

The Impact of Talent Introduction Intensity on Corporate Artificial Intelligence Levels: Empirical Evidence from Chinese A-Share Listed Companies

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Abstract

Talent introduction has become an important factor shaping enterprise development in recent years. Using panel data for Shanghai and Shenzhen A-share listed companies, this paper examines how talent introduction affects firms' artificial intelligence (AI) development and explores the channels through which this effect operates. The empirical findings suggest that talent introduction is associated with higher levels of AI development among firms. This relationship remains robust after a series of robustness tests and instrumental variable estimations. Further analysis indicates that talent introduction may contribute to AI development by easing financing constraints and improving workforce quality. The effects are not uniform across firms, however. They appear to be more pronounced depending on characteristics such as pollution status, regional location, and industry affiliation, particularly in the manufacturing sector. Overall, the findings highlight the role of talent introduction in supporting corporate AI development and provide evidence that may be useful for the design of talent-related policies and the promotion of the AI industry.

Keywords

talent introduction intensity, corporate artificial intelligence level, financing constraints, employee quality, propensity score matching

1. Introduction

The Report to the 20th National Congress of the Communist Party of China emphasized the importance of education, scientific and technological self-reliance, and talent-driven development. It also highlighted the need to strengthen the national strategic talent workforce, providing policy support for talent development in key sectors such as artificial intelligence (AI). In recent years, a new wave of technological change and industrial transformation has accelerated the development and diffusion of emerging technologies [1,2]. Among them, AI has attracted considerable attention because of its growing role in industrial upgrading and business innovation. As AI technologies become increasingly integrated into production and management activities, firms' ability to develop and apply AI is often regarded as an important source of competitiveness. In this process, talent plays a particularly important role. The quality, structure, and allocation of human resources may affect how effectively firms adopt and utilize AI-related technologies.

Despite the rapid expansion of China's AI industry, shortages of qualified talent remain a major challenge. Competition for highly skilled AI professionals, especially those engaged in algorithm development and large-model research, has intensified in recent years, leading to substantial salary premiums. Existing estimates suggest that China's AI talent gap may reach 4 million by 2030, with shortages being especially severe in basic research and interdisciplinary fields [3]. At the same time, mismatches between university training and industry demand, rising recruitment costs, and difficulties in integrating newly recruited personnel have limited the efficiency of talent allocation and constrained the development of AI capabilities within firms [4,5].

From the perspective of enterprise practice, the relationship between talent introduction and AI development is not always straightforward. Recruiting highly qualified personnel does not necessarily lead to immediate improvements in technological capability. In many cases, firms still face challenges in transforming talent advantages into measurable innovation outcomes. The effectiveness of talent introduction may also differ across firms because of variations in industrial characteristics, regional environments, and organizational conditions. Some firms continue to rely heavily on high-salary recruitment strategies, while mechanisms for integrating talent into long-term AI development remain relatively underdeveloped. As a result, talent investment and actual AI performance do not always move in parallel.

At the global level, the movement of high-end AI talent from universities and research institutions toward industry has accelerated, and competition for skilled professionals has become increasingly intense. Under these circumstances, talent allocation efficiency is emerging as an important factor influencing the diffusion and application of AI technologies [6]. Against this backdrop, examining the impact of talent introduction on corporate AI development from a micro-level perspective is of both theoretical and practical significance. Such an analysis can contribute to the literature on technological innovation and talent allocation, while also providing evidence for firms seeking to improve talent strategies and for policymakers designing talent-related policies.

The measurement of corporate AI development has received increasing attention in recent years, and a number of approaches have been proposed in the literature. Existing studies often rely on patent information, textual analysis, or technology-related investment indicators to capture firms' AI activities. For instance, An Tongliang et al. (2025) [7] measured corporate AI technology levels using hierarchical patent identification and network embedding methods. Other studies have used AI-related keywords disclosed in annual reports to construct indicators of AI application intensity at the firm level. These approaches have provided useful tools for examining the adoption and development of AI technologies within enterprises.

