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Building the efficiency bridge: Artificial intelligence innovation, high-growth firms and industry competition through governance

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ABSTRACT

High-growth firms serve as vital drivers of economic vitality; however, sustaining their rapid growth remains a formidable challenge. Although researchers widely regard artificial intelligence (AI) innovation as a key competitive advantage, the specific mechanisms through which it fosters high-growth firms remain underexplored. We analyse 20,178 firm–year observations from China (2007–2022) using technology affordance actualisation theory to investigate this relationship. Results show that AI innovation drives high growth primarily by enhancing firm efficiency. Particularly, we identify a critical contingency: the intensity of industry competition negatively moderates the effect of AI innovation on firm efficiency. A novel finding reveals that board size conditions whether this moderating effect persists. Specifically, industry competition undermines efficiency gains only in firms with small boards, thereby hindering high growth. By contrast, large boards nullify this negative effect, enabling AI innovation to drive firms towards high-growth status even under competitive pressure. Our study theoretically advances the literature by elucidating the contingent role of industry competition and establishing board size as a crucial governance mechanism that determines the success of AI innovation in promoting high growth.

Introduction

High-growth firms—defined by the Organisation for Economic Co-operation and Development (OECD) as firms achieving over 20 % annual revenue growth for three consecutive years (OECD, 2007)—function as vital engines of job creation and economic dynamism, attracting considerable practical, policy and scholarly attention (Araki et al., 2024; Belitski et al., 2023a; Duruflé et al., 2018; Jansen et al., 2023). Sustaining high growth presents a formidable challenge: only 12 % of firms worldwide achieve this level, with the proportion even lower in emerging economies[1], due to resource constraints and environmental limitations (Audretsch et al., 2024; Bohan et al., 2024; Coad, 2009; Garnsey & Heffernan, 2005; Jansen et al., 2023). Prevailing literature predominantly attributes high growth to rare resources (Gartner & Moro, 2024; Iurkov et al., 2023; Kotha et al., 2022), firm attributes (Audretsch et al., 2024; Belitski et al., 2023b) or favourable environmental factors, often portraying it as a privilege for well-resourced incumbents. This resource-centric perspective, however, leaves a critical theoretical gap: it fails to explain the rise of 'obscure players' like ByteDance and Scale AI, which achieved hypergrowth despite lacking traditional advantages. In today's competitive and resource-constrained landscape, what enables such firms to become high-growth firms? This question remains underexplored (Coviello et al., 2024; Jansen et al., 2023; Palmié et al., 2023).

Artificial intelligence (AI) innovation serves as a key competitive advantage and presents a promising yet unclear solution (Acemoglu & Restrepo, 2018; Chalmers et al., 2021; Kemp, 2024; Liu et al., 2024). Although recent studies have begun examining AI's influence on firm development, they primarily focus on short-term outcomes such as firm performance (Babina et al., 2024; Liu et al., 2024) and employment (Yang, 2022). A significant gap exists in understanding whether and how AI innovation fosters the sustained, rapid growth characteristic of high-growth firms—a process that reflects a firm's sustained competitive advantage (Bohan et al., 2024). Therefore, our study addresses a pivotal question: How do firms aiming for high-growth status benefit from AI innovation?

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[1] https://www.mckinsey.com.cn/wp-content/uploads/2023/02/the-state-of-ai-in-2022-and-a-half-decade-in-review.pdf

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To answer this question, we draw on technology affordance actualisation theory. The theory suggests that AI innovation continuously improves the autonomy, interactivity and adaptability characteristics of AI (Liu et al., 2022; Majchrzak et al., 2016; Wallach & Allen, 2008). These improvements enable firms to continuously acquire value, thereby creating latent potential for achieving high growth. Additionally, this theory posits that a firm's ability to capture value from AI innovation depends not only on technological affordance but also on the surrounding industry environment (Ma et al., 2024; Yao et al., 2024). This concept is particularly relevant in emerging markets, such as China, where high industry uncertainty and weak regulatory frameworks hinder firms from fully capitalising on innovation (Yao et al., 2024). Furthermore, existing research has overlooked the moderating role of industry competition—such as technology diffusion across industries and technological imitation by competitors (Belitski et al., 2023b)—in shaping the influence of AI innovation. This gap hinders the development of actionable strategies for leveraging AI innovation in diverse competitive contexts.

To address these gaps, this study utilises 20,178 firm–year observations from firms listed on the Shanghai and Shenzhen Stock Exchanges in China from 2007 to 2022. Our primary objective involves testing a model that clarifies how AI innovation fosters high growth through the mediating mechanism of firm efficiency, and under what conditions this effect holds by examining the moderating role of industry competition. In this approach, we aim to provide a nuanced understanding of how and under what conditions AI innovation serves as a catalyst for sustained high growth.

Theoretical background

AI innovation: characteristics and outcomes

At present, scholars commonly distinguish AI into two dimensions: AI innovation and AI application. Although these two dimensions substantially differ, existing literature rarely draws a clear distinction between them. AI application refers to the extent to which enterprises implement and utilise existing, mature AI technologies across production, operational and managerial processes (Lin et al., 2024). The central objective of this dimension lies in leveraging readily available technologies to optimise specific workflows, enhance operational efficiency or achieve predetermined goals, typically without engaging in original innovation of core technologies. Research in this domain primarily focuses on how AI technologies enhance short-term performance metrics and transform employment structures (Babina et al., 2024; Liu et al., 2024; Yang, 2022).

However, the research perspective on AI application overlooks technological origins, thereby offering limited insights into how firms cultivate disruptive long-term competitive advantages and fundamental growth through pioneering and uncertain R&D activities. In contrast with the utilisation-focused nature of AI application, AI innovation reflects a firm's level of independent R&D efforts within AI-related technological fields (Yang, 2022). This dimension encompasses R&D in foundational, core and general-purpose technologies, with outcomes typically manifesting through patent applications, academic publications and R&D expenditures (Czarnitzki et al., 2023; Yao et al., 2024). AI innovation, a more advanced and specialised form of technological innovation, constitutes a critical component of enterprise innovation (Berente et al., 2021). Moreover, AI innovation entails greater risk and uncertainty compared with conventional innovation or even AI application (Babina et al., 2024), given that it involves venturing into uncharted technological territories. Furthermore, AI innovation provides the foundation for internal AI applications, supports the sustainable development of AI and generates far-reaching effects (Yao et al., 2024). Accordingly, we define AI innovation as enterprise-led R&D activities focused on foundational, core and general-purpose AI technologies, while excluding the application of existing AI technologies. This delineation centres our research on the origin of value creation—specifically, how firms achieve enduring competitive advantages and fundamental growth by generating new technological affordances. This approach distinguishes our work from the stream of literature primarily concerned with short-term benefits derived from AI application. Despite these insights, a research gap remains in understanding why some firms capture value from AI innovation more effectively and sustainably than others.

Technology affordance actualisation theory in AI context

Technology affordance actualisation theory—comprising technology affordance and affordance actualisation (Liu et al., 2022; Majchrzak et al., 2016)—provides a theoretical foundation for assessing how firms capture value from AI and how AI interacts with organisations. This theory defines technology affordances as the potential actions that individuals or organisations can undertake with a technology to achieve specific goals. The possibilities a technology offers vary depending on its users and objectives (Liu et al., 2022; Majchrzak et al., 2016). Although AI affordances can drive innovation and create value, the ability to capture value from AI innovation significantly varies (Yao et al., 2024). Therefore, technology affordance actualisation theory closely aligns with our research question, enabling us to examine why different innovators achieve varying outcomes when adopting the same AI technology.

