



The strategic role of Artificial Intelligence in Attracting Foreign Institutional Investors: A comparative analysis of new and old firms

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ABSTRACT

The rapid advancements in artificial intelligence (AI) and its deployment by firms are important factors in attracting investors. By using the data of A-share Chinese listed firms from 2016 to 2022, this study attempts to estimate the possible linkage of AI adoption by firms in appealing the Foreign Institutional Investors (Foreign II's). The study findings indicate the following: (1) AI is positively linked to Foreign II's. (2) The heterogeneity analysis shows that this linkage is stronger in new firms. (3) Firm performance significantly improves the relationship between AI and Foreign II's. (4) In contrast, firm age negatively influences this relationship. After employing several robustness tests, the study findings remain validated. Overall, we provide important insights and actionable references to support the strategic incorporation of AI into organizational operations, aiming to attract foreign investments.

1. Introduction

Artificial intelligence (henceforth, AI) is rapidly transforming and reshaping businesses globally and has received significant attention from investors and society. Especially, its ability to improve managerial decision-making, firm's competitiveness and achieving sustainable economic growth is widely acknowledged by both scholars and regulators (Fatima et al., 2021; Giachino et al., 2024; Truong & Papagiannidis, 2022). AI can be defined as a computing system that automates decision-making tasks such as problem identification and comprehension through repeated learning from large datasets (Berente et al., 2021; Hasan & Ojala, 2024). At the firm level, this form of AI indicates a socio-technical shift that creates both opportunities and challenges for organizations. Despite these challenges, firms increasingly adopt AI for its strategic and economic value. In particular, AI assist firms strengthen innovation capabilities, improve work efficiency, and enhance long-term competitiveness. Accordingly, the present study focuses on how firm-level AI adoption acts as a strategic signal that influences foreign institutional investors' (henceforth, Foreign II's) investment decisions.

From the perspective of firms and stakeholders, using AI by firms is not just a technological adoption but also a strategic signal to its

stakeholders. Undeniably, it signals a firm's capacity to innovate and its commitment to long-term competitiveness (Fatima et al., 2021; Truong & Papagiannidis, 2022; Zhong & Song, 2025). AI adoption becomes a crucial factor in determining the attractiveness of investments by lowering uncertainty and boosting confidence in a firm's future course. According to Ding et al., 2020, Foreign II's face more asymmetric information than domestic investors. Therefore, Foreign II's may use such AI signals to more accurately assess firms for investment purposes. In addition, Foreign II's plays a key role in raising capital-funds which help firms to grow and perform better in the market (Zou et al., 2016). However, information asymmetry challenges are higher for Foreign II's than domestic investors. Such challenges can be minimized by adopting AI in firm operations. Building upon this discussion, the present study highlights that AI functions as an economic and strategic signal influencing Foreign II's investment choices.

AI has influenced industries such as education, healthcare, and transportation, leading them to develop innovative methods across different fields. It further significantly assists management decision-making (Pietronudo et al., 2022; Galaz et al., 2021; Choi et al., 2025). As a result, AI is classified as capital, since they may potentially affect investment decisions. Subsequently, integrating AI technologies into the economy has gained both practical and theoretical recognition for

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high-quality economic development (Besiroglu et al., 2024). This growing consensus is reflected not only in policy discussions but also in rapidly expanding firm-level adoption. For example, a Statista report on China's technology market projects a compound annual growth rate (CAGR) of 26.89% for 2025–2031, forecasting a market volume of US \$194.19 billion by 2031. Consistent with these projections,¹ Fig. 1 illustrates the rising adoption of AI technologies across firms in China.

Furthermore, AI technologies can enhance firm performance by upgrading day-to-day operations in all departments. The deep integration of AI technologies in the firm-settings increases the market value of their business projects (Giachino et al., 2024; Wamba-Taguimdje et al., 2020). However, firm characteristics do matter to adopt AI technologies. Some of the scholars contend that implementing AI in firm-settings requires spending of significant financial and managerial resources, which less capable firms remain unable to obligate (Lee et al., 2022, 2023). For example, conventional firms are quick to accept mature technologies and hesitate to adopt evolving techs like AI (Calvino & Fontanelli, 2023; Khan et al., 2020). Whereas young firms are quick to adopt evolving techs like AI. That said, Foreign II's exhibiting a strong interest in the technological innovations of host firms, which shows their preference for the firm's technological adoption (Yi et al., 2023). These firms present lower investment risks and offer the potential for higher returns, making them more appealing to investors seeking growth opportunities in competitive markets. Likewise, previous studies documented that using extensive applications of AI reduces investment expenses, thereby enhancing work productivity (Baryannis et al., 2019; Lundvall & Rikap, 2022; Rammer et al., 2022; Wilson & Daugherty, 2018). As a result, the profitability of foreign investors increases remarkably, which ultimately attracts a significant number of investments from the Foreign II's. Therefore, we argue that AI tends to attract more Foreign II's.

This study makes three significant contributions to literature. First, our study elaborates on the firm-level research of AI. However, the current research dilemma involves the ongoing adaptation of digital innovations to improve economic practices, and these adoptions are progressing gradually (Goldfarb & Tucker, 2019). The existing literature so far explores various economic achievements (Al-khatib et al., 2024; Giachino et al., 2024) and labor market transformations (Cheng et al., 2019; Graetz & Michaels, 2018) from a broader perspective. Many researchers have used game theory modeling to examine duopoly competition in AI-related technologies, while others highlight the positive influence of AI technologies on organizations (Johnson et al., 2022). However, the association between AI technologies and Foreign II's received limited scholarly attention. By making Foreign II's primary focus, we investigate how AI adoption by firms tends to attract them.

Second, the present findings are helpful in encouraging enterprises to integrate AI technologies. AI is an integral part of the industrial competition. It has become an important element of technological transformation in business startups, drawing attention from external investors. Through this channel, we show the advantages of AI adoption in attracting foreign investments, while addressing the strategic question of whether adopting AI is essential for competing effectively in international markets. Our study further exhibits that the association between AI and Foreign II's is influenced by firm performance, providing a clearer understanding of this relationship. Finally, we used firm age as a moderating variable to examine whether there is a difference in benefits of AI adoption between new and established firms. Our findings reveal interesting results (1) new firms which adopt AI in their business models attracted a greater number of Foreign II's. On the other hand, older firms are less likely to adopt AI and, as a result, attract fewer Foreign II's.

The rest of the article is organized as follows. Section 2 presents the theoretical framework and hypothesis development of the study. Section

¹ For reference https://www.statista.com/outlook/tmo/artificial-intelligence/china?currency=USD#revenue_449279.

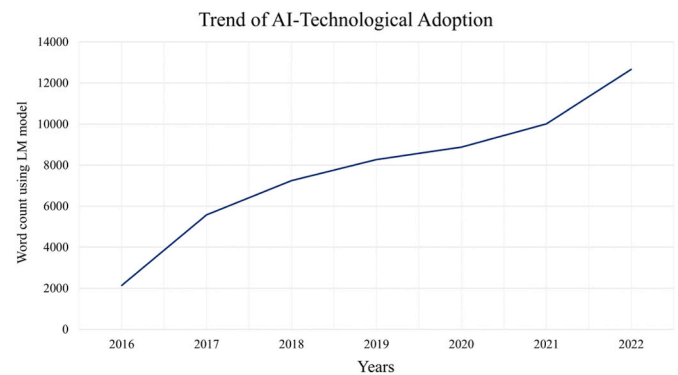


Fig. 1. Firm's adoption of AI Technology in China.

3 explains the research context, data and methodology. Section 4 provides the empirical findings. Section 5 offers an insightful discussion of results and implications. Finally, Section 6 presents the conclusion, limitations and future research directions.

2. Theoretical framework and hypothesis development

2.1. AI at the firm level: concept and definition

AI refers to computing systems that support or automate decision-making functions such as problem detection, prediction, and pattern recognition through repeated learning from large datasets (Berente et al., 2021; Hasan & Ojala, 2024). AI enables firms to emulate key aspects of human decision-making using algorithms and large datasets. This view sees AI as a strategic resource for organizations that are built into their business operations and the decisions that managers make.

In practice, firms use AI technologies such as algorithmic decision-support tools, predictive analytics, and intelligent automation. These advanced technologies are extensively used in supply chain management, financial analysis, and marketing practices. Such AI technologies require significant investment in skilled personnel, organizational learning, and building data infrastructure. Therefore, AI adoption is considered a long-term strategic investment rather than a simple technological upgrade.

2.2. Signaling theory and AI adoption

The present study uses signaling theory to explain how the organization's AI adoption influences Foreign II's investment choices. According to Spence (1973), signaling is the process by which one entity tries to convey helpful information that can influence the other entity to make a wise decision. The party sending the signal is known as the signaler, and the party receiving the signal is known as the receiver (Connelly et al., 2011). Business entities use observable techniques to communicate otherwise unobservable characteristics when there is information asymmetry. Adoption of AI is a signal that indicates organizations' long-term competitiveness and innovation capacity (Fatima et al., 2021; Truong & Papagiannidis, 2022; Zhong & Song, 2025).

