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Artificial intelligence and innovation capability: A dynamic capabilities perspective

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ABSTRACT

In the digital age and a complex and ever-changing environment, artificial intelligence technology is gradually penetrating various aspects of social life. It has a profound impact on the innovation practices of enterprises. For enterprises, actively utilizing artificial intelligence technology has become a key strategic decision to enhance innovation capabilities and effectiveness in a challenging environment. Based on this, this study is based on the theory of dynamic capabilities, exploring the mediating role of digital adaptability and its continuous mediating role with market perception, to construct a chain mediation model of "enterprise artificial intelligence use digital adaptability (perceptual adaptability, social adaptability, production adaptability) market perception enterprise innovation capability" mechanism. This study first verified the existence of the main effect relationship through pre-experimental analysis of data from Chinese A-share listed companies from 2010 to 2021 and further conducted empirical research based on 511 paired questionnaire data. The results indicate that there is a significant positive correlation between the use of artificial intelligence in enterprises and their innovation capabilities; The use of artificial intelligence in enterprises affects their innovation capabilities through digital adaptability (perception adaptability, social adaptability, production adaptability); Market perception plays a mediating role in the process of how the use of artificial intelligence in enterprises affects their innovation capabilities; Digital adaptability (perceptual adaptability, social adaptability, production adaptability) and market perception play a chain mediating role between the use of artificial intelligence in enterprises and their innovation capabilities. This study aims to provide theoretical guidance and practical inspiration for enterprises to use AI technology to improve innovation efficiency.

1. Introduction

As a leader in the new round of technological revolution and industrial transformation (Pan et al., 2024), artificial intelligence (AI) technology has become the core driving force for industry development (Zhong et al., 2024). The rapid development of AI technology has improved the efficiency and effectiveness of the innovation process and opened up new breakthroughs for enterprise innovation practices, helping traditional industries to transform and upgrade, thereby promoting the quality improvement and efficiency growth of the entire industry (Fuller et al., 2022; Olan et al., 2022; Rana et al., 2022). Enterprises are transitioning from traditional

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experience-based models to data-driven intelligent models, utilizing the powerful action potential provided by AI to respond in real time to market demand and changes. For example, Airbnb uses AI technology to accurately predict customer search behavior, analyze product pricing, and scan customer profiles to optimize its business strategy and market positioning. In addition, AI-CRM tools with built-in predictive analytics and machine learning capabilities (such as Demandbase, Terminus, HubSpot, Salesforce Einstein, and Hootsuite) are widely used by enterprises to improve customer relationship management performance, optimize marketing strategies, and enhance competitive advantages (Rahman et al., 2023). Similar examples are common in various fields, such as industry (Kim et al., 2023), manufacturing (Dou et al., 2024; Li et al., 2022), and services (Akter et al., 2023; Chen et al., 2021). Based on the above background, it is particularly important to conduct in-depth research on the mechanism of AI technology in the innovation capability of enterprises. Understanding how AI affects the innovation capability of enterprises is of great significance for the widespread application of new technologies and the sustainable and healthy development of enterprises.

Enterprises face unprecedented challenges and opportunities in the current dynamic and digital innovation environment (Zhang et al., 2024). How to effectively utilize AI technology to reshape the decision-making mode of enterprises, enhance their market competitiveness, and benefit their development is a research worthy of in-depth exploration (Tian et al., 2022). Therefore, how to fully unleash the production potential of artificial intelligence and improve the efficiency and success rate of enterprise digital transformation still requires continuous and in-depth exploration and joint efforts from both theoretical and practical circles. To better explain the impact of artificial intelligence on enterprises' innovation capabilities, this study introduces the dynamic capability theory, which provides theoretical explanations for the perception adaptability, social adaptability, and production adaptability formed by using artificial intelligence in enterprises on their innovation capabilities. The dynamic capability theory emphasizes that a company's capabilities are dynamic and continuously evolve with changes in the external market environment. This is mainly reflected in the ability to integrate and allocate internal and external resources, enabling the company to quickly adapt to environmental changes and maintain competitive advantages. Enterprises must shape unique digital adaptability in a complex and ever-changing external market environment to successfully build and develop their dynamic capabilities, drive innovation, and gain sustained competitive advantages. Digital adaptability is a dynamic capability that emphasizes the interactive relationship between users and technology and can flexibly respond to and adapt to technology-driven external market demands and internal operational needs. It has become an important basis for analyzing how digital technology promotes organizational change (Nuryanto et al., 2024). Among them, perceptual adaptability emphasizes the organization or individual's keen insight into external market trends, technological developments, and user needs in a rapidly changing digital environment, which is the starting point of digital innovation; Social adaptability helps companies integrate innovative resources more efficiently by enhancing collaboration and online interaction capabilities; Production adaptability focuses on optimizing business processes and improving operational efficiency, emphasizing how to use digital technology to optimize internal production and service processes, improve efficiency, and promote the implementation and application of innovative achievements.

In addition, influenced by the digital revolution, the complex and ever-changing external market environment has brought tremendous pressure on business leaders (Hartwell & Devinney, 2021). In the rapidly changing market environment, a company's keen insight into external dynamics has become an important driving factor for innovation (Pundziene et al., 2022; Köhler et al., 2022). By gaining a profound understanding of market demand, competitive environment, and industry trends, enterprises can more accurately identify opportunities and challenges, thereby providing direction for innovation activities. The widespread application of artificial intelligence technology further enhances the insight capability of enterprises. With the real-time analysis and interpretation of massive market data by AI, enterprises can more flexibly adjust their product development strategies, optimize resource allocation, and respond quickly to market changes. In the era of the digital economy, whether market perception, as an external situational factor, plays a role in the impact of artificial intelligence use on corporate innovation capability has not been fully explored. Therefore, this study incorporates market perception into the influencing mechanism and explores its role in the relationship between the use of artificial intelligence in enterprises and their innovation capabilities.

