Artificial Intelligence Empowering Corporate Innovation Performance: Chain Mediation Mechanism and the Moderating Effect of Growth Capacity

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Abstract. This study investigates whether and through what mechanisms artificial intelligence (AI) application is associated with the innovation performance of Chinese listed firms. Based on a balanced panel of A-share manufacturing enterprises from 2015 to 2023, a firm- and year-fixed-effects framework is employed to estimate the relationship between AI application and innovation performance. The empirical evidence indicates that firms with higher levels of AI application exhibit stronger innovation performance. Further analysis identifies knowledge integration, labor demand, and organizational resilience as three mediating channels, while corporate growth capacity strengthens the association between AI application and innovation performance. Subsample estimates suggest that the relationship is more evident among large enterprises, state-owned enterprises, and high-tech enterprises.

Keywords: artificial intelligence, corporate innovation performance, organizational resilience, knowledge integration, labor demand.

1. Introduction

Digital technologies are increasingly reshaping the conditions under which enterprises compete and innovate. In particular, the use of data-related capabilities has become closely connected with firms' ability to pursue sustainable and high-quality development[1]. Within this broader technological transformation, artificial intelligence (AI) is receiving growing attention in manufacturing because it can be incorporated into production, decision-making, and innovation activities [2]. Existing evidence also suggests that digital technologies may contribute to firm performance by supporting productivity improvement and product or service innovation [3].

Research on digital transformation has already identified a positive connection with corporate innovation performance [4]. Related studies have extended the discussion of AI to broader corporate outcomes, including environmental, social and governance (ESG) performance [5], while sector-specific evidence from new energy enterprises also suggests that AI application may be associated with improved innovation performance. Nevertheless, the existing literature leaves two issues insufficiently addressed. First, firm-level evidence on the relationship between AI application and innovation performance remains limited in the context of Chinese listed enterprises. Second, the organizational mechanisms through which AI may influence innovation performance have not yet been adequately examined within a unified analytical framework.

Building on these research gaps, this study develops an analytical framework that links AI application with corporate innovation performance through three potential mediating channels: knowledge integration, labor demand, and organizational resilience. It further examines whether corporate growth capacity changes the strength of the relationship between AI application and innovation performance. In this way, the study moves beyond the direct-effect perspective and evaluates how organizational conditions may shape the innovation outcomes associated with AI application.

The study contributes to the existing literature by bringing direct effects, mediating channels, moderating conditions, and heterogeneous firm characteristics into one empirical framework. Its findings may also provide evidence for enterprises seeking to coordinate AI application with

innovation resources and for policymakers seeking to design differentiated measures for the digital transformation of manufacturing enterprises.

2. Literature Review

2.1. Connotation and Measurement of AI

Artificial intelligence is generally regarded as an important component of new-generation information technology, with its commercial application expanding alongside developments in technological innovation and industrial deployment [5]. At the enterprise level, existing research has examined AI from several outcome-oriented perspectives. Some studies focus on whether AI supports firms' green transformation and green competitiveness [24,25,29], whereas others examine its association with corporate competitiveness, strategic decision-making, or ESG performance[10,14]. These studies suggest that AI is relevant to firm performance, but they do not fully explain its connection with corporate innovation performance.

The measurement of AI application also differs across studies. Innovation-output-based measures use AI-related patent applications or authorizations to represent firms' involvement in AI technologies, while text-based measures infer AI application from the occurrence of related terms in corporate disclosures [5]. Other research employs indicators such as technical equipment per employee or technological total factor productivity [9]. Since no single measurement approach has become universally accepted, the choice of indicator remains an important consideration when interpreting empirical findings.

2.2. Corporate Innovation Performance

Corporate innovation performance describes the observable outcomes arising from firms' innovation activities [10]. Previous studies have linked such outcomes to different organizational and technological factors. Knowledge management has been examined as an antecedent of innovation performance, with leadership conditions potentially affecting the strength of this relationship [13] More recent research has considered AI-related factors: [8] provide evidence concerning AI application and innovation performance, while [19] examine how capability-related mechanisms connect generative AI with innovation outcomes in construction enterprises.