Technology affordance actualisation theory posits that the value firms capture from AI innovation depends not only on technological accessibility but also on the industry environment (Ma et al., 2024; Yao et al., 2024). This notion proves especially relevant in emerging markets, where high industry uncertainty and weak regulatory frameworks require AI to help firms overcome industry barriers and drive high growth (Coviello et al., 2024). Investigating the interaction between AI innovation and industry competition helps explain why some firms benefit more from AI than others.

Thus, we use technology affordance actualisation theory to reveal the relationship between AI innovation and high-growth status and the interaction between firms and their industry competition environments.

Hypothesis development

AI innovation and high-growth firms

Drawing on technology affordance actualisation theory (Liu et al., 2022; Majchrzak et al., 2016), we propose that AI innovation continuously improves the autonomy, interactivity and adaptability of AI (Wallach & Allen, 2008). This advancement allows firms to acquire value continuously, thereby creating latent potential for achieving high growth. This theoretical framework is particularly suitable for examining how enterprises leverage AI-driven innovation to foster growth. The extent to which firms translate AI affordances into tangible value depends not only on the objective properties of the technology but also on the subjective initiatives of organisations through goal-oriented actualisation behaviours. Firms can recurrently capture value from AI innovations by continuously leveraging these affordances, thereby facilitating their evolution into high-growth enterprises. Firstly, AI innovation imparts autonomy to machine equipment (Kim & Lee, 2025; Shen et al., 2025). Intelligent machine systems perform certain production tasks, which minimises human involvement in the production process. This autonomy facilitates the intelligent and automated transformation of traditional production processes, thereby increasing firm-level output (Babina et al., 2024; Brynjolfsson & Mitchell, 2017; Hughes et al., 2025; Yao et al., 2024) and supporting high-growth development (Bohan et al., 2024; Jansen et al., 2023). Secondly, AI introduces technologies that facilitate human-like interaction, including natural language processing, computer vision and machine learning. These technologies support autonomous decision-making in specific scenarios via interaction with and self-learning from the external environment (Sjödin et al., 2021; Yang et al., 2025). This interactivity significantly enhances the efficiency of enterprise operations and management (Gregory et al., 2021), thereby facilitating high growth. Thirdly, AI frequently encounters challenges such as difficulties in understanding 'tacit knowledge', model vulnerability and generalisation problems (Townsend et al., 2025). AI innovation continuously enhances AI's adaptability to diverse contexts through algorithm iterations and knowledge base updates to overcome these challenges (Li et al., 2024). Accordingly, the autonomous, interactive and adaptive affordances generated by AI innovation equip firms with systematic capabilities to optimise operational processes, enhance decision-making quality and adapt to dynamic market conditions, consistent with the core logic of technology affordance actualisation theory. Firms can significantly increase value capture by leveraging and actualising these technological properties within specific operational and managerial practices, thereby building a sustained competitive advantage that ultimately manifests as high growth. Thus, we hypothesise the following:

Hypothesis 1. AI innovation positively affects the likelihood of a firm achieving high-growth status.

Mediating role of firm efficiency

Technology affordance actualisation theory provides an appropriate framework for understanding how firms leverage AI innovation to achieve high growth. AI innovation introduces new technologies that create affordances—action possibilities rooted in AI's objective characteristics—which directly enhance the potential for firms to achieve high-growth status. The extent to which these affordances are transformed into tangible outcomes depends on firms' subjective agency, particularly their goal-oriented affordance actualisation behaviours. AI affordances indirectly foster sustained competitive advantages and growth by enhancing operational efficiency. The theory emphasises that the connection between technological affordances and eventual outcomes must be established through acts of actualisation. In this study, firm efficiency constitutes the central mechanism through which AI affordances are actualised, translating technological potential into sustainable competitive advantages. This process represents the means by which firms materialise the potentialities promised by AI technology. We define AI affordance as the potential enabled by AI innovation, actualisation as the integration of AI into firm operations and performance as the attainment of high growth; this follows the 'technological affordance–actualisation–performance' logic (Liu et al., 2022; Majchrzak et al., 2016).

Drawing on Wallach & Allen (2008), we propose that AI innovation enhances efficiency primarily through three affordance types: autonomy, interactivity and adaptability. Autonomous affordance reflects AI's ability to perform tasks with minimal human intervention, offering significant efficiency potential (Ma et al., 2024). AI innovation helps produce advanced technologies that autonomously learn from and integrate diverse knowledge embedded in large-scale text data, constructing complex networks of linguistic patterns and concepts. This innovation enables the revitalisation of underutilised resources and improves resource efficiency, thereby reducing costs and boosting productivity (Issa et al., 2022). Additionally, AI can autonomously analyse massive image and video datasets to extract visual patterns, identify issues from input data, predict future outcomes and make real-time adjustments. AI continuously self-optimises and improves operational efficiency through these interactions with external environments (Goel & Gupta, 2020).

Interactive affordance lies in AI's capability to efficiently collect, identify and transmit information using industrial big data (Issa et al., 2022). AI-driven machine learning algorithms automate data collection and iterative analysis (Li et al., 2024), enhancing decision-making at the management level and operational capabilities amongst employees. This framework improves internal business processes and increases efficiency in economic activities. Furthermore, real-time analysis of market trends and customer data enables precision marketing, allowing firms to effectively understand market conditions and promptly respond to dynamic changes.

Adaptive affordance appears in AI's ability to facilitate efficient cross-functional collaboration (Giustiziero et al., 2023). AI innovation provides scalable resources—such as automated workflows and modular processes—that help integrate internal departments and promote information sharing. This innovation strengthens collective task performance (Briscoe & Rogan, 2016), enabling firms to quickly adapt to diverse scenarios (Wang et al., 2024), thereby enhancing overall operational efficiency (Giustiziero et al., 2023).

Case studies confirm the efficiency gains driven by AI innovation. For example, Baosteel's intelligent blast furnace, developed using digital twin technology, optimised process parameters, resulting in a 15 % reduction in energy consumption and a 33 % decrease in equipment downtime. Xiangtan Steel, a subsidiary of Hualing Steel, implemented the world's first AI large model in the steel industry, enabling full-process intelligence from raw material procurement to finished product delivery. This mechanism shortened the development cycle for new steel grades by 30 % and reduced R&D costs by 25 %.

Furthermore, this enhanced efficiency plays a crucial role for firms striving to achieve high growth, as highlighted in previous research (Bohan et al., 2024; Chalmers et al., 2021; Jansen et al., 2023). Enhanced operational efficiency constitutes a fundamental driver for sustaining competitive advantage and facilitating scale expansion (Bohan et al., 2024). Firms with enhanced efficiency can deliver products or services at reduced costs, thereby capturing increased market share and generating resources for reinvestment—a hallmark of high-growth trajectories (Coviello et al., 2024; Jansen et al., 2023). Accordingly, such firms are well positioned to expand their market share and accelerate revenue growth. For example, enhanced production and operational efficiency in the manufacturing sector not only helps firms reduce unit costs but also improves their responsiveness to market fluctuations, such as surges in demand or shifts in customer preferences. This approach enables firms to gain a sustainable competitive edge through price leadership or timely delivery and product customisation (Bohan et al., 2024; Coad, 2009). In summary, these advantages contribute to a firm's capacity for sustained high growth. Thus, we hypothesise the following:

Hypothesis 2. Firm efficiency mediates the positive relationship between AI innovation and the likelihood of a firm achieving high-growth status.

