Proceedings of the 10th International Conference on Economic Management and Green Development
DOI: 10.54254/2754-1169/2026.36681

Management Knowledge Diversity and Corporate AI Technological Innovation: U-Shaped Relationship, Mediating Mechanism and Contingency Boundaries

Jiani Xue*, Yaxuan Wang, Xingyu Li, Rongrong Cao

Beijing Jiaotong University, Beijing, China
Corresponding Author. Email: 23725071@bjtu.edu.cn

Abstract. Based on the knowledge-based view and temporal orientation theory, this study explores the nonlinear impact of management knowledge diversity on corporate AI innovation, the mediating role of executive long-term orientation, and the contingency effects of institutional ownership, digital economy and cooperative innovation. Using a sample of 51,029 observations from 5,120 A-share listed companies in China from 2011 to 2024, we adopt hierarchical regression, instrumental variable method and propensity score matching (PSM) for empirical analysis. The findings show that: management knowledge diversity has a U-shaped relationship with AI innovation; executive long-term orientation partially mediates this U-shaped relationship; institutional ownership and digital economy negatively moderate the relationship (flattening the curve), while cooperative innovation positively moderates it (steepening the curve). Heterogeneity analysis indicates that the promoting effect is more significant in low-pollution industries, firms with high management shareholding, eastern regions, highly competitive markets and regions with strong intellectual property protection. This study distinguishes between management knowledge and technological knowledge diversity, reveals the U-shaped impact, challenges the inverted U-shaped pattern, and provides a new framework and practical implications for knowledge management in AI innovation.

Keywords: Management Knowledge Diversity, AI Technological Innovation, Executive Long-term Orientation, Institutional Ownership, Digital Economy

1. Introduction

In the era of digital economy, artificial intelligence (AI) technology is reshaping the industrial landscape with unprecedented depth and breadth, and has become a key force driving corporate innovation and competitive advantage. However, AI technological innovation features high investment, long cycle and strong uncertainty, which poses severe challenges to corporate knowledge base and strategic decision-making. Enterprises rely not only on technological accumulation, but also on diversified management knowledge to cope with the complex and changing organizational and market environment in the process of AI innovation [1]. Management knowledge diversity — the horizontal coverage breadth of a firm's knowledge base across functional

DOI: 10.54254/2754-1169/2026.36681

fields such as strategy, organization, human resources and marketing — provides enterprises with the possibility of integrating cognitive resources across fields and identifying emerging technological opportunities [2-4]. Nevertheless, existing research has not yet given a clear answer to whether and how management knowledge diversity affects corporate AI technological innovation, especially lacking in-depth discussion of its nonlinear mechanism.

Most existing studies on knowledge diversity and innovation focus on the field of technological knowledge, and generally find an inverted U-shaped relationship between the two: moderate technological diversification contributes to innovation, while excessive diversification inhibits innovation due to rising coordination costs [5-7]. However, management knowledge diversity involves non-technical dimensions such as strategy formulation, organizational design and human resource allocation, and its integration logic is essentially different from that of technological knowledge. From the resource-based view, heterogeneous knowledge, as a strategic asset that is difficult to imitate, can be transformed into competitive advantage [8]; but from the perspective of top management team interaction, differences in knowledge background may also trigger cognitive conflicts and communication barriers [9], increasing coordination difficulty [10]. When management knowledge diversity is at a low level, the management team has a narrow cognitive vision and is difficult to form strategic consensus on long-term projects such as AI innovation; as diversity rises to a medium level, coordination costs and cognitive conflicts intensify, leading to lower decision-making efficiency; only when diversity crosses a critical threshold can the information complementarity and cross-boundary integration effects brought by diversified management knowledge dominate [11, 12], and significantly promote AI innovation. On this basis, there may be a U-shaped relationship between management knowledge diversity and AI innovation, rather than the inverted U-shaped pattern commonly found in traditional studies — this theoretical expectation needs to be empirically tested.

Furthermore, this U-shaped effect does not occur in isolation, but works by shaping the cognition and decision-making tendency of the top management team. According to temporal orientation theory, executives' long-term orientation — the tendency to prioritize decisions with long-term impacts — is a key psychological mechanism driving enterprises to make high-risk, long-cycle innovation investments [13, 14]. When management knowledge diversity is at a low level, it inhibits long-term orientation due to cognitive limitations; at a medium level, it further weakens long-term orientation due to coordination costs; only at a high level can it activate executives' recognition of the long-term value of AI innovation through information complementarity [15]. Executives with long-term orientation are more inclined to increase R&D investment to enhance long-term corporate value, and can tolerate and encourage strategic decisions with unclear short-term value but long-term potential [16]. Therefore, executive long-term orientation may become an important mediating path connecting management knowledge diversity and AI innovation.

Meanwhile, this U-shaped relationship is also deeply affected by internal and external governance and resource conditions. As an important external supervision force, institutional investors can restrain management's self-interested behavior [17]. According to the "monitoring hypothesis", institutional investors generally value the long-term sustainability of enterprises [18], and can guide management to focus on long-term value. In the declining segment of the U-shaped curve, it weakens the inhibitory effect of coordination costs; in the rising segment, it dilutes the marginal contribution of information complementarity, making the curve flatter. The development of digital economy may also replace or supplement the knowledge integration function within the management team. In regions with developed digital economy, enterprises can reduce internal communication costs with the help of digital platforms, and weaken the intensity of the impact of changes in management knowledge diversity on AI innovation. On the contrary, cooperative innovation may not only strengthen the information complementarity effect at the stage of high diversity by introducing external knowledge, but also aggravate innovation inhibition at the stage of medium diversity by increasing coordination costs and opportunistic risks [19, 20], thus making the U-shaped curve steeper [21]. A systematic investigation of the above moderating mechanisms will deepen our understanding of the boundary of the role of management knowledge diversity.

The theoretical contributions of this study are mainly reflected in the following three aspects. First, different from the existing research's general focus on the inverted U-shaped relationship between technological knowledge diversity and innovation performance, this study focuses on the neglected important dimension of management knowledge diversity, proposes and tests the U-shaped relationship between it and corporate AI innovation for the first time, reveals the unique action logic of "conflict first, then synergy" in management knowledge integration, and expands the theoretical boundary of the knowledge-based view in the context of artificial intelligence. Second, this study introduces executive long-term orientation as the mediating mechanism, opens the cognitive black box of how management knowledge diversity affects AI innovation, clarifies how diversified management knowledge affects enterprises' long-term technological investment decisions by shaping the temporal cognitive framework of the top management team, and responds to the academic call for research on the micro-foundations of innovation antecedents. Third, this study simultaneously examines the differential moderating effects of institutional ownership, digital economy and cooperative innovation on the U-shaped relationship, constructs a contingency analysis framework integrating internal governance, external environment and strategic choice, which not only reveals the boundary conditions of the intensity of the role of management knowledge diversity, but also provides theoretical guidance for enterprises to optimize knowledge management strategies and promote AI innovation in different contexts.

The structure of this paper is arranged as follows: the second part conducts theoretical analysis and puts forward research hypotheses; the third part introduces the research design; the fourth part reports the empirical analysis results; the fifth part discusses the research conclusions and clarifies theoretical contributions and management implications; the sixth part summarizes the full text and points out research limitations and future directions.

2. Theoretical analysis and hypothesis development

2.1. The knowledge-based view

The knowledge-based view evolves from the resource-based view and regards "knowledge" as the most strategic resource of enterprises [22, 23]. This theory holds that tangible resources bring limited competitive advantages and are easy to imitate, while knowledge-based resources, especially tacit knowledge, are difficult to replicate due to their social complexity and causal ambiguity, and constitute the source of sustained competitive advantage [8, 22]. Knowledge creation is mainly an individual activity, and one of the core purposes of the existence of enterprises is to effectively integrate specialized knowledge scattered among individuals [22]. Due to limited individual cognition and time, individuals must specialize in knowledge acquisition, while valuable innovation activities require the comprehensive use of multiple kinds of specialized knowledge. Therefore, the key capability of an enterprise lies not in possessing knowledge, but in establishing an effective knowledge coordination and integration mechanism to transform individual knowledge into organizational capability [24, 25].

DOI: 10.54254/2754-1169/2026.36681

2.2. Management knowledge diversity and corporate AI technological innovation

Management knowledge diversity refers to the breadth of a firm's knowledge base covering various categories of management knowledge, reflecting the coverage of professional knowledge of enterprises in different management fields such as strategy, organization, human resources and marketing. The development of AI innovation requires a large amount of digital resource support, and the diversified knowledge, technology, talents and innovation resources provided by management knowledge diversity exactly meet the prerequisites for enterprises to research, develop and introduce cutting-edge AI technologies, laying a solid foundation for the internal implementation and application of AI in enterprises.

From the resource-based view, the competitive advantage of an enterprise stems from the unique and valuable resources it owns and controls. As a key intangible resource, the diversity of knowledge can provide enterprises with broader innovation possibilities [1]. Knowledge diversity refers to the agglomeration degree of heterogeneous knowledge elements owned within an organization, reflecting the breadth and depth of a firm's knowledge reserve [2, 4]. As a strategic asset that is difficult to imitate, heterogeneous knowledge can be transformed into the competitive advantage of enterprises [8, 22]. In essence, enterprises will get involved in multiple fields to realize knowledge recombination and innovation [26, 27]. Krafft et al. argue that the higher the diversity of a firm's knowledge base, the wider the new fields it involves, and the greater the possibility of achieving radical innovation [28].