However, implementing AI technologies requires a large financial outlay as well as organizational change (Lee et al., 2022, 2023). Therefore, it is difficult for inept organizations to duplicate this reliable and expensive source of signal. In addition, prior research shows that foreign II's witness greater information asymmetry than domestic investors (Ding et al., 2020). Thus, the adoption of AI is interpreted by Foreign II's as evidence of a strategic approach and decreased uncertainty, which increases the likelihood of investments.

Therefore, signaling theory offers a logical framework on how AI functions as a technological tool and sends a strategic signal to attract Foreign II's. Moreover, AI capabilities translate into credible signals that enable Foreign II's to observe and revise their expectations regarding the

firms' future prospects. The adoption of AI signals to investors that the firm is forward-looking, capable of maintaining a sustainable competitive advantage, and well-aligned with Foreign II's goals of long-term value-creation and risk-minimization. This implies that employing AI technologies symbolizes a strategic choice that enhances a firm's attractiveness to investors seeking efficient and competitive enterprises. Hence, integrating signaling theory in current research study highlights a transmission mechanism in which firms develop their AI potential, and Foreign II's subsequently responds to that potential.

2.3. Hypothesis development

2.3.1. AI and foreign II's

AI technology adoption serves as a signal of adaptability, innovation-capacity, and long-term competitiveness of the firm, which Foreign II's tend to disentangle while making investment-related decisions. Previous research shows that modern technologies frequently reconfigure competitiveness and transform global investment dynamics, while also improving organizational competence and boosting firms' sources of competitive advantage (Dubey et al., 2019; Gupta & George, 2016). For example, Ahi et al. (2022) emphasize how advanced technological transformation helps organizational competitiveness in global markets, even though their focus is on big data analytics and industrial robots. This more comprehensive technological lens supports the claim that the use of AI is not an isolated development but rather a component of a broader digital transformation trend that signals how organizations are prepared for future competition. In addition, the adoption of AI also has unique features. According to Berente et al. (2021), managing AI necessitates addressing three interrelated aspects: autonomy, learning, and inscrutability.

Such attributes of AI increase their significance as a reliable indicator of firm capabilities while simultaneously making it a tool for improving performance. Building upon this view, Hasan and Ojala. (2024) highlights that AI technology autonomy, learning, and combinative capacities can support sustainable development and international business management practices through resource-optimization and global expansion. These distinctive characteristics imply that the adoption of AI by Foreign II not only indicates the current technological sophistication but also signals adaptability for navigating in uncertain economic environments.

Also, the contexts of institutional and national innovation systems of AI must be considered in the present debate. Lundvall and Rikap (2022) reveal that acceptance of AI technologies is accelerating among firms and institutions in China. This implies that AI-related signals are transmitted not only by organization-level decisions but also by national strategies and systemic support, which take the leading role in shaping these signals. These institutional aspects may strengthen the credibility of AI adoption as a signal for Foreign II's. Because they specify both organizational and policy-level commitment to technological development.

Prior studies emphasize how AI technologies influence the decision-making capabilities (Choi et al., 2025; Gupta et al., 2022; Jussupow et al., 2021; Shrestha et al., 2019). Plenty of evidence indicates that foreign institutional investments benefit the host country due to their positive impact on domestic firms' productivity and technology development (Buckley et al., 2002; MacDougall, 1960; Meyer & Sinani, 2009). However, there is a lack of theoretical consensus regarding the influence of AI on foreign firms' ability to adapt to market changes and invest in host firms. The potential of AI management capability is peculiar to strategic planning, strengthening relationships within and between organizations, investment decision-making, coordination, and control (Ha & Jeong, 2010; Hamet & Tremblay, 2017; Kim et al., 2011). Thus, the use of AI technologies conveys signals that indicate firms' innovation capacity and adds value to elevate firm performance (Al-khatib et al., 2024; Fatima et al., 2021; Giachino et al., 2024; Wamba-Taguimdje et al., 2020; Zhong & Song, 2025). Foreign II's often

face limited access to firm-specific information and may rely on such signals when making investment related decisions. Therefore, Foreign II's are more likely to invest in organizations that adopt AI technologies in their business operations. Hence, based on above discussions and informed by prior literature, we hypothesize.

H1. A positive association exists between AI adoption in firms and the level of Foreign II's they attract.

2.3.2. Moderating role of firm performance

AI and firm performance are strongly correlated (Giachino et al., 2024; Wamba-Taguimdje et al., 2020). AI technologies serve as a signal of long-term competitiveness and innovation (Fatima et al., 2021; Truong & Papagiannidis, 2022; Zhong & Song, 2025). Therefore, the credibility of the signals depends on the performance of the organization. Business entities that perform well are better able to interpret AI attributes such as autonomy, learning, and inscrutability into a useful competitive advantage (Berente et al., 2021). Their solid operational and financial status provides them with the managerial capabilities and required resources to pursue expensive and intricate projects (Barney, 1991; Connelly et al., 2011). Therefore, these capabilities of the organization support AI technologies to become a trustworthy signal. Furthermore, high-performing organizations provide a strategic and flexible vision that attracts Foreign II's by demonstrating AI learning and combinative capabilities for sustainable development and international growth (Hasan & Ojala, 2024).

Conversely, low-performing organizations are usually less attracted towards AI projects because AI technology adoption is considered a risky and costly investment that is challenging for firms having limited financial resources (Lee et al., 2022, 2023). Therefore, firm performance influences how Foreign II's perceive and react to AI adoption, considering it a strong signal for long-term competitiveness. Guided by these important insights, we assert that high performing firms which are adopting AI technologies tend to attract more Foreign IIs and thereby hypothesize that.

H2. Firm performance moderates the positive association between AI and Foreign II's

2.3.3. New and old firms' AI adoption and foreign II's

Firm age can affect how Foreign II's interpret technological signals and influence the adoption of cutting-edge technologies like AI. Traditional organizations frequently have established processes and hierarchies that are challenging to alter (Calvino & Fontanelli, 2023). The integration and implementation of AI technologies need the induction of technical personnel, which may spur higher transition costs and causes a reluctance among management to adapt (Khan et al., 2020; Lee et al., 2022, 2023).

In addition, old and conservative firms typically have a culture deeply rooted in traditional working methods and may see new technologies like AI as disruptive factors (Calvino & Fontanelli, 2023). Most of the employees in such firms may be uneasy with technological changes caused by AI adoption (Khan et al., 2021; Sircar et al., 2021). Furthermore, top management in these organizations are less likely to take risks and may lack confidence in the potential returns on AI-related investments, affecting strategic decision-making (Khan et al., 2021; Sircar et al., 2021). Traditional firms often lack technical education and expertise in AI and machine learning. These skills are typically more common in young tech-oriented organizations (Calvino & Fontanelli, 2023). It becomes challenging to adopt and implement AI technologies without such expertise.

Previous discussions suggest that established firms tend to be more conservative and risk-averse, often concerned about potential operational disruptions, data security risks, and the high costs associated with adopting AI. Moreover, depending on their size and sector, older firms are unwilling to adopt AI (Calvino & Fontanelli, 2023). However, Foreign II's exhibit a strong interest in the technological innovations of

host firms, showing a preference for those firms that demonstrate robust technological capabilities (Yi et al., 2023). Therefore, we postulate that old firms are less likely to adopt AI, making Foreign II's more inclined to invest in new firms that incorporate the latest technologies into their business operations. Thereby projecting stronger signals of adaptability and future orientation to Foreign II's.

H3. Old firms are established businesses with strong governance, operational processes and culture, and are unlikely to adopt evolving and less-mature AI technology.

3. Research context, data and methodology

3.1. Research context

The present empirical research investigates the association between AI and Foreign II's in the context of China as a major developing economy. China provides a unique empirical setting due to its rapid digital transformation and strong state support for artificial intelligence adoption. China is considered a developing country with a rapidly changing national innovation structure. AI growth in the Chinese context is formulated by the relationship between national innovation policies, firm-level initiatives, and industrial policies (Lundvall & Rikap, 2022). This institutional setting affects both the benefits organizations gain from adopting AI and the outcomes of such adoption as perceived by investors. However, the existence of innovation-driven regulatory policies, and strategic frameworks affect how investors perceive AI adoption by organizations (Yoon et al., 2025). Many Chinese firms are under pressure to modernize while operating in an environment characterized by high uncertainty and information asymmetry. This makes signaling especially important for firms seeking external capital.

This study focuses on A-share non-financial Chinese listed firms on the Shenzhen and Shanghai Stock Exchanges. These listed firms operate under standardized disclosure regulations but vary greatly in strategic orientation and technological capabilities. Therefore, firms AI adoption becomes a significant and meaningful signal to external investors. This organizational setting is worth investigating how AI adoption operates as a strategic signal for Foreign II's who face restrictions to access the firm-level information. The Chinese economy therefore offers an important opportunity to examine the signaling role of AI in an emerging economy where digitalization and institutional expansion are growing rapidly.

3.2. Sample data

The sample data for this study includes A-share non-financial listed Chinese firms of the Shanghai and Shenzhen Stock Exchanges. We access financial statements data from CSMAR.² The same period data for AI and foreign institutional holdings of stocks is taken from CNRDS.³ The two databases are regarded as highly reliable sources for financial statements, governance indicators, and other firm-level information. CSMAR provides statistics extracted from annual reports through the application of LM-based data mining approaches. However, CNRDS has an edge over other databases. It offers unique financial and governance information about listed firms (i.e., Percentage of Foreign Institutional Holdings and Qualified Foreign Institutional Holding QFII of Chinese firms).