Based on the intersection of practical development and theoretical progress, this study proposes the research question: How does the use of artificial intelligence in enterprises affect their innovation capabilities, and what is the underlying impact mechanism? This study is based on the theory of dynamic capabilities. It constructs a chain mediation model of the mechanism by which the use of artificial intelligence affects the innovation capability of enterprises in order to clarify the inherent relationship between the use of artificial intelligence and the innovation capability of enterprises. This study has made two important contributions. Firstly, this study elucidates how enterprises' use of artificial intelligence affects their innovation capabilities. Exploring the mediating chain of digital adaptability and market perception opens up the "black box" of how the use of artificial intelligence affects enterprise innovation capabilities and expands the understanding of the positive impact mechanism of artificial intelligence use (Mikalef & Gupta, 2021; Wamba, 2022; Pietronudo et al., 2022). Secondly, based on existing research literature, this study extends the application of digital adaptability in the field of artificial intelligence management (Brem et al., 2021). Further, it clarifies the three key dimensions of digital adaptability - perceptual, social, and production adaptability - based on dynamic capability theory, providing new insights into digital adaptability. This study provides theoretical guidance and practical reference for enterprises to better utilize artificial intelligence technology in the process of digital transformation. Also, it lays the foundation for future research to further explore the innovative potential of artificial intelligence in organizational change.

2. Theory, literature review and research hypotheses

2.1. Dynamic capabilities perspective

In today's rapidly changing digital age, how enterprises can enhance their innovation capabilities through artificial intelligence technology has become a core issue in both theory and practice. The dynamic capability theory provides an important analytical framework for this issue, emphasizing that enterprises respond to changes in the dynamic environment through sensing, seizing opportunities, and reconfiguring resources to achieve sustained competitive advantage (Teece, 2007). Based on the theory of dynamic capabilities, the chain mediation model of "enterprise artificial intelligence use digital adaptability market perception enterprise innovation capability" can be regarded as the specific application and extension of artificial intelligence technology to the core mechanism of dynamic capabilities, revealing how technology use indirectly promotes the realization of enterprise innovation capability through multidimensional paths. In this model, AI technology, as an enabling tool for enterprises' dynamic capabilities, provides basic support for enterprises' perception, collaboration, and resource reorganization capabilities in a dynamic environment by improving digital adaptability. Digital adaptability, as the core mediator variable of the model, is subdivided into three dimensions: perceptual adaptability, social adaptability, and production adaptability, which correspond one-to-one with the three core elements of dynamic capability theory.

Firstly, perceived adaptability reflects how enterprises enhance their sensitivity and responsiveness to external environmental changes through artificial intelligence technology. According to the dynamic capability theory, perceptual ability is the core element for enterprises to identify market opportunities and potential threats in a dynamic environment (Dias & Lages, 2021). Secondly, social adaptability describes how artificial intelligence technology promotes resource integration and value creation by optimizing internal and external collaboration efficiency within the enterprise. This dimension corresponds to the ability to seize opportunities in the dynamic capabilities theory. The dynamic capability theory emphasizes that after identifying opportunities, enterprises need to transform these opportunities into actual results through effective resource integration (Zahra et al., 2022). Finally, production adaptability reflects the improvement of artificial intelligence technology on the ability of enterprise resource restructuring, which is the concretization of resource restructuring capability in dynamic capability theory. The dynamic capability theory suggests that resource restructuring capability enables enterprises to dynamically adjust resource allocation to cope with environmental changes (Chari et al., 2022; Ghosh et al., 2022), while artificial intelligence significantly enhances the flexibility and efficiency of enterprises through process optimization, automation, and intelligent scheduling.

Digital adaptability becomes a key intermediary in forming enterprise innovation capability by enhancing the market perception ability of enterprises. Market perception is an important component of dynamic capabilities, reflecting a company's insight into external market changes, technological trends, and customer needs (Hernández-Linares et al., 2021). Perceived adaptability expands market perception depth by enhancing data acquisition and analysis capabilities; Social adaptability improves market perception efficiency by optimizing information flow and knowledge integration; Production adaptability is achieved through resource optimization and process improvement, accelerating the transformation of market feedback into practical actions. Furthermore, the relationship between market perception ability and corporate innovation ability further demonstrates the applicability of dynamic capability theory in this model. Market perception ability, as an extension of perception ability, provides direction for innovation by identifying technological and market breakthrough points (Tortora et al., 2021; Hossain et al., 2022); The ability to seize opportunities and restructure resources ensures that enterprises can efficiently integrate resources and transform market insights into innovative results.

In summary, the chain mediation model of "enterprise artificial intelligence use digital adaptability market perception enterprise innovation capability" aligns with the core logic of dynamic capability theory. Introducing artificial intelligence technology enables enterprises to enhance their perception, collaboration, and resource restructuring capabilities in a dynamic environment, thereby promoting the development of their innovation capabilities by strengthening their market perception capabilities.

2.2. AI adoption and firm innovation capability

In existing research, the use of artificial intelligence (AI) is often seen as a single dimension that primarily focuses on applying programs and functions. However, with the continuous development and increasing frequency of application of artificial intelligence technology, individuals' dependence on it is gradually deepening, which makes the use of AI not limited to surface functional operations, but also involves comprehensive exploration of its deep potential. The commercialization and popularity of AI are closely related to its definition, indicating that the deeper meaning of AI usage may vary depending on the definition (Fredstrom et al., 2022). In this study, the use of artificial intelligence is defined as individuals utilizing AI systems to analyze and learn external data, and achieving established goals and tasks through continuous upgrades.