Building on these measurement methods, recent research has explored a range of factors associated with corporate AI development. Existing evidence suggests that digital infrastructure, technological innovation, and R&D investment can facilitate firms' intelligent transformation and AI-related activities [8,9]. Nevertheless, relatively little attention has been paid to the role of talent introduction, despite the fact that talent is widely regarded as an important resource for technological development and innovation. Research concerning AI-related talent has mainly focused on the broader effects of talent policies on industrial development and labor market outcomes. Comparatively fewer studies have examined whether talent introduction influences firms' AI development and, if so, through what channels this influence operates. As a result, evidence from the micro-level perspective of enterprises remains limited.

To address this gap, this paper investigates the relationship between talent introduction and corporate AI development using panel data from Chinese A-share listed companies. Particular attention is paid to the mechanisms through which talent introduction may affect firms' AI development, and empirical tests are conducted to examine these potential channels. This study contributes to the existing literature in several respects. First, it examines the mechanisms linking talent introduction to corporate AI development, focusing on the roles of financing constraints and employee quality. Second, unlike much of the existing literature that emphasizes policy effects at the industry or regional level, this paper adopts a firm-level perspective and considers both the quantity and quality dimensions of introduced talent. Third, by using micro-level panel data and conducting a series of robustness and endogeneity tests, the study provides additional evidence on the relationship between talent introduction and firms' AI development.

2. Theoretical Analysis and Research Hypotheses

2.1 Talent Introduction Intensity and Corporate Artificial Intelligence Levels

In the context of the digital economy, artificial intelligence (AI) has become increasingly important for firms seeking to improve productivity, enhance innovation capacity, and maintain competitive advantages. As the development and application of AI technologies depend heavily on human capital, talent introduction may play an important role in shaping firms' AI development. Previous studies suggest that relying solely on employees in explicitly AI-related positions is often insufficient. Firms may also benefit from attracting individuals with complementary skills and implicit AI-related capabilities, which can broaden the scope of AI adoption and facilitate the integration of AI technologies into business operations [10].

One possible channel is innovation enhancement. The introduction of highly skilled personnel can provide firms with access to new knowledge, technical expertise, and industry experience. In the field of AI, talents with backgrounds in algorithm development, machine learning, or industry-specific applications may help firms overcome technological constraints and accelerate the adoption of new technologies. In addition, newly introduced employees can facilitate knowledge diffusion within organizations, encourage collaboration across departments, and support the transformation of technological knowledge into practical applications. These effects may contribute to improvements in firms' AI development over time.

At the same time, the benefits of talent introduction are not automatic. Whether newly recruited employees can effectively contribute to AI development depends on firms' organizational capacity and resource allocation. High recruitment costs, difficulties in integrating new employees into existing teams, and mismatches between talent structure and business needs may reduce the effectiveness of talent introduction [11]. Excessive reliance on external recruitment may also weaken incentives for internal talent cultivation and limit the accumulation of firm-specific knowledge [12]. These factors suggest that the impact of talent introduction may vary across firms and may depend on the extent to which enterprises are able to effectively absorb and utilize newly acquired human capital.

Overall, although talent introduction may face certain constraints in practice, it is generally expected to provide firms with valuable knowledge resources and innovation capabilities that support the development and application of AI technologies. Accordingly, this paper proposes the following hypothesis:

Hypothesis 1: Talent introduction is positively associated with corporate AI development.

2.2 Talent Introduction Intensity, Financing Constraints, and Corporate Artificial Intelligence Levels

Financing constraints may represent an important channel through which talent introduction influences corporate AI development. By improving firms' access to financial resources, talent introduction can create more favorable conditions for AI-related investment and technological upgrading.

Talent introduction may help reduce financing constraints in several ways. The recruitment of highly educated and highly skilled employees, particularly those with expertise in frontier technologies, can signal stronger growth potential and innovation capacity to external investors. Such signals may improve firms' reputation in capital markets and increase the availability of external financing. In addition, high-quality talent can contribute to improvements in corporate governance, operational efficiency, and information disclosure, thereby reducing information asymmetry and lowering financing costs. These factors may expand financing channels and provide greater financial support for AI-related R&D activities and technology investment [13].

At the same time, adequate financial resources are often required for the development and application of AI technologies. AI projects typically involve substantial expenditures on infrastructure, software and hardware investment, technological research, and scenario-based implementation. When financing constraints are eased, firms may be better positioned to sustain long-term and high-risk innovation activities and to allocate resources to AI-related projects. Greater financial flexibility can also facilitate the integration of AI technologies into production, management, and decision-making processes, thereby supporting the further development of corporate AI capabilities [14].