Moderating effect of industry competition

Although the earlier discussion suggests that AI innovation supports the evolution of firms into high-growth entities, in practice, only some firms achieve high growth through AI innovation, whereas others with comparable innovation levels do not. Teece (2018, p. 1370) asserted that 'these circumstances render profiting from innovation complex and difficult', emphasising the need for policymakers and courts to understand the challenges of value appropriation. On this basis, several scholars have argued that the ability to capture value from AI innovation depends not only on technological availability but also on the surrounding industry environment (Ma et al., 2024; Yao et al., 2024). This notion is particularly relevant in emerging markets, such as China, where high industry uncertainty and weak regulatory frameworks hinder firms from benefiting from innovation (Yao et al., 2024). Therefore, the interaction between AI innovation and the industry environment determines whether a firm can achieve high growth.

Building on existing research, we posit that industry competition influences the efficacy of AI innovation through two key channels: accelerating technology diffusion and imposing resource constraints.

Firstly, drawing upon the research of Belitski et al. (2023b), intense industry competition fosters technological imitation and knowledge spillover, thereby eroding the appropriability regime and diminishing the returns available to innovators. The empirical analysis presented by Ma et al. (2024) demonstrated that firms in highly competitive market environments encounter significant challenges in translating innovation investments into sustainable competitive advantages, as competitors compress profit margins and imitators rapidly emerge. Consequently, other firms may quickly acquire the new knowledge generated through AI innovation, making it difficult for the original innovators to develop unique competitive advantages. This situation hinders efficiency gains and reduces the likelihood of enterprises becoming high-growth firms.

Secondly, industry competition can exacerbate resource constraints, forcing enterprises to make substantial efforts to safeguard their resources (Belitski et al., 2023b). Research shows that as industry competition intensifies, enterprises reallocate resources from high-risk activities to more stable ones (Bustamante, 2015), such as advertising or promotional activities (Chen et al., 2024; Martin & Javalgi, 2016). Accordingly, enterprises may apply the scalable resources generated through AI innovation only to conservative traditional scenarios rather than more promising new ones. This shift hinders efficiency improvements and reduces the likelihood of achieving high-growth status.

Thirdly, firms in environments with low industry competition face fewer decision-making challenges (Giroud & Mueller, 2011), which creates numerous opportunities for performance growth (Chang & Rhee, 2011). Accordingly, firms have sufficient resources and market space to leverage AI innovation for enhancing efficiency and subsequent high growth. Conversely, firms must work harder to protect their resources when industry competition increases; this pressure requires firms to maintain strategic consistency by pursuing short-term competitive advantages and unified resource allocation to manage intense competitive pressures (Belitski et al., 2023b; Bustamante & Donangelo, 2017). This strategy significantly reduces firm efficiency, making it challenging to achieve high growth. Accordingly, industry competition is expected to weaken the efficiency-enhancing effect of AI innovation and, in turn, reduce the strength of the indirect pathway through which AI innovation promotes high-growth outcomes via firm efficiency. As illustrated in the theoretical model in Fig. 1, we hypothesise the following:

Hypothesis 3. Industry competition negatively moderates the relationship between AI innovation and firm efficiency.

Hypothesis 4. Industry competition negatively moderates the indirect effect of AI innovation on high-growth status through firm efficiency.

Research design

Data and sample

China presents an ideal context for studying the relationship between AI innovation and high-growth firms. The AI industry in China is rapidly expanding, with the core sector valued at RMB 578.4 billion in 2023—a 13.9 % increase. Meanwhile, the adoption rate of generative AI amongst enterprises has reached 15 %, contributing to a projected market size of RMB 14.4 trillion. McKinsey estimated that generative AI can add up to USD 2 trillion to China's economy by 2030, nearly one-third of the global total. China also leads globally in AI patent activity. The AI Index Report 2025[2] indicated that China's share of global AI patent applications increased from under 15 % in 2010 to 69.7 % in 2023, solidifying its leadership position. Meanwhile, a comprehensive policy framework—including key regulations issued since 2017—supports ethical, secure and responsible AI development across sectors. Public sentiment further reinforces this environment: the proportion of Chinese respondents perceiving AI as more beneficial than harmful increased from 78 % in 2022 to 83 % in 2024, the highest rate worldwide.

We developed an unbalanced panel dataset encompassing all Chinese manufacturing firms listed on the Shenzhen and Shanghai Stock Exchanges from 2007 to 2022. The selection of 2007 as the research starting point stems from two primary reasons. Firstly, the 2017 China Artificial Intelligence Industry Research Report[3] highlighted that deep learning algorithms, introduced in 2006, marked a significant technological breakthrough, enabling large-scale computing driven by data and computing power. Consequently, AI's advantages became particularly apparent starting in 2007. Secondly, the Research Report on the Market Prospects of China's Artificial Intelligence Industry 2019[4] showed that China's patents in the field of AI entered the development stage after 2007, allowing for the allocation of relevant patent data (Yao et al., 2024). Finally, we selected the end of 2022 as the cutoff point, given that China introduced the *Interim Provisions on the Accounting Treatment of Enterprise Data Resources* in 2023. This first regulation specifically addresses the accounting of data resources and affects various areas, including financial accounting; information disclosure; industry ecosystems; international standards; and the calculation of several financial indicators, such as high-growth status, leverage, total asset size, cash flow and return on assets. We excluded samples from 2023 onwards to avoid inconsistencies in the calculation methods of these indicators across different years.

We obtained the data from three main sources: financial information from the China Stock Market and Accounting Research database, patent records from the Chinese Research Data Services Platform and regional statistics from the China National Bureau of Statistics. The data processing involved several steps. Firstly, we excluded financial firms from the dataset. Thereafter, we removed special treatment (*ST*), particular transfer (*PT*) and delisted firms, and discarded any observations with missing values. Additionally, we applied 1 % winsorization to the upper and lower ends of all continuous variables to minimise the influence of outliers. Finally, we obtained a total of 20,178 firm–year observations from 2007 to 2022.

Variable definition

1) *AI innovation (AII):* We used invention patents for AI applied for by the firm as a proxy for AI innovation (Parteka & Kordalska, 2023; Yao et al., 2024). Firstly, we verified the International Patent Classification numbers for AI patents based on the *Key Digital Technology Patent Classification System* (2023)[5] issued by the China National Intellectual Property Administration. Secondly, we utilised text analysis to match these AI-related International Patent Classification numbers with those of listed firms, thereby determining the number of AI patent applications. We sourced the International Patent Classification numbers for listed firms from the Chinese Research Data Services Platform. Finally, we measured *AII* using the natural logarithm of the number of AI patents applied for by listed firms in the previous year plus 1 (Kopka & Fornahl, 2024).
2) *High-growth firm (HGF):* OECD (2007) defined a firm as high-growth if it achieves an average annual growth of more than 20 % in sales turnover or number of employees over a 3-year period. We defined high-growth firms based solely on sales turnover, as we focused on the influence of AI innovation on economic performance rather than changes in employment. Therefore, we used a binary variable (0 or 1) to identify firms whose average annual sales turnover grows by more than 20 % for 3 consecutive years.