The annual data is taken for 2016–2022. Annual data is considered the most reliable because external auditors audit it yearly. The reason

for taking this sample size is that the annual reports of firms rarely report on the use of AI before the Year 2016. Adding years earlier to 2016 may make our findings biased. Hence, we exclude such information. Furthermore, we exclude firms that fulfill the following criteria to make our findings more robust, i.e., ST firms, negative net assets, and negative inventories. Summary statistics of the study are provided in Table 1.

3.3. Main variables

3.3.1. Dependent variable (foreign II's)

Our main dependent variable, Foreign II's, is calculated by approximating the number of shares owned by Foreign II's to the total share capital of the firm in a given year. Foreign II's play a pivotal role in shaping the dynamics of firms by providing not only financial capital but also signaling effects that enhance firm credibility in global markets. Particularly, Foreign II's participation helps in promoting knowledge transfers across different economies. We have standardized Foreign II's before estimating regression. Standardization tends to place the predictors on a common scale, thereby allowing for more relevant comparisons of effect sizes among variables (Gelman, 2008). This study also uses the data for the qualified foreign institutional investor (QFIIs) as a proxy to check for the robustness of our baseline results.

3.3.2. Independent variable and data cleaning process

This study employs the annual data for firms' AI, as reported by CNRDS. The database has taken a data mining approach using certain fuzzy words search from the management discussions section of financial statements of firms, to calculate the variable 'Artificial Intelligence'. These words are mentioned in Appendix B. This data offers a unique approximation for the degree of transformation of a firm's digitization. For example, if the management section of a firm's annual report discusses AI more than other firms, it indicates a higher degree of AI technological adoption in operations by firms.

To operationalize firms' technological adoption, we construct a binary indicator based on the 75th percentile of the AI variable. The choice of the 75th percentile is motivated by the need to distinguish firms with a relatively higher degree of AI adoption, as reflected in the intensity of AI-related discourse in their annual reports. Firms that exceed this threshold are more likely to exhibit substantive adoption and integration of AI technologies into their operations. Accordingly, this dummy variable refers to '1' for firms above the 75th percentile, representing high AI adopters, and '0' otherwise. This threshold captures the upper quartile of AI adoption, allowing for a more meaningful differentiation between firms with significant AI involvement and those with limited or no adoption. The definitions and data sources for the rest of the control variables are presented in Appendix A.

The data-cleaning process and measurement for the AI variable is presented as follows. Firstly, the data is structured into a matrix F , where each row represents a firm i and each column shows the financial variables j for a given year t .

$$F = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1j} \\ f_{21} & f_{22} & \cdots & f_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ f_{i1} & f_{i2} & \cdots & f_{ij} \end{bmatrix} \quad (1)$$

where f_{ij} represents the financial data for the firm i in year j . In this study, we are focusing only on non-financial firms; hence, we remove the financial firms from our dataset using a diagonal matrix M , where $m_{ii} = 1$ if firm i is non-financial and $m_{ii} = 0$ otherwise. We then filter F as follows:

$$F_{\text{Non-Financial}} = M \cdot F \quad (2)$$

We proceed by removing special treatment (ST) firms, which may otherwise bias our findings. For this purpose, we apply the filter S , where $s_{ij} = 1$ if firm i is not under special treatment (ST), and $s_{ij} = 0$

² The website for Chinese Stock Market and Accounting Research (CSMAR) is www.data.csmar.com. CSMAR offers high-quality financial data of listed firms and macroeconomic data for a range of variables.

³ The website for the Chinese Research Data Services Platform (CNRDS) is www.cnrd.com. CNRDS, in addition to providing high-quality financial and governance data for listed firms, offers a wide range of survey data on various firm-specific, microeconomic, and macroeconomic variables.

Table 1
Summary statistics.

Variables	Panel A: Full Sample							
	N	Mean	SD	Min	P25	P50	P75	Max
Foreign II	10043	0.059	0.110	0.001	0.007	0.015	0.045	0.622
Artificial Intelligence	10043	0.396	0.489	0.000	0.000	0.000	1.000	1.000
Sales	10043	0.638	0.460	0.009	0.380	0.550	0.774	10.691
Leverage	10043	0.430	0.206	0.014	0.276	0.421	0.570	3.919
Cash Flows	10043	0.154	0.114	0.000	0.073	0.126	0.205	0.831
Size	10043	22.726	1.419	17.954	21.699	22.551	23.545	28.615
Current Ratio	10043	2.321	2.276	0.106	1.168	1.650	2.625	48.116
ROA	10043	0.040	0.107	−4.946	0.017	0.043	0.077	0.829
Firm Age	10043	11.198	7.983	0.000	4.000	10.000	18.000	32.000
Selling expenses	10043	0.077	0.114	0.000	0.015	0.037	0.092	4.843
Board Size	10043	2.204	0.218	1.386	2.079	2.197	2.351	3.045
Compensation	10043	14.899	0.821	9.210	14.398	14.892	15.383	18.440
CEO Duality	10043	0.016	0.124	0.000	0.000	0.000	0.000	1.000

	Panel B: AI Firms								Panel C: Non-AI Firms							
	N	Mean	SD	Min	P25	P50	P75	Max	N	Mean	SD	Min	P25	P50	P75	Max
Foreign II	3974	0.061	0.110	0.001	0.008	0.016	0.054	0.622	6069	0.057	0.110	0.001	0.006	0.014	0.040	0.622
Artificial Intelligence	3974	1.000	0.000	1.000	1.000	1.000	1.000	1.000	6069	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sales	3974	0.629	0.438	0.014	0.378	0.540	0.769	6.331	6069	0.644	0.474	0.009	0.380	0.558	0.777	10.691
Leverage	3974	0.427	0.197	0.024	0.275	0.418	0.567	2.290	6069	0.432	0.211	0.014	0.276	0.423	0.572	3.919
Cash Flows	3974	0.167	0.118	0.000	0.081	0.138	0.223	0.831	6069	0.145	0.110	0.001	0.067	0.117	0.192	0.819
Size	3974	22.775	1.436	19.485	21.713	22.570	23.568	28.293	6069	22.694	1.408	17.954	21.688	22.530	23.519	28.615
Current Ratio	3974	2.402	2.195	0.151	1.253	1.736	2.723	33.005	6069	2.267	2.326	0.106	1.112	1.601	2.567	48.116
ROA	3974	0.037	0.101	−2.071	0.017	0.043	0.075	0.786	6069	0.042	0.110	−4.946	0.016	0.042	0.079	0.829
Firm Age	3974	10.689	7.679	0.000	4.000	9.000	15.000	31.000	6069	11.531	8.160	0.000	4.000	10.000	19.000	32.000
Selling expenses	3974	0.077	0.090	0.000	0.019	0.044	0.101	0.694	6069	0.077	0.127	0.000	0.013	0.033	0.084	4.843
Board Size	3974	2.195	0.219	1.386	2.079	2.197	2.303	3.045	6069	2.210	0.217	1.386	2.079	2.197	2.351	2.970
Compensation	3974	15.025	0.811	11.632	14.510	15.001	15.499	18.143	6069	14.816	0.817	9.210	14.330	14.808	15.300	18.440
CEO Duality	3974	0.017	0.128	0.000	0.000	0.000	0.000	1.000	6069	0.015	0.122	0.000	0.000	0.000	0.000	1.000

This table reports the summary statistics of the sample data. Panels A, B, and C show the summary statistics for Full Sample, AI Firms, and Non AI Firms, respectively. The data spans from 2016 to 2022. Definitions and data sources for the variables are present in [Appendix A](#). The data cleaning process is modelled mathematically and presented in the data and methodology section of this study.

otherwise. It removes firms receiving ST and offers us a cleaned dataset as follows:

$$F_{\text{Firms}} = S \cdot F_{\text{Non-Financial}}$$

$$\text{Foreign II}_{it} = \delta_0 + \delta_1 \text{Artificial Intelligence}_{i,t} + \delta_2 \text{Age}_{i,t} + \delta_3 \text{Artificial Intelligence}_{i,t} * \text{Age}_{i,t} + \delta_4 \text{Controls}_{i,t} + \text{Year} + u_{i,t} \quad (8)$$

Furthermore, the data for AI is represented as matrix A, where each row corresponds to a firm i and each column corresponds to the year t . The elements a_{it} demonstrate the word frequency count of AI in firms' annual reports.

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1t} \\ a_{21} & a_{22} & \dots & a_{2t} \\ \vdots & \vdots & \ddots & \vdots \\ a_{it} & a_{i2} & \dots & a_{it} \end{bmatrix} \quad (3)$$

We then use a matrix A to create the dummy variable D_{AI} where "dit" is defined as follows for the binary representation of the AI used in firms.

$$d_{it} = \begin{cases} 1, & \text{if } a_{it} > 0 \\ 0, & \text{if } a_{it} = 0 \end{cases} \quad (4)$$

The final step involves merging the financial dataset F_{Firms} with our AI dummy variable D_{AI} based on firm stock codes and Year. The final dataset F_{Final}

$$F_{\text{Final}} = F_{\text{Firms}} \oplus D_{AI} \quad (5)$$

where $\oplus$ represents the merger operation using firm stock codes and years. This dataset allows us to run regressions and investigate the impact of AI use in firms to attract Foreign IIs.