Based on this reasoning, the following hypothesis is proposed:

Hypothesis 2: Talent introduction promotes corporate AI development by alleviating financing constraints.

2.3 Talent Introduction Intensity, Employee Quality, and Corporate Artificial Intelligence Levels

Talent introduction may influence corporate AI development not only through the direct recruitment of technical personnel but also through improvements in overall employee quality. As AI technologies become increasingly integrated into business operations, the quality of the workforce may affect firms' ability to adopt, apply, and further develop these technologies.

One way in which talent introduction affects employee quality is through the optimization of workforce structure. By recruiting highly educated and skilled employees, firms can supplement existing human capital and address capability gaps in areas such as artificial intelligence, data analysis, and digital technologies. In addition, newly recruited talent may bring new knowledge, technical experience, and working methods that can gradually spread within the organization. Through day-to-day collaboration and learning, these effects may contribute to broader improvements in employee skills and professional capabilities [15].

At the same time, employee quality is closely related to the implementation and use of AI technologies. Employees with stronger technical backgrounds and digital skills are generally better able to understand and utilize AI-related tools in their daily work. A more skilled workforce may also facilitate the integration of AI technologies into different business processes and support the exploration of new application scenarios. In addition, employees with higher levels of expertise are often more capable of identifying practical problems and adapting technological solutions to business needs, which may improve the effectiveness of AI applications and innovation activities within firms [16].

Taken together, talent introduction may contribute to corporate AI development by improving the quality of the workforce and strengthening firms' capacity to absorb and apply AI-related knowledge. Accordingly, the following hypothesis is proposed:

Hypothesis 3: Talent introduction promotes corporate AI development by improving employee quality.

3. Research Design

3.1 Sample Selection and Data Sources

The sample consists of Chinese A-share listed companies during the period 2015–2024. Data on firms' digitalization and intelligent transformation are obtained from the MarkData database, while firm characteristics, financial information, and corporate governance variables are collected from the CSMAR database. Following common practice, ST and *ST firms, financial enterprises, and observations with missing values for key variables are excluded. The final sample contains 41,098 firm-year observations. To reduce the influence of extreme values, all continuous variables are winsorized at the 1% level.

3.2 Variable Definitions

(1) Independent Variable

Talent introduction intensity (Intensity). Following Chen Xi et al. [17–21], talent introduction intensity is measured using the frequency of talent-related recruitment information extracted from textual data. The variable is constructed by adding one to the original value and then taking its natural logarithm.

(2) Dependent Variable

Corporate AI development (AI). Following Sun Wenyan et al. [22], corporate AI development is measured based on the degree of AI adoption at the firm level.

(3) Mediating Variables

Financing constraints (SA). Financing constraints are measured using the SA index proposed in the literature [23,24]. The index is calculated based on firm size and firm age and is widely used as a proxy for financing constraints. A lower absolute value of the SA index indicates weaker financing constraints. In the

empirical analysis, the SA index is used to examine whether financing constraints serve as a channel through which talent introduction affects corporate AI development.

Employee quality (Quality). Employee quality is measured by the proportion of employees holding a master’s degree, calculated as the number of employees with master’s degrees divided by total employment. Compared with broader educational indicators, this measure reflects the share of employees with relatively high levels of professional training and technical expertise [25]. It is used to capture the role of workforce quality in the relationship between talent introduction and corporate AI development.

(4) Control Variables

Following the existing literature, several firm-level characteristics are included as control variables, including listing age (ListAge), the Herfindahl–Hirschman Index (HHI), firm size (Size), quick ratio (Quick), return on assets (ROA), revenue growth rate (Growth), book-to-market ratio (BM), ownership concentration (Top1), and board size (Board). Specifically, ListAge is measured as the number of years since listing. HHI is calculated as the sum of squared market shares of firms within the same industry and is used to capture industry concentration. Size is measured by the natural logarithm of total assets. Quick is defined as the ratio of quick assets to current liabilities. ROA is calculated as net profit divided by average total assets. Growth is measured by the annual growth rate of operating revenue. BM is the ratio of book value to market value. Top1 represents the shareholding ratio of the largest shareholder, and Board is measured by the number of directors on the board.