[2] https://hai.stanford.edu/ai-index/2025-ai-index-report?ref=hackernoon.com

[3] http://www.caict.ac.cn/kxyj/qwfb/ztbg/201804/t20180412_158431.html

[4] https://report.iimedia.cn/repo1-0/38979.html?iimediaId=73130

[5] https://www.cnipa.gov.cn/attach/0/d32119ae1faa4fbf9e308824862f87dd.pdf

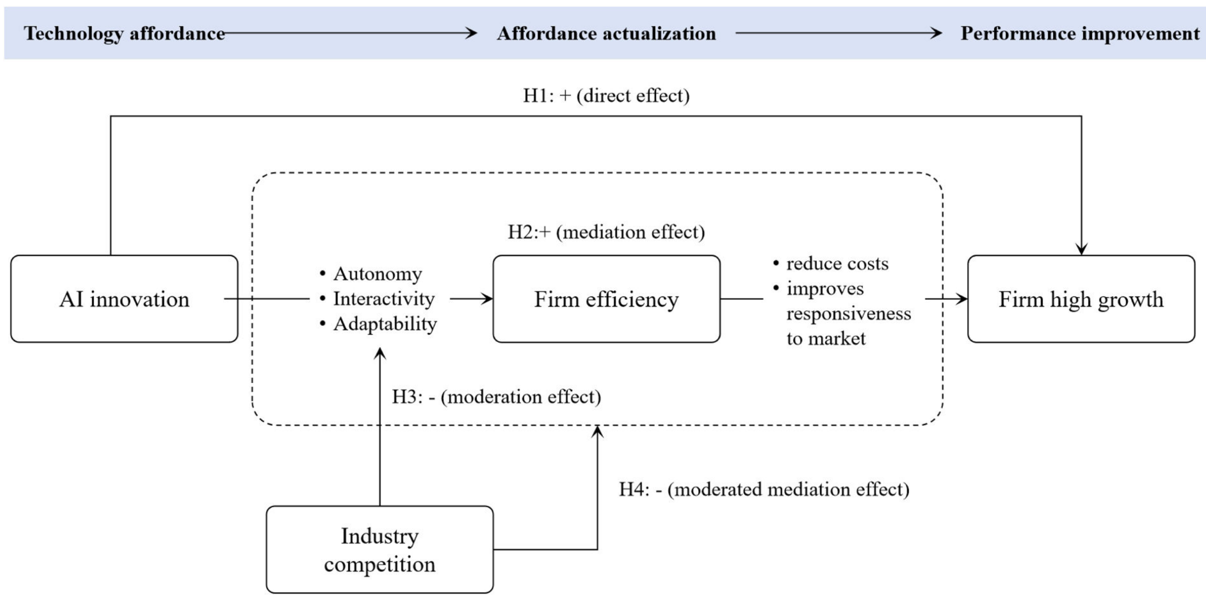

Fig. 1. Theoretical model.
Note: H1, H2, and H3 represent the direct, mediation, and moderation effects, respectively. H4 proposes a moderated mediation effect, wherein the strength of the indirect effect of AI innovation on firm high growth via firm efficiency is contingent on the level of industry competition.

3) *Firm efficiency (FE):* We used total factor productivity (TFP) as a proxy for firm efficiency. TFP captures the efficiency with which a firm transforms inputs (labour and capital) into outputs, reflecting comprehensive productivity in production, management and resource allocation (Bartelsman & Doms, 2000; Solow, 1957). Accurate TFP estimation requires addressing potential endogeneity issues, notably simultaneity bias, where unobserved productivity shocks correlate with input choices. Widely adopted approaches to mitigate this bias include the methods developed by Olley & Pakes (1996) and Levinsohn & Petrin (2003). Both methods use proxies for unobservable productivity shocks: investment for Olley & Pakes's (1996) method and intermediate inputs for Levinsohn & Petrin's (2003) method.

However, a practical limitation of Olley and Pakes's (1996) method in our empirical setting involves its requirement for strictly positive investment data every year for each firm. Given that a nontrivial number of firms in our sample report zero investment in some fiscal years, applying Olley & Pakes's (1996) method would exclude these observations, resulting in significant sample loss and potential selection bias. By contrast, Levinsohn & Petrin's (2003) method utilises intermediate inputs (e.g. materials and energy) as the proxy variable. Given that intermediate inputs are invariably positive for all operating firms in our sample, Levinsohn & Petrin's (2003) method circumvents the zero-investment problem inherent in Olley & Pakes's (1996) approach (Wooldridge, 2009). Therefore, we utilised Levinsohn & Petrin's (2003) method to estimate firm-level TFP as our measure of firm efficiency to preserve sample size and mitigate selection bias concerns.

4) *Industry competition (HHI):* We used the Herfindahl–Hirschman index (HHI) to measure industry competition (Abdoh & Varela, 2017; Haw et al., 2015; Markarian & Santaló, 2014). We initially calculated the market share of each firm based on the operating revenue of all firms within the industry. Thereafter, we computed the sum of the squares of the market shares of all firms in the industry to obtain the HHI for that year. We calculate the HHI using the following formula:

$$HHI = \sum (X_i/X)^2,$$

where X_i represents the operating revenue of firm i in the industry, and X is the total operating revenue of the industry. The HHI acts as an inverse indicator; specifically, a smaller HHI signifies more intense competition. Therefore, we used the negative value of the HHI to represent industry competition.

5) *Control variables:* We selected several control variables to improve model efficiency and explanatory power, following the framework established by Belitski et al. (2023b). These include firm age (*Age*), measured as the number of years of since the firm's establishment, and (2) firm size (*Size*), calculated as the natural logarithm of total assets in year *t*. We also accounted for leverage (*LEV*), defined as the ratio of total liabilities to total assets, and industry change (*IC*), a binary variable that equals 1 if the firm changed its two-digit standard industrial classification (SIC) code between year t and year $t-1$. Additionally, we included foreign employee share (*Hckd*), representing the share of employment in foreign-owned firms relative to total employment by two-letter postcode at $t-1$, and (6) cash flow (*Cashflow*), calculated as the ratio of cash flow to total assets. Finaly, we controlled for return on assets (*ROA*), which represents the ratio of a firm's net return to its total assets.

Methodology

We utilised a regression analysis using fixed effects instead of random effects to test the hypotheses. Fixed effects models effectively control for time-related and unobserved invariant factors at the firm level (Certo et al., 2017). We implemented several measures to address potential endogeneity. Firstly, the independent and control variables lag the dependent variable by one period. Secondly, we included industry, year and province fixed effects. Thirdly, we clustered robust standard errors at the industry * year level to eliminate the influence of industry–time factors on standard errors (Li et al., 2024).

Results

Descriptive statistics

Table 1 reports the descriptive statistical results for the main variables. Within the sample, high-growth firms exhibit a mean value of 0.0567, with minimum and maximum values of 0 and 1, respectively, and a standard deviation of 0.2313. These statistics highlight significant variations in high growth across firms. AI innovation shows a mean value of 0.3400, with minimum and maximum values of 0 and 4.0775,

Table 1
Descriptive statistics.