It is worth noting that most existing studies on technological knowledge diversity or technological diversification find an inverted U-shaped relationship with innovation performance — moderate technological diversification contributes to innovation, while excessive diversification inhibits innovation due to rising coordination costs [5-7]. When enterprises allocate resources to vastly different fields for technological diversification, higher coordination, communication and integration costs will arise [6]. The complexity and coordination costs of managing multiple technologies begin to offset their benefits. However, the management knowledge diversity concerned in this paper is essentially different from technological innovation knowledge — management knowledge involves functional fields such as strategy, organization, human resources and marketing, and its integration logic is different from the integration in the technological field, which may lead to different nonlinear patterns.

From the perspective of top management team interaction, the impact of management knowledge diversity is consistent with research on team composition. When an enterprise spans multiple management knowledge fields, top management team members need to process heterogeneous information and resources from different fields, which may increase the difficulty of reaching consensus and delay the decision-making process. According to social identity theory, when top management team members develop automatic categorization cognition, in-group favoritism and out-group prejudice will emerge, which will further increase communication barriers and reduce trust level. Age differences within the team will intensify internal division, ultimately reduce team cohesion [29], and then increase coordination difficulty, leading to decision delays and even hindering the investment process [30] — these together constitute the micro-foundation of the declining segment of the U-shaped curve.

At the same time, the positive effect of management knowledge diversity cannot be ignored. When diversified management knowledge bases interact with each other, they can promote the formation of novel combinations of knowledge and give birth to innovation results. A diverse knowledge base is the foundation for enterprises to carry out various innovation activities, and is

DOI: 10.54254/2754-1169/2026.36681

more likely to create opportunities for the recombination of old and new knowledge [11, 12]. Knowledge diversity continuously empowers technological innovation by expanding the scope of enterprise knowledge and introducing multiple perspectives and ideas [31, 3]. Knowledge breadth helps enterprises identify specific knowledge widely and quickly, and promote the creation of new knowledge [32, 33]. With the improvement of knowledge diversity, enterprises can obtain wider information channels and form a more comprehensive perspective, accurately identify distant market opportunities [34, 35], and realize adaptation and value creation in unfamiliar environments [26, 36] — this is the driving force of the rising segment of the U-shaped curve.

Specifically in the context of AI innovation, interdisciplinary knowledge integration capability is the core driving force of enterprise AI innovation. The diverse requirements of AI innovation for AI and technological innovation urge enterprises to break down knowledge barriers between departments and build a compound knowledge structure covering multiple dimensions through interdisciplinary collaboration. Literature has found that non-technical knowledge diversity promotes digital technology innovation and artificial intelligence development [37]. Knowledge spillovers brought by technological diversification can promote higher innovation output [38], and the integration of heterogeneous technologies is more likely to give birth to successful breakthrough innovations [39]. Executives with different professional backgrounds can provide diverse problem-solving frameworks for innovation decisions and enhance the team's environmental adaptability [40].

Based on the above analysis, the impact of management knowledge diversity on AI innovation presents a U-shaped feature. Benefits and costs, as two offsetting forces, jointly determine the relationship between the two: when diversity is at a low level, negative effects such as coordination costs and cognitive conflicts dominate, and AI innovation declines with the increase of management knowledge diversity — this is the declining segment of the U-shaped curve; when diversity crosses the critical threshold, positive benefits such as knowledge complementarity and cross-boundary integration begin to exceed coordination costs, and AI innovation rises significantly with the increase of management knowledge diversity — this is the rising segment of the U-shaped curve. On this basis, this paper puts forward the following hypothesis:

H1. Management knowledge diversity has a U-shaped relationship with AI innovation.

2.3. The mediating role of executive long-term orientation

According to temporal orientation theory, managers' cognition and way of thinking about time will profoundly affect corporate strategic decision-making [14]. Temporal orientation can be divided into two core dimensions: long-term orientation and short-term orientation. Long-term orientation refers to the tendency of decision-makers to prioritize decisions and behaviors with long-term impacts, which is reflected in the attention to future returns, the planning and evaluation of long-term results, and the emphasis on strategic continuity [13]. Executives with long-term orientation are more likely to accept a forward-looking temporal cognitive framework, resist managerial myopia, and tend to enhance long-term corporate value through innovation and optimizing stakeholder relationships [15]. Given that artificial intelligence innovation has the characteristics of long payback period, high uncertainty and continuous exploration, such activities naturally require the long-term orientation of enterprises.

The impact of management knowledge diversity on executive long-term orientation is not a simple linear relationship, but presents a U-shaped feature. When management knowledge diversity is at a low level, the management team has a relatively narrow cognitive vision, and members are often limited to the mindset of their respective professional fields, making it difficult to form

DOI: 10.54254/2754-1169/2026.36681

strategic consensus on long-term projects such as AI innovation. As management knowledge diversity gradually rises to a medium level, cognitive differences within the team begin to appear, the information complementarity effect has not been fully released, but coordination costs have begun to rise, which may instead weaken managers' long-term orientation. When management knowledge diversity crosses the critical threshold, the information advantage brought by diversified knowledge backgrounds begins to dominate. Rich cognitive perspectives enable managers to examine industry development trends and technological change paths from different dimensions, more clearly identify the future value and long-term significance of AI innovation, and enable managers to transcend short-term interest constraints and focus on long-term competitive advantages. Therefore, there is a U-shaped relationship between management knowledge diversity and executive long-term orientation.

As a key mediating mechanism connecting management knowledge diversity and corporate AI innovation, executive long-term orientation plays its role through two paths: strategic planning and resource allocation. At the strategic planning level, executives with long-term orientation have excellent long-term strategic planning capabilities, are more inclined to explore and adopt action paths that can achieve long-term optimal results, and can tolerate even encourage strategic decisions with unclear short-term value but long-term potential. At the resource allocation level, long-term orientation prompts managers to regard AI innovation as a key strategic long-term investment, give full attention to it in resource allocation, and continuously allocate necessary funds and talents to AI projects. Executives with long-term incentives are more inclined to increase R&D investment to enhance long-term corporate value. On this basis, this paper puts forward the following hypotheses:

H2a. There is a U-shaped relationship between management knowledge diversity and executive long-term orientation.

H2b. Executive long-term orientation has a positive impact on AI innovation.

H2. Executive long-term orientation plays a mediating role in the U-shaped relationship between management knowledge diversity and AI innovation.

2.4. Analysis of moderating effects

2.4.1. The moderating effect of institutional ownership

As an important external supervision force, institutional investors can restrain management's self-interested behavior [17]. According to the "monitoring hypothesis", institutional investors generally value the long-term sustainability and value of enterprises [18], and can guide management to focus on long-term value. Bushee [18] finds that if an enterprise is mainly held by institutional investors, management's tendency to cut R&D expenditure to manipulate earnings will be significantly reduced. The moderating effect of institutional ownership is reflected in two stages of the U-shaped curve: in the declining segment, institutional ownership alleviates team coordination problems through supervision functions, reduces communication costs and decision-making frictions, and weakens the innovation inhibition effect; in the rising segment, the governance advantages and long-term value orientation provided by institutional ownership [18] replace the demand for knowledge integration within the management team to a certain extent, dilute the marginal contribution of information complementarity, and make the curve flatter. Accordingly, this paper proposes:

H3. Institutional ownership can weaken the U-shaped impact of management knowledge diversity on AI innovation.

DOI: 10.54254/2754-1169/2026.36681

2.4.2. The moderating effect of digital economy

Digital economy refers to the digitization of information realized by relying on the Internet, as well as a series of economic activities in the field of information and communication technology [41]. There are significant heterogeneities in the development level of digital economy among Chinese cities: core coastal innovation hub cities such as Shenzhen, Hangzhou and Beijing have a highly mature digital ecology, while some inland cities or small and medium-sized cities are still in the early stage of digital application. These differences provide completely different external environments for enterprises to implement AI innovation. The U-shaped impact of corporate management knowledge diversity on AI innovation not only depends on the cognitive structure and integration ability within the team, but also is deeply affected by the external digital economic environment. The higher the development level of regional digital economy, the stronger external technical support, more complete infrastructure guarantee and richer digital resources enterprises can obtain in AI innovation. A developed digital economy can provide supporting infrastructure, network systems and market environment, thus replacing or supplementing the leading role of management in AI innovation to a certain extent, and weakening the intensity of the impact of management knowledge diversity on AI innovation.

Specifically, the moderating effect of digital economy is reflected in two stages of the U-shaped curve. In the declining segment of the U-shaped curve (diversity from low to medium level), the improvement of management knowledge diversity will inhibit AI innovation due to rising coordination costs. However, in regions with a high level of digital economy development, enterprises can reduce internal communication costs and coordination difficulty with the help of external resources such as digital platforms, open-source technology communities and online collaboration tools. Digital technology breaks enterprise boundaries, improves information transparency, and enables managers to integrate heterogeneous information brought by diversified knowledge backgrounds more efficiently, thus alleviating the innovation inhibition effect caused by rising coordination costs — this means that the negative impact of the declining segment is weakened, and the curve tends to be flat.