In empirical research, patent applications are commonly used to capture observable innovation output because they represent firms' active attempts to generate new technological achievements [4,11]. Although the existing literature provides useful evidence on individual determinants of innovation performance, less attention has been paid to whether several organizational mechanisms operate alongside AI application within a large-sample setting of Chinese listed enterprises.

3. Theoretical Analysis and Research Hypotheses

3.1. Direct Effect of AI on Corporate Innovation Performance

A study [21] using data from Chinese A-share listed companies concludes that AI application significantly improves resource allocation efficiency. Meanwhile, research finds that the evolution of digitally driven dynamic capabilities helps growth-oriented enterprises improve innovation performance under resource constraints [16]. Accordingly, we argue that AI positively promotes the optimization of resource allocation. AI changes the way enterprises acquire and manage knowledge. AI-driven digital platforms break down knowledge barriers and facilitate knowledge flows [17]. This enables enterprises to absorb valuable technologies more quickly and improve their capacity to respond to innovation [18]. Therefore, deeply integrating AI into organizational processes can promote knowledge sharing and collaborative innovation, thereby enhancing innovation performance. Based on the above analysis, the following hypothesis is proposed:

H1: AI promotes corporate innovation performance.

3.2. Indirect Effect of AI on Corporate Innovation Performance

3.2.1. Mediating Effect of Knowledge Integration

Knowledge integration concerns the process through which enterprises convert dispersed information into resources that can be used in innovation activities. Existing studies describe this capability in terms of organizing distinctive information and recombining knowledge originating from different professional domains [6,7]. This perspective is relevant to AI application because information generated or processed by AI only contributes to innovation when it can be absorbed and connected with firms' existing knowledge base.

Prior evidence indicates that knowledge-related capabilities may connect generative AI with innovation outcomes in construction enterprises [19] More broadly, knowledge integration has been treated as part of firms' dynamic capabilities and as a means of responding more flexibly to market change. Since useful knowledge is often distributed across departments and organizational levels, integrating such information can support its transformation into shared innovation inputs. Research further suggests that cross-domain knowledge combination may stimulate new solutions and technological complementarities. Based on this reasoning, AI application is expected to improve innovation performance partly through stronger knowledge integration. Accordingly:

H2a: AI further promotes corporate innovation performance by enhancing enterprise knowledge integration.

3.2.2. Mediating Effect of Labor Demand

From a capability-based theoretical perspective,[23] proposes a firm-level theoretical framework. She argues that mainstream analyses of labor demand generally assume that firms face unlimited supply at market prices, whereas Fernández-Huerga E. proposes that the quantity of labor demanded by firms is jointly determined by the internal and external capabilities that firms can mobilize, their knowledge reserves, and their product-market strategies. Labor demand is regarded as an endogenous variable, especially dependent on enterprises' requirements for technological proficiency and problem-solving capabilities in the innovation process. When examining the relationship between intelligent manufacturing transformation and innovation performance, [29] explicitly indicate that optimization of the labor structure plays a partial mediating role. AI application reshapes the structure of enterprise labor demand: it replaces routine medium- and low-skilled labor while increasing demand for highly skilled personnel. Improvements in informatization promote an increase in enterprises' total labor demand. As an important innovation factor of enterprises, human capital, an increase in the quantity of labor helps facilitate communication and collaboration among employees, improves innovation efficiency, and ultimately positively influences corporate innovation performance. Accordingly, the following hypothesis is proposed:

H2b: AI improves the innovation performance of manufacturing enterprises by increasing their total labor demand.