Variable	N	Mean	Std	Min	Max
HGF	20178	0.0567	0.2313	0.0000	1.0000
AII	20178	0.3400	0.8056	0.0000	4.0775
FE	20178	8.4528	1.0649	6.1162	11.1938
HHI	20178	–0.0774	0.0759	–0.5183	–0.0116
Age	20178	16.5681	5.5217	5.0000	31.0000
Size	20178	7.7266	1.2660	4.6151	11.2289
Lev	20178	0.4458	0.2035	0.0586	0.8764
IC	20178	0.0310	0.1734	0.0000	1.0000
Hckd	20178	0.3459	0.8065	0.0000	5.3268
Cashflow	20178	0.0473	0.0699	–0.1551	0.2456
ROA	20178	0.0442	0.0529	–0.1453	0.2112

respectively, and a standard deviation of 0.8056. Table 2 shows the Spearman correlations between all variables; these coefficients remained generally small (correlation coefficients <0.5). In addition, the VIFs of the explanatory variables all fell below 4 (with a mean VIF of 1.32), suggesting that multicollinearity does not pose a concern for our data.

Hypothesis testing

Table 3 reports the regression results. Column (1), which includes only the control variables, indicates that firm age, size, leverage, foreign employee share, cash flow and ROA positively influence high-growth status. The results in Column (2) show that AI innovation significantly and positively influences high growth ($\beta = 1.1745$, $p < 0.001$). These findings suggest that firms achieve superior development when they engage in AI innovation, resulting in high growth. Thus, the data support H1.

H2 predicted that firm efficiency mediates the influence of AI innovation on the likelihood of a firm achieving high growth. Column (3) in Table 3 indicates that the coefficient of *AII* on firm efficiency is positive and significant at the 1 % level ($\beta = 0.1210$, $p < 0.001$), suggesting that AI innovation enhances firm efficiency. Column (4) shows that the coefficients of *AII* ($\beta = 1.1300$, $p < 0.001$) and firm efficiency ($\beta = 1.3867$, $p < 0.001$) are significantly positive. This result indicates that AI innovation facilitates firms' transition to high-growth status primarily by enhancing their efficiency. Thus, the results partially support H2. We further utilised Sobel and Bootstrap tests to assess the robustness of the mediation results. The empirical findings indicate that the indirect effect of AI innovation, mediated through enhanced firm efficiency, is estimated at 0.0076 and is statistically significant at the 1 % level. A Sobel test statistic of $z = 0.0020$ ($p < 0.001$) and a Goodman test statistic of $z = 0.0020$ ($p < 0.001$) further corroborate the mediating role of efficiency (Appendix C: Tables C1 and C2).

H3 predicted that the degree of industry competition negatively moderates the relationship between AI innovation and firm efficiency. Column (6) reveals that the coefficient for $AII \times HHI$ is -0.3102 and significant at the 1 % level, suggesting that industry competition negatively moderates the effect of AI innovation on firm efficiency. Therefore, our results confirm the validity of H3. We further performed a simple slope analysis of the interaction between *HHI* and *AII*, as shown in Fig. 2. Particularly, AI innovation correlates positively with firm efficiency regardless of industry competition levels ($\beta_{High\_HHI} = 0.1011$, $p < 0.001$; $\beta_{Low\_HHI} = 0.1482$, $p < 0.001$). The slope for low *HHI* gradually surpassed that for high HHI. This result indicates that AI innovation has a stronger promoting effect on firm efficiency when industry competition is low, further verifying H3.

H4 predicted that industry competition negatively moderates the mediating role of firm efficiency between AI innovation and high-growth status. Although industry competition negatively regulates the '*AII* → *FE*' path ($\beta = -0.3102$, $p < 0.01$; Column (6) of Table 3), this regulation does not transmit to the indirect effect level of '*AII* → *FE* → *HGF*' ($\beta = 0.7340$, $p > 0.1$; Column (7) of Table 3). Therefore, the regression results preliminarily suggest that H4 is not valid. We utilised the moderated mediation analysis approach proposed by Edwards & Lambert (2007) to further validate this hypothesis. The results of this analysis are presented in Table 4. After conducting 500 bootstrap resamples, the results indicate that the indirect effect of AI innovation on high growth via firm efficiency is statistically significant at high ($\beta = 0.0011$, $p < 0.05$) and low ($\beta = 0.0006$, $p < 0.001$) levels of industry competition. However, the difference in the strength of this indirect effect across the two levels of competition lacks statistical significance ($\Delta = 0.0005$, $p > 0.1$). This result indicates that although the mediating role of firm efficiency is robust, the intensity of industry competition does not significantly moderate its strength. Therefore, the data do not support H4, which posited a significant moderated mediation. The post-hoc analysis section explores the potential underlying reasons for this outcome.

Endogeneity and robustness tests

We conducted several endogeneity and robustness tests to ensure the validity of our findings. Particularly, we initially used PSM–OLS regression as an alternative analytic strategy and the Heckman two-stage model to test for sample selection bias. Afterward, we added a city-level fixed effect to the model to minimise the potential influence of geographic factors on our conclusions. We followed this test by lagging the independent and control variables by two periods to mitigate concerns regarding reverse causality. Subsequently, we excluded observations after 2019 because the COVID-19 pandemic exerted a considerable negative influence on firm development. These additional tests confirmed the robustness of our findings. Finally, to mitigate potential

Table 2
Correlations analysis.

	HGF	AI	FE	HHI	Age	Size	Lev	IC	Hckd	Cashflow	ROA
HGF	1.0000										
AII	0.0455***	1.0000									
FE	–0.0024	0.1054***	1.0000								
HHI	0.0211**	0.0934***	–0.1190***	1.0000							
Age	–0.0995***	–0.0270***	0.1378***	0.0187**	1.0000						
Size	–0.0383***	0.1539***	0.5885***	–0.0950***	0.0498***	1.0000					
Lev	–0.0371***	–0.0427***	0.4756***	–0.1739***	0.1136***	0.3383***	1.0000				
IC	–0.0006	–0.0475***	0.0054	–0.0555***	0.0034	–0.0166*	0.0306***	1.0000			
Hckd	0.0016	0.1136***	0.0601***	0.0065	0.1459***	–0.0555***	–0.0572***	–0.0138†	1.0000		
Cashflow	–0.0260***	0.0176*	0.0594***	0.0167*	–0.0104	0.1554***	–0.1493***	–0.0229**	–0.0139*	1.0000	
ROA	0.0607***	0.0677***	0.0746***	0.0769***	–0.1059***	0.0197**	–0.3942***	–0.0117†	0.0520***	0.3892***	1.0000

† $p < 0.1$,
* $p < 0.05$,
** $p < 0.01$,
*** $p < 0.001$.

Table 3
Model results: fixed effects regressions.