In the rising segment of the U-shaped curve (diversity from medium to high level), the further increase of management knowledge diversity promotes AI innovation through the information complementarity effect. However, in regions with a high level of digital economy development, enterprises can obtain rich technical knowledge, market information and innovation resources from the outside with the help of developed digital infrastructure and platforms. Enterprises can use digital technology to quickly track cutting-edge technology trends and explore innovation opportunities, which means that the information advantage that originally needed to be realized through the integration of diversified knowledge within the management team can be replaced by the external digital environment to a certain extent. Therefore, the marginal contribution brought by the knowledge diversity within the management team is relatively weakened — that is, the positive promotion effect of the rising segment is diluted, and the curve also tends to be flat.

Based on the above analysis, digital economy plays a role in weakening the intensity of the impact of management knowledge diversity in both stages of the U-shaped curve: in the declining segment, it alleviates the inhibition effect brought by coordination costs; in the rising segment, it dilutes the marginal contribution brought by the information complementarity effect. In other words, the higher the development level of digital economy, the flatter the U-shaped curve of management knowledge diversity on AI innovation — that is, the impact of changes in diversity on AI innovation is reduced.

DOI: 10.54254/2754-1169/2026.36681

In other words, the higher the development level of digital economy, the flatter the U-shaped curve of management knowledge diversity on AI innovation — that is, the impact of changes in diversity on AI innovation is reduced. On this basis, this paper puts forward the following hypothesis:

H4. The development level of digital economy will weaken the U-shaped impact of management knowledge diversity on AI innovation.

2.4.3. The moderating effect of cooperative innovation

As an important strategy for external knowledge acquisition, cooperative innovation plays a key moderating role in the U-shaped relationship between management knowledge diversity and AI innovation. When enterprises rely more on cooperative innovation, the role of internal management decision-making is relatively weakened, and the influence of external partners is enhanced, thus changing the boundary of the role of diversity in AI innovation.

Cooperative innovation can build competitive advantages. By jointly developing new products or optimizing processes with supply chains, universities and scientific research institutions, enterprises create more cooperation opportunities [42, 43]. Heil and Bornemann [44] point out that cooperative innovation helps enterprises learn the proprietary knowledge of partners and enhance competitive advantage; Zhou et al [9]. also emphasize its key value in acquiring external technical knowledge and complementary resources. In this process, cooperative innovation amplifies the information advantage of management knowledge diversity: a management team with diversified backgrounds can more effectively identify and screen external opportunities, accurately integrate heterogeneous knowledge resources, and then realize knowledge synergy in long-term projects such as AI innovation. Therefore, cooperative innovation strengthens the positive information complementarity effect at the stage of high diversity.

However, cooperative innovation may also lead to opportunistic risks and increase coordination and management costs, which strengthens the negative effect of diversity. There is often opportunistic tendency in cooperative relationships, such as fraud, shirking, information distortion or embezzlement of core resources [10]. Badir and O'Connor [45] particularly point out that such behaviors are prone to occur in cooperative innovation. Curbing opportunism requires a lot of time for negotiation, establishment of supervision and control mechanisms, and investment in relationship-specific assets [46], which increases the cost burden. At the same time, differences in culture and organizational models among cooperative parties increase coordination difficulty, requiring relational investment to promote communication [23]; in addition, the risk of involuntary knowledge leakage [22] also pushes up refined management costs. These cost pressures are particularly prominent at the medium diversity level — internal coordination costs have already risen, and additional external costs further squeeze the attention and investment in AI innovation, thus strengthening the inhibition effect.

To sum up, the moderating effect of cooperative innovation is manifested as two-way strengthening: it not only strengthens the information complementarity effect at the high diversity stage through external knowledge resources, but also aggravates the cost constraint effect at the medium diversity stage through coordination costs, management costs and opportunistic risks. In other words, cooperative innovation makes the U-shaped curve steeper — the negative effect is stronger when diversity is low or medium, and the positive effect is stronger when diversity is high. On this basis, this paper puts forward the following hypothesis:

H5. Cooperative innovation can strengthen the U-shaped impact of management knowledge diversity on AI innovation.

DOI: 10.54254/2754-1169/2026.36681

3. Method

3.1. Data and sample

Our sample includes Chinese A-share listed companies from 2011 to 2024. Financial data and innovation data are from the CSMAR database, and text-based indicators such as management knowledge diversity are from the annual reports of listed companies. To improve the accuracy of the results, we exclude financial companies (due to their special asset-liability structure), companies with abnormal financial conditions (ST or *ST companies), and samples with missing data on key variables. Finally, we obtain 51,029 unbalanced panel observations from 5,120 companies. To reduce the impact of extreme values, this paper winsorizes continuous variables at the 1% level.

3.2. Variable definitions

3.2.1. Dependent variable

Corporate artificial intelligence innovation (lnainno) is measured by the natural logarithm of the number of artificial intelligence-related invention and utility model patent applications of the enterprise in the current year plus 1. This indicator can directly reflect the innovation output level and technological R&D capability of enterprises in the field of artificial intelligence. The higher the value, the stronger the enterprise's artificial intelligence innovation capability.

3.2.2. Independent variable

Management knowledge diversity (Mgmtknowdiv) is measured by the information entropy index based on Laplace smoothing. It quantifies the breadth and balance of enterprise management knowledge coverage through the word frequency distribution of different management fields in the Management Discussion and Analysis (MD&A) text of the enterprise. The higher the index value, the more diversified the knowledge structure of the enterprise management and the richer the cross-border knowledge reserve.

3.2.3. Mediating variable

Long-term orientation (Long1): measured by the natural logarithm of the word frequency of "long-term orientation" in the Management Discussion and Analysis text plus 1, reflecting the long-term development willingness and resource allocation tendency at the corporate strategic level. The higher the value, the stronger the enterprise's long-term orientation, which is the mediating transmission variable for management knowledge diversity to affect enterprise artificial intelligence innovation.

3.2.4. Moderating variables

Digital economy development level (Digecon): measured by the prefecture-level digital economy development index, calculated by the entropy method with weighted multi-dimensional indicators such as digital infrastructure and digital industry development, reflecting the digital economy development environment where the enterprise is located. The higher the value, the more perfect the regional digital economy foundation.

DOI: 10.54254/2754-1169/2026.36681

Open innovation (Openinv): measured by the natural logarithm of the number of jointly-filed invention and utility model patent applications of the enterprise in the current year plus 1, reflecting the degree of enterprises carrying out innovation through external cooperation. The higher the value, the higher the level of enterprise open innovation.

Institutional investor ownership (Inst): measured by the proportion of institutional investors' shareholding in the total number of shares of the enterprise, reflecting the participation degree of institutional investors in the enterprise's ownership structure. The higher the value, the stronger the supervision and governance role of institutional investors on the enterprise.

3.2.5. Control variables

We include the following control variables. At the corporate operation level, we control for firm size (Size), firm age (Age), asset-liability ratio (Lev), growth (Growth), cash flow ratio (Cashflow), and profitability (ROA). At the corporate governance level, we control for board size (Board), duality of chairman and general manager (Dual), ownership concentration (Top1), ownership nature (SOE), and proportion of independent directors (Indep). The variable definitions are shown in Table 2.

Table 1. Definitions of key variables

Type	Variable	Symbol	Definition
Dependent variable	*Natural logarithm of the number of firm*	lnainno	Natural logarithm of the number of firm artificial intelligence invention and utility model patent applications plus 1.
Independent variable	*Management knowledge diversity*	Mgmtknowdiv	Index reflecting the breadth and equilibrium of a firm's knowledge coverage, quantified by information entropy based on Laplace-smoothed word frequency distributions across management domains.
Mediating variable	*Long-term orientation*	Long1	Natural logarithm of the word frequency of long-term orientation in Management Discussion and Analysis plus 1.
Moderating variables	*Digecon*	Digecon	Digital Economy Index of prefecture-level cities, measured using the entropy method.
	Openinv	Openinv	Natural logarithm of the number of jointly-filed invention and utility model patent applications plus 1.
	Inst	Inst	Institutional investor ownership as a percentage of total shares.
Control variables	*Size*	Size	Natural logarithm of the firm's total assets at the end of the year.
	Listage	ListAge	Natural logarithm of the number of years since the firm's listing plus 1.
	Lev	Lev	Total liabilities at the end of the year divided by total assets at the end of the year.
	Top1	Top1	Shareholding of the largest shareholder at the end of the year as a proportion of the firm's total shares.

Table 1. (continued)

	Indep	Indep	Percentage of independent directors on the board.
	Growth	Growth	Growth rate of firm operating revenue, measured as (current year revenue − previous year revenue) divided by previous year revenue.
	Cashflow	CashFlow	Net cash flow from operating activities divided by total assets at the end of the year.
	Tobinq	TobinQ	Market value of equity scaled by total assets.
	Roa	ROA	Net profit divided by the average balance of total assets.

