	Yes	
Year	Yes	Yes	
N	22801	23039	15459
F	246***	14***	
r2	0.879	-1.121	
r2_a	0.853	-1.572	
Notes: * p < 0.1, ** p < 0.05, *** p < 0.01			

Analysis of transmission mechanism. AI technology will increase the demand for high skilled labor while reducing the need for low skilled labor. AI tends to reallocate work toward more skill-intensive tasks, leading to an increased demand for skilled talent in companies. Manufacturing companies' investment in AI technology has increased the demand for high skilled labor [16]. Teams with a higher proportion of employees who have received higher education are more likely to produce innovative results. Digital transformation has significantly increased the proportion of highly educated and technically skilled employees and R&D personnel in companies [17]. As shown in Table 5, at the 1% level, AITR has a significant positive effect on TPR, and at the 1% level, TPR also has a significant positive effect on BDR. Empirical evidence shows that AI investment can significantly increase the demand for technical personnel in enterprises, and the increase in the proportion of technical personnel promotes the company's talent reserve. The empirical results support hypothesis 2.

Table 5 - Mediating regression results

Variable	1	2
	TPR	BDR
AITR	0.00250***	
	4.37	
TPR		0.269***
		41.14
CONTROLS	Yes	Yes
Firm	Yes	Yes
Year	Yes	Yes
N	23145	23145
F	12***	170***
r2	0.923	0.954
r2_a	0.907	0.944
Notes: * p < 0.1, ** p < 0.05, *** p < 0.01		

Moderation effect analysis. Government subsidies can significantly stimulate corporate innovation inputs and outputs. This indicates that well-designed AI subsidy policies can effectively lower the financial threshold for companies to adopt AI. Regional policies can attract and retain AI talent, thereby enhancing the human capital element of the regional innovation system. This study conducted a regression analysis on the moderating effect, and the results are shown in Table 6. The coefficient of the interaction term AIVG*AITR on the dependent variable BDR is 0.00109, which is significant at the 1% significance level. This is consistent with the direction of the influence of AITR on BDR in the benchmark regression, and is also significant, indicating that the moderating effect is valid. Regional subsidy funds can enhance the positive impact of corporate AI technology investment on talent reserves, thus verifying hypothesis 3.

Table 6 - Moderator analysis results

Variable	BDR
AITR	0.00365***
	(6.07)
AIVG*AITR	0.00109***
	(2.97)
AIVG	0.00847***
	(3.77)
CONTROLS	Yes
Firm	Yes
Year	Yes
N	19131
F	24***
r2	0.951
r2_a	0.940
Notes: * p < 0.1, ** p < 0.05, *** p < 0.01	

Heterogeneity analysis. According to the analysis of the nature of the enterprise, the results are shown in Table 7. The impact coefficient of AITR on BDR of state-owned enterprises is 1.55, indicating no significant correlation. For private enterprises, the impact coefficient of AITR on BDR is 5.1, which is significantly correlated at the 1% level. Through the analysis results, it is concluded that AI technology investment has a significant promoting effect on talent reserves in private enterprises.

Table 7 - Heterogeneity Analysis result

Variable	State-owned enterprise BDR	Private enterprises BDR
AITR	0.00167	0.00315***
	(1.55)	(5.10)
CONTROLS	Yes	Yes
Firm	Yes	Yes
Year	Yes	Yes
N	5577	17519
F	14***	16***
r2	0.957	0.950
r2_a	0.947	0.939
Notes: * p < 0.1, ** p < 0.05, *** p < 0.01		

Private enterprises have a more flexible market competition environment and higher decision-making efficiency than state-owned enterprises. Private enterprises aim to maximize efficiency [18], and therefore tend to increase investment in technology to achieve higher benefits. This prompts private enterprises to quickly use AI technology to build knowledge teams and give full play to the role of AI investment. The mission objectives of state-owned enterprises limit their investment in AI and talent training, and they are susceptible to administrative and political factors. State-owned enterprises bear more policy and social responsibilities, and their decision-making focuses on serving national strategic stability and fulfilling social responsibilities [19]. When state-owned enterprises increase investment in artificial intelligence, there is no need to make major adjustments to personnel, so the effect of improving "talent reserves" through AI investment is not significant. An empirical analysis of Chinese small and medium-sized enterprises found that AI investment only showed a labor structure adjustment effect in private enterprises, while this coefficient was not significant in state-owned enterprises [20]. Therefore, the effect of enterprise AI investment on enterprise talent reserves is more obvious in private enterprises.

Conclusion. AI investment promotes the reserve of talent in enterprises, which is a key issue in transforming AI investment into productivity. This study aims to analyze the impact of AI investment on corporate talent. This article uses data from Chinese listed companies from 2014 to 2023 to analyze the impact of enterprise AI investment on talent reserves. Empirical analysis shows that AI investment promotes talent reserves in enterprises; AI investment promotes enterprises to increase the proportion of technical personnel, thereby promoting the improvement of talent reserves; Government subsidies can strengthen the role of AI investment in enhancing the talent pool of enterprises; AI investment plays a more significant role in private enterprises.