	(1) HGF	(2) HGF	(3) FE	(4) HGF	(5) FE	(6) FE	(7) HGF
AII		1.1745***	0.1210***	1.1300***	0.1210***	0.1262***	1.1390***
		(0.0442)	(0.0064)	(0.0429)	(0.0064)	(0.0065)	(0.0454)
HHI					0.0641	–0.0036	0.2125†
					(0.1443)	(0.1478)	(0.1801)
AII × HHI						–0.3102**	0.7340
						(0.1049)	(0.4500)
FE				1.3867***			1.3859***
				(0.0704)			(0.0705)
Age	0.9349***	0.9355***	–0.0016	0.9357***	–0.0016	–0.0016	0.9358***
	(0.0066)	(0.0067)	(0.0012)	(0.0066)	(0.0012)	(0.0012)	(0.0066)
Size	0.8436***	0.8260***	0.4144***	0.7260***	0.4145***	0.4135***	0.7252***
	(0.0293)	(0.0287)	(0.0083)	(0.0273)	(0.0083)	(0.0083)	(0.0274)
Lev	1.7087***	1.6771**	1.6071***	0.9562	1.6073***	1.6088***	0.9609
	(0.3546)	(0.3481)	(0.0558)	(0.2230)	(0.0558)	(0.0558)	(0.2248)
IC	0.9920	1.0049	–0.0250	1.0092	–0.0251	–0.0256	1.0192
	(0.2053)	(0.2095)	(0.0373)	(0.2108)	(0.0373)	(0.0373)	(0.2130)
Hckd	1.1094*	1.1109*	–0.0039	1.1103*	–0.0038	–0.0037	1.1094*
	(0.0555)	(0.0547)	(0.0057)	(0.0541)	(0.0057)	(0.0057)	(0.0539)
Cashflow	0.0426**	0.0431**	–0.2071*	0.0487**	–0.2064*	–0.2040*	0.0473**
	(0.0233)	(0.0237)	(0.1001)	(0.0265)	(0.1000)	(0.0999)	(0.0257)
ROA	424.1154**	342.6846**	4.2052***	94.2941**	4.2060***	4.2090***	93.9497**
	(350.5905)	(284.9227)	(0.1458)	(80.3632)	(0.1459)	(0.1460)	(80.1928)
Constant	0.0407**	0.0416**	0.0665***	0.0425**	0.0662***	0.0680***	0.0372**
	(0.0183)	(0.0186)	(0.0054)	(0.0191)	(0.0054)	(0.0054)	(0.0167)
Industry fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20178	20178	20178	20178	20178	20178	20178
Log-likelihood	–3981.7935	–3974.0848	–1.95e+04	–3951.7646	–1.95e+04	–1.95e+04	–3950.0275
Preudo R^2/R^2	0.0939	0.0956	0.6447	0.1007	0.6447	0.6449	0.1011
LR(chi^2)/F	983.6700	1067.1028	1863.2277	1114.5839	1656.1138	1605.3122	1183.3191

Note: clustered robust standard errors at the industry*year-level in parentheses; (1), (2), (4) and (7) are exponentiated coefficients.
† $p < 0.1$,
* $p < 0.05$,
** $p < 0.01$,
*** $p < 0.001$.

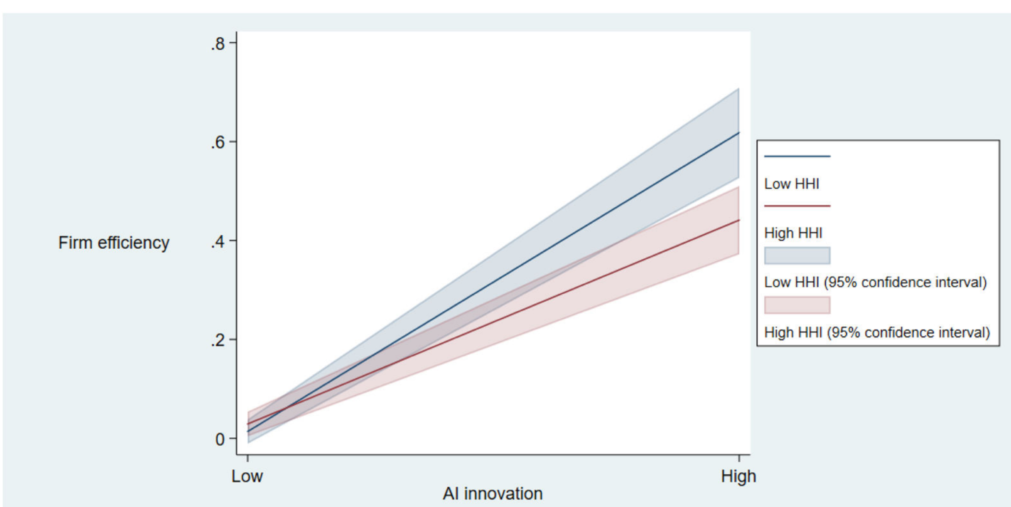

Fig. 2. The interaction of AI innovation and firm efficiency.

omitted variable bias—and specifically to account for factors that may uniquely influence a firm's ability to translate AI innovation into high growth—we incorporated three additional control variables as a further robustness check. We included these variables based on the following rationale. (1) We controlled for state ownership (*SOE*) because state-owned enterprises may pursue sociopolitical objectives alongside economic goals, which can significantly influence their innovation adoption and growth patterns (Yu & Ma, 2026). (2) We included the variable ownership concentration (*Top1*) because large shareholders can exert significant influence on a firm's risk-taking and long-term investment strategies regarding technologies like AI (Liu et al., 2024). (3) We controlled for board size (*Board*) because a larger board provides a broader spectrum of expertise and strategic oversight; this capacity is crucial for evaluating, implementing and managing complex AI

Table 4
Model results: mediated-moderated effects regressions.

Moderator Variable (Industry competition, HHI)		Stage		Effect		
		First stage AII→FE	Second stage FE→HGF	Direct effect AII→HGF	Indirect effect AII→FE→HGF	Total effect AII→HGF
High (Mean + 1sd)	Effect quantity coefficient	0.0127***	0.0001*	0.0064†	0.0011*	0.0081*
	95 % confidence interval	0.0096 0.0159	0.0001 0.0002	−0.0012 0.0139	0.0002 0.0021	0.0001 0.0155
Low (Mean - 1sd)	Effect quantity coefficient	0.0050***	0.0001**	0.0142***	0.0006***	0.0155***
	95 % confidence interval	0.0033 0.0067	0.0001 0.0002	0.0086 0.0197	0.0003 0.0009	0.0100 0.0210
Difference (High – Low)	Effect quantity coefficient	0.0077***	−0.0001	−0.0078	0.0005	−0.0074
	95 % confidence interval	0.0053 0.0101	−0.0001 0.0001	−0.0171 0.0015	−0.0003 0.0014	−0.0164 0.0016

† $p < 0.1$,
* $p < 0.05$,
** $p < 0.01$,
*** $p < 0.001$.

innovations, thereby directly influencing a firm's capacity to achieve high growth (Abeysekera, 2010; Liu et al., 2024) Appendix B provides detailed measurements for these additional variables and the corresponding check results.