3.4. Empirical methodology

We model that AI adoption by firms exerts a significant influence in attracting foreign IIs. To test our model, we employ the fixed-effect estimation technique represented by the following econometric equation:

$$\text{Foreign II}_{it} = \delta_0 + \delta_1 \text{Artificial Intelligence}_{i,t} + \delta_2 \text{Controls}_{i,t} + \text{Year} + u_{i,t} \quad (6)$$

Where Foreign II represents the Foreign Institutional Holding of Chinese stocks, i shows the firm, t represents the time, Controls denote the control variables used in the present study, and Year denotes the time-fixed effect. In equation (1), control variables are used to control unobserved factors because these factors can influence the outcomes. Aligning with the previous literature, we used turnover as a control variable because the increase in firm turnover could ultimately influence foreign investors (Zou et al., 2016). Leverage is used as a control variable because Foreign II's investment approach is influenced by safety hazards, unlike local investors. Therefore, we are expecting a negative relationship between Foreign II's and leverage. However, the firm's quick ratio, size, and current ratio also influence Foreign II's preferences to invest in a particular firm (Zou et al., 2016). Moreover, consistent with the previous studies, we further use board size, CEO compensation, and CEO duality as controls because firm internal control and governance aspects are primary factors in attracting and resisting foreign investors (Gomtsian, 2024; Hong & Linh, 2023).

$$\begin{aligned} \text{Foreign II}_{it} = & \delta_0 + \delta_1 \text{Artificial Intelligence}_{i,t} + \delta_2 \text{ROA}_{i,t} \\ & + \delta_3 \text{Artificial Intelligence}_{i,t} * \text{ROA}_{i,t} + \delta_4 \text{Controls}_{i,t} + \text{Year} \\ & + u_{i,t} \end{aligned} \quad (7)$$

In equation (7), we interact AI with return on assets (ROA) to verify hypothesis 2. However, investors are more concerned about wealth maximization and profitability (Li et al., 2016); therefore, we use ROA in our regression model. Other interpretations are similar to equation (6).

Finally, in equation (8), we used Firm Age (Age) as a moderator variable. The interaction term between AI and Firm Age represents the moderation of firm age in the setting of AI and Foreign II's of listed firms' stock. Older firms are likely to rely on traditional and less risky methods of operations in highly reliant businesses, which are likely to benefit firms (Khan et al., 2021; Sircar et al., 2021). Whereas younger firms are aggressive and have an appetite to take risks and experiment with the newly emerging technologies in their business (Calvino & Fontanelli, 2023). Hence, we moderate the impact of firm age and AI in attracting Foreign IIs to uncover interesting findings.

4. Empirical findings

4.1. Descriptive and correlation matrix

Panel A of Table 1 reveals substantial heterogeneity across firms. The summary statistics show that the mean value of AI is 0.396 and SD is 0.489, indicating that about 39.6% of firms adopt AI technologies. This further suggests that Chinese listed firms are experiencing a broader technological transformation. Although, the mean of Foreign II is 0.059 and SD is 0.110, implying that Foreign II's holds on average roughly 6% of firm equity. But, the relatively high SD indicates a considerable variation in foreign investor participation, with some firms attracting substantially greater attention than others. From the control variables point of view, the mean of firm size and firm age are 22.73 and 11.20, respectively. It suggests a broad mix of old and new firms. Whereas the mean and median of firm performance (ROA) are 0.040 and 0.043, respectively, revealing heterogeneous performance across the sample firms. However, governance indicators such as board size and CEO duality show limited variation (i.e. board size = 2.20; CEO duality = 0.016), while CEO compensation is relatively concentrated around its mean (=14.90). Overall, the full-sample statistics point to a setting where foreign institutional ownership is discreet on average and firm characteristics vary significantly. These insights provide a substantive ground for investigating how AI adoption correlates with foreign investor allocation.

Furthermore, this study presents interesting insights into the firms exhibiting AI adoption in Panel B, and no evidence of AI adoption by firms in Panel C of Table 1. The Panel B statistics revealed that Foreign II's has a mean value of 0.061 and SD is 0.110 and a median of 0.016, slightly above the corresponding figures for non-AI firms in Panel C. Especially, firm age of AI firms indicates that their mean firm age is 10.69, which is slightly lower than 11.53 of non AI firms, revealing that AI firms are younger than non AI firms. This difference extends further with respect to the executive compensations in AI (=15.025) and non-AI firms (=14.816). AI firms show a pattern of stronger liquidity than non-AI firms (i.e. 2.402 > 2.267). Hence, the summary statistics presented in Panels A, B, and C of Table 1 suggest that AI firms' cohort pools possess technological advancements, liquidity cushions with comparable median profitability, dynamic governance incentives and structures that may enhance firms' attractiveness to Foreign II's.

Table 2 reports the matrix of correlation of the sample variables. We find that AI is associated with Foreign II's. Moreover, the untabulated variance inflation factors (VIFs) for all the variables are less than five (i.

Table 2
Matrix of correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Foreign II	1.00												
(2) Artificial Intelligence	0.02	1.00											
(3) Sales	0.01	−0.02	1.00										
(4) Leverage	−0.08	−0.01	0.14	1.00									
(5) Cash Flows	0.03	0.10	0.00	−0.37	1.00								
(6) Size	−0.07	0.03	0.08	0.46	−0.18	1.00							
(7) Current Ratio	0.03	0.03	−0.14	−0.61	0.40	−0.34	1.00						
(8) ROA	0.05	−0.03	0.04	−0.42	0.19	0.05	0.16	1.00					
(9) Firm Age	−0.13	−0.05	0.07	0.29	−0.14	0.45	−0.24	−0.09	1.00				
(10) Selling Expenses	0.08	−0.00	−0.09	−0.17	0.14	−0.17	0.15	−0.01	−0.07	1.00			
(11) Board Size	−0.05	−0.03	0.02	0.18	−0.06	0.29	−0.15	−0.02	0.27	−0.04	1.00		
(12) Compensation	0.07	0.12	0.10	0.05	0.04	0.32	−0.05	0.14	0.03	0.05	0.17	1.00	
(13) CEO Duality	0.02	0.01	−0.00	−0.03	0.01	−0.05	0.03	−0.00	−0.06	0.01	−0.05	−0.00	1.00

This table demonstrates the correlation matrix of the study variables. The data spans from 2016 to 2022. Definitions and data sources for the variables are present in [Appendix A](#). The data cleaning process is modelled mathematically and presented in the data and methodology section of this study.

e. > 5), which is far lower than the critical threshold, indicating that multicollinearity is not a problem in our selected sample.

4.2. Baseline results of AI and foreign II's

[Table 3](#) presents the baseline regression results for equation (6), examining the impact of AI adoption on Foreign II's. Across all columns, the coefficient of AI adoption remains positive and statistically significant, which suggests that firms with higher AI-adoption are more likely to attract Foreign II's. The results are consistent with Hypothesis H1. This finding further aligns with the signaling theory, posits that firms adopting AI exhibits a plausible signal to Foreign II's about information transparency and firm's potential to grow, leading them to invest in such firms.

Particularly, the stepwise inclusion of firm-level controls (such as size, leverage, profitability, and governance characteristics) in columns (1) to (12) of [Table 3](#), do not diminish the robustness of the AI effect, reinforcing the argument that AI adoption constitutes a distinctive capability that strengthens firms' attractiveness to Foreign II's. In line with conjecture of this study, we find that firm age is negatively significant at 5% level, suggesting that an increase in firm age attracts less Foreign II's. This finding corroborates with previous literature ([Calvino & Fontanelli, 2023](#)), which asserts that old firms are less likely to adopt AI technologies in their business operations than young firms.

4.3. Heterogeneity analysis

[Table 4](#) present the findings for the heterogeneity analysis, which examines how relationship between AI and Foreign II's varies across different types of firms. In column (4), (5), and (8) of [Table 4](#), we find that low risk, large, and new firms respectively exhibit a strong and positive link between AI and Foreign II's. Especially, the impact is greater for new firms in column (8) of [Table 4](#) (i.e. 0.085**). The present findings validate hypothesis H3, indicating that new firms are more open to AI adoption, attracting more Foreign II's. These findings also suggest that Foreign II considers not only the adoption of AI but also the broader context of a firm's financial and strategic profile when making Foreign II's investment decisions, consistent with hypothesis H2. On the other hand, the relationship is weaker or insignificant for strong cash, weak cash, high risk, small firms, and old firms, in columns (1), (2), (3), (6), and (7) of [Table 4](#). Hence, the association between AI and Foreign II's is influenced by firm nature.

4.4. The moderating role of ROA and firm age

[Table 5](#) reports the findings of equation (7) for the moderating effect of firm performance (ROA) on the association between AI and Foreign II's. In Columns (1) and (2) of [Table 5](#), the effect of AI on Foreign II's is

positive but insignificant. However, the interaction term between ROA and Foreign II is positive and significant at 5% in columns (1) and (2) of [Table 5](#). This indicates that profitability amplifies the attractiveness of AI-related capabilities to foreign investors, i.e., AI adaptability is more highly rewarded in firms that demonstrably convert resources into returns. Furthermore, the interaction effects hold whether time fixed effects are included or not, increasing confidence in our findings. These results support the Hypothesis H2 of this study. Our findings are consistent with the previous literature, suggesting that AI and firm performance are positively correlated; however, foreign investors are more attracted to high-performing organizations ([Giachino et al., 2024](#); [Yildiz, 2021](#)).