The widespread application of artificial intelligence in enterprises is widely believed to significantly improve innovation efficiency and bring about outstanding results. The promoting effect of artificial intelligence on enterprise innovation efficiency is mainly reflected in its support for lean and agile product development methods (Agarwal et al., 2023; Cooper, 2021), where lean development methods focus on reducing waste and improving efficiency, while AI shortens the product innovation cycle and reduces resource waste in the development process by analyzing data in real-time, identifying potential problems, and providing improvement suggestions (Babina et al., 2024). In addition, AI technology can quickly analyze users' feedback on product functions on the Internet (Kushwaha et al., 2021), help enterprises quickly determine the functional requirements of new versions of products, and accelerate the "build test modify" cycle (Raneri et al., 2023) in the product development process so that enterprises can respond to market changes more quickly and improve the market adaptability and competitiveness of products. In summary, the following assumptions can be made.

Hypothesis1. There is a significant positive correlation between AI adoption and firm innovation capability; as enterprises adopt AI, their innovation capability is significantly enhanced.

2.3. Mediating effects of digital adaptability

2.3.1. AI adoption and digital adaptability

The use of artificial intelligence has a significant positive impact on the three core dimensions of digital adaptability - perception, socialization, and productivity. Firstly, the frequent application of artificial intelligence technology significantly improves the efficiency of enterprises in data processing, knowledge integration, and task allocation, thereby significantly enhancing perception. By utilizing artificial intelligence, enterprises can process large amounts of complex data, uncover potential information and patterns, and enhance their understanding of the business environment. The advanced algorithms of artificial intelligence can automatically analyze data, identify important trends and anomalies, provide accurate descriptive, predictive, and normative insights for enterprises (Di Vaio et al., 2020), and provide technical support to help enterprises timely identify market opportunities and potential threats, enabling them to maintain a competitive advantage in dynamic environments.

Secondly, the application of artificial intelligence technology plays an important role in promoting communication and interaction between enterprises, users, and intelligent products, thereby enhancing socialization. Enterprises improve user experience and enhance the interactivity of products and services through artificial intelligence technology. Artificial intelligence can analyze user behavior and feedback, adjust product features and service content in real-time, and promote innovation and development of intelligent products (Du & Xie, 2021). The communication and interaction between enterprises, users, and intelligent products not only enhance user satisfaction but also promote continuous product innovation. With the continuous advancement of natural language processing technology, personalized recommendation systems and intelligent customer service systems have achieved more efficient user interaction and personalized service experience through artificial intelligence (Chiu et al., 2021), further promoting the relationship building between enterprises and users.

Finally, productivity represents the advanced stage of artificial intelligence in its application, reflecting a higher level and more comprehensive adaptability of artificial intelligence. At this stage, artificial intelligence processes and analyzes data and makes independent decisions. Through advanced machine learning and optimization algorithms, artificial intelligence can intelligently identify and solve problems, reducing reliance on human intervention (Kaplan & Haenlein, 2020; Leyer & Schneider, 2021; Johnson, Albizri, Harfouche, & Fosso-Wamba, 2022), enabling AI to play a critical role in supporting product and innovation activities. Enterprises can utilize artificial intelligence for automated decision-making and optimization, improving production efficiency and innovation capabilities to maintain a leading position in complex market environments. In summary, artificial intelligence technology positively impacts the perception, socialization, and productivity dimensions of digital adaptability. This study proposes the following hypothesis.

Hypothesis 2a. AI adoption has a positive impact on perceived adaptability.

Hypothesis 2b. AI adoption has a positive impact on social adaptability.

Hypothesis 2c. AI adoption has a positive impact on productive adaptability.

2.3.2. Digital adaptability and firm innovation capability

The relationship between digital adaptability and enterprise innovation capability is particularly important in modern enterprise management. The perceptual nature of digital adaptability enables enterprises to identify problems, discover opportunities, and perceive potential threats, driving the stimulation of new thinking (Sjödin et al., 2023; Haefner et al., 2021). When a company has high digital adaptability, it often has closer team collaboration, clear collective goals, and efficient resource sharing within the company. This cultural atmosphere significantly enhances employees' enthusiasm for knowledge sharing, continuously builds the company's knowledge base, and brings higher levels of corporate innovation capabilities (Wilson & Daugherty, 2018).

The socialization of digital adaptability directly affects the ability of enterprises and users to create value together (Vargo & Lusch, 2017). Through real-time interaction with users, enterprises can flexibly add new features and designs to products, achieve continuous evolution and updates of products, promote personalized customization of products, and allow users to participate in product development according to specific needs, which helps to enhance the experience accumulation of enterprises, discover new potential markets, and improve innovation capabilities. Improving sociality also helps businesses establish long-term relationships with users, providing more resources and inspiration for innovation.

The productivity of digital adaptability reflects a higher level and more comprehensive digital adaptability. At this stage, digital systems can autonomously identify problems and propose solutions, typically without or with minimal human intervention, enabling businesses to conduct production and innovation activities more efficiently, thereby enhancing their analytical and creative capabilities in complex market environments.

Despite the many advantages brought by digital technology, it should be recognized that digital technology cannot completely replace all employees' job positions. With increased task automation, employees will have more time to engage in creative work, promoting new inventions and creations (Jia et al., 2024; Mikalef & Gupta, 2021). The collaboration between digital technology and employees can help accelerate the speed of innovation, increase openness, reshape innovation structures, and even potentially change the entire innovation process (Ciarli et al., 2021; Chirumalla, 2021a, 2021b). Therefore, digital technology promotes human-machine collaboration, drives the transformation of innovation models, and enhances innovation capabilities. In summary, various dimensions of digital adaptability, including perceptual, social, and production adaptability, provide strong support for enterprise innovation by enhancing the perception of the market and technological environment, strengthening interaction between enterprises and users, and optimizing decision-making processes. Based on this, the following hypotheses are made in this study.