3.2.3. Mediating Effect of Organizational Resilience

Based on existing research, organizational resilience is defined as a systematic and multidimensional capability of an organization to resist risks, adapt and adjust, recover, and surpass prior conditions [15], reflecting the dual ability of enterprises to maintain growth and stability in adversity. As a dynamic capability of enterprises, organizational resilience directly promotes corporate growth by enhancing environmental perception, optimizing resource allocation, and improving crisis recovery and innovation capabilities. Highly resilient enterprises can accurately capture market demand, reduce operating costs, and achieve counter-trend growth in adversity, thereby laying a foundation for sustainable corporate development [30,31]. Meanwhile, organizational resilience indirectly promotes corporate growth by driving strategic change. Highly resilient enterprises can rapidly perceive external shocks, flexibly allocate resources, adjust development strategies, and adapt to changes in the dynamic environment, thereby breaking through development bottlenecks and cultivating new growth momentum [32,33]. In addition, organizational

resilience can assist corporate growth by restraining managerial myopia. Highly resilient organizations possess willingness to assume risk, a culture of tolerance for failure, and a stable operating environment, which can alleviate managers' career concerns, reduce short-term profit-seeking decisions, guide them to focus on long-term R&D investment and the development of core capabilities, and ensure long-term corporate value growth [34,35]. Accordingly, the following hypothesis is proposed:

H2c: AI further promotes corporate innovation performance by enhancing organizational resilience.

3.2.4. Moderating Effect of Corporate Growth Capacity

Corporate growth capacity reflects the dynamic potential of an enterprise to acquire resources and expand markets. Enterprises with stronger growth capacity generally have more abundant cash flows, higher risk tolerance, and more agile organizational learning mechanisms.[36] argue that the realization of value from digital technology depends on the organization's learning and absorptive capacity, which provides a micro-level mechanism through which enterprises transform AI into innovation performance. [35] further maintain that enterprises with weaker growth capacity face evident resource constraints; such enterprises are prone to managerial myopia, making it difficult to achieve deep integration of AI and corporate innovation and thereby weakening AI's empowering effect. From a dynamic perspective of capability growth, [26] propose that market conditions moderate the relationship between corporate capability and growth performance. Accordingly, the following hypothesis is proposed:

H3: Corporate growth capacity positively moderates the facilitating effect of AI on corporate innovation performance.

Based on the above analysis, the research framework of this paper is shown in Figure 1:

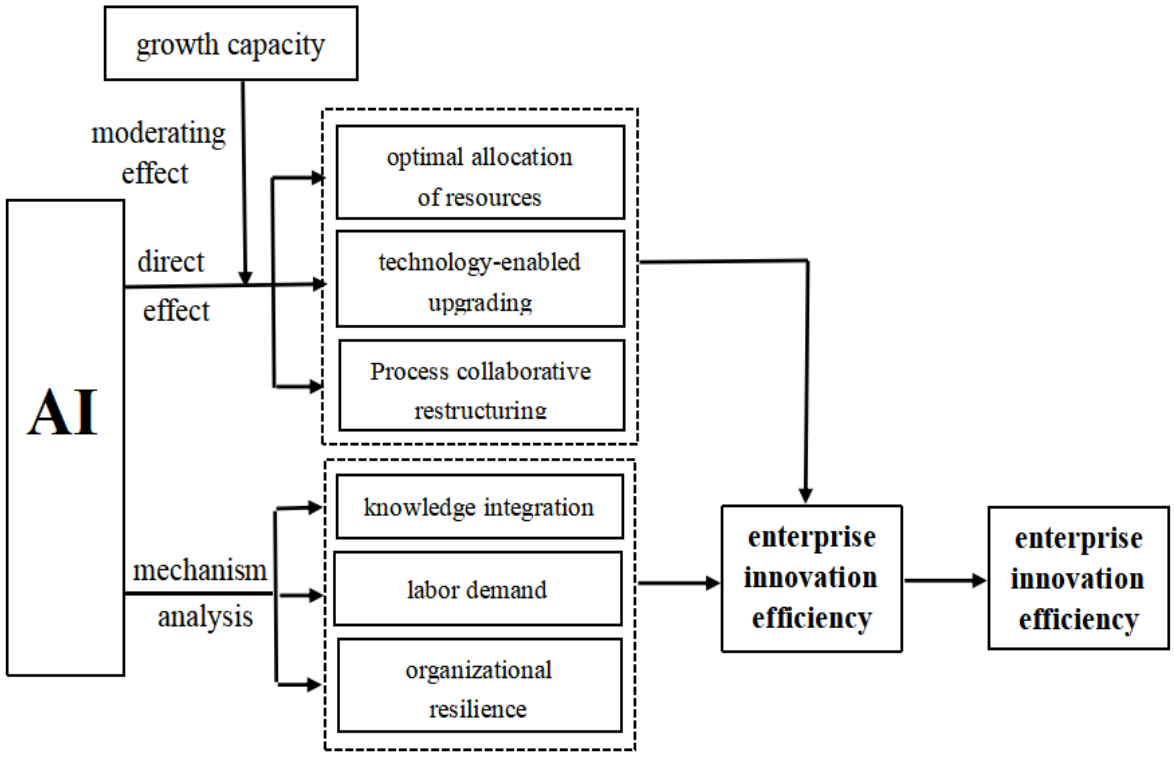


Figure 1. Research Framework

4. Research Design

4.1. Model Construction

4.1.1. Baseline Regression Model

To verify the overall effect of AI application on corporate innovation performance, this paper constructs the following baseline regression model:

$$Inv_{it} = \alpha_0 + \alpha_1 AI_{it} + \sum_j \alpha_j Ctrl_{jit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In the equation, Inv_{it} denotes the innovation performance of enterprise i in year t; AI_{it} denotes the degree of AI application; $Ctrl_{jit}$ denotes a series of control variables including enterprise size, asset-liability ratio, and enterprise age; μ_i denotes individual fixed effects, which control for inherent heterogeneous characteristics of enterprises; λ_t denotes year fixed effects, which control for time shocks such as macroeconomic policies and industry cycles; and ε_{it} denotes the random error term. If α_1 is significantly positive, this demonstrates that AI application can significantly promote corporate innovation performance, and the core research hypothesis H1 is supported.

4.1.2. Mediation Effect Model

Knowledge integration, labor demand, and organizational resilience are selected as mediating variables, and the transmission mechanism is tested in two steps. The first step specifies the impact of AI on the mediating variables:

$$M_{it} = \beta_0 + \beta_1 AI_{it} + \sum_j \beta_j Ctrl_{jit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

In the equation, M_{it} denotes the mediating variable, which is used to test the mediating effects of knowledge integration, labor demand, and organizational resilience; the definitions of the other variables are consistent with those in the baseline model.

In the second step, the mediating variables are incorporated into the baseline model to construct the following mediation effect test model, so as to identify the transmission role of the mediating variables:

$$Inv_{it} = \theta_0 + \theta_1 AI_{it} + \theta_2 M_{it} + \sum_j \theta_j Ctrl_{jit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

If θ_2 is significant, and θ_1 is significantly smaller than α_1 in the baseline model or is no longer significant, this indicates that knowledge integration, labor demand, and organizational resilience play mediating roles between AI and corporate innovation performance; that is, Hypotheses H2a, H2b, and H2c are supported.

4.1.3. Moderation Effect Model

To examine whether the effect of AI on corporate innovation performance is moderated by growth capacity, this paper introduces growth capacity and its interaction term with AI and constructs the following moderation effect model:

$$Inv_{it} = \rho_0 + \rho_1 AI_{it} + \rho_2 TAG_{it} + \omega(AI_{it} \times TAG_{it}) + \sum_k \rho_k X_{kit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

In the equation, TAG_{it} denotes growth capacity; $AI_{it} \times TAG_{it}$ denotes the interaction term, whose coefficient ω is the moderation effect coefficient and reflects the direction and strength of the moderating effect of growth capacity on the relationship between AI and innovation performance. If ω is significantly positive, this indicates that growth capacity positively moderates the relationship between AI and corporate innovation performance; that is, Hypothesis H3 is supported, meaning that the stronger the growth capacity, the more pronounced the facilitating effect of AI on corporate innovation performance.

4.2. Variable Selection

4.2.1. Explained Variable

The explained variable selected in this paper is corporate innovation performance. Considering that a certain period of time is required from patent application to patent authorization, this paper measures corporate innovation performance by the natural logarithm of the number of invention patent applications plus one.