Columns (3) and (4) of [Table 5](#) show the results for equation (8). By contrast, the interaction term between AI and Firm Age is small in magnitude but negative and statistically significant across both specifications in columns (3) and (4) of [Table 5](#). This implies that the incremental benefit of AI adoption for attracting foreign investors diminishes with firm age. Correspondingly, young firms are risk takers and embrace newly emerging technologies more quickly than old firms. Old firms may hesitate to adopt new technologies with greater reputational risks due to their less mature nature. appear to realize greater investor recognition from AI adoption than older firms do. The present results support Hypothesis H3. Consistent with previous research, the findings further indicate that older firms are less likely to adopt AI technologies than younger firms ([Calvino & Fontanelli, 2023](#)).

4.5. Robustness tests

[Table 6](#) presents quantile regression results, which are used to confirm the robustness of the baseline findings. Specifically, Columns 1, 2, and 3 in the table provide results consistent with baseline regression, indicating that the observed relationships or trends hold across different quantiles of the dependent variable's distribution, with exceptions in column (3) of [Table 6](#). The results imply heterogeneity in how foreign investors respond to AI signals: AI matters more when a firm's conditional level of Foreign II is low-to-moderate but provides little incremental explanatory power for firms that already have relatively high foreign ownership.

[Table 7](#) presents the findings of the robustness test conducted in this study to enhance the robustness of the baseline results. Dealing with Endogeneity issues is crucial, as they may arise due to omitted variables bias, reverse causality, simultaneity, and other unobserved factors. Moreover, each industry and firm's home cities have different regulations and local economic conditions. Such factors may influence the baseline findings of the present study. Therefore, we conduct several robustness tests and sensitivity tests to ensure our estimates are accurate and free from all Endogeneity biases.

Table 3
Baseline results.

VARIABLES	Foreign Institutional Investor (Foreign IIs)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Artificial Intelligence	0.0380** (0.0170)	0.0375** (0.0169)	0.0379** (0.0170)	0.0379** (0.0170)	0.0299* (0.0169)	0.0297* (0.0169)	0.0294* (0.0169)	0.0294* (0.0169)	0.0291* (0.0171)	0.0296* (0.0171)	0.0363** (0.0173)	0.0363** (0.0173)
Sales		−0.0892** (0.0389)	−0.0923** (0.0390)	−0.0925** (0.0390)	−0.0601 (0.0390)	−0.0545 (0.0391)	−0.0479 (0.0397)	−0.0479 (0.0397)	−0.0448 (0.0400)	−0.0466 (0.0401)	−0.0476 (0.0404)	−0.0475 (0.0404)
Leverage			−0.0694 (0.0664)	−0.0722 (0.0681)	−0.1620** (0.0686)	−0.1072 (0.0728)	−0.1382* (0.0801)	−0.1382* (0.0801)	−0.1315 (0.0808)	−0.1285 (0.0808)	−0.1138 (0.0814)	−0.1140 (0.0814)
Cash Flows				−0.0170 (0.0927)	−0.0482 (0.0923)	−0.0892 (0.0941)	−0.0873 (0.0941)	−0.0873 (0.0941)	−0.0876 (0.0947)	−0.0874 (0.0947)	−0.0760 (0.0959)	−0.0776 (0.0959)
Size					0.1867*** (0.0221)	0.1872*** (0.0221)	0.1920*** (0.0227)	0.1920*** (0.0227)	0.1948*** (0.0230)	0.1954*** (0.0230)	0.1980*** (0.0235)	0.1983*** (0.0235)
Current Ratio						0.0144** (0.0064)	0.0140** (0.0064)	0.0140** (0.0064)	0.0140** (0.0065)	0.0140** (0.0065)	0.0133** (0.0065)	0.0133** (0.0065)
ROA							−0.0834 (0.0898)	−0.0834 (0.0898)	−0.0841 (0.0904)	−0.0814 (0.0904)	−0.0721 (0.0909)	−0.0719 (0.0909)
Firm Age								−0.0108** (0.0046)	−0.0108** (0.0046)	−0.0109** (0.0046)	−0.0103** (0.0048)	−0.0102** (0.0048)
Selling Expenses									0.2015 (0.1328)	0.2018 (0.1328)	0.1890 (0.1342)	0.1897 (0.1343)
Board Size										−0.0783 (0.0495)	−0.0595 (0.0506)	−0.0591 (0.0506)
Compensation											−0.0101 (0.0162)	−0.0102 (0.0162)
CEO Duality												0.0223 (0.0476)
Constant	−0.0379* (0.0199)	0.0153 (0.0306)	0.0453 (0.0419)	0.0494 (0.0474)	−4.1050*** (0.4939)	−4.1712*** (0.4947)	−4.2659*** (0.5051)	−4.1855*** (0.4903)	−4.2657*** (0.4969)	−4.1066*** (0.5069)	−4.0733*** (0.5214)	−4.0784*** (0.5215)
Observations	10,296	10,296	10,296	10,296	10,296	10,296	10,296	10,296	10,165	10,165	10,043	10,043
R-squared	0.0049	0.0057	0.0058	0.0058	0.0159	0.0166	0.0168	0.0168	0.0172	0.0176	0.0182	0.0182
Number of Firms	3339	3339	3339	3339	3339	3339	3339	3339	3301	3301	3291	3291
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table shows findings for the impact of artificial intelligence adoption by firms on attracting foreign institutional investors. The dependent variable remains the same across all columns, i.e., Foreign Institutional Investor (Foreign II). Column (1) shows the individual influence of AI on Foreign II's, whereas columns (2) to (12) sequentially introduce additional firm characteristics and governance controls, allowing for a stepwise assessment of the robustness of the AI effect. The data spans from 2016 to 2022. Definitions and data sources for the variables are present in [Appendix A](#). The data cleaning process is modelled mathematically and presented in the data and methodology section of this study. Parentheses contain standard errors. Significance levels are indicated as follows: *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$.

Table 4
Heterogeneity analysis.

VARIABLES	Foreign Institutional Investor (Foreign IIs)							
	Strong Cash	Weak Cash	High Risk	Low Risk	Large Firms	Small Firms	Old Firms	New Firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Artificial Intelligence	0.036 (0.034)	0.041* (0.021)	−0.037 (0.025)	0.075*** (0.026)	0.036** (0.018)	0.020 (0.035)	−0.003 (0.012)	0.085** (0.034)
Sales	−0.141 (0.091)	0.007 (0.051)	−0.067 (0.055)	0.063 (0.072)	0.058 (0.044)	−0.165** (0.077)	0.040 (0.027)	−0.220** (0.089)
Leverage	0.128 (0.223)	−0.158* (0.095)	−0.052 (0.105)	−0.296* (0.176)	−0.150 (0.111)	0.082 (0.130)	−0.147** (0.067)	−0.034 (0.148)
Cash Flows	−0.067 (0.170)	0.098 (0.265)	−0.115 (0.119)	−0.201 (0.205)	0.068 (0.123)	−0.261* (0.154)	0.074 (0.083)	−0.078 (0.167)
Size	0.299*** (0.058)	0.124*** (0.028)	0.201*** (0.034)	0.235*** (0.043)	0.245*** (0.030)	0.241*** (0.054)	0.181*** (0.019)	0.188*** (0.046)
Current Ratio	0.021** (0.010)	−0.011 (0.010)	0.015** (0.007)	0.014 (0.023)	0.001 (0.010)	0.016* (0.010)	0.013** (0.007)	0.015 (0.011)
ROA	−0.047 (0.223)	−0.034 (0.105)	−0.060 (0.123)	−0.179 (0.211)	−0.004 (0.125)	−0.110 (0.136)	−0.104 (0.067)	0.139 (0.184)
Firm Age	−0.015 (0.011)	−0.001 (0.006)	−0.020*** (0.007)	−0.002 (0.008)	−0.004 (0.005)	−0.039*** (0.009)	−0.001 (0.003)	−0.008 (0.011)
Selling Expenses	1.048*** (0.405)	0.043 (0.139)	0.189 (0.142)	0.174 (0.420)	0.039 (0.127)	0.535 (0.338)	−0.043 (0.169)	0.221 (0.199)
Board Size	−0.133 (0.097)	−0.034 (0.063)	−0.166** (0.071)	−0.027 (0.080)	0.086 (0.054)	−0.289*** (0.095)	−0.007 (0.037)	−0.090 (0.097)
Compensation	−0.002 (0.032)	−0.043** (0.021)	0.005 (0.024)	−0.014 (0.025)	−0.023 (0.016)	−0.017 (0.036)	−0.005 (0.011)	−0.045 (0.036)
CEO Duality	0.214** (0.100)	−0.021 (0.057)	0.020 (0.066)	−0.035 (0.081)	0.081 (0.057)	0.028 (0.077)	0.003 (0.045)	0.029 (0.076)
Constant	−6.343*** (1.266)	−2.068*** (0.621)	−3.984*** (0.754)	−5.063*** (0.944)	−5.624*** (0.661)	−3.961*** (1.183)	−4.282*** (0.425)	−3.081*** (1.028)
Observations	3865	6178	5652	4391	5709	4334	4619	5424
R-squared	0.037	0.012	0.019	0.034	0.041	0.025	0.060	0.016
Number of Firms	1801	2353	2508	1792	1658	1995	1564	2172
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES

This table presents the heterogeneity analysis of the impact of firms' artificial intelligence adoption on attracting foreign institutional investors. The dependent variable remains the same across all columns, i.e., Foreign Institutional Investor (Foreign II). In columns (1) and (2), we measure the strong and weak cash firms, respectively, using the mean year-end balance of cash and cash equivalents. The above mean value characterizes '1' as strong cash firms; '0' otherwise. Moreover, in columns (3) and (4), we measure the high and low risk firms using Altman Z-score, whereas columns (5) and (6) show the large and small firms measured by taking the 75th percentile of the total assets of firms. In columns (7) and (8), we divided the sample into old and new firms by calculating the mean firm age. Firms above the mean are classified as old firms, while those below the mean are classified as new firms. The data spans from 2016 to 2022. Definitions and data sources for the variables are present in [Appendix A](#). The data cleaning process is modelled mathematically and presented in the data and methodology section of this study. Parentheses contain standard errors. Significance levels are indicated as follows: *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$.