3.3 Regression Model Specification

To examine the relationship between talent introduction and corporate AI development, the following econometric models are constructed:

$$AI_{i,t} = \alpha_0 + \alpha_1 Intensity_{i,t} + \alpha_2 controls_{i,t} + \delta_{year} + \eta_{Firm} + \varepsilon_{i,t} \tag{1}$$

$$SA_{i,t} = \alpha_0 + \alpha_1 Intensity_{i,t} + \alpha_2 controls_{i,t} + \delta_{year} + \eta_{Firm} + \varepsilon_{i,t} \tag{2}$$

$$employee_{i,t} = \alpha_0 + \alpha_1 TechConv_{i,t} + \alpha_2 controls_{i,t} + \delta_{year} + \eta_{Firm} + \varepsilon_{i,t} \tag{3}$$

where i and t denote firm and year, respectively; AI represents the corporate artificial intelligence level; *Intensity* denotes talent introduction intensity; *SA* is the financing constraints index; *employee* represents employee quality level; *controls* denotes the set of control variables; δ_{year} represents year fixed effects; η_{Firm} represents firm fixed effects; and ε is the random disturbance term.

4. Empirical Analysis

4.1 Descriptive Statistics

The descriptive statistics are reported in Table 1.

Table 1: Descriptive Statistics

Variable	N	Min	Max	Mean	p50	SD
	41098	8.038	15.740	12.600	12.650	1.285
Intensity	41098	0.788	5.013	3.364	3.651	1.092
ListAge	41098	0.693	3.367	2.186	2.303	0.788
HHI	41098	0.013	0.582	0.088	0.062	0.094
Size	41098	19.840	26.300	22.250	22.060	1.304
Quick	41098	0.187	14.120	1.955	1.238	2.220
ROA	41098	-0.257	0.194	0.033	0.034	0.064
Growth	41098	-0.585	2.401	0.155	0.095	0.397
	41098	0.114	1.199	0.621	0.618	0.253
Top1	41098	0.082	0.739	0.336	0.312	0.148
Board	41098	1.609	2.639	2.117	2.197	0.198

The dependent variable, corporate AI development (AI), includes 41,098 firm-year observations. The minimum value is 8.038, the maximum is 15.740, the mean is 12.600, and the standard deviation is 1.285. Overall, there is noticeable variation in AI development across firms.

The key explanatory variable, talent introduction intensity (Intensity), also consists of 41,098 observations. Its minimum value is 0.788, maximum is 5.013, mean is 3.364, and standard deviation is 1.092. The results suggest that firms differ in the extent of talent introduction, with both relatively high and relatively low values observed in the sample.

4.2 Benchmark Regression Results

The benchmark regression results are reported in Table 2. The table presents the estimated effect of talent introduction intensity on corporate AI development, controlling for year fixed effects, province fixed effects, and a set of firm-level covariates. The results indicate that the coefficient on talent introduction intensity is 0.030 and is statistically significant at the 1% level, suggesting a positive association between talent introduction and corporate AI development. In terms of economic magnitude, the estimate implies that a one-unit increase in talent introduction intensity is associated with an increase of about 0.030 units in corporate AI development, holding other variables constant. This result suggests that talent introduction is positively related to firms' intelligent transformation. Overall, the finding is consistent with Hypothesis 1.

Table 2: Benchmark Regression Results

VARIABLES	(1)
	AI
Intensity	0.030*** (2.765)
ListAge	0.225*** (10.517)
HHI	0.178** (2.100)
Size	0.077*** (6.774)
Quick	-0.022*** (-6.445)
ROA	-0.393*** (-4.461)
Growth	-0.061*** (-5.371)
BM	0.179*** (5.166)
Top1	0.104 (1.459)
Board	0.002 (0.046)
Constant	10.145*** (41.812)
Observations	41,098
R-squared	0.666
YearFE	YES
ProvinceFE	YES
Adj.R ²	0.618

Note: ***, *, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics (or Z-statistics) are reported in parentheses. The same applies below.

4.3 Robustness Tests

The robustness test results are reported in Table 3. A series of alternative specifications are used to examine the stability of the baseline results, including adding additional control variables, propensity score matching

(PSM), excluding observations from special periods, excluding municipalities, and applying an alternative winsorization method.