4.2.2. Explanatory Variable

The explanatory variable in this paper is AI. Drawing on the view of [22], AI is measured by the frequency with which AI-related keywords appear in enterprises' annual reports. Considering the right-skewed characteristics of such data, this paper uses the logarithm of the number of AI-related words plus one as a proxy for the degree of adoption of AI technology.

4.2.3. Mediating Variables

The mediating variables in this paper are knowledge integration, labor demand, and organizational resilience. Regarding knowledge integration, existing literature proposes measuring knowledge integration capability using enterprise dynamic capabilities. Drawing on [38], this paper uses the logarithm of R&D investment plus one as a measure of opportunity-sensing capability within dynamic capabilities. Regarding labor demand, this paper uses the natural logarithm of the total number of employees of the enterprise as a quantitative measure of total labor demand. Regarding organizational resilience, following [37], it is measured through financial volatility and long-term growth capacity. Specifically, financial volatility reflects the stability of an enterprise's financial performance under shocks and embodies its resistance and recovery capacity; long-term growth capacity reflects an enterprise's long-term adaptability and opportunity-capturing capability and embodies its sustainable growth capacity. In this study, the year-end net profit difference (rx) is used as the measurement indicator of organizational resilience.

4.2.4. Moderating Variable

The moderating variable in this paper is corporate growth capacity. The study uses the total asset growth rate as a proxy variable for the moderating variable. This indicator is used to measure the expansion rate of an enterprise's asset scale and its growth capacity, reflecting its dynamic characteristics in terms of resource expansion, scale growth, and investment deployment. Specifically, it is calculated as the difference between the ending total assets and beginning total assets of a listed company divided by its beginning total assets.

4.2.5. Control Variables

Combining the relevant theories and existing literature, this paper selects six core control variables: enterprise size (ta), asset-liability ratio (lev), operating revenue (rev), total asset turnover ratio (ato), enterprise age (age), and Tobin's Q value (q).

4.3. Data Sources

The data sources of this paper are as follows: (1) data for the explanatory and explained variables are obtained from the China Stock Market & Accounting Research (CSMAR) database; and (2) data for the mediating variables, moderating variable, and other control variables are obtained from the CSMAR and Wind databases. This paper selects Chinese A-share listed companies from 2015 to 2023 as the initial research sample and screens them according to the following criteria: financial enterprises and ST and *ST listed companies are excluded; observations with missing values for key variables are excluded; and all continuous variables are winsorized at the 1% quantiles to eliminate the influence of extreme values. A balanced panel dataset is ultimately formed.

5. Empirical Results

5.1. Baseline Regression Analysis

Table 1 reports positive estimates for AI application in all three specifications. After the inclusion of control variables and fixed effects, the coefficient remains positive and statistically significant at the 5% level. Therefore, Hypothesis H1 is verified. The main reason is that AI can optimize resource allocation and improve enterprises' response speed, thereby significantly enhancing innovation performance. This conclusion is consistent with the findings of Wang (2024) and Guan (2026).

Table 1. Baseline Regression Analysis Results

	(1)	(2)	(3)
	inv	inv	inv
ai	0.066***	0.161***	0.065**
	(2.624)	(6.929)	(2.549)
rev			2.105*
			(1.724)
ta			1.679
			(1.215)
lev			-6.945***
			(-2.639)
age			0.146***
			(3.413)
q			0.928***
			(4.040)
ato			-1.142
			(-0.744)
Constant	15.658***	19.273***	-73.299***
	(25.009)	(13.867)	(-4.650)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	14292	14292	14292
r2	0.418	0.367	0.220

5.2. Robustness Tests

(1) Replacement of the Explained Variable

To improve the reliability of the conclusions, this paper replaces the measure of corporate innovation performance from the number of patent applications to the number of granted patents and reruns the regression after logarithmic transformation. The results show that the AI coefficient remains significantly positive, consistent with the baseline conclusion, and Hypothesis H1 remains robust.

(2) Replacement of the Explanatory Variable

The core explanatory variable is replaced from the logarithm of AI-related word frequency with two measurement approaches, namely the total frequency of AI-related words and a dummy variable indicating whether AI is applied, and the regressions are conducted again. The results show that the positive effect of AI on innovation performance remains significant, and the conclusion is not affected by the method used to measure the variable.