4.5.1. System Generalized Method of Moments (GMM)

First, we apply the System Generalized Method of Moments (GMM) in column (1) of [Table 7](#). Methodologically, System GMM removes time-invariant firm heterogeneity by transforming the model using system moments. It explicitly instruments potentially endogenous regressors, including the lagged dependent variable and any contemporaneous endogenous covariates, with their own lagged levels and differences. This instrumentation reduces bias from (a) simultaneity/reverse causation (for example, where rising Foreign II's might itself induce firms to adopt more AI), (b) measurement error in the regressors (since lagged values serve as instruments), and (c) omitted time-invariant firm characteristics that correlate with both AI adoption and Foreign II's. The System GMM results provide strong evidence that the positive association between AI adoption and Foreign II's is not driven by simple omitted-variable bias, reverse causality, or dynamic panel bias.

First, the estimated coefficient on AI (0.351, significant at conventional levels) is consistent with the baseline estimate. The diagnostic statistics support the validity of this approach. The AR (1) test p -value = 0.012 indicates rejection of the null of no first-order serial correlation in the first-differenced residuals, an expected outcome in differenced panels, whereas the AR (2) test p -value = 0.698 indicates we fail to reject the null of no second-order serial correlation, which is the critical requirement for the consistency of the GMM instruments. Finally, the insignificant Hansen J test p -value = 0.927 implies that overidentifying restrictions are not violated at conventional levels. Taken together, these

diagnostics suggest that the instruments are valid and that the System GMM estimates credibly lessen the principal sources of Endogeneity in the panel. Hence, the consistency of GMM results with the baseline findings exhibit the reliability of the estimates.

4.5.2. Pooled OLS with city and industry fixed effects

The pooled OLS specification augmented with firm, time, industry, and city fixed effects yields an estimated AI coefficient of 0.036 (statistically significant), which aligns in sign and significance with the baseline result and therefore reinforces the robustness of the positive AI–Foreign II's association. By absorbing time-invariant firm heterogeneity, common temporal shocks, and persistent industry and city-level differences, this fixed-effects estimator identifies the effect from within-firm changes in AI adoption over time, thereby mitigating bias from unobserved, time-constant confounders.

The inclusion of Firm * City FE and Firm * Industry FE in Columns (3) and (4), respectively, provides a critical robustness check for our baseline findings. It accounts for unobserved, time-invariant heterogeneity at both geographic and sectoral levels. This heterogeneity could otherwise invalidate the baseline findings for the relationship between AI adoption and Foreign II's by absorbing persistent, unobserved heterogeneity at the firm level, along with any constant characteristics associated with a firm's location or sector. These specifications force identification to come from within-firm changes over time while holding city and industry-level factors constant. As a result, they (i) substantially

Table 5

The moderating role of ROA and Firm Age.

VARIABLES	Foreign Institutional Investor (Foreign II's)			
	Without Time FE	With Time FE	Without Time FE	With Time FE
	(1)	FE (2)	(3)	(4)
Artificial Intelligence * ROA	0.327** (0.145)	0.320** (0.145)		
Artificial intelligence * Firm Age			−0.004** (0.002)	−0.004** (0.002)
Artificial Intelligence	0.020 (0.018)	0.022 (0.018)	0.089*** (0.032)	0.092*** (0.032)
Sales	−0.239** (0.117)	−0.235** (0.117)	−0.077 (0.091)	−0.077 (0.091)
Leverage	−0.048 (0.040)	−0.043 (0.040)	−0.054 (0.040)	−0.048 (0.040)
Cash Flows	−0.119 (0.081)	−0.121 (0.081)	−0.113 (0.081)	−0.115 (0.081)
Size	−0.054 (0.096)	−0.068 (0.096)	−0.064 (0.096)	−0.079 (0.096)
Current Ratio	0.197*** (0.023)	0.198*** (0.023)	0.198*** (0.023)	0.198*** (0.023)
ROA	0.013** (0.007)	0.014** (0.007)	0.013** (0.007)	0.014** (0.007)
Firm Age	−0.004 (0.004)	−0.010** (0.005)	−0.003 (0.004)	−0.009* (0.005)
Selling Expenses	0.180 (0.134)	0.200 (0.134)	0.171 (0.134)	0.192 (0.134)
Board Size	−0.053 (0.051)	−0.059 (0.051)	−0.052 (0.051)	−0.058 (0.051)
Compensation	−0.009 (0.016)	−0.010 (0.016)	−0.010 (0.016)	−0.011 (0.016)
CEO Duality	0.021 (0.048)	0.020 (0.048)	0.024 (0.048)	0.022 (0.048)
Constant	−4.150*** (0.519)	−4.067*** (0.521)	−4.179*** (0.519)	−4.094*** (0.521)
Observations	10,043	10,043	10,043	10,043
R-squared	0.018	0.019	0.018	0.019
Number of Firms	3291	3291	3291	3291
Time FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

This table reports regression results examining how firm profitability (ROA) and firm age moderate the effect of artificial intelligence adoption by firms in attracting foreign institutional investors. The dependent variable remains the same across all columns, i.e., Foreign Institutional Investor (Foreign II). Columns (1) and (3) present regression estimates without time fixed effects, while Columns (2) and (4) demonstrate the findings with time fixed effects to control for temporal heterogeneity. The data spans from 2016 to 2022. Definitions and data sources for the variables are present in [Appendix A](#). The data cleaning process is modelled mathematically and presented in the data and methodology section of this study. Parentheses contain standard errors. Significance levels are indicated as follows: *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$.

reduce omitted-variable bias stemming from time-invariant firm, geographic, and sectoral attributes (for example, longstanding managerial quality, local regulatory regimes, industry technology intensity, city specific heterogeneities across firms); (ii) address the possibility that the baseline result is driven by geographic and industry clustering of AI adopters and foreign investors; and (iii) strengthen external validity by showing the effect persists under alternative controls for spatial and sectoral heterogeneity.

Additionally, this narrows the set of plausible alternative explanations for a positive AI - Foreign II's coefficient, thereby increasing confidence that observed within-firm changes in AI are associated with changes in Foreign II's. Therefore, by absorbing persistent firm-specific characteristics together with city and industry-specific fixed effects in columns (3) and (4) of [Table 7](#), the results of these high-dimensional fixed effects suggest that the coefficients are positive and significant, endorsing our baseline findings that are free from any heterogeneous biases.

Table 6

Quantile regression.

VARIABLES	Foreign Institutional Investor (Foreign IIs)		
	(1)	(2)	(3)
	25%	50%	75%
Artificial Intelligence	0.009*** (0.002)	0.012*** (0.004)	0.022 (0.031)
Sales	0.004* (0.002)	0.022*** (0.005)	0.140*** (0.033)
Leverage	−0.039*** (0.007)	−0.092*** (0.016)	−0.287** (0.112)
Cash Flows	0.022** (0.009)	0.041* (0.021)	−0.012 (0.147)
Size	0.010*** (0.001)	0.024*** (0.002)	0.035** (0.014)
Current Ratio	−0.002*** (0.001)	−0.003*** (0.001)	−0.014* (0.009)
ROA	0.080*** (0.010)	0.078*** (0.024)	0.092 (0.164)
Firm Age	−0.001*** (0.000)	−0.003*** (0.000)	−0.013*** (0.002)
Selling Expenses	0.082*** (0.008)	0.223*** (0.019)	1.399*** (0.134)
Board Size	−0.016*** (0.004)	−0.012 (0.010)	−0.012 (0.073)
Compensation	0.019*** (0.001)	0.031*** (0.003)	0.063*** (0.020)
CEO Duality	0.016** (0.007)	0.026 (0.017)	0.049 (0.119)
Constant	−0.928*** (0.022)	−1.327*** (0.051)	−1.708*** (0.350)
Observations	10,043	10,043	10,043

This table presents the quantile regression estimates for the impact of artificial intelligence adoption by firms in attracting the foreign institutional investors. The dependent variable remains same across all columns i.e. Foreign Institutional Investor (Foreign II). Columns (1), (2), and (3) shows the estimates at 25%, 50%, and 75%, respectively. The data spans from 2016 to 2022. Definitions and data sources for the variables are present in [Appendix A](#). The data cleaning process is modelled mathematically and presented in data and methodology section of this study. Parentheses contain standard errors. Significance levels are indicated as follows: *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$.