Based on the research results, the following policy recommendations are proposed:

1) Financial subsidies enhance the impact of enterprise AI investment on talent reserves. Subsidies are divided into policy subsidies and financial subsidies. Policy subsidies

promote the sharing of AI resources, while funding subsidies help companies absorb technical talents during their development stage and promote talent reserves.

2) Enterprises utilize AI technology to train internal talents. Internal AI training can quickly increase talent reserves, enhance enterprises' ability to respond to the challenges of AI technology investment, and maintain a competitive advantage in AI technology transformation.

This study focuses on the impact of AI investment on enterprise talent reserves. Although the data is accurate, there may still be some differences between AI financial indicators and the actual AI investment and application status of enterprises. Therefore, future research can further integrate industry and productivity indicators of enterprises to analyze their talent needs.

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ЖАСАНДЫ ИНТЕЛЛЕКТКЕ ИНВЕСТИЦИЯЛАРДЫҢ КАДРЛЫҚ РЕЗЕРВІНЕ ӘСЕРІ: ҚЫТАЙ КӘСІПОРЫНДАРЫНЫҢ ТӘЖІРИБЕСІ НЕГІЗІНДЕ

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Түйін. *Бұл зерттеудің мақсаты - жасанды интеллектке (ЖИ) инвестициялардың компаниялардың кадрлық резервіне әсер ету механизмін және рөлін зерттеу, ЖИ-мен байланысты трансформация процесінде кәсіпорындардың бәсекелестік артықшылықтарын сақтауды қамтамасыз ету. StataMP 17 деректерді талдау бағдарламалық құралын пайдалана отырып, мақалада 2014-2023 жылдар аралығындағы биржада тіркелген қытайлық компаниялардың корпоративтік деректері талданып, технологиялық трансформацияның жаңа көзқарасы бойынша ЖИ инвестицияларының компаниялардың кадрлық резервін қалыптастыруға әсері туралы эмпирикалық зерттеулер жүргізіледі. Нәтижелер ЖИ инвестициялары компаниялардың кадр резервіне айтарлықтай ынталандырушы әсер ететінін көрсетеді; ЖИ инвестицияларының 1 бірлікке ұлғаюы кадр резервінің коэффициентін 0,378%-ға арттырады. ЖИ-ке инвестициялар техникалық персоналдың үлесін ұлғайту есебінен компаниялардың кадрлық резервін қалыптастыруға ықпал етеді. Сондай-ақ өңірлік деңгейдегі ЖИ-ді субсидиялау саясаты ЖИ-ге инвестициялардың кадрлық резервке әсерін күшейте алатынын көрсетті. Сонымен қатар ЖИ-ге инвестициялардың кадрлық резервке ынталандырушы ықпалы жеке меншік кәсіпорындарда неғұрлым айқын байқалатынын көрсетті.*

Түйінді сөздер: *жасанды интеллект, кадрлық резерв, инвестициялар, эмпирикалық талдау, технологиялық трансформация.*

ВЛИЯНИЕ ИНВЕСТИЦИЙ В ИСКУССТВЕННЫЙ ИНТЕЛЛЕКТ НА КАДРОВЫЙ РЕЗЕРВ ПРЕДПРИЯТИЙ: ОПЫТ НА ПРИМЕРЕ КИТАЙСКИХ ПРЕДПРИЯТИЙ

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Резюме. *Цель данного исследования - изучить механизм воздействия и роль инвестиций в искусственный интеллект (ИИ) на кадровый резерв компаний, обеспечивая сохранение конкурентных преимуществ предприятий в процессе трансформации, связанной с ИИ. Используя программное обеспечение для анализа данных StataMP 17, в статье анализируются корпоративные данные китайских компаний, котирующихся на бирже, за период с 2014 по 2023 год, и проводится эмпирическое исследование влияния инвестиций в ИИ на формирование кадрового резерва компаний с новой точки* *зрения технологической трансформации. Результаты показывают, что инвестиции в ИИ оказывают значительное стимулирующее воздействие на кадровый резерв компаний; при увеличении инвестиций в ИИ на единицу коэффициент кадрового резерва возрастает на 0,378%. Инвестиции в ИИ способствуют формированию кадрового резерва компаний за счет увеличения доли технического персонала. Исследование также показало, что региональная политика субсидирования ИИ может усилить влияние инвестиций в ИИ на кадровый резерв, причем стимулирующее воздействие инвестиций в ИИ на кадровый резерв более значительно в частных предприятиях.*

Ключевые слова: *искусственный интеллект, кадровый резерв, инвестиции, эмпирический анализ, технологическая трансформация.*

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