Hypothesis 3a. Perceived adaptability positively impacts a firm's innovation capability.

Hypothesis 3b. Social adaptability positively impacts a firm's innovation capability.

Hypothesis 3c. Productive adaptability positively impacts a firm's innovation capability.

2.3.3. AI adoption, digital adaptability and firm innovation capability

Firstly, artificial intelligence plays an important role in enterprise innovation. Its powerful data processing and analysis capabilities enable enterprises to quickly extract valuable information from complex data while promoting human-machine collaboration, knowledge sharing, and task optimization, providing support for innovation activities. Through the efficient data analysis and knowledge integration of artificial intelligence, enterprises can more quickly identify emerging trends and potential problems in the market, thereby stimulating new thinking and innovation. The application of artificial intelligence enables enterprises to have a more comprehensive understanding of complex market dynamics and technological developments than relying on a single human expert, which helps to maintain a leading position in a fiercely competitive environment (Loureiro et al., 2021; Abou Soul et al., 2023).

Secondly, the social adaptability of artificial intelligence promotes close connections between enterprises and users through real-time interaction with them (Baabdullah et al., 2021), enabling enterprises to quickly respond to users' immediate needs while continuously optimizing products and services based on user feedback. Not only does it enhance the innovation capability of enterprises, but it also increases user participation and satisfaction, which helps enterprises better meet the specific needs of users and further promotes the optimization and development of innovation achievements.

Furthermore, the frequent use of artificial intelligence in innovation activities has led to the formation of production adaptability, which represents the advanced stage of digital adaptability (Hutchinson, 2020). At this stage, artificial intelligence can autonomously perform complex tasks and decisions with minimal or no human intervention and even achieve self-innovation in some cases, optimizing the operational processes of enterprises and driving innovation in products and services. The adaptability of artificial intelligence in production has changed the nature of work, including the types of work performed by AI itself and the types of work performed by employees (Wilson & Daugherty, 2018), further helping employees to invest more energy in creative work and enhancing the overall innovation capability of the enterprise.

Based on the above analysis, we can propose the following hypothesis.

Hypothesis 4a. Perceived adaptability mediates the relationship between AI adoption and a firm's innovation capability.

Hypothesis 4b. Social adaptability mediates the relationship between AI adoption and a firm's innovation capability.

Hypothesis 4c. Productive adaptability mediates the relationship between AI adoption and a firm's innovation capability.

2.4. Mediating effects of market perception

2.4.1. AI adoption and market perception

In market competition, the use of artificial intelligence plays a central role (Krakowski et al., 2023). With the continuous development and deeper application of artificial intelligence technology, enterprises can analyze market data more accurately, predict customer behavior, and respond quickly. Artificial intelligence systems with high usage intensity can process and analyze vast market information in real-time, reveal market trends for enterprises, innovate in response to constantly changing market demands, and make more informed decisions (Carbonell & Escudero, 2010). Artificial intelligence can also optimize supply chain management, improve customer service experience, enhance product customization, and improve market perception speed and efficiency through automation and intelligent means (Boso et al., 2017). Therefore, strengthening the use of artificial intelligence will undoubtedly have a positive driving effect on the intelligent perception ability of enterprises in the market, enhancing their market competitiveness. We have reason to propose the following hypothesis.

Hypothesis 5. AI adoption can enhance a firm's market perception.

2.4.2. Market perception and firm innovation capability

Enterprises can respond to user needs and expectations in a timely and accurate manner through artificial intelligence, quickly capture market demand trends, and develop and launch new products that meet market needs, thereby enhancing the value of products to users and more effectively meeting their needs (Pehrsson, 2019). In the rapidly changing market environment, enterprises must quickly adjust their innovation strategies to adapt to the constantly changing market environment. By enhancing market perception, enterprises can quickly identify new opportunities and potential risks in the market and make strategic adjustments in a timely manner based on the strengths and weaknesses of competitors (Alshanty & Emeagwali, 2019). Enabling enterprises to quickly launch innovative products that meet market demand, seize market opportunities, and enhance their market competitiveness improves innovation efficiency. Based on the above discussion, we construct the following hypothesis.

Hypothesis 6. Market perception positively promotes a firm's innovation capability.

2.4.3. AI adoption, market perception and firm innovation capability

Market perception is crucial in exploring the connection between artificial intelligence and corporate innovation capabilities. By strengthening the use of artificial intelligence, enterprises can gain powerful data analysis and processing capabilities (Ghasemaghaei & Calic, 2019), enhance their insight into market information and sensitivity to market changes, respond quickly to market demand and trends, and adjust their products and services in a timely manner (Feng et al., 2020), thereby improving their innovation capabilities. The reason is that traditional enterprise innovation processes often rely on empirical judgment and static data, which have certain lags and uncertainty. However, the introduction of artificial intelligence overcomes this limitation. With real-time analysis of massive data, artificial intelligence can quickly identify new demands and potential business opportunities in the market, driving enterprises to conduct more targeted innovative research and development. Therefore, as a key link between artificial intelligence applications and enterprise innovation, market perception enhances market perception to enable enterprises to more accurately capture market demand and trends (Wei et al., 2014), ensuring that the application of artificial intelligence technology more effectively drives innovation activities. We propose the following hypothesis here.

Hypothesis 7. Market perception mediates the relationship between AI adoption and a firm's innovation capability.