4.5.3. Sensitivity analysis

To assess the sensitivity of our results, we re-estimated our model using qualified foreign institutional investors (QFIIs) as an alternative dependent variable. This sensitivity analysis is presented in column (5) of [Table 7](#), the coefficient of AI adoption is 0.127 (significant at the 1% level), thereby reinforcing the robustness of the baseline findings. Unlike the broader category of Foreign II's, QFIIs represent a subset of professional investors who meet stringent regulatory and financial requirements and are granted direct access to China's onshore capital markets. Thus, their investment behavior is usually regarded as more sophisticated, informed, and sensitive to firm-level fundamentals. This positive association between AI and QFII strongly supports the argument that AI adoption serves as a credible signal of innovation capacity and long-term competitiveness in influencing the strategic capital allocation preferences of QFIIs. Hence, the sensitivity analysis of this study reveals that our baseline regression results are qualitatively consistent with our main analysis. Moreover, it further shows that our baseline findings are not sensitive to the choice of foreign institutional investors.

4.5.4. Moderating effect of industry concentration (HHI assets)

Although, this study results are robust to different specifications (1) GMM (2) POLS using firm, city, and industry fixed effects (3) Firm*City FE (4) Firm*Industry FE (5) alternative proxy to Foreign II's as QFIIs, still this study rely on a conventional approach in further validation of our baseline results by examining the role of industry concentration (proxied by Herfindahl–Hirschman Index HHI) in explaining the relationship between AI and Foreign II's. Column (6) of [Table 7](#) presents these

Table 7
Robustness tests.

VARIABLES	Foreign Institutional Investor (Foreign IIs)					
	GMM	POLS	Firm * City FE	Firm*Industry FE	QFII	HHI
	(1)	(2)	(3)	(4)	(5)	(6)
Artificial Intelligence	0.351** (0.164)	0.036** (0.017)	0.036** (0.017)	0.034* (0.017)	0.127*** (0.032)	0.017 (0.019)
AI * HHI Assets						0.289* (0.153)
Sales	0.074 (0.328)	−0.041 (0.041)	−0.048 (0.040)	−0.027 (0.041)	−0.041 (0.035)	0.017 (0.023)
Leverage	0.603 (1.181)	−0.109 (0.082)	−0.114 (0.081)	−0.040 (0.083)	−0.161 (0.116)	−0.143** (0.064)
Cash Flows	0.024 (0.890)	−0.115 (0.097)	−0.078 (0.096)	−0.101 (0.097)	−0.402*** (0.144)	−0.022 (0.079)
Size	0.321 (0.445)	0.227*** (0.024)	0.198*** (0.023)	0.255*** (0.025)	0.006 (0.016)	0.067*** (0.011)
Current Ratio	−0.274 (0.217)	0.012* (0.007)	0.013** (0.007)	0.015** (0.007)	−0.007 (0.009)	0.001 (0.005)
ROA	3.962 (3.641)	−0.057 (0.092)	−0.072 (0.091)	−0.051 (0.095)	0.802*** (0.202)	0.009 (0.076)
Firm Age	−0.052 (0.137)	−0.013*** (0.005)	−0.010** (0.005)	−0.014*** (0.005)	0.019*** (0.002)	−0.011*** (0.002)
Selling Expenses	3.764 (3.367)	0.177 (0.135)	0.190 (0.134)	0.195 (0.135)	0.537*** (0.162)	0.396*** (0.089)
Board Size	−4.529 (3.298)	−0.056 (0.051)	−0.059 (0.051)	−0.055 (0.051)	−0.133* (0.076)	−0.080* (0.041)
Compensation	−0.122 (0.776)	−0.011 (0.016)	−0.010 (0.016)	−0.015 (0.016)	0.178*** (0.022)	0.039*** (0.013)
CEO Duality	2.053 (3.604)	0.027 (0.048)	0.022 (0.048)	0.023 (0.048)	0.158 (0.114)	0.022 (0.046)
Foreign II ($t - 1$)	0.936*** (0.155)					
HHI Assets						−0.123 (0.126)
Constant	4.354 (7.914)	−4.631*** (0.643)	−4.052*** (0.523)	−5.282*** (0.563)	−2.534*** (0.375)	−1.933*** (0.255)
Observations	5994	9121	9121	9045	4115	10,043
R-squared	2126	0.846	0.843	0.847	0.061	
Firm FE	YES	YES	-	-	-	YES
Time FE	YES	YES	-	-	YES	YES
Industry FE	-	YES	-	-	-	-
City FE	-	YES	-	-	-	-
Firm * Industry FE	-	-	-	YES	-	-
Firm * City FE	-	-	YES	-	-	-
Arellano-Bond test for AR(1)	0.012	-	-	-	-	-
Arellano-Bond test for AR(2)	0.698	-	-	-	-	-
Sargan Test	0.993	-	-	-	-	-
Hansen test	0.927	-	-	-	-	-

This table serves as a robustness test for our baseline findings, i.e., the impact of artificial intelligence adoption by firms in attracting foreign institutional investors. The dependent variable remains the same in columns (1), (2), (4), (5), and (6), i.e., Foreign Institutional Investor (Foreign IIs). In column (3), we take the Qualified Foreign Institutional Investor QFII as a dependent variable, rendering it as a sensitivity analysis. Column (1) shows the results after employing the Two-Step System Generalized Method of Moments (GMM). Column (2) presents the findings after employing Pooled OLS with Firm FE, Time FE, Industry FE, and City FE. Column (3) and (4) demonstrates the estimates after employing Firm * City FE and Firm * Industry FE, respectively. Column (5) presents the sensitivity analysis for our baseline findings, using the Qualified Foreign Institutional Investor (QFII) as a dependent variable. At the same time, column (6) reveals the findings for the moderating effect of industry concentration (i.e., Herfindahl-Hirschman Index HHI) in influencing the relationship of artificial intelligence adoption by firms and the foreign institutional investors. The data spans from 2016 to 2022. Definitions and data sources for the variables are present in [Appendix A](#). The data cleaning process is modelled mathematically and presented in the data and methodology section of this study. Parentheses contain standard errors. Significance levels are indicated as follows: *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$.

findings for the moderating role of industry concentration. The results indicate that the interaction between AI adoption and HHI is strongly positive and significant (i.e. 0.289 at 10%), whereas the independent effects of AI and HHI alone are insignificant. This pattern suggests that neither AI adoption in isolation nor industry concentration by itself suffices to attract Foreign II's instead, the impact emerges when the two factors operate jointly.

Furthermore, these findings show that in concentrated industries, the effect of AI adoption on Foreign II's becomes stronger. This implies that AI is valued by foreign investors, particularly in settings where firms hold relatively larger shares of industry assets and thus possess stronger competitive positions. Overall, it underpins the robustness of the AI-Foreign II's association and highlights that the attractiveness of AI

adoption by firms, to foreign investors is improved in industries characterized by higher concentration levels.

5. Discussion of results and implications

This study examines the role of Firm's AI adoption in attracting Foreign II's. Leaning on signaling theory, we theorize on how firm's strategic decision of adopting AI would impact the foreign investments by Foreign II's. By inspecting the significant role of AI in firms ([Fatima et al., 2021](#); [Zhong & Song, 2025](#)), we argued that AI adoption by firms improves decision-making processes, firm competitiveness, and thereby serves as a signal to Foreign II's in several important ways. (1) Institutional investors are forward-looking entities that are seeking both

stability and growth opportunities in an increasing competitive and information asymmetric environment (Gomtsian, 2024; Hong & Linh, 2023; Zou et al., 2016). Since, AI adoption by firms enhances the decision-making processes, and boosts the firm's ability to scale its operations. Consequently, investors' perception of adopting AI in firm operations changes plausibly and plays a decisive role to invest in such firms. The result of current study corroborates with this understanding and reveals a significant positive association between AI adoption and Foreign II's. (2) In addition to that, the heterogeneity analysis demonstrates that baseline effect is more pronounced in low risk, large and new firms. Large firms have better resources, which allow AI technologies to be scaled effectively, thereby maximizing their potential to drive higher gains. Also, the findings of this study show strong evidence that high performing firms tend to play a positive moderating role between AI and Foreign II's. Building upon the signaling aspect, this finding is important to understand that AI followed by a strong firm performance, exhibits a more credible signal to Foreign II's for investments. It portrays that AI adoption by firms offers a tool for mitigating the information asymmetries that often prevent Foreign II's from committing capital to emerging market firms.

In addition to that, this study attempts to undertake the moderating role of firm age in influencing the relationship between AI and Foreign II's. We reveal that this effect is negative and offer potential explanations for such findings. First, previous literature stipulates that young firms are likely to invest more in R&D when entering new markets (Czarnitzki & Kraft, 2004) than incumbents (older firms). However, it is riskier for new firms to take up such investments. Coad et al., 2016 disentangles this phenomenon and find that young firms face larger performance benefits from R&D at the upper quantiles but face larger decline at the lower quantiles. Secondly, such young and new firms are quick in adopting new technological tools (BarNir et al., 2003; Calvino & Fontanelli, 2023), to increase productivity (Lawless & Rehill, 2025).⁴ Unlike old firms, new firms may lack long operating histories, reputational capital, and established disclosure practices. Therefore, AI adoption plays a significant signaling role in bringing information transparency to the firms and helps them to project credible information to Foreign II's. In view of the above discussion, the negative moderating role of firm age in impacting the association between AI and Foreign II's confirms this mechanism. Conclusively, our findings highlight the signaling role of AI adoption (Fatima et al., 2021; Zhong & Song, 2025) and show how technology is viewed and accepted by new and old firms. Hence, adoption of AI by firms to attract Foreign II's negatively moderates by firm age and positively by the firm performance.