3.3. Empirical models

To explore the impact of management knowledge diversity on corporate artificial intelligence innovation, this paper constructs the following regression model:

$$lnainno_{i,t} = a_0 + a_1 Mgmtknowdivi_{i,t} + a_2 Mgmtknowdivi^2{}_{i,t} + \sum a_3 Controls_{i,t} + Industry_i + Year_t + \varepsilon_{i,t} \quad (1)$$

Where i represents the individual enterprise, and t represents the year. $\mathrm{lnainno}_{i,t}$ represents the level of artificial intelligence innovation of enterprise i in year t; $\mathrm{Mgmtknowdivi}_{i.t}$ represents the measurement indicator of management knowledge diversity; $\mathrm{Mgmtknowdivi}^2{}_{i,t}$ represents the square term of management knowledge diversity, which is used to test the nonlinear relationship between variables; $\mathrm{Controls}_{i,t}$ represents a series of control variables of the model; $\varepsilon_{i,t}$ is the random error term. The model controls for industry fixed effects and year fixed effects at the same time, and the standard errors of all regressions are clustered at the enterprise level.

Model (1) is used to test H1, H5 and H6.

To test the mediating role of executive long-term orientation between management knowledge diversity and corporate artificial intelligence innovation, this paper constructs the following progressive regression models:

First, test the impact of management knowledge diversity on the mediating variable (executive long-term orientation), and construct model (2) to verify hypothesis H2a:

$$long1_{i,t} = \gamma_0 + \gamma_1 Mgmtknowdivi_{i,t} + \gamma_2 Mgmtknowdivi^2{}_{i,t} + \sum \gamma_3 Controls_{i,t} + Industry_i + Year_t + \varepsilon_{i,t} i \quad (2)$$

Where $\mathrm{long1}_{i,t}$ represents the level of executive long-term orientation of enterprise i in year t, and the meanings of other variables are consistent with the benchmark model (1). The model controls for industry fixed effects and year fixed effects at the same time, and standard errors are clustered at the enterprise level. Model (2) is used to test hypothesis H2a.

Second, test the impact of the mediating variable (executive long-term orientation) on corporate artificial intelligence innovation, and construct model (3) to verify hypothesis H2b:

DOI: 10.54254/2754-1169/2026.36681

$$\mathrm{lnainno_{i,t}} = \delta_0 + \delta_1 \mathrm{long1_{i,t}} + \sum \delta_2 \mathrm{Controls_{i,t}} + \mathrm{Industry_i} + \mathrm{Year_t} + \varepsilon_{i,t} \tag{3}$$

Where the meanings of all variables are consistent with the previous text. Model (3) is used to test hypothesis H2b.

Finally, the core explanatory variable and the mediating variable are included in the regression at the same time, and model (4) is constructed to test the transmission mechanism of the mediating effect and verify hypothesis H2:

$$lnainno_{i,t} = \theta_0 + \theta_1 Mgmtknowdivi_{i,t} + \theta_2 Mgmtknowdivi^2{}_{i,t} + \theta_3 long1_{i,t} \tag{4}$$

$$+ \sum \theta_4 Controls_{i,t} + Industry_i + Year_t + \varepsilon_{i,t}$$

Where the meanings of all variables are consistent with the previous models. Model (4) is used to test hypothesis H2.

To explore whether moderating variables will strengthen the effect of management knowledge diversity on corporate artificial intelligence innovation, this paper constructs interaction terms and sets up the following model:

$$lnainno_{i.t} + 1 = \beta_0 + \beta_1 Mgmtknowdiv_{i,t} + \beta_2 Moderate_{i,t} \tag{5}$$

$$+\beta_3 Moderate \times Mgmtknowdiv_{i,t} + \sum \beta_4 Controls_{i,t} + Firm_i + Year_t + Industry + \varepsilon_{i,t}$$

Where Moderate represents the moderating variable, and the meanings of other variables are consistent with the benchmark model above. Model (5) is used to test H3, H4 and H5.

4. Empirical results

4.1. Descriptive statistics

Table 2 reports the descriptive statistics of the variables. The mean value of management knowledge (mgmtknow) is 1.715, with a standard deviation of 0.168, indicating that there are certain differences in the management knowledge level of listed companies. The mean value of enterprise innovation input (Inaiinno) is 0.193, with a standard deviation of 0.558, indicating that there are large differences in the level of enterprise innovation input among enterprises.

Table 2. Descriptive statistics

Variables	N	Mean	SD	Min	Max
Mgmtknowdiv	61,057	1.715	0.168	1.201	2.041
Inaiinno	54,744	0.193	0.558	0	2.996
Long1	61,057	4.077	0.780	1.609	5.537
Digecon	50,669	0.140	0.207	0.002	0.862
Openinv	54,744	0.370	0.836	0	4.043
Inst	56,502	0.442	0.251	0.002	0.916
Size	57,756	22.06	1.292	19.720	26.130
Listage	57,756	2.007	0.924	0	3.555
Lev	57,756	0.424	0.206	0.052	0.902
Top1	56,279	0.345	0.151	0.084	0.743

DOI: 10.54254/2754-1169/2026.36681

Table 2. (continued)

Indep	56,963	36.89	6.126	13.330	57.14
Growth	57,659	0.151	0.368	-0.576	2.112
Cashflow	57,756	0.0470	0.070	-0.167	0.244
Tobinq	57,756	1.918	1.174	0.846	7.809
Roa	57,752	0.037	0.078	-1.859	1.285

4.2. Baseline regression results

Table 3 reports the estimation results of the nonlinear impact of management knowledge diversity (Mgmtknowdiv) on enterprise innovation input (Inaiinno). Among them, column (1) does not add control variables, and column (2) adds control variables.

The results show that the coefficient of management knowledge diversity (Mgmtknowdiv) is -1.4684 (column 1) and -1.4463 (column 2), which is significantly negative at the 1% level; while the coefficient of its quadratic term ($Mgmtknowdiv^2$) is 0.3936 (column 1) and 0.3866 (column 2), which is significantly positive at the 1% level. This indicates that management knowledge diversity has a U-shaped relationship with enterprise innovation input, that is, with the improvement of management knowledge diversity, enterprise innovation input first decreases and then increases.

Table 3. Baseline regression results

Variables	(1) Inaiinno	(2) Inaiinno
Mgmtknowdiv	-1.468***	-1.446***
	(-4.302)	(-4.266)
Mgmtknowdiv2	0.394***	0.387***
	(3.981)	(3.937)
Size		0.024***
		(3.098)
Listage		-0.003
		(-0.338)
Lev		0.044*
		(1.874)
Top1		-0.078
		(-1.851)
Indep		0.001
		(1.207)
Growth		-0.013**
		(-2.558)
Cashflow		-0.028
		(-0.806)
Tobinq		0.001
		(0.383)
Roa		0.118***
		(3.162)

DOI: 10.54254/2754-1169/2026.36681

Table 3. (continued)

Constant	1.548***	0.972***
	(5.272)	(2.990)
Ind FE	Yes	Yes
Year FE	Yes	Yes
N	51,029	51,029
R-squared	0.5449	0.5455

*Note: *** p<0.01, ** p<0.05, * p<0.1, t-statistics in parentheses.*

4.3. Robustness tests

4.3.1. Sample interval adjustment

To test whether the research conclusions are sensitive to the specific time window used in the analysis, the sample is limited to the data from 2012 to 2024. The results show that the coefficient of Mgmtknowdiv is still significantly negative, which is consistent with the baseline regression results, further confirming the robustness of our research conclusions.

Table 4. Results of adjustment of sample interval

Variables	(1) Inaiinno
Mgmtknowdiv	-0.129***
	(-4.450)
Size	0.022***
	-2.960
Listage	-0.005
	(-0.520)
Lev	0.015
	-0.610
Top1	-0.031
	(-0.720)
Indep	0.001
	-1.520
Growth	-0.006
	(-1.100)
Cashflow	-0.005
	(-0.140)
Tobinq	0.004
	-1.110

DOI: 10.54254/2754-1169/2026.36681

Table 4. (continued)

Roa	0.108***
	-2.690
Constant	-0.084
	(-0.490)
Firm FE	Yes
Year FE	Yes
Industry FE	NO
N	43,306
Adj.R^2	0.521

*Notes: t-statistics are in parentheses. ***, *, and * indicate 1%, 5%, and 10% significance, respectively.*

4.3.2. Control for different fixed effects

While controlling for year and industry fixed effects, we add firm fixed effects to control for unobserved firm heterogeneity characteristics. The regression results show that the coefficient of Mgmtknowdiv is significantly negative, which is consistent with the baseline regression results. At the same time, we adjust the clustered standard errors of the baseline regression to the industry level for regression, to alleviate the interference of intra-industry serial correlation problems on the regression results. The regression results show that the coefficient of Mgmtknowdiv is still significantly negative, which is consistent with the baseline regression results, indicating that our main conclusions are not sensitive to the setting method of clustered standard errors.

Table 5. Results of adjusting the clustering level

Variables	(1) Inaiinno
Mgmtknowdiv	-0.091***
	(-3.140)
Size	0.076***
	-10.130
Listage	0.040***
	-6.040
Lev	-0.047**
	(-2.020)
Top1	-0.131***
	(-3.050)
Indep	0.001**
	-2.180
Growth	-0.036***
	(-7.120)
Cashflow	0.222***
	-6.000

DOI: 10.54254/2754-1169/2026.36681

Table 5. (continued)

Tobinq	-0.012***
	(-4.140)
Roa	0.043
	-1.140
Constant	-1.388***
	(-8.660)
Firm FE	Yes
Industry FE	Yes
Year FE	NO
N	51,029
Adj.R^2	0.391

*Notes: t-statistics are in parentheses. ***, *, and * indicate 1%, 5%, and 10% significance, respectively.*

4.3.3. Instrumental variable regression

To address potential endogeneity problems, this paper adopts the instrumental variable (IV) method for endogeneity testing.