2.5. The chain mediation effect of digital adaptability and market perception

2.5.1. Digital adaptability and market perception

One of the three dimensions of digital adaptability, perceptual adaptability, helps businesses identify and understand various signals and trends in the market environment. Specifically, data visualization tools and dashboards enable enterprises to intuitively analyze market data, become more adept at handling massive amounts of data and information and better understand market dynamics and consumer demands, thereby improving the accuracy and timeliness of market perception and adjusting strategies in a timely manner to address market challenges. Secondly, social adaptability directly affects a company's market perception ability, especially in the digital age, where social media and online communities have become important tools for companies to gain insights into consumer behavior and opinions (Chen et al., 2011; Garrigos-Simon et al., 2012Garrigos-Simon et al., 2012). Social adaptability drives the establishment of connections between users, enabling enterprises to monitor and analyze conversations, feedback, and trends on social platforms in real-time, more sensitively perceive changes in market demand, and capture consumers' immediate reactions, thereby quickly adjusting their product and service strategies to better meet market demand. Finally, production adaptability helps enterprises utilize advanced technologies such as 3D printing and automated production lines, enabling them to quickly translate market feedback into actual product innovation (Savolainen & Collan, 2020), and enabling them to meet consumers' diverse needs more accurately through lean production and personalized customization, enhancing market competitiveness and brand loyalty. Through the above methods, production adaptability plays an important role in enhancing the market perception of enterprises.

Perceived adaptability, social adaptability, and production adaptability, as the three core dimensions of digital adaptability, strengthen the market perception ability of enterprises from different perspectives. Therefore, this article proposes hypotheses 8a, 8b, and 8c.

Hypothesis 8a. Perceived adaptability positively promotes market perception.

Hypothesis 8b. Social adaptability positively promotes market perception.

Hypothesis 8c. Productive adaptability positively promotes market perception.

2.5.2. Proposing a chain mediation model

Based on the discussion of hypotheses 1 to 8, the use of artificial intelligence in enterprises does not directly affect enhancing innovation capabilities. However, it is indirectly achieved through multiple mediating factors. Specifically, in the operational model where enterprises rely on artificial intelligence for data analysis, decision optimization, and intelligent interaction, digital adaptability, and market perception play a key role as a "bridge and link." Digital adaptability helps enterprises balance information processing and market insight generation through perceptual adaptability. With the help of artificial intelligence data analysis tools, enterprises can more comprehensively grasp market dynamics and generate profound market insights. Social adaptability strengthens the interaction between enterprises and consumers. Enterprises can obtain real-time user feedback and market trends through social platforms and online communities, making their decisions more accurate. Production adaptability enables enterprises to quickly transform market feedback into innovative products or services and enhance market competitiveness by optimizing production processes and supply chain management. In this process, market perception plays a crucial connecting role, closely linking the use of artificial intelligence, digital adaptability, and innovation capabilities of enterprises, forming a key driving force. Therefore, based on the above analysis, this article proposes hypothesis 9.

Hypothesis 9a. Perceived adaptability and market perception are sequentially mediating between AI adoption and corporate innovation capability.

Hypothesis 9b. Social adaptability and market perception are sequentially mediating between AI adoption and corporate innovation capability.

Hypothesis 9c. Productive adaptability and market perception are sequentially mediating between AI adoption and corporate innovation capability.

This study constructed a chain mediation model based on dynamic capability theory (see Fig. 1).

3. Pilot study

This article assumes that using artificial intelligence in enterprises will promote the improvement of their innovation capabilities. In order to clarify whether the main effect exists, this article designed a preliminary study to verify whether there is a main effect relationship. Specifically, this pilot study has several objectives. Firstly, by preliminarily verifying the relationship between the independent and dependent variables in the hypothesis, ensure the rationality and feasibility of the research direction. A pilot study helps to construct a more persuasive theoretical framework, providing necessary theoretical support and background information for subsequent research designs based on first-hand questionnaires. Secondly, the results of pre-research can be used to optimize the formal questionnaire design and improve the effectiveness and reliability of the questionnaire. By analyzing secondary data, it is possible to identify which issues can most effectively capture the relationships between variables, thereby collecting data more targeted in formal surveys and improving the overall quality and credibility of the research.

3.1. Data source

The "Artificial Intelligence White Paper (2022)" released by the China Academy of Information and Communications Technology mentions that artificial intelligence technology has developed rapidly in the past decade, especially since 2010, with breakthroughs in technologies such as deep learning (Deng, 2018), artificial intelligence has entered a new stage of development. Based on this, we selected data from Chinese A-share listed companies from 2010 to 2021 as the research sample for this preliminary experiment. The artificial intelligence data was sourced from the annual reports of listed companies, the enterprise innovation capability data was sourced from the CNRDS database (Chinese Research Data Services Platform), and the remaining financial data mainly came from the CSMAR and Wind databases. To ensure the reliability of the pre-experimental empirical results, the research samples were screened and processed as follows: firstly, samples from the financial and insurance industries were excluded to avoid interference from industry specificity on the results; Secondly, remove ST* ST and PT samples are used to reduce the impact of abnormal enterprise data; Secondly, delete samples with severe data loss or obvious outliers; Finally, in order to further reduce the bias of extreme values on the analysis results, all continuous variables were truncated at the 1% and 99% quantiles, thereby improving the robustness of the data and the credibility of the conclusions.

3.2. Variables

3.2.1. Explanatory variable (AI adoption)

There are several key factors that contribute to the selection of artificial intelligence keywords in Chinese A-share listed companies as the main basis for constructing enterprise artificial intelligence level indicators in this study. Firstly, the target audience of industrial robots is mainly concentrated in China's manufacturing industry. Secondly, industrial robots are only a part of artificial intelligence. If only data from Chinese manufacturing companies is used, it cannot be used as a sample for studying Chinese listed companies, resulting in sample selection bias and affecting research conclusions.