After including additional firm-level controls (Column 1), the coefficient of Intensity is 0.0230 and remains statistically significant at the 5% level, consistent with the baseline results. In Column (2), the PSM approach with 1:2 nearest-neighbor matching is applied. The balance test shows that standardized differences for all covariates are below 5% after matching. The estimated coefficient of Intensity is 0.0240 and remains significant at the 5% level. In Column (3), after excluding observations from special periods, the coefficient increases to 0.0368 and is significant at the 1% level. In Column (4), when municipality samples are excluded, the coefficient remains positive but is no longer statistically significant. In Column (5), using an alternative winsorization method, the coefficient is 0.0330 and remains significant at the 1% level.

Overall, the results across different specifications are broadly consistent with the baseline findings, suggesting that the relationship between talent introduction intensity and corporate AI development is relatively stable.

Table 3: Robustness Test Regression Results

	(1)	(2)	(3)	(4)	(5)
	Add Controls	PSM	Exclude Special Periods	Exclude Municipalities	Change Winsorization
VARIABLES	AI	AI	AI	AI	AI
Intensity	0.023** (1.999)	0.024** (2.019)	0.037*** (3.175)	0.009 (0.661)	0.033*** (3.864)
ListAge	0.232*** (9.966)	0.200*** (8.979)	0.216*** (9.122)	0.154*** (7.055)	0.167*** (11.304)
HHI	0.084 (0.943)	0.070 (0.743)	0.294*** (3.507)	0.227*** (2.738)	0.222** (2.549)
Size	0.078*** (6.586)	0.082*** (6.894)	0.124*** (10.135)	0.099*** (8.949)	0.109*** (13.137)
Quick	-0.023*** (-6.644)	-0.021*** (-5.857)	-0.024*** (-6.132)	-0.027*** (-6.940)	-0.035*** (-8.623)
ROA	-0.434*** (-4.694)	-0.452*** (-4.757)	-0.624*** (-5.901)	-0.516*** (-5.512)	-0.822*** (-8.421)
Growth	-0.063*** (-5.311)	-0.052*** (-4.349)	-0.052*** (-4.143)	-0.060*** (-4.893)	-0.058*** (-4.351)
BM	0.170*** (4.728)	0.204*** (5.640)	0.185*** (4.589)	0.193*** (5.417)	0.119*** (4.497)
Top1	0.080 (1.055)	0.077 (1.024)	0.037 (0.484)	-0.104 (-1.495)	-0.049 (-0.919)
Board	0.034 (0.806)	0.026 (0.610)	0.012 (0.273)	-0.036 (-0.882)	0.009 (0.284)
Constant	10.102*** (39.603)	10.015*** (39.300)	9.131*** (36.161)	9.930*** (42.869)	9.707*** (55.312)
Observations	38,478	36,510	34,567	36,994	46,121
R-squared	0.664	0.680	0.632	0.630	0.695
Adj.R ²	0.628	0.628	0.569	0.583	0.657

4.4 Mechanism Tests

Table 4 reports the mechanism test results on the relationship between talent introduction intensity and corporate AI development, focusing on two channels: financing constraints (SA index) and employee quality.

Column (1) presents the results with the SA index as the dependent variable. The coefficient on talent introduction intensity (Intensity) is -0.003 and is statistically significant at the 1% level. Given that the SA index is a reverse measure of financing constraints, this result indicates that higher talent introduction intensity is associated with weaker financing constraints. This pattern suggests that firms with stronger talent introduction may face fewer financing frictions, which could be related to improved access to external financing and better internal governance conditions.

Column (2) reports the results using employee quality as the dependent variable. The coefficient on Intensity is 0.069 and is significant at the 10% level. This implies a positive association between talent introduction intensity and employee quality. One possible explanation is that talent introduction increases the share of highly educated and skilled employees and may also contribute to broader improvements in workforce capabilities through knowledge diffusion within the firm.

Overall, the results are consistent with the existence of two potential channels linking talent introduction to corporate AI development, namely financing conditions and employee quality. These findings provide supporting evidence for Hypotheses 2 and 3.