In this study, we select the average level of management knowledge diversity among other enterprises in the same industry in the current year as the instrumental variable. The Cragg-Donald-Wald F statistic is 437.301, which is greater than the critical value of the Stock-Yogo weak instrumental variable test, rejecting the null hypothesis of weak instrumental variables. It can be seen from column (1) of Table 6 that the regression coefficient of the instrumental variable in the first stage is significantly positive (β=-13.770, p<0.01), indicating that the instrumental variable is effective. In the second-stage regression, the coefficient of management knowledge diversity is significantly negative (β=3.964, p<0.01), which once again indicates that management knowledge diversity significantly first reduces and then improves enterprise innovation input.

Table 6. Instrumental variable method

Variables	(1) First stage	(2) First stage	(3) Second stage
	Mgmtknowdiv	Mgmtknowdiv²	Inainno
IV_Mgmtknowdiv_indyear	0.661***	2.134***	
	-20.5	-20.58	
IV_Mgmtknowdiv_cityyear	0.850***	2.926***	
	-50.23	-51.33	
Mgmtknowdiv			-13.770***
			(-5.40)
Mgmtknowdiv²			3.964***
			-5.27
Size	0.001	0.005	0.021**
	-0.48	-0.6	-2.45
Listage	-0.003	-0.008	-0.019*
	(-1.19)	(-0.92)	(-1.91)

DOI: 10.54254/2754-1169/2026.36681

Table 6. (continued)

Lev	-0.001	-0.001	0.039
	(-0.09)	(-0.03)	-1.51
Top1	0.01	0.037	-0.082*
	-0.62	-0.71	(-1.81)
Indep	0.001	0	0.001
	-0.38	-0.4	-1.05
Growth	-0.003	-0.01	-0.014***
	(-1.83)	(-1.81)	(-2.60)
Cashflow	0.022**	0.072***	-0.002
	-2.25	-2.16	(-0.06)
Tobinq	-0.001	-0.002	0.011
	(-0.67)	(-0.76)	-0.33
Roa	0.050***	0.163***	0.162***
	-4.5	-4.36	-4.1
Constant			-3.119***
			(-6.10)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Kleibergen-Paap rk LM test			107.512***
Cragg-Donald Wald F			437.301
N	51029	51029	51029
Adj.R^2			0.55

*Notes: t-statistics are in parentheses. ***, *, and * indicate 1%, 5%, and 10% significance, respectively.*

4.3.4. Propensity score matching

In this paper, we take the mean value of management knowledge diversity (Mgmtknowdiv) as the cut-off point, and divide the sample into treatment group and control group. The control variables in the baseline regression (Size, Listage, Lev, Top1, Indep, Growth, Cashflow, Tobinq, Roa) are used as covariates for 1:3 nearest neighbor matching.

Table 7 reports the results of the balance test. The absolute values of the standardized deviations of each covariate are controlled within 10%, indicating that PSM matching effectively improves the comparability between the treatment group and the control group.

Table 7. Results of propensity score matching

Variables	(1) lnainno
Mgmtknowdiv	-1.228***
$Mgmtknowdiv^2$	0.321***
Size	0.021**
Listage	-0.007***
Lev	0.038**
topl	-0.081***

DOI: 10.54254/2754-1169/2026.36681

Table 7. (continued)

Indep	0.000**
Growth	-0.011***
Cashflow	-0.031**
Tobinq	0.029***
Roa	0.059**
Constant	0.874***
Industry	Yes
Year	Yes
N	39240
Adj.R^2	0.482

*Notes: t-statistics are in parentheses. ***, *, and * indicate 1%, 5%, and 10% significance, respectively.*

4.4. Mechanism analysis

According to the discussion of the previous research hypotheses, this paper argues that management knowledge diversity (Mgmtknowdiv) may affect enterprise artificial intelligence innovation (lnainno) through long-term orientation (long1).

4.4.1. Long-term orientation (long1)

In this paper, we use the natural logarithm of the word frequency of "long-term orientation" in Management Discussion and Analysis plus 1 to measure long-term orientation (long1). The results are shown in Table 8. Among them, column (1) shows that management knowledge diversity (Mgmtknowdiv) has a significant positive impact on long-term orientation (longl) (coefficient is 0.0147, t-value is 2.0076, significant at the 5% level), indicating that management knowledge diversity promotes long-term orientation. Column (2) shows that when management knowledge diversity (Mgmtknowdiv, $Mgmtknowdiv^2$) and long-term orientation (longl) are introduced at the same time, the coefficient of Mgmtknowdiv on enterprise artificial intelligence innovation (lnainno) is -1.415 (significant at the 1% level), the coefficient of $Mgmtknowdiv^2$ on enterprise artificial intelligence innovation (lnainno) is 0.3769 (significant at the 1% level), and the coefficient of long-term orientation (longl) on enterprise artificial intelligence innovation (lnainno) is 0.0147 (significant at the 5% level). The coefficients of the three are all significantly positive or negative and the direction conforms to the logic of mediating effect. This indicates that long-term orientation (longl) plays a partial mediating role in the relationship between management knowledge diversity and enterprise artificial intelligence innovation. Therefore, Hypothesis 2 is verified.

To explore the U-shaped action path of management knowledge diversity (Mgmtknowdiv) on enterprise artificial intelligence innovation (lnainno), this paper tests the mediating role of long-term orientation (longl). First, management knowledge diversity (Mgmtknowdiv) has a significant positive impact on long-term orientation (longl) (the coefficient of the linear term is 0.0147, significant at the 5% level), and does not form a U-shaped structure. Second, long-term orientation (longl) has a significant positive impact on enterprise artificial intelligence innovation (lnainno) (coefficient is 0.0147, significant at the 5% level). At the same time, management knowledge diversity (Mgmtknowdiv) has a U-shaped impact on enterprise artificial intelligence innovation (lnainno) (the coefficient of the linear term is -1.415, significant at the 1% level; the coefficient of

DOI: 10.54254/2754-1169/2026.36681

the quadratic term is 0.3769, significant at the 1% level). This shows that management knowledge diversity promotes enterprise artificial intelligence innovation by improving long-term orientation; at the same time, the U-shaped direct effect of management knowledge diversity itself on enterprise artificial intelligence innovation is still significant. The partial mediating role of long-term orientation (longl) is verified.

Table 8. Mechanism analysis

Variables	(1) longl	(2) lnainno
Mgmtknowdiv	0.015**	-1.415***
	(2.008)	(-4.169)
Mgmtknowdiv²		0.377***
		(3.829)
longl		0.015**
		(2.008)
Size	0.022***	0.022***
	(2.808)	(2.808)
Listage	-0.002	-0.002
	(-0.213)	(-0.213)
Lev	0.047**	0.047**
	(2.003)	(2.003)
Top1	-0.080*	-0.080*
	(-1.910)	(-1.910)
Indep	0.001	0.001
	(1.233)	(1.233)
Growth	-0.013***	-0.013***
	(-2.681)	(-2.681)
Cashflow	-0.028	-0.028
	(-0.800)	(-0.800)
Tobinq	0.001	0.001
	(0.374)	(0.374)
Roa	0.116***	0.116***
	(3.110)	(3.110)
Constant	0.927***	0.927***
	(2.847)	(2.847)
Firm FE	Yes	Yes
Year FE	Yes	Yes
N	51,029	51,029
Adj.R²	0.546	0.546
Sobel	3.214***	

Note: *, *, and * denote significance at the 10 %, 5 %, and 1 % Levels, respectively. T-statistics are reported in parentheses.*

DOI: 10.54254/2754-1169/2026.36681

4.5. Moderating effects

Table 9 examines the moderating effect of the development level of digital economy on the relationship between management knowledge diversity and enterprise innovation input. Column (1) shows that the coefficient of the interaction term between management knowledge diversity and digital economy development level is significantly positive, and the coefficient of the interaction term between the quadratic term of management knowledge diversity and digital economy development level is significantly negative, indicating that the development level of digital economy has a negative moderating effect on the U-shaped relationship between management knowledge diversity and enterprise innovation input. The improvement of digital economy development level will weaken the first-inhibition-then-promotion effect of management knowledge diversity on enterprise innovation input. To sum up, the U-shaped impact of management knowledge diversity on enterprise innovation input can be weakened by the development level of digital economy. Therefore, the moderating effect hypothesis of this paper is verified.