In addition, although the number of artificial intelligence patent applications to some extent reflects the innovation output of enterprises in the field of artificial intelligence (Yao et al., 2024), using the number of enterprise artificial intelligence patent applications as an indicator of the level of enterprise artificial intelligence may also lead to sample bias in research conclusions. This is because many companies reduce costs by purchasing ready-made technologies, which may not necessarily be reflected through patents when integrated into operations; The number of patents only reflects innovation output but is not equivalent to actual application; Different enterprises have significant differences in application fields and methods, and may have high-level artificial intelligence applications in certain fields (such as manufacturing, finance, healthcare, etc.). However, the number of patents may not be high. Due

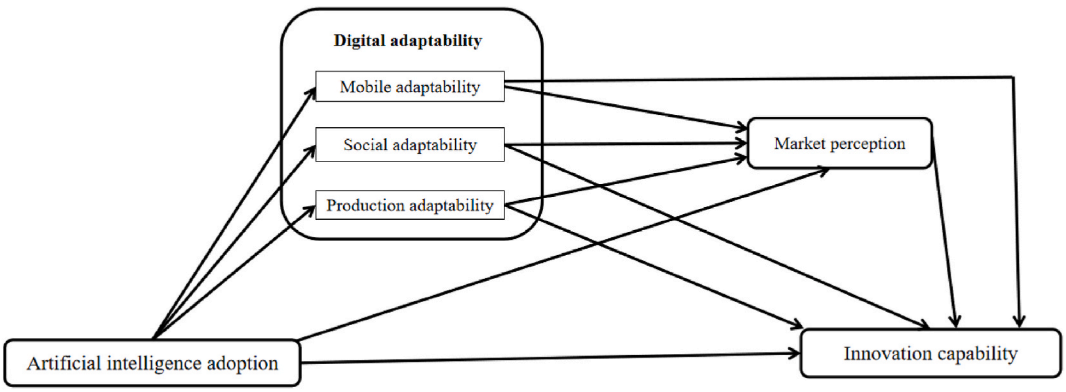

Fig. 1. A model of the mechanism of the role of AI adoption on firms' Innovation capability.

to considerations of trade secrets, some companies do not disclose their core technologies. Therefore, the number of patents as a measurement indicator has significant limitations, and this indicator fails to fully and accurately demonstrate the specific application of companies in the field of artificial intelligence.

The annual report not only covers the financial status of the company and has undergone multiple audits and verifications, but also provides detailed records of various aspects such as the company's strategy, operations, and technological applications, providing comprehensive information that can showcase the company's actual operations and applications in various fields. As an official document disclosed to the public, the information in the annual report ensures authenticity and accuracy, and has undergone multiple audits and verifications, with high credibility. The annual report reflects the enterprise's strategic adjustments and technological progress in different years. It can track and understand the dynamic changes in the enterprise's application of artificial intelligence technology. Therefore, extracting artificial intelligence keywords from annual reports can obtain highly reliable application data and comprehensively understand the development of enterprises in the field of artificial intelligence through dynamic analysis (Wang et al., 2024).

Based on the above analysis, this study adopts the research method of Yao et al. (2024) and uses text analysis to construct indicators of the level of artificial intelligence in enterprises. In response to the lack of Chinese space segmentation in annual reports of listed companies, words are regarded as basic language processing units. Using the Python open-source library "jieba" for text segmentation to address the challenges in Chinese text analysis, including segmentation granularity, ambiguous word recognition, and new word discovery. Especially for technical terms such as "deep learning, machine learning, and image recognition", to avoid incorrect segmentation, we have constructed a proprietary noun dictionary and integrated it into the "jieba" segmentation module to ensure that these terms are correctly recognized. Finally, based on the frequency of occurrence of artificial intelligence-related vocabulary in the annual report, the artificial intelligence indicators of the enterprise were defined, and the level of artificial intelligence of the enterprise was measured by retaining the frequency of keywords related to artificial intelligence and adding 1 to take the natural logarithm.

3.2.2. Explained variable (firm innovation capability)

The main methods academia uses to measure a company's innovation capability include the number of patents and the number of patent citations. Most studies use the number of patents to evaluate a company's innovation capability. Design patents usually protect the visual design of products, while invention patents cover new technologies and functional innovations. So compared to invention patents, invention patents represent higher technological innovation and are more representative in measuring enterprises' innovation level. Relying solely on the number of patents to measure a company's innovation level cannot distinguish these differences, resulting in an inaccurate evaluation of innovation output. The number of citations of a patent reflects the recognition and use of the patent by other technologies or research. When a patent is frequently cited, it indicates that the technology or innovation of the patent has been widely applied or referenced, indicating its important role in promoting technological progress and knowledge transfer. Therefore, the number of patent citations can reveal the knowledge transfer process between different departments and reflect the technology's importance and influence (Caviggioli, 2016). Sternitzke (2010) also suggests a positive correlation between the number of patent citations and the market value of inventions. In order to avoid the interference that self-citation may bring (Wagner&Wakeman, 2016), the evaluation method of this study excluded the company's own citations. It used the logarithm of the number of other citations of patent data plus 1 as the measurement method of enterprise innovation capability.

Table 1
Baseline regression results.

VARIABLES	(1)	(2)
	lninnovation	*lninnovation*
AI − adoption	0.136***	0.082***
	(16.251)	(10.127)
Size		0.392***
		(29.993)
Lev		0.277***
		(5.277)
ROA		−0.853***
		(-8.582)
Board		−0.063
		(-1.381)
Dual		−0.010
		(-0.614)
Constant	2.485***	−6.123***
	(294.593)	(-21.113)
FIRM FIXED	YES	YES
YEAR FIXED	YES	YES
N	25,772	24,897
R^2	0.806	0.829

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

3.2.3. Control variables

Firms' innovation capabilities may be influenced by their adoption of artificial intelligence (AI) and various factors such as business conditions and senior management's ability. To address these factors, this study builds on the previous research and includes several control variables that may significantly impact business decisions (Zhou et al., 2023; Liu et al., 2023; Liang et al., 2024). The specific control variables selected are: firm size (size), financial leverage (lev), profitability (ROA), number of directors on the board (board), and the duality of positions (dual; where 1 indicates the chairman and CEO are the same person, and 0 indicates they are not).