Table 4: Mechanism Regression Results

VARIABLES	(1) SA	(2) employee
Intensity	-0.003*** (-3.710)	0.069* (1.814)
ListAge	-0.066*** (-43.929)	-0.644*** (-8.658)
HHI	-0.012** (-1.979)	0.821*** (2.689)
Size	0.010*** (12.409)	0.523*** (12.784)
Quick	0.003*** (12.329)	0.118*** (9.741)
ROA	-0.023*** (-3.662)	-0.911*** (-2.944)
Growth	-0.009*** (-11.070)	-0.050 (-1.263)
BM	-0.032*** (-13.174)	-0.611*** (-5.084)
Top1	0.020*** (4.013)	0.930*** (3.587)
Board	-0.012*** (-4.281)	-0.033 (-0.240)
Constant	-3.628*** (-213.225)	-6.908*** (-7.850)
Observations	41,098	29,944
R-squared	0.966	0.899
Adj.R ²	0.883	0.883

4.5 Heterogeneity Analysis

4.5.1 Heterogeneity Test Based on Enterprise Pollution Attributes

To examine whether the impact of talent introduction intensity on corporate AI development varies by pollution characteristics, the sample is divided into polluting and non-polluting firms based on industry pollution intensity, and regressions are conducted separately.

The results show that the coefficient of talent introduction intensity is 0.074 and statistically significant at the 1% level in polluting firms. In non-polluting firms, the coefficient is 0.010 and not statistically significant. The difference may be related to variation in environmental regulation pressure and transformation incentives across the two groups. Polluting firms generally face stronger regulatory constraints and more urgent emission reduction needs, which may create clearer demand for intelligent transformation and more identifiable application scenarios for AI technologies. In contrast, non-polluting firms face relatively weaker external pressure, and the role of talent introduction in driving AI development appears more limited.

4.5.2 Heterogeneity Test Based on Enterprise Registration Region

To examine whether regional differences affect the relationship between talent introduction and corporate AI development, the sample is divided into eastern and western regions based on firms' registration locations, and regressions are conducted separately.

The results show that the coefficient of talent introduction intensity is 0.037 and significant at the 5% level in the western region. In the eastern region, the coefficient is 0.013 and not statistically significant. The difference may be related to variation in regional development conditions. The eastern region generally has more developed digital infrastructure and more intense competition for talent, where firms may rely more on external cooperation and existing technological resources for AI development, reducing the marginal role of talent introduction. In contrast, firms in the western region tend to face relatively weaker talent availability and larger technological gaps, so talent introduction may play a more noticeable role in supporting AI-related development, especially when combined with local policy support.

4.5.3 Heterogeneity Test Based on Enterprise Industry Type

To examine whether industry characteristics affect the relationship between talent introduction and corporate AI development, the sample is divided into manufacturing and non-manufacturing firms based on the National Economic Industry Classification Standard, and regressions are conducted separately.

The results show that the coefficient of talent introduction intensity is 0.051 and significant at the 1% level in the manufacturing group. In the non-manufacturing group, the coefficient is -0.004 and not statistically significant. The difference may be related to variations in production and application contexts across industries. Manufacturing firms typically have more standardized production processes and more clearly defined AI application scenarios, such as intelligent manufacturing and process optimization, where talent introduction may be more directly reflected in technological upgrading. In contrast, non-manufacturing firms, especially service-oriented ones, tend to rely more on heterogeneous and scenario-based service activities, where AI applications are less standardized and the role of talent introduction appears less pronounced.