Post-hoc analysis

Given the invalidity of H4, we conducted a post-hoc test to explore potential scenarios where industry competition does not significantly moderate the mediating effect of firm efficiency. Board size, a critical element of corporate governance, reflects a firm's strategic advisory capacity and resource provision capabilities (Abeysekera, 2010). When a firm maintains a large board, it can leverage collective wisdom to process complex information, thereby reducing decision-making flaws. This capacity mitigates the 'decision dilemma' caused by intense industry competition (Gartner & Moro, 2024; Iurkov et al., 2023; Narasimhan et al., 2015), increasing the probability of AI-powered high growth. Conversely, industry competitive pressure may create a decision dilemma that prevents managers from effectively tapping into the value of AI innovation. A smaller board size further exacerbates these decision-making difficulties, suppressing the driving effect of AI investment on high growth (Huang & Wang, 2015). Therefore, we divided the full sample into two subsamples based on the median board size: high and low board size (using a dummy variable where 1 represents a high board size and 0 represents a low board size. We aim to clarify why industry competition does not significantly moderate the mediating effect of firm efficiency in the full sample.

Our analysis of Table 5 reveals board size as a critical boundary condition. The significantly negative *AII* × *HHI* interaction in Column (1) ($BS = 0; \beta = -0.5221, p < 0.01$) supports H3, indicating that industry competition negatively moderates the link between AI innovation and firm efficiency only when board size is small. By contrast, the insignificant interaction in Column (2) ($BS = 1$, $\beta = -0.2180$, $p > 0.1$) shows that H3 does not hold for firms with large boards. Regarding the moderated mediation (H4), the significant coefficients for firm efficiency (*FE*) in Columns (3) and (4) confirm its mediating role. Since the first-stage moderating effect (H3) exists only with small board sizes, the strength of the indirect effect depends on industry competition solely under that condition. Thus, the data support H4 only when board size is small. This conditional indirect effect is evidenced by the significantly positive *AII* × *HHI* coefficient in the high-growth regression for the small-board group (Column (3): $\beta = 0.0956$, $p < 0.1$). Conversely, the insignificant coefficient for the large-board group (Column (4): $\beta = 0.6194$, $p > 0.1$) underscores that the effect does not persist under that condition. Overall, these findings demonstrate that the efficacy of AI

Table 5
Post hoc effect results.

	BS=0 FE	(2) BS=1 FE	(3) BS=0 HGF	(4) BS=1 HGF
AII	0.1126***	0.1310***	1.2085***	1.1258*
	(0.0086)	(0.0097)	(0.0881)	(0.0592)
HHI	−0.1593	0.4400*	0.4494	0.1315
	(0.2221)	(0.1951)	(0.6589)	(0.1777)
AII × HHI	−0.5221**	−0.2180	0.0956†	0.6194
	(0.1782)	(0.1547)	(0.1317)	(0.4887)
FE			1.4612***	1.3538***
			(0.1017)	(0.1187)
Age	0.0001	−0.0012	0.9366***	0.9307***
	(0.0016)	(0.0017)	(0.0102)	(0.0098)
Size	0.4117***	0.4077***	0.6722***	0.7871***
	(0.0102)	(0.0121)	(0.0382)	(0.0491)
Lev	1.5263***	1.7787***	0.9878	0.6216
	(0.0602)	(0.0790)	(0.3294)	(0.2266)
IC	−0.0173	−0.0020	0.8550	1.3560
	(0.0476)	(0.0472)	(0.2203)	(0.4503)
Hckd	−0.0196*	0.0118	1.1160†	1.1395†
	(0.0099)	(0.0093)	(0.0673)	(0.0785)
Cashflow	−0.0488	−0.3326*	0.1141**	0.0319**
	(0.1346)	(0.1496)	(0.0868)	(0.0268)
ROA	3.8639***	4.6765***	14.4744*	887.4964**
	(0.1713)	(0.2172)	(17.3394)	(995.8343)
Constant	0.0633***	0.1001***	0.0325**	0.0366**
	(0.0072)	(0.0081)	(0.0202)	(0.0296)
Industry fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
Province fixed	Yes	Yes	Yes	Yes
Observations	10192	8002	10192	8002
Log-likelihood	−9.99e+03	−7.15e+03	−1976.0150	−1590.4802
Preudo R^2/R^2	0.6076	0.6863	0.1019	0.1397
LR(chi^2)/F	847.8129	885.5721	638.0657	592.3103

Note: clustered robust standard errors at the industry*year-level in parentheses; (3) and (4) are exponentiated coefficients.
† $p < 0.1$,
* $p < 0.05$,
** $p < 0.01$,
*** $p < 0.001$.

innovation depends on governance structures. The direct moderating effect (H3) and the moderated mediation (H4) function as a result of board size, appearing significant only when board size is small. This result underscores the crucial role of corporate governance.

We further performed a simple slope analysis of the interaction between *HHI* and *AII*. Fig. 3 shows that when board size is small, industry competition weakens the promoting effect of AI innovation on firm

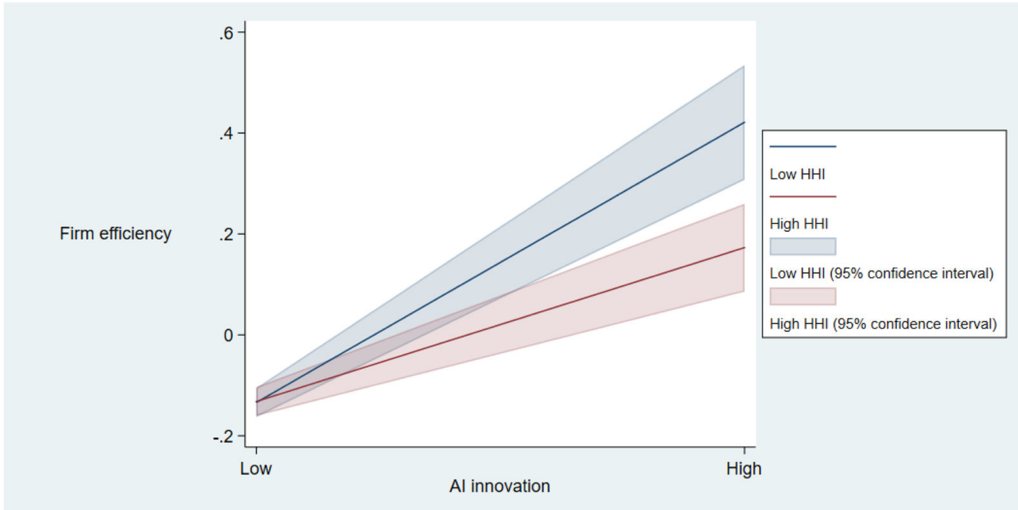

Fig. 3. The interaction of AI innovation and firm efficiency (BS=0).

efficiency ($\beta_{High\_HHI} = 0.0742, p < 0.001$; $\beta_{Low\_HHI} = 0.1351, p < 0.001$). Fig. 4 illustrates the following results. The influence of AI innovation on high growth gradually disappears as industry competition increases in the small-board group ($\beta_{High\_HHI} = 0.0008$, p > 0.1; $\beta_{Low\_HHI} = 0.0153, p < 0.05$).