3.3. Baseline estimation results

Table 1 presents the baseline regression results regarding the impact of firms' AI adoption on their innovation capabilities. Column (1) shows the regression results without control variables, where the coefficient for AI adoption is 0.136 and is significantly positive at the 1% level. Column (2) includes control variables, with the AI adoption coefficient at 0.082, also significantly positive at the 1% level. These results indicate that AI adoption significantly enhances firms' innovation capabilities, with this effect being statistically significant at the 99% confidence level. Specifically, according to the results in Column (2), a 1-unit increase in AI adoption corresponds to an 8.2% increase in innovation capability. Additionally, the coefficient for firm size (Size) is significantly positive, suggesting that larger firms tend to have higher innovation capabilities and stronger incentives for innovation. The coefficient for financial leverage (Lev) is also significantly positive, indicating that a firm's financial condition positively impacts its innovation capability. Higher financial leverage implies greater access to funding, which allows firms to allocate more resources to research and development activities.

3.4. Endogeneity test

Given that endogeneity issues among variables can lead to unstable and inaccurate regression results, this study addresses the independent variable's potential endogeneity to ensure the findings' reliability. To mitigate the impact of endogeneity in this study, the lagged value of AI adoption is used as an instrumental variable for endogeneity testing. The results of the second stage of the 2SLS (Two-Stage Least Squares) analysis are presented in Table 2. The coefficient for AI adoption remains significantly positive at the 1% level, consistent with the baseline regression results shown in Table 1. Therefore, it can be concluded that AI adoption significantly enhances firms' innovation capabilities (see Table 3).

3.5. Discussion

Through the Pilot study, we demonstrated the positive effect of enterprise AI adoption on firms' innovation ability. For this reason, this study will further hypothesize in the main text that this is due to AI increasing the technology available to firms. In order to prove this point more robustly, formal research will continue to be conducted to prove this hypothesis.

4. Research methods

4.1. Research sample and procedure

In the formal research of this paper, we adopted the stratified random sampling method to select samples. First, according to the

Table 2
Endogeneity test results.

VARIABLES	*lninnovation*
AI – adoption	0.244***
	(0.0654)
Size	0.493***
	(0.0131)
Lev	−0.459***
	(0.0864)
ROA	−0.180
	(0.196)
Board	0.0710
	(0.0683)
Dual	0.0200
	(0.0274)
Constant	−8.470***
	(0.252)
N	16,639
R^2	0.195

Robust standard errors in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

Table 3
Results of reliability and convergent validity tests.

Variables	Measurement questions	Cronbach's α	AVE	CR
Artificial intelligence adoption	A1-A3	0.845	0.646	0.845
Perceived adaptability	B1-B4	0.878	0.643	0.878
Social adaptability	C1-C3	0.836	0.628	0.835
Production adaptability	D1-D3	0.821	0.604	0.821
Market perception	T1-T6	0.910	0.630	0.910
Innovation capability	G1-G5	0.898	0.638	0.898

N = 511.

2023–2024 Evaluation Report on the Development of China's Artificial Intelligence Computing Power jointly issued by IDC and Inspur Information, we limited the research objects to the industries with the highest use of AI, namely the Internet, telecommunications, finance, and manufacturing industries, to more clearly reflect the impact of AI use on enterprise economic activities. This study excluded the government industry, which has significant specificity in using artificial intelligence due to policy orientation and nonmarket characteristics and, therefore, has lower comparability compared to other industries. Regarding regional selection, according to the "China New Generation Artificial Intelligence Technology Industry Regional Competitiveness Evaluation Index 2023″ ranking, we further divided China into three gradients based on provinces, autonomous regions, and municipalities directly under the central government. We selected the top three regions in terms of regional competitiveness for research in each gradient, including Beijing, Guangdong, and Shanghai in the first gradient, Fujian, Hubei, and Shaanxi provinces in the second gradient, and Guangxi Zhuang Autonomous Region, Shanxi, and Guizhou provinces in the third gradient. Regarding research methods, we use project research and enterprise visits to randomly collect enterprise questionnaires in selected regions and industries. The target audience for the questionnaire is limited to senior management of the enterprise, as they can determine the strategy and plan for the use of artificial intelligence in the enterprise and grasp the current direction of artificial intelligence use in the enterprise.

This data collection is divided into three time periods. Considering the delay in the use of artificial intelligence and innovation capabilities of enterprises, based on previous experience, each measurement is separated by at least 2–3 months. This can improve the causality between variables and effectively alleviate the problem of common method bias. The investigation period is from April 2023 to April 2024. In the first phase, senior management of enterprises was invited to fill out artificial intelligence usage scales and demographic variable data. A total of 236 questionnaires were distributed, and 205 data were collected. After excluding invalid questionnaires with incomplete responses, obvious patterns, and errors, 189 valid data were sorted out. In the second period, senior management of enterprises was invited to fill out perception adaptability, social adaptability, production adaptability, and market perception scales. A total of 230 questionnaires were distributed, and 189 data were actually collected, resulting in 160 valid data. In the third period, senior management of enterprises was invited to fill out the Data Quality and Enterprise Innovation Capability Scale. 232 questionnaires were distributed, and 181 data were collected, resulting in 162 valid data. Through multiple rounds of matching with multiple data sources, 511 valid questionnaires were obtained, with effective questionnaire response rates of 73.2%. Among the participants in the survey, managers and supervisors accounted for a relatively high proportion of positions, accounting for 39.53% and 29.16%, respectively; State-owned companies account for 31.9%, while non-state-owned companies account for 68.1%; The company's scale is mainly concentrated between 101-499 people and 500–999 people, accounting for 42.66% and 38.75% respectively; The industries are distributed in the Internet (42%), manufacturing (28%), finance (10%) and telecommunications (20%). It can be seen that the Internet industry has the widest coverage in this survey.