5.1. Theoretical implications

This research provides various theoretical implications. The findings of the study extend the signaling theory by emphasizing the importance of AI as a reliable signal for investment purposes. Particularly, these AI signals are more important in the situation where asymmetric information is higher (i.e., younger organizations). In addition, the present findings demonstrate that AI-related signals are not always constant. The reliability of signals depends upon firm-level characteristics that include profitability and the degree of firm risk. In this way, the investors' response may increase or decrease by considering these firm-level characteristics. Therefore, this research indicate that top-management in Chinese organizations should consider the importance of AI as a strategic tool to attract foreign investors. Moreover, the findings of the study indicates that AI adoption in younger organizations

is an important mechanism to establish credibility in the opinion of foreign investors. These AI signals built trustworthiness where firms lack long historical presence in the market. However, large and profitable organizations can also adopt AI technologies to further enhance their signaling strength to guarantee long-term foreign inflows.

5.2. Policy implications

The findings of the present study provide various implications for policymakers. The policymakers should promote the responsible use of AI at firm-level. They should create benefits and provide the required assistance to organizations to promote responsible use of AI, particularly in younger organizations and new startups. However, older organizations are less likely to adopt AI, because such organizations have more data privacy issues, and shortage of required technical personnel (Khan et al., 2021; Sircar et al., 2021). Therefore, policymakers need to maintain a secure data ecosystem and promote responsible AI to target both new and older organizations. This might help in attracting potential foreign investors and further improve domestic capital markets.

Moreover, the findings of the study suggest that investors shouldn't only evaluate the use of AI in the organizations but also monitor how efficiently they integrate it into their business operations. Adoption of AI technologies without considering their efficient and responsible use may not always produce required results. The credibility of AI signals is improved when integrated with firm financial performance and sound attributes. For financial advisors, these findings are beneficial to understand that AI technology disclosures should be assessed with both organization performance and risk elements to better evaluate which organization is fairly adopting AI as a strategic tool to attract foreign investments. In conclusion, the results of the present research emphasize that adoption of AI is not only a key factor for business operations but also considered an important determinant of international asset allocation. Aligning with the signaling viewpoint, the findings of the present study acknowledge how technological expertise redefines the organization internal strengths and performs externally as reliable signals that mitigate asymmetric information and encourage investments from Foreign II's.

6. Conclusion, limitations, and future research directions

AI technology is an emerging concept in current business setups and is also known as a rising industry. In previous years, the development of AI technologies has significantly contributed to business operations. Recent studies add some interesting outcomes in the existing literature related to AI, firm performance, and risk-taking (Sullivan & Wamba, 2024; Chen et al., 2024), but none of them explored the outcomes of AI on Foreign II's. From a novel approach, the present research paper attempts to uncover the impact of AI on attracting foreign investors to invest in Chinese-listed firms. Our findings reveal that AI-powered firms attract more Foreign II's. Moreover, the findings demonstrate that profitable firms with AI technologies attract more Foreign IIs in Chinese listed firms. Finally, our study shows that firm age is essential in Chinese listed firms. Old firms are less attractive to the Foreign II's than younger firms because young firms are more interested in incorporating AI technologies into their business models. Our findings hold after employing several robustness tests.

Although the primary focus of the present research is on the economic and strategic signaling role of AI technology adoption. It is crucial to recognize that the advantages of AI adoption at the organizational level extend beyond financial gains. Adoption of AI affects workforce dynamics, ethical obligations, organizational structures, and decision-making procedures. Therefore, to actively participate in technological developments and contribute to sustainable value creation projects while avoiding unintended adverse outcomes. The organizations must responsibly organize the autonomy, learning capacity, and inscrutability of AI-related procedures (Berente et al., 2021; Hasan & Ojala, 2024).

⁴ By using the Spanish firms data from 2004 to 2011, Pellegrino (2018) finds that young firms have human expertise in driving the innovation projects. Additionally, research on organizational behavior indicates that investment efficiency significantly deteriorates with growing firm age (Ushijima, 2025) The study reveals that young firms are more efficient in investing than older firms.

Understanding these broader prospects, it assists organizations in considering both strategic and responsible approaches when adopting AI technologies.

6.1. Limitations of the study

The present study has various limitations that need to be considered when interpreting the findings. First, there are still many unanswered questions regarding its practical implications. Until now, there are no concrete laws controlling how AI tends to operate or ensuring it doesn't go against the moral principles of society (Dignum, 2018; Hooker & Kim, 2019). In addition, several organizations, such as IEEE and CERN, have initiated debate and released guidelines to help researchers and developers create ethical and intelligent systems (Hooker & Kim, 2019; Davis John, 2005).

Second, AI variable is measured using disclosures of AI related words in the annual reports of Chinese firms. This technique expresses whether firms report AI in the annual reports but doesn't fully capture the actual implementation of AI in their business operations. While some organizations might underreport their adoption of AI technologies, others may deliberately use AI related terms without having significant AI abilities. Third, we must admit that AI is still in its early phases of development. However, the present research is limited to A-share Chinese non-financial listed organizations that operate inside China's unique institutional and innovation structure. The findings of this research might not be generalized to other nations having different levels of technical maturity and legal frameworks. Finally, this study doesn't differentiate between various kinds or levels of AI technologies; therefore, the present analysis cannot fully capture the difference in AI scale, sophistication among firms. We anticipate that more researchers will explore the macroeconomic effects of AI adoption in future studies. This text also examines the best ways to create policies that mitigate the enormous impacts of technological change, ensure society benefits from AI technologies, and help individuals appropriately understand the opportunities and risks associated with AI.

6.2. Future research directions

This study focuses on strategic signaling for firm's adoption of AI in attracting Foreign II's. In light of our findings, future researchers may like to inspect the credibility of AI adoption signals. First, do Foreign IIs respond differently to symbolic AI related disclosure practices versus actual AI investments, such as AI-skilled personnel development, patents or dedicated AI spending? A second interesting research question for future studies is to look at how different kinds of AI systems impact investor perceptions and business outcomes. Compared to AI technologies primarily focused on operational efficiency, investors are likely to receive stronger signals from AI technologies used in strategic decision-

making, such as forecasting, international operations, and risk management. Modern AI technologies have characteristics that demonstrate their legitimacy, and elevate their strategic value, such as autonomy, learning capability, and integration into core business processes (Berente et al., 2021; Hasan & Ojala, 2024). Future research could use these attributes to categorize AI adoption and evaluate how different kinds of AI technologies affect company performance, and investment decisions. Third, cross-national and institutional comparisons provide a significant research direction. The signaling importance of AI is more likely to vary across national contexts due to dissimilarities in legal settings, governmental interference, and innovation systems. In market-oriented economies, investors may trust more on firm-level evidence of AI capacity, but if it's a coordinated innovation framework like China, government backing might enhance the legitimacy of AI signals (Lundvall & Rikap, 2022). Comparative studies can be beneficial to clarify how investors' perceptions of AI related signals are influenced by institutional context.

CRediT authorship contribution statement

Talat Mehmood Khan: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Muhammad Awais Khan:** Writing – review & editing, Validation, Software, Resources, Investigation, Data curation. **Boris Popesko:** Writing – review & editing, Supervision, Project administration.

Ethics approval

This research didn't involve any human and animal related data. Therefore, no need to take any ethical approval.

Financial interests

The authors have no relevant financial or non-financial interests to disclose.

All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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Appendix A. Definitions of the variables

Name	Definitions	Sources
Foreign II	Foreign institutional investors holding percentage of unrestricted tradable A Shares	CNRDS
Artificial Intelligence	Calculated using the LM model by the number of appearances of word mentions in the annual report	CNRDS
Sales	Sales/Total Assets	CSMAR
Leverage	Total Liabilities/Total Assets	CSMAR
Cash Flows	Cash flows relative to total assets	CSMAR
Size	Log of Total Assets	CSMAR
Current Ratio	Current Assets/Current Liabilities	CSMAR
ROA	Net Profit/Total Assets	CSMAR
Firm Age	Age of the firm since its listing year	CSMAR
Selling Expenses	Selling expenses relative to the total sales	CSMAR
Board Size	Ln (number of board members)	CSMAR
Compensation	Compensation of directors	CSMAR
CEO Duality	A dummy variable '1' if the CEO holds both positions of CEO and Chairman, otherwise '0'	CSMAR

Appendix B. Fuzzy words search for AI Technology

Variable	Identification by words
Artificial Intelligence	Artificial Intelligence, AI, Authentication, Biometrics, Business Intelligence, Deep Learning, Face Recognition, Image Understanding, Intelligent Data Analysis, Intelligent Robot, Machine Learning, ML, Natural Language Processing, NLP, Large Learning Models, LLM, Semantic Search, Speech Recognition

Data availability

Data will be made available on request.

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