(3) Change in the Sample

Sample enterprises with an AI-related word frequency of zero are removed to exclude interference from observations in which AI has not actually been applied. After rerunning the regression, the core conclusion remains unchanged, demonstrating the sample stability of the research results.

(4) Change in the Research Period

The research window is shortened and regression analysis is rerun using a subsample period. The results show that the positive effect of AI on corporate innovation performance remains significant, indicating that the research conclusion does not depend on a specific time interval and has temporal robustness.

5.3. Heterogeneity Tests

5.3.1. Scale Heterogeneity

Enterprise size determines differences in endowments in terms of technological resources, financial reserves, and talent structure, which may affect innovation performance. Therefore, it is necessary to conduct group-based tests of heterogeneity effects by size.

Based on the mean total assets of the sample enterprises, this paper divides the sample into large-scale enterprises and small and medium-sized enterprises to test the heterogeneous influence of AI application on the innovation performance of enterprises of different sizes. The results in Column (1) of Table 2 show that the coefficient of AI is significantly positive at the 1% level, whereas the coefficient in Column (2) is significantly positive at the 5% level, indicating that AI application has a more pronounced facilitating effect on the innovation performance of large-scale enterprises. One possible reason is that large enterprises control richer infrastructure and can form technological barriers, making it difficult for small and medium-sized enterprises to obtain key core technologies. Meanwhile, large enterprises have more sufficient financial support, enabling them to continuously invest in AI R&D and application and more readily identify and seize innovation opportunities. In addition, with high salaries and sound development platforms, large enterprises attract large numbers of high-level professional and technical personnel, thereby improving innovation performance. Therefore, the innovation-driving effect of AI application is more significant in large-scale enterprises.

Table 2. Heterogeneity Test Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Large enterprises	**Small and medium-sized enterprises**	**State-owned enterprises**	**Non-state-owned enterprises**	**High-tech**	**Non-high-tech**
inv	0.321***	0.313**	0.374***	0.356**	0.347***	0.327*
	(3.622)	(2.472)	(3.557)	(2.385)	(3.540)	(1.836)
Constant	-9.655***	-7.375**	-6.980***	-5.273***	9.631***	-2.095**
	(4.585)	(2.853)	(-48.562)	(-3.042)	(10.754)	(2.319)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	6897	6906	5375	8019	2837	9548
r2	0.532	0.323	0.559	0.324	0.538	0.264

5.3.2. Ownership Heterogeneity

Enterprises with different ownership types differ in their institutional environment and innovation incentives, which may moderate the effect of AI on innovation performance. Accordingly, heterogeneity analysis is conducted from the perspective of ownership.

Based on the nature of enterprises' actual controllers, this paper divides the sample into state-owned enterprises and non-state-owned enterprises to investigate the moderating role of ownership attributes. The regression results in Column (3) of Table 2 show that the coefficient of AI is significantly positive at the 1% level, while the coefficient in Column (4) is significantly positive at the 5% level, indicating that AI application has a stronger facilitating effect on the innovation performance of state-owned enterprises. One possible reason is that state-owned enterprises have stronger resource sustainability and are more likely to obtain government fiscal subsidies and tax

preferences, which can reduce the upfront costs and risks of AI application, thereby more fully releasing the empowering effect of AI on innovation performance.

5.3.3. Industry Differences

Enterprises in high-tech industries and those outside such industries differ significantly in their technological foundations and R&D intensity, potentially leading to industry heterogeneity in the effects. Therefore, tests should be conducted according to industry attributes.

According to the Guidelines for the Industry Classification of Listed Companies revised by the Chinese government in 2012, this paper classifies enterprises by whether they belong to high-tech industries in order to test the heterogeneous influence of AI application across industries with different levels of technology intensity. The results in Columns (5) and (6) of Table 2 show that the coefficients of AI are significantly positive at the 1% and 10% levels, respectively, and that AI application has a more pronounced facilitating effect on the innovation performance of high-tech enterprises. One possible reason is that high-tech enterprises have stronger technological foundations and higher R&D investment intensity and can therefore improve innovation performance more significantly. However, both types of enterprises exhibit significant positive effects, indicating that the innovation-driving effect of AI has universal applicability while possessing greater potential in high-tech industries.