Table 9. Moderating effect

Variables	(1) lnainno	(2) lnainno	(3) lnainno
Mgmtknowdiv	-1.3517	-1.548	-1.419
	(-4.662)	(-4.263)	(-4.216)
$Mgmtknowdiv^2$	0.357	0.411	0.381
	(4.218)	(3.904)	(3.915)
Openinv	0.151		
	(19.982)		
Mgmtknowdiv × Openinv	-1.560**		
	(-2.993)		
$Mgmtknowdiv^2$ × Openinv	0.418***		
	(2.697)		
Digecon		-0.027	
		(-1.149)	
Mgmtknowdiv × Digecon		4.980***	
		(4.175)	
$Mgmtknowdiv^2$ × Digecon		-1.454***	
		(-4.050)	
Inst			-0.078
			(-2.713)
Mgmtknowdiv × Inst			3.947***
			(3.234)
$Mgmtknowdiv^2$ × Inst			-1.157***
			(-3.222)
Size	0.008	0.026	0.029
	(1.076)	(2.882)	(3.563)
Listage	-0.004	0.009	-0.006
	(-0.505)	(0.882)	(-0.658)
Lev	0.050	0.056	0.040

DOI: 10.54254/2754-1169/2026.36681

Table 9. (continued)

	(2.304)	(2.065)	(1.669)
Top1	-0.059	-0.093	-0.035
	(-1.513)	(-1.924)	(-0.767)
Indep	0.001	0.001	0.001
	(1.023)	(1.390)	(1.032)
Growth	-0.008	-0.012	-0.011
	(-1.720)	(-2.329)	(-2.173)
Cashflow	-0.010	-0.037	-0.028
	(-0.292)	(-0.960)	(-0.807)
Tobinq	0.001	0.001	0.003
	(0.206)	(0.198)	(0.873)
Roa	0.099	0.132	0.124
	(2.756)	(3.102)	(3.318)
Constant	1.209	1.019	0.863
	(4.230)	(2.882)	(2.661)
Ind FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	51,029	42,227	50,965
Adj.R^2	0.565	0.557	0.546

*Note: t-statistics in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.*

4.6. Heterogeneity analysis

To verify the promoting effect of management knowledge diversity on enterprise artificial intelligence innovation, this paper further discusses its heterogeneous impact from five dimensions: industry pollution degree, management shareholding ratio, enterprise regional heterogeneity, market competition degree, and intellectual property protection degree.

4.6.1. Industry pollution degree

Enterprises with different pollution degrees differ in environmental compliance pressure, resource input direction and social responsibility goals, which may lead to different degrees of impact of management knowledge diversity on enterprise artificial intelligence innovation. We divide the sample enterprises into low-pollution enterprises and high-pollution enterprises according to the pollution degree of the industry to which the enterprise belongs. The results are shown in columns (1) and (2) of Table 10. It can be seen that the promoting effect of management knowledge diversity on artificial intelligence innovation of low-pollution enterprises is more significant. This indicates that in industries with low emission reduction pressure, enterprise operations are less constrained by environmental compliance, and more management resources and knowledge reserves can be invested in intelligent R&D upgrading. Therefore, management knowledge diversity has a more obvious promoting effect on artificial intelligence innovation of low-pollution enterprises.

DOI: 10.54254/2754-1169/2026.36681

4.6.2. Management shareholding ratio

Enterprises with different management shareholding ratios differ in governance structure, interest binding degree and innovation decision-making preference, which may lead to different degrees of impact of management knowledge diversity on enterprise artificial intelligence innovation. We divide the sample enterprises into enterprises with low shareholding ratio and enterprises with high shareholding ratio according to the management shareholding ratio. The results are shown in columns (1) and (2) of Table 11. It can be seen that the promoting effect of management knowledge diversity on artificial intelligence innovation of enterprises with high management shareholding ratio is more significant. This indicates that high management shareholding can deeply bind the long-term innovation interests of managers and enterprises, motivate management to layout artificial intelligence R&D based on diversified knowledge structure, and strengthen the willingness of innovation input, so the promotion effect is stronger.

4.6.3. Enterprise regional heterogeneity

Due to the differences in digital infrastructure and the agglomeration level of scientific and technological innovation resources in eastern, central and western China, the effect of management knowledge diversity empowering artificial intelligence innovation may also show regional differences. We divide the sample enterprises into non-eastern region enterprises and eastern region enterprises according to the location of the enterprise. The results are shown in columns (3) and (4) of Table 11. It can be seen that the promoting effect of management knowledge diversity on artificial intelligence innovation of enterprises in eastern regions is more significant, and the impact is not significant in the non-eastern region sample. This indicates that the eastern region has complete supporting digital industries and intensive high-end talents and scientific and technological innovation elements, which can fully release the synergistic value of diversified management knowledge and help enterprises carry out artificial intelligence innovation activities.

4.6.4. Market competition degree

Enterprises under different market competition environments differ in innovation forcing pressure, resource allocation efficiency and technological iteration motivation, which may lead to different degrees of impact of management knowledge diversity on enterprise artificial intelligence innovation. We divide the sample enterprises into low market competition enterprises and high market competition enterprises according to the market competition degree of the industry where the enterprise is located. The results are shown in columns (3) and (4) of Table 10. It can be seen that the promoting effect of management knowledge diversity on artificial intelligence innovation of enterprises with high market competition is more significant, and the impact is not significant in the low competition sample. This indicates that high market competition forces enterprises to break through technical bottlenecks with differentiated and diversified management knowledge, accelerate the R&D and implementation of artificial intelligence technology, so as to build core competitive advantages.

4.6.5. Intellectual property protection degree

The intellectual property protection level in different regions differs in institutional perfection and law enforcement intensity, which may lead to different degrees of impact of management knowledge diversity on enterprise artificial intelligence innovation. We divide the sample enterprises into enterprises with low intellectual property protection degree and enterprises with high intellectual property protection degree according to the intellectual property protection degree of the region where the enterprise is located. The results are shown in columns (5) and (6) of Table 10. It can be seen that the promoting effect of management knowledge diversity on artificial intelligence innovation of enterprises with high intellectual property protection degree is more significant. This indicates that strong intellectual property protection can reduce the risk of infringement of artificial intelligence R&D achievements, ensure the transformation of diversified management knowledge into innovation benefits, and improve the enthusiasm of enterprises to carry out intelligent technological innovation based on knowledge advantages.

Table 10. Heterogeneity Analysis Results (External Environment Dimension)

Variables	Industrial Pollution		Market Competition		IPR Protection	
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	High	Low	High	Low	High
Mgmtknowdiv	-1.657***	0.925*	-0.216	-1.700***	-0.637*	-1.835***
	(-4.290)	-1.84	(-0.430)	(-4.290)	(-1.930)	(-3.310)
$Mgmtknowdiv^2$	0.445***	-0.260*	0.047	0.469***	0.153	0.527***
	-3.92	(-1.770)	(-0.320)	(-4.080)	-1.61	-3.22
Size	0.039***	-0.01	0.016	0.027**	0.026***	-0.014
	-3.94	(-0.840)	-1.76	-2.39	-2.85	(-0.840)
Listage	0.003	-0.036**	-0.019*	0.013	0.033***	-0.028*
	-0.3	(-2.500)	(-1.700)	(-0.980)	-2.99	(-1.850)
Lev	0.034	0.011	0.077**	-0.012	0.04	0.058
	-1.14	-0.28	-2.47	(-0.380)	-1.41	-1.29
Top1	-0.038	-0.136*	-0.098*	0.009	-0.036	-0.066
	(-0.710)	(-1.830)	(-1.930)	(-0.150)	(-0.700)	(-0.800)
Indep	0.001	0.002	0.002*	0	0	0.001
	-0.56	-1.21	-1.81	(-0.230)	-0.24	-0.88
Growth	-0.013**	0	-0.002	-0.015**	-0.015***	-0.008
	(-2.260)	(-0.030)	(-0.230)	(-2.440)	(-2.720)	(-0.930)
Cashflow	-0.004	-0.085	0.038	-0.078*	-0.043	-0.016
	(-0.090)	(-1.600)	-0.71	(-1.790)	(-1.110)	(-0.300)
Tobinq	0.001	0.005	0.002	0.002	0	-0.002
	-0.2	-1.22	-0.6	(-0.410)	(-0.080)	(-0.360)
Roa	0.111**	0.153***	0.088	0.103**	0.109**	0.132**
	-2.47	-2.69	-1.38	-2.16	-2.21	-2.31
Constant	0.844**	-0.438	0.049	1.088***	0.108	2.173***
	-2.24	(-0.900)	-0.11	-2.66	-0.31	-3.87
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	23888	25233	24377	26215	23993	26615
Adj.R^2	0.59	0.558	0.604	0.556	0.524	0.633

*Note: t-statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

DOI: 10.54254/2754-1169/2026.36681

Table 11. Heterogeneity analysis results (firm characteristic & regional dimension)

Variables	Management Ownership		Regional Location	
	(1)	(2)	(3)	(4)
	Low	High	Non-eastern	Eastern
Mgmtknowdiv	-1.140**	-2.032***	-0.531	-1.778***
	(-2.280)	(-4.550)	(-1.160)	(-4.170)
Mgmtknowdiv²	0.298**	0.554***	0.139	0.477***
	-2.06	-4.26	-1.03	-3.86
Size	0.019*	0.040***	0.016	0.029***
	-1.7	-3.27	-1.3	-2.85
Listage	-0.019	0.033***	-0.01	0
	(-1.040)	-3.46	(-0.560)	(-0.060)
Lev	0.071*	0.001	0.083**	0.034
	-1.89	-0.02	-2.04	-1.17
Top1	-0.115*	-0.053	-0.069	-0.063
	(-1.830)	(-0.830)	(-0.960)	(-1.200)
Indep	0.001	0	0	0.001
	-1.2	(-0.100)	-0.12	-1.56
Growth	-0.009	-0.016**	0	-0.020***
	(-1.280)	(-2.100)	(-0.000)	(-3.270)
Cashflow	-0.016	-0.019	-0.031	-0.029
	(-0.310)	(-0.400)	(-0.520)	(-0.680)
Tobinq	0.001	0.003	0.010**	-0.002
	-0.19	-0.6	-2.06	(-0.540)
Roa	0.051	0.158***	0.076	0.129***
	-0.92	-2.76	-1.28	-2.75
Constant	0.851*	1.114***	0.285	1.163***
	-1.68	-2.64	-0.58	-2.86
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	23888	25233	14768	36243
Adj.R²	0.59	0.558	0.498	0.56