Table 5: Heterogeneity Tests

	(1)	(2)	(1)	(2)	(1)	(2)
	Polluting	Non-polluting	Eastern	Western	Manufacturing	Non-manufacturing
Intensity	0.074*** (4.344)	0.010 (1.002)	0.013 (1.169)	0.037** (2.385)	0.051*** (5.100)	-0.004 (-0.284)
ListAge	0.201*** (6.330)	0.157*** (9.401)	0.240*** (13.715)	0.023 (0.805)	0.094*** (5.528)	0.212*** (7.542)
HHI	0.687*** (2.686)	0.113 (1.158)	0.351*** (3.344)	0.036 (0.227)	0.403*** (2.998)	0.357** (2.540)
Size	0.142*** (8.038)	0.108*** (11.253)	0.104*** (10.218)	0.096*** (6.638)	0.128*** (12.995)	0.066*** (4.197)
Quick	-0.072*** (-8.301)	-0.024*** (-5.346)	-0.025*** (-5.333)	-0.064*** (-8.265)	-0.047*** (-10.297)	-0.026*** (-3.338)
ROA	-0.106 (-0.550)	-1.219*** (-10.826)	-0.997*** (-8.492)	-0.435** (-2.492)	-0.951*** (-8.580)	-0.999*** (-5.490)
Growth	0.024 (0.835)	-0.080*** (-5.390)	-0.054*** (-3.369)	-0.062*** (-2.636)	-0.066*** (-4.171)	-0.053** (-2.350)
BM	0.229*** (4.221)	0.023 (0.774)	0.088*** (2.795)	0.170*** (3.546)	0.136*** (4.561)	0.154*** (3.019)
Top1	-0.131 (-1.231)	-0.007 (-0.117)	0.152** (2.312)	-0.441*** (-4.914)	-0.080 (-1.297)	0.049 (0.460)
Board	-0.057 (-0.830)	0.061 (1.642)	0.123*** (3.057)	-0.233*** (-4.044)	-0.064* (-1.702)	0.099 (1.596)
Constant	9.096*** (24.327)	9.728*** (47.788)	9.540*** (43.703)	10.775*** (35.312)	9.395*** (45.294)	10.439*** (30.215)
Observations	10,635	35,486	32,322	13,799	29,870	16,251
R-squared	0.674	0.688	0.706	0.682	0.685	0.748
YearFE	YES	YES	YES	YES	YES	YES
ProvinceFE	YES	YES	YES	YES	YES	YES
Adj.R ²	0.645	0.645	0.645	0.645	0.715	0.715

5. Conclusions and Implications

This paper uses Chinese A-share listed companies from 2015 to 2024 to examine the relationship between talent introduction intensity and corporate AI development, as well as the related mechanisms and heterogeneity patterns. The empirical results suggest that talent introduction is generally associated with higher levels of corporate AI development. This finding remains stable across different robustness checks and after addressing potential endogeneity issues.

The mechanism analysis shows that talent introduction may work through two channels, including easing financing constraints and improving employee quality. These channels do not operate in isolation but appear to jointly support firms' ability to adopt and apply AI-related technologies. The heterogeneity results further indicate that the effect is more evident in polluting firms, firms located in western regions, and manufacturing industries. In contrast, the relationship is weaker or not statistically significant in non-polluting firms, eastern regions, and non-manufacturing sectors.

Based on these findings, several policy and managerial implications can be considered. First, firms may need to think more carefully about how talent is introduced and used. Simply increasing recruitment may not be sufficient. More attention could be given to matching talent with existing organizational needs, especially for employees with cross-disciplinary backgrounds, while also strengthening internal training and knowledge absorption. Second, policy support may still matter, but it does not need to be uniform. Regions and industries with weaker talent bases, such as western areas and manufacturing-related sectors, may require more targeted support in terms of funding and talent policies, while also improving the connection between university training and firm demand. Third, from an industry perspective, reducing unnecessary talent competition and improving channels for talent and knowledge sharing may help. At the same time, the way AI is applied still differs across industries, so it may be more practical to encourage firms to develop AI applications according to their own business contexts rather than following a single model.

References

- [1] Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. *NZ Business*, 14(11), 1895-1896.
- [2] Jia, G. L. (2016). The third industrial revolution and industrial intelligence. *Social Sciences in China*, (06), 87-106+206.
- [3] Yu, F. X. (2026). Research on the challenges and paths of artificial intelligence talent cultivation in China. *China Development Observation*, (01), 33-38.
- [4] Hu, Y., Su, S. L., & Jiang, Q. X. (2025). Research on the cultivation path of artificial intelligence talents in China's "Double First-Class" universities from the perspective of interdisciplinary integration. *Journal of Innovation and Entrepreneurship Education*, 16(03), 138-143.
- [5] Tang, G. Y., & Sun, Q. (2024). Crossing technical boundaries: The dilemma and coping strategies of AI recruitment. *Quarterly Journal of Management*, 9(03), 37-46+143.
- [6] Akcigit, U., Chikis, C. A., Dinlersoz, E., & Goldschlag, N. (2026). *Attention (and money) is all you need: Why universities are struggling to keep AI talent* (NBER Working Paper No. 34964). National Bureau of Economic Research.
- [7] An, T. L., & Wu, Z. Y. (2025). Hierarchical measurement of corporate artificial intelligence technology level and its innovation effect: From the perspective of global knowledge network. *China Industrial Economy*, (06), 81-100. <https://doi.org/10.19581/j.cnki.ciejournal.2025.06.005>.
- [8] Li, X. Y., & Ye, C. S. (2026). New measurement methods of artificial intelligence and their applications. *The Journal of World Economy*, 49(04), 68-110. <https://doi.org/10.19985/j.cnki.cassjwe.2026.04.009>.
- [9] Yu, M. G., He, M. M., & Zhang, M. M. (2024). Talent introduction policy, optimal allocation of labor force and intelligence of manufacturing industry. *China Industrial Economy*, (05), 116-134.
- [10] Westover, J., & Tang, F. (2025). The invisible AI workforce: Redefining technical talent acquisition for artificial intelligence. Preprints 2025, 2025091488.