5.4. Mediation Effect Tests

As shown in Table 3, the results in Columns (1)-(2) indicate that AI promotes the improvement of enterprises' knowledge integration capability at the 1% significance level, and knowledge integration further promotes the improvement of corporate innovation performance at the 5% significance level. Thus, the mediating effect of knowledge integration is established, and Hypothesis H2a is verified. Through data processing and intelligent analysis, AI enhances enterprises' knowledge integration capability; knowledge integration capability can break down knowledge barriers among departments, thereby improving innovation performance. [28] find that AI technology adoption positively influences the knowledge integration capability of R&D teams and that knowledge integration plays a significant mediating role between AI and product development performance. [36] find that AI technology adoption positively influences the knowledge integration capability of R&D teams and that knowledge integration plays a significant mediating role between AI and product development performance.

The results in Columns (3)-(4) indicate that AI promotes an increase in enterprise labor demand at the 1% significance level, and enterprise labor demand further promotes improvements in corporate innovation performance at the 5% significance level. Therefore, the mediation mechanism of labor demand is verified, and Hypothesis H2b is supported. Through intelligent transformation, AI optimizes enterprises' employment structure, replacing repetitive labor in the short term while creating compound-skilled positions and reshaping the logic of talent allocation in the long term, thereby improving overall innovation output. [29] also confirms this viewpoint.

Columns (5)-(6) show that AI promotes improvements in enterprise organizational resilience at the 5% significance level, and organizational resilience further promotes improvements in corporate innovation performance at the 5% significance level. Therefore, organizational resilience serves as a mediating mechanism in the process by which AI improves corporate innovation performance, and Hypothesis H2c is verified. [22] argue that AI empowers organizational learning and helps enterprises enhance dynamic capabilities, continuously recover from shocks under uncertainty, and iteratively conduct innovation activities, thereby amplifying innovation output.

Table 3. Mediation Effect Tests

	(1)	(2)	(3)	(4)	(5)	(6)
	rd	**inv**	**emp**	**inv**	**rx**	**inv**
ai	0.001***	0.063**	0.002***	0.060**	0.021**	0.027**
	(3.221)	(2.472)	(6.557)	(2.365)	(2.940)	(2.180)
rd		1.276**				
		(2.538)				
emp				3.021***		
				(3.078)		
rx						2.343***
						(2.937)
rev	0.568***	1.383	0.312***	1.165	0.425***	0.154***
	(26.007)	(1.100)	(28.043)	(0.926)	(11.147)	(7.448)
ta	0.289***	1.304	1.364***	0.578	1.021***	0.752
	(11.728)	(0.936)	(28.877)	(0.405)	(3.398)	(1.584)
lev	-0.372***	-6.503**	0.261***	-7.738***	1.931***	-0.278***
	(-7.920)	(-2.463)	(10.883)	(-2.928)	(12.658)	(-3.359)
age	0.003***	0.143***	0.913	0.147***	0.038**	0.024***
	(4.283)	(3.316)	(0.044)	(3.423)	(2.522)	(2.938)
q	0.012***	0.912***	0.010***	0.896***	0.213***	0.032*
	(3.046)	(3.969)	(4.917)	(3.897)	(6.373)	(1.747)
ato	-0.175***	-0.919	-0.117***	-0.788	-0.189***	-0.081**
	(-6.395)	(-0.597)	(-8.369)	(-0.512)	(-2.779)	(-2.209)
constant	-0.655**	-72.375***	-6.980***	-52.273***	9.631***	-2.095***
	(-2.330)	(-4.585)	(-48.562)	(-3.042)	(10.754)	(-4.319)
N	14062	14062	14077	14077	13347	13347
r2	0.560	0.427	0.559	0.404	0.538	0.336

5.5. Moderation Effect

The moderation effect results are shown in Table 4. Column (1) indicates that the interaction term between AI and corporate growth capacity significantly promotes the growth of corporate innovation performance at the 1% significance level. Therefore, corporate growth capacity can positively moderate the facilitating effect of AI on corporate innovation performance. Hypothesis H3 is verified.