*Note: t-statistics are in parentheses. * p <0.1, ** p <0.05, *** p <0.01.*

5. Discussion

In the era of digital economy, artificial intelligence technology has become a key force driving enterprise innovation and competitive advantage. However, the characteristics of high investment, long cycle and strong uncertainty of AI innovation pose severe challenges to enterprise knowledge base and strategic decision-making. This study focuses on the long-neglected important dimension of management knowledge diversity, and discusses its impact mechanism and boundary conditions on corporate AI innovation. Based on an empirical analysis of 5,120 Chinese A-share listed companies, this study finds that: First, there is a significant U-shaped relationship between

DOI: 10.54254/2754-1169/2026.36681

management knowledge diversity and AI innovation. This finding is in sharp contrast to the inverted U-shaped relationship commonly found in existing studies on technological knowledge diversity, and reveals the unique action logic of "conflict first, then synergy" in management knowledge integration. Second, executive long-term orientation plays a mediating role in the U-shaped relationship between management knowledge diversity and AI innovation, and management knowledge diversity affects corporate AI innovation by shaping the temporal cognitive framework of the top management team. Third, both institutional ownership and digital economy development level negatively moderate the U-shaped relationship between management knowledge diversity and AI innovation, making the U-shaped curve flatter; while cooperative innovation positively moderates this relationship, making the U-shaped curve steeper. These findings systematically reveal the action mechanism and boundary conditions of management knowledge diversity affecting AI innovation, and provide theoretical guidance for enterprises to optimize knowledge management strategies and promote AI technological innovation.

5.1. Theoretical implications

First of all, this study expands the theoretical boundary of the knowledge-based view in the context of artificial intelligence, and proposes and verifies the U-shaped relationship between management knowledge diversity and AI innovation for the first time. Different from existing studies that generally focus on the inverted U-shaped relationship between technological knowledge diversity and innovation performance [5-7], this study focuses on the long-neglected management knowledge dimension, and finds that it presents a unique U-shaped pattern with AI innovation, revealing that management knowledge integration follows the logic of "conflict first, then synergy": when diversity is low, cognitive limitations and coordination costs inhibit AI innovation; only when diversity crosses a critical threshold can the effects of information complementarity and cross-boundary integration be fully released and significantly promote innovation, thus providing a new analytical framework for knowledge management in the AI context.

Second, this study opens the cognitive black box of how management knowledge diversity affects AI innovation, and reveals the mediating mechanism of executive long-term orientation. Although existing studies have recognized the importance of knowledge diversity, there is insufficient discussion on the micro-foundation of "how knowledge is transformed into innovation". Based on temporal orientation theory [13, 14], this study finds that management knowledge diversity affects AI innovation by shaping the long-term orientation of the top management team, that is, the integration of diversified management knowledge backgrounds can activate executives' cognitive recognition of the long-term value of AI, prompting them to adopt long-term strategic decisions [36] and continuously allocate resources to AI projects. This finding clarifies that diversified management knowledge does not directly act on innovation, but works through the psychological mechanism of changing executives' temporal cognitive framework, and enriches the application of temporal orientation theory in enterprise innovation decision-making.

Finally, this study constructs a contingency analysis framework integrating internal governance, external environment and strategic choice, and systematically reveals the boundary conditions of management knowledge diversity affecting AI innovation. By examining the differential moderating effects of institutional ownership, digital economy development level and cooperative innovation, it is found that: as an internal governance mechanism, institutional ownership alleviates the inhibition effect of coordination costs in the declining segment of the U-shaped curve, and dilutes the marginal contribution of information complementarity in the rising segment, thus making the curve flatter; as an external environmental factor, the development level of digital economy weakens the intensity of

DOI: 10.54254/2754-1169/2026.36681

the impact of internal knowledge diversity on AI innovation by providing technical support and infrastructure; while cooperative innovation, as an open innovation strategy [19, 20], strengthens the information complementarity effect at the high diversity stage by introducing external knowledge, and at the same time aggravates innovation inhibition at the medium diversity stage by increasing coordination costs and opportunistic risks [10, 11], making the U-shaped curve steeper. This contingency framework not only reveals the boundary conditions of the action intensity, but also provides theoretical guidance for enterprises to optimize knowledge management strategies and promote AI innovation in different contexts.

5.2. Managerial implications

For enterprise managers, the first enlightenment of this study is to face up to the "double-edged sword" effect of management knowledge diversity and avoid blindly pursuing diversification. When building the top management team, enterprises should first diagnose their own diversity level: if they are at the left end of the U-shaped curve, they should systematically introduce cross-functional and cross-field talents to break cognitive limitations; if they are already at the right end, they should focus on establishing knowledge integration mechanisms, such as setting up cross-functional innovation teams or regular strategic seminars, to release synergy effects. At the same time, enterprises should attach importance to cultivating and motivating executives' long-term orientation. In view of its key mediating role in the transformation from diversity to AI innovation, enterprises can guide managers to transcend short-term interests and focus on AI directions that build long-term competitive advantages by adjusting salary structure, incorporating long-term innovation indicators into assessment, and setting up strategic investment projects. In addition, enterprises need to manage diversity differently according to internal and external conditions: when the proportion of institutional ownership is high, they can moderately reduce their dependence on internal integration and make use of the governance advantages and long-term value orientation of institutional investors; in regions with a high level of digital economy development, they should use digital platforms to reduce coordination costs; while in enterprises with active cooperative innovation, they need to be alert to the superposition of coordination costs and opportunistic risks at the medium diversity stage, and strengthen knowledge protection and relationship governance.

For policy makers, this study also provides important enlightenment. The government should help enterprises cross the "conflict zone" of management knowledge diversity and move towards the "synergy zone" through policy tools. For example, set up cross-industry management talent exchange platforms, hold cross-border management innovation forums, and encourage cross-border management research with industry-university-research cooperation funds to accelerate knowledge integration. At the same time, the government should continue to promote the construction of digital economy and improve digital infrastructure, which can replace the internal knowledge integration function of enterprises and reduce coordination costs to a certain extent. This is especially crucial for enterprises whose diversity has not reached the critical value. The government can help enterprises make up for the lack of internal integration with the help of external environment by building industrial digital platforms, promoting digital technology application scenarios, and providing transformation subsidies. In addition, the government should guide enterprises to establish a scientific cooperative innovation management mechanism. Given that cooperative innovation may amplify coordination costs, the government can issue guidelines for cooperative innovation, promote best practices of knowledge protection and relationship governance, and at the same time reform the education and training system to strengthen the training of compound management talents, so as to provide continuous talent reserve for the management knowledge diversity of enterprises. In general,

DOI: 10.54254/2754-1169/2026.36681

management knowledge diversity needs to dynamically adapt to the internal and external environment, long-term orientation is the key transmission mechanism, and policies should assist enterprises in balancing the benefits and costs of diversity through platform construction, digital empowerment and cooperation norms.

6. Conclusion and future research

6.1. Conclusions

Based on the knowledge-based view and temporal orientation theory, this paper takes Chinese A-share listed companies from 2011 to 2024 as samples, and empirically investigates the impact mechanism and boundary conditions of management knowledge diversity on corporate AI technological innovation. The main conclusions are as follows:

First, there is a significant U-shaped relationship between management knowledge diversity and corporate AI technological innovation, revealing the unique logic of "conflict first, then synergy" in management knowledge integration. Second, executive long-term orientation plays a partial mediating role between the two. Diversified management knowledge indirectly promotes corporate AI innovation by shaping the temporal cognitive framework of the top management team. Third, institutional ownership and digital economy negatively moderate the U-shaped relationship, while cooperative innovation positively moderates it, indicating that the effect of management knowledge diversity is highly dependent on internal governance structure, external digital environment and strategic cooperation choices. Fourth, the promoting effect is more significant in low-pollution industries, high management shareholding, eastern regions, high market competition and high intellectual property protection contexts.

6.2. Theoretical and practical implications

The theoretical contributions of this study are mainly reflected in three aspects: first, it expands the applicable context of the knowledge-based view to the field of AI technological innovation, verifies the U-shaped impact pattern of management knowledge diversity for the first time, and challenges the inertial cognition of "beneficial first, then harmful" in research on technological knowledge diversity; second, it identifies the cognitive path of executive long-term orientation as the mediator, and opens the "black box" of how knowledge diversity affects innovation; third, it constructs a contingency analysis framework integrating internal governance, external environment and strategic choice, and systematically reveals the boundary conditions under which management knowledge diversity plays its role.