Discussion

Theoretical implications

The theoretical contributions of this study involve two primary aspects. Firstly, we provide a new perspective on the antecedents of high-growth firms based on technology affordance actualisation theory, responding to scholars' call for identifying 'what factors can make it easier for firms to achieve high growth in today's fiercely competitive and resource poor era' (Coviello et al., 2024; Jansen et al., 2023; Palmié et al., 2023). Previous literature primarily views rare resources as the key mechanisms influencing high growth (Audretsch et al., 2024; Belitski et al., 2023b; Gartner & Moro, 2024; Iurkov et al., 2023; Kotha et al., 2022), often considering such growth a privilege that only few firms possess. Building on the thesis that AI application drives productivity growth (Manyika & Spence, 2023), we examine the underlying mechanisms and boundary conditions of AI innovation's influence on high-growth firms from an efficiency perspective. Our results provide evidence that AI innovation significantly elevates the probability of firms achieving high-growth status, thereby extending the framework on growth drivers. Moreover, although our empirical context is China, the core theoretical mechanism—that AI innovation creates affordances for efficiency and growth—is not geographically bounded. It offers a replicable framework for understanding how firms in other emerging economies and developed markets can leverage technology for rapid scaling.

Second, our study expands the literature on AI failure. Although existing research primarily focuses on the benefits of AI innovation, it often overlooks AI failures within specific contexts (Dwivedi et al., 2021; Wirtz et al., 2022). Our findings demonstrate that industry competition can limit the efficiency-enhancing effects of AI innovation. This situation may be attributed to the intense industry competition, indicating significant uncertainty in the business environment (Narasimhan et al., 2015). However, this negative moderating effect of industry competition occurs only when a firm maintains a small board size. This insight resonates with global cases where governance mitigates external pressures. For instance, the ability of large multinationals like Siemens to navigate competitive disruptions through robust board oversight aligns with our

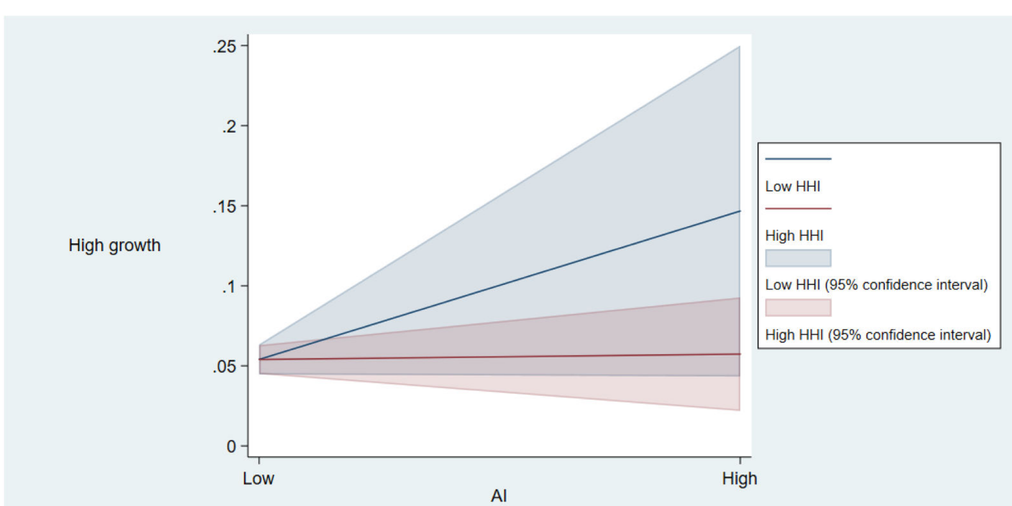

Fig. 4. The interaction of AI innovation and high growth (BS=0).

finding that governance can buffer external threats (Gartner & Moro, 2024; Iurkov et al., 2023; Narasimhan et al., 2015). Conversely, the struggles of some traditional retailers in the US and Europe to adapt to AI-driven competition may stem from boards that lack the scale or diversity required for rapid strategic pivots (Hudson & Morgan, 2024). Consequently, managers must analyse user needs and market trends derived from data. When a firm has a large board, managers can combine their expertise to process complex information. This mechanism helps mitigate gaps and errors in firm decision-making (Narasimhan et al., 2015), enabling AI innovation to realise its value fully, as demonstrated by Haier Smart Home. Conversely, when board size is small, managerial decision-making may suffer from gaps and errors, making it difficult for firms to leverage AI innovation value. This finding suggests that AI currently serves mainly as a tool for providing results rather than an entity widely involved in firm decision-making. Our empirical investigation reveals a significant interaction between industry competition and board size in the process of innovation value actualisation. This finding significantly contributes to the broader literature on strategic management and corporate governance theory.

Practical implications

Our findings offer significant implications for policymakers and managers, with relevance extending beyond China to international contexts. (1) For policymakers, we provide two key recommendations. Firstly, we advise governments to implement corporate-level incentive mechanisms, such as financial subsidies and tax reductions, to support AI innovation. Secondly, they should increase investments in AI infrastructure, vigorously cultivate AI talent and optimise the broader business environment to create more opportunities for AI-driven growth. (2) For managers and firms worldwide, the moderating role of board size offers a crucial lesson. For instance, a large multinational like Siemens has effectively leveraged its diverse and experienced board to navigate global competitive pressures and steer its AI-driven industrial transformation (Industry 4.0). Conversely, the struggles of some traditional retailers in the US and Europe to adapt to AI-driven competition may stem from boards that lack the scale or diversity required for rapid strategic pivots (Hudson & Morgan, 2024). Thus, reassessing board composition is critical for harnessing AI innovation successfully. We encourage firms to optimise organisational structures by, for example, introducing technical talent into the board team to facilitate more professional strategic decisions regarding AI innovation.

Limitations and future direction

We recognize certain limitations that future research must address. The first limitation concerns industry selection. Heterogeneity across different industries may influence the results of this study. Accordingly, future research can focus on whether AI innovation drives high growth in specific industries, such as banking, asset management, securities and insurance. The second limitation concerns the measurement of high growth. Identifying high growth as a phenomenon generally requires three consecutive years of growth (Belitski et al., 2023b). However, some firms may experience more rapid exponential growth over shorter intervals (Bohan et al., 2024), such as several months (Huang et al., 2017). Consequently, future research can develop more specialized tools for measuring high growth across varying time horizons. The third limitation concerns the research sample. Our study focuses on China's listed firms; because broad samples may not capture the specific characteristics of all emerging market firms, this focus potentially limits the generalisability of the findings. Therefore, we encourage future research to include additional samples from other emerging markets to corroborate our findings.

Conclusion

We investigate the influence of AI innovation on high-growth firms based on technology affordance actualisation theory. Our results demonstrate that AI innovation exerts a substantial positive influence on the likelihood of firms attaining high-growth status, with firm efficiency serving as a pivotal mediating factor in this relationship. Although industry competition negatively moderates the direct link between AI innovation and firm efficiency, it does not significantly alter the overall strength of the indirect mediation pathway. Furthermore, post-hoc tests identify board size as a critical boundary condition for these relationships. Specifically, industry competition weakens the positive effect of AI innovation on firm efficiency when board size is limited, thereby hindering high growth. Conversely, a large board size neutralises this negative effect, allowing AI innovation to promote high-growth prospects fully.

Declaration

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Patient consent statement: Not applicable

Permission to reproduce material from other sources: Not applicable.

Clinical trial registration: Not applicable.

Declaration of competing interest

The authors have no relevant financial or nonfinancial competing interests to disclose.

Data availability

Data supporting the research results were obtained from the China Stock Market & Accounting Research (CSMAR) Database, Chinese Research Data Services (CNRDS) Database, China National Bureau of Statistics and it can also be obtained from the corresponding author on a reasonable request.

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