Table 4. Moderation Effect Results

	(1)
	inv
ai	0.068***
	(2.680)
tag	0.008***
	(4.731)
ai*tag	0.002***
	(2.710)
rev	0.115***
	(6.852)
ta	0.232***
	(4.405)
lev	0.052***
	(3.207)
age	0.205***
	(2.743)
q	0.020***
	(3.024)
ato	0.020***
	(3.024)
constant	-71.289***
	(-4.433)
N	14078
r2	0.463

6. Conclusion

6.1. Research Conclusions

Using balanced panel data for Chinese A-share listed companies from 2015 to 2023, this study empirically examines the effects and mechanisms of AI application on corporate innovation performance and draws the following main conclusions: (1) AI application has a significant positive facilitating effect on corporate innovation performance. By optimizing resource allocation and promoting knowledge flows and collaborative innovation, AI effectively improves corporate innovation output and R&D efficiency; both the baseline regression and multiple robustness tests support this conclusion. (2) Knowledge integration, labor demand, and organizational resilience play significant chain mediating roles between AI and corporate innovation performance. AI indirectly promotes improvements in corporate innovation performance through three paths: enhancing knowledge integration capability, expanding labor demand, and strengthening organizational resilience. (3) Corporate growth capacity plays a significant positive moderating role: the faster the expansion of corporate assets and the stronger the growth capacity, the more resource support is available for AI implementation, thereby strengthening the facilitating effect of AI on innovation performance. (4) The effect of AI in empowering innovation performance exhibits potential heterogeneity. Under different distributions of enterprise size, ownership nature, and industry differences, the driving role of AI on innovation performance varies, providing a basis for differentiated policy formulation.

6.2. Policy Implications

Based on the above conclusions, this study derives the following implications.

First, the integration of AI and innovation activities should be deepened. Enterprises should embed AI throughout the entire process, rely on technology to optimize resource allocation, and promote data-driven innovation. At the same time, they should focus on strengthening three transmission paths: increasing R&D investment to improve knowledge integration capability; rationally optimizing the scale and structure of labor to bring into play the supporting role of human capital in innovation; and strengthening the resilience of internal processes and improving risk response capacity, thereby amplifying innovation performance.

Second, the positive moderating role of corporate growth capacity should be fully leveraged. Enterprises with high total asset growth rates should continue to increase investment in AI, improve the layout of intelligent equipment and digital platforms, and achieve synergistic enhancement between growth capacity and AI application. Enterprises with slower growth should prioritize addressing resource shortcomings and steadily advance intelligent transformation, so as to avoid weakening the innovation-empowering effect of AI due to resource constraints.

Third, differentiated development strategies should be implemented. In view of enterprise size differences, large-scale enterprises should leverage their advantages in capital, technology, and talent, take the lead in tackling key AI technologies, and open platform resources to drive collaborative innovation along the industrial chain. Small and medium-sized enterprises should focus on segmented scenarios and use lightweight, low-cost AI tools to improve innovation efficiency; the government may reduce the threshold for intelligent transformation among small and medium-sized enterprises through special subsidies and technology-sharing platforms. In terms of ownership nature, state-owned enterprises should further optimize innovation incentive mechanisms, incorporate AI application results into assessment systems, and use policy and resource advantages to form demonstration effects in key fields. Non-state-owned enterprises should enhance market sensitivity and decision-making flexibility and actively seek industry-university-research cooperation and external technology acquisition channels. In addition, as industry leaders, high-tech enterprises should continuously increase AI R&D investment and maintain technological advantages. Non-high-tech enterprises should focus on enhancing technological absorptive capacity, gradually introduce mature AI solutions through industry public service platforms or third-party service institutions, and the government may establish a special fund for the intelligent transformation of manufacturing tospecifically support technological transformation and talent cultivation in traditional industries.

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