In practice, managers should face up to the "double-edged sword" effect of management knowledge diversity, systematically introduce cross-functional talents when the diversity level is low, and focus on establishing knowledge integration mechanisms when the level is high; at the same time, they should attach importance to cultivating executive long-term orientation, and guide managers to focus on long-term value creation through salary design, performance appraisal and other means. Policy makers should help enterprises accelerate crossing the "conflict zone" of the U-shaped curve and release the innovation dividend of management knowledge diversity through policy tools such as cross-industry talent exchange platforms, digital infrastructure construction and intellectual property protection.

DOI: 10.54254/2754-1169/2026.36681

6.3. Limitations and future research

This study has the following limitations: First, the sample only covers Chinese A-share listed companies, and the cross-context universality of the conclusions needs to be tested. Second, the measurement of management knowledge diversity is based on annual report text analysis, which fails to distinguish the correlation and dynamic evolution characteristics between different knowledge fields. Third, although the instrumental variable method and PSM are used to control endogeneity, it is still difficult to completely eliminate the problems of reverse causality and omitted variables. Fourth, the study focuses on the top management team level and does not involve the micro impact of middle managers and front-line employees.

Future research can be extended to different institutional environments or enterprise types, use questionnaire method or case method to deeply depict the structure and dynamic changes of management knowledge diversity, try stricter causal identification strategies such as quasi-natural experiments, and explore the interaction effects of management knowledge diversity at different levels from a multi-level perspective.

References

[1] Meso, P., & Smith, R. (2000). A resource-based view of organizational knowledge management systems. *Journal of Knowledge Management, 4*(3), 224-234.
[2] Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review, 32*(4), 1199-1228.
[3] Malhotra, A., & Majchrzak, A. (2019). Greater associative knowledge variety in crowdsourcing platforms leads to generation of novel solutions by crowds. *Journal of Knowledge Management, 23*(8), 1628-1651.
[4] Wang, Y., Roijakkers, N., & Vanhaverbeke, W. (2013). Learning-by-licensing: How Chinese firms benefit from licensing-in technologies. *IEEE Transactions on Engineering Management, 60*(1), 46–58.
[5] Garcia-Vega, M. (2006). Does technological diversification promote innovation? An empirical analysis for European firms. *Research Policy, 35*(2), 230-246.
[6] Leten, B., Belderbos, R., & Van Looy, B. (2007). Technological diversification, coherence, and performance of firms. *Journal of Product Innovation Management, 24*(6), 567-579.
[7] Kim, J., Lee, C. Y., & Cho, Y. (2016). Technological diversification, core-technology competence, and firm growth. *Research Policy, 45*(1), 113-124.
[8] Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99-120.
[9] Zhou, J., Liu, Z., Li, J., & Zhang, G. (2021). The effects of collaboration with different partners: A contingency model. *IEEE Transactions on Engineering Management, 68*(6), 1546–1557.
[10] Schmid, S., & Mitterreiter, S. (2020). International top managers on corporate boards: Dissimilarity and tenure. *Management International Review, 60*(5), 787–825.
[11] Katila, R. (2002). New product search over time: Past ideas in their prime? *Academy of Management Journal, 45*(5), 995-1010.
[12] Kang, T., Baek, C., & Lee, J. D. (2019). Effects of knowledge accumulation strategies through experience and experimentation on firm growth. *Technological Forecasting and Social Change, 144*, 169-181.
[13] Lumpkin, G. T., & Brigham, K. H. (2011). Long-term orientation and intertemporal choice in family firms. *Entrepreneurship Theory and Practice, 35*(6), 1149–1169.
[14] Venkatraman, N. (1989). The concept of fit in strategy research: Toward verbal and statistical correspondence. *Academy of Management Review, 14*(3), 423–444.
[15] Flammer, C., & Bansal, P. (2017). Does a long-term orientation create value? Evidence from a regression discontinuity. *Strategic Management Journal, 38*(9), 1827–1847.
[16] Sternad, D., & Kennelly, J. J. (2017). The sustainable executive: Antecedents of managerial long-term orientation. *Journal of Global Responsibility, 8*(2), 179–195.
[17] Lassoued, N., & ElMir, A. (2012). Portfolio selection: Does corporate governance matter? *Corporate Governance: The International Journal of Business in Society, 12*(5), 626–639.
[18] Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *The Accounting Review, 73*(3), 305–333.

DOI: 10.54254/2754-1169/2026.36681

[19] Das, T. K., & Teng, B.-S. (1998). Between trust and control: Developing confidence in partner cooperation in alliances. *Academy of Management Review, 23*(3), 491–512.
[20] Kobarg, S., Stumpf-Wollersheim, J., & Welpe, I. M. (2019). More is not always better: Effects of collaboration breadth and depth on radical and incremental innovation performance at the project level. *Research Policy, 48*(1), 1–10.
[21] Faems, D., Janssens, M., Madhok, A., & Van Looy, B. (2008). Toward an integrative perspective on alliance governance: Connecting contract design, contract application, and trust dynamics. *Academy of Management Journal, 51*, 1053–1078.
[22] Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal, 17*(S2), 109-122.
[23] Spender, J. C. (1996). Making knowledge the basis of a dynamic theory of the firm. *Strategic Management Journal, 17*(S2), 45–62.
[24] Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science, 3*(3), 383–397.
[25] Nonaka, I., & Takeuchi, H. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. Oxford University Press.
[26] Moreira, S., Markus, A., & Laursen, K. (2018). Knowledge diversity and coordination: The effect of intrafirm inventor task networks on absorption speed. *Strategic Management Journal, 39*(9), 2517-2546.
[27] Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science, 47*(1), 117-132.
[28] Krafft, J., Quatraro, F., & Saviotti, P. P. (2011). The knowledge-base evolution in biotechnology: A social network analysis. *Economics of Innovation and New Technology, 20*(5), 445-475.
[29] Simons, T. L., & Peterson, R. S. (2000). Task conflict and relationship conflict in top management teams: The pivotal role of intragroup trust. *Journal of Applied Psychology, 85*(1), 102–111.
[30] Collewaert, V., & Sapienza, H. J. (2016). How does angel investor–entrepreneur conflict affect venture innovation? It depends. *Entrepreneurship Theory and Practice, 40*(3), 573–597.
[31] Tortoriello, M., McEvily, B., & Krackhardt, D. (2015). Being a catalyst of innovation: The role of knowledge diversity and network closure. *Organization Science, 26*(2), 423-438.
[32] Wang, C., & Han, Y. (2011). Linking properties of knowledge with innovation performance: The moderate role of absorptive capacity. *Journal of Knowledge Management, 15*(5), 802-819.
[33] Phelps, C. C. (2010). A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. *Academy of Management Journal, 53*(4), 890-913.
[34] Berry, H. (2023). Diverse knowledge exploration and diffusion in MNCs. *Strategic Management Journal, 44*(7), 1589-1615.
[35] Choi, M., & Lee, C. Y. (2021). Technological diversification and R&D productivity: The moderating effects of knowledge spillovers and core-technology competence. *Technovation, 104*, 102249.
[36] Qi, Y., Chen, Q., Yang, M., & Sun, Y. (2024). Ambidextrous knowledge accumulation, dynamic capability and manufacturing digital transformation in China. *Journal of Knowledge Management, 28*(8), 2275-2305.
[37] Li, W., Lv, B., & Sun, H. (2025). Impact of executive team heterogeneity on enterprise digital technology innovation: The moderating effect based on digital finance. *Finance Research Letters*, 109276.
[38] Almeida, P., & Phene, A. (2004). Subsidiaries and knowledge creation: The influence of the MNC and host country on innovation. *Strategic Management Journal, 25*(8-9), 847-864.
[39] Chen, Y.-M., Yang, D.-H., & Lin, F.-J. (2013). Does technological diversification matter to firm performance? The moderating role of organizational slack. *Journal of Business Research, 66*(10), 1970-1975.
[40] Pereira, V., & Bamel, U. (2021). Extending the resource and knowledge based view: A critical analysis into its theoretical evolution and future research directions. *Journal of Business Research, 132*, 557-570.
[41] Zou, J., & Deng, X. (2022). To inhibit or to promote: How does the digital economy affect urban migrant integration in China? *Technological Forecasting and Social Change, 179*, 121647.
[42] Howard, M., Steensma, H. K., Lyles, M., & Dhanaraj, C. (2016). Learning to collaborate through collaboration: How alliance with expert firms influences collaborative innovation within novice firms. *Strategic Management Journal, 37*(10), 2092-2103.
[43] Zhang, W., Jiang, Y., & Zhang, W. (2021). Capabilities for collaborative innovation of technological alliance: A knowledge-based view. *IEEE Transactions on Engineering Management, 68*(6), 1734–1744.
[44] Heil, S., & Bornemann, T. (2017). Creating shareholder value via collaborative innovation: The role of industry and resource alignment in knowledge exploration. *R&D Management, 48*(4), 394–409.
[45] Badir, Y. F., & O'Connor, G. C. (2015). The formation of tie strength in a strategic alliance's first new product development project: The influence of project and partners' characteristics. *Journal of Product Innovation*

Management, 32(1), 154–169.
[46] Williamson, O. E. (1985). Assessing contract. *Journal of Law, Economics, & Organization, 1*(1), 177–208.