- [11] Ma, B. C., & Liao, K. Z. (2025). How does artificial intelligence application affect firm innovation: Evidence from online recruitment. *Journal of Zhongnan University of Economics and Law*, (06), 132-145. <https://doi.org/10.19639/j.cnki.issn1003-5230.2025.0061>.
- [12] Lu, D., Yu, D., Huang, D., & Yang, R. M. (2020). Internal training or external recruitment: Which one better promotes firm innovation? *China Industrial Economy*, (10), 157-174. <https://doi.org/10.19581/j.cnki.ciejournal.2020.10.007>.
- [13] Wang, Z. Q., Wang, Y. Z., & Wang, S. H. (2019). An analysis of the real level of capital efficiency and financial risk in China's real economy: What is the crux of the low efficiency and level of financial services for the real economy? *Management World*, 35(2), 19.
- [14] Ju, X. S., Lu, D., & Yu, Y. H. (2013). Financing constraints, working capital management and the sustainability of firm innovation. *Economic Research Journal*, 48(01), 4-16.
- [15] Yavuz, M. S., & Çalık, H. (2025). AI and ML patent intensity and firm performance: A machine learning-based lagged analysis. ResearchGate.
- [16] Huang, Q. H., Yu, Y. Z., & Zhang, S. L. (2019). Internet development and manufacturing productivity improvement: Internal mechanism and Chinese experience. *China Industrial Economy*, (08), 5-23. <https://doi.org/10.19581/j.cnki.ciejournal.2019.08.001>.
- [17] Chen, X., Wu, Y. J., & Zhu, J. H. (2024). Local talent introduction and total factor productivity from the perspective of new quality productive forces. *Journal of Business Economics and Management*, 46(12), 104-120. <https://doi.org/10.19616/j.cnki.bmj.2024.12.006>.
- [18] Li, L., & Wang, T. Y. (2023). "Peacocks flying southeast": High-quality economic development and talent flow. *The Journal of Quantitative & Technological Economics*, 40(02), 5-24. <https://doi.org/10.13653/j.cnki.jqte.2023.02.001>.
- [19] Mao, F. F., & Zheng, F. (2021). How do talent introduction policies affect the labor market?. *Journal of Business Economics and Management*, (11), 62-77. <https://doi.org/10.14134/j.cnki.cn33-1336/f.2021.11.005>.
- [20] Sun, R. & Sun, Y. J. (2021). Quantitative research on local innovation and entrepreneurship talent introduction policies in China. *Science Research Management*, 42(06), 29-44. <https://doi.org/10.20201/j.cnki.ssstm.2021.06.003>.
- [21] Zhang, T. B., & Wang, L. (2024). Policy signals and long-term residence intention of floating population. *The Journal of World Economy*, 47(07), 97-122. <https://doi.org/10.19985/j.cnki.cassjwe.2024.07.003>.
- [22] Sun, W. Y., & Liu, Y. S. (2023). Research on the impact mechanism of artificial intelligence on the labor market. *East China Economic Management*, 37(03), 1-9. <https://doi.org/10.19629/j.cnki.34-1014/f.220706008>.
- [23] Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies*, 23(5), 1909-1940.
- [24] Du, Y. H., Zhao, R., & Zhao, X. Y. (2024). The contribution of higher education to innovation economy: An empirical study based on firm panel data. *Peking University Education Review*, 22(01), 18-40+187-188.

Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.

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