4.2. Measurement of variables

To ensure the high validity and reliability of the variable measurements in this study, we utilized established and widely recognized scales from core domestic and international journals. When translating English scales, our research team followed a rigorous translation-back-translation procedure to ensure the accuracy and applicability of the scales. After thoroughly analyzing the research objectives and pretest results, we localized the English scales to better suit the Chinese research context.

This study selected five core research variables: AI adoption, digital adaptability (perceived adaptability, social adaptability, and production adaptability), market perception, and enterprise innovation capability. All items were measured using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), to ensure precision and consistency in the research results. This method allows for a comprehensive assessment of the research variables and provides reliable data for subsequent analysis.

The use of artificial intelligence. Drawing on the scale developed by Baabdullah (2024), the scale for this study was designed with three items, such as "What is the frequency range of interactive artificial intelligence (IAI) usage in enterprises," and "The range of frequency in which enterprises use functional artificial intelligence (FAI)."

Perceived adaptability. Drawing on the scales developed by Liang et al. (2023) and Lin (2023), this study designed a scale with four items, such as: "The enterprise is capable of employing systematic methods to monitor market and industry trends to identify potential business opportunities and threats," and "The enterprise can promptly analyze market data and competitors' dynamics to adjust its strategic planning and resource allocation."

Social adaptability. Drawing on the scales developed by Liang et al. (2023) and Lin (2023), this study designed a scale with three items, such as: "The enterprise effectively utilizes AI platforms to interact with users, collecting feedback and suggestions," and "The enterprise actively establishes connections with customers through social media and online communities to identify potential needs."

Production adaptability. Drawing on the scales developed by Liang et al. (2023) and Lin (2023), this study designed a scale with three items, such as: "The enterprise invests in AI and other advanced technologies to enhance production efficiency and innovation capabilities," and "The enterprise leverages big data analytics to optimize supply chain management, reducing costs and improving product delivery efficiency."

Market perception. Drawing on the scales developed by Matsuno and Mentzer (2000) and Lin (2023), this study designed a scale with six items, such as: "The enterprise has an in-depth understanding of industry trends and can predict future market developments," and "The enterprise closely monitors changes in policies and regulations and quickly assesses their potential impact on business operations."

Enterprise innovation capability. Drawing on the scale developed by Rajapathirana and Hui (2018), the scale for this study was designed with a total of five items, such as "Has the enterprise successfully transformed its innovative achievements into new products or services in the market?" and "The enterprise introduces new technologies or methods through internal R&D or external collaborations to enhance market competitiveness."

Control variables. Drawing on previous research on the enterprise level, this study uses control variables, including the age, size, and nature of the enterprise (Duan et al., 2024; Zhou et al., 2021). The age of the enterprise affects the accumulation of innovation ability; Enterprise size affects resource allocation and market influence; The nature of the enterprise involves market strategy and policy environment adaptation, which collectively affect the innovation performance of the enterprise.

5. Empirical results

5.1. Reliability and validity analysis

This study employed SPSS 24.0 and Amos 26.0 to analyze the reliability and validity of the measured variables, with the results summarized in the table below. First, the reliability of all variables, as indicated by Cronbach's α, exceeded 0.8, demonstrating high internal consistency. The Average Variance Extracted (AVE) for all variables was above 0.5, indicating good convergent validity. The Composite Reliability (CR) values, which are close to Cronbach's α and above 0.8, also suggest high composite reliability for the variables. Overall, the measurement items for all variables exhibit high reliability and validity, making them suitable for further empirical analysis and research.

Furthermore, since the questionnaire was completed through self-assessment by employees, Harman's single-factor test was conducted using SPSS 24.0 to check for significant common method bias. The principal component analysis showed that the maximum explained variance by a single factor was 31.343%, which is below the 40% threshold, indicating that common method bias is not severe. Additionally, the Variance Inflation Factor (VIF) for all variables was less than 5, suggesting that multicollinearity does not affect the model's validity and reliability.

5.2. Confirmatory factor analysis

To validate the structural validity of the hypothesized model, this study compared the fit indices of various factor models. The table below shows that the hypothesized six-factor model demonstrated the best fit among the different factor models assessed through confirmatory factor analysis. The fit indices for this model indicate excellent model suitability: $\chi^2/df = 1.146$, which is close to 1, CFI $= 0.995$, TLI $= 0.994$, all exceeding the recommended value of 0.9, and SRMR $= 0.026$ and RMSEA $= 0.017$, both below the thresholds of 0.05 and 0.08, respectively. These results suggest that the six-factor model most accurately reflects the data structure. In contrast, the fit indices for other models progressively decreased, particularly for the four-factor model (which combines perceived adaptability, social adaptability, and production adaptability), which showed a $\chi^2/df = 4.544$, exceeding the critical value of 3, indicating poor model fit and unsuitability for data analysis. This comparison also demonstrates that measuring digital adaptability as three distinct components is more effective than a combined measure. Therefore, the original six-factor model is the optimal choice for this study, exhibiting strong discriminant validity (see Table 4).

Table 4
Confirmatory factor analysis.

Measurement model	χ^2/df	CFI	TLI	SRMR	RMSEA
The hypothesized 6-factor model	1.146	0.995	0.994	0.026	0.017
5-factor model	2.822	0.908	0.901	0.051	0.060
4-factor model	4.544	0.871	0.855	0.067	0.083
3-factor model	7.192	0.684	0.663	0.112	0.110
2-factor model	7.908	0.646	0.624	0.113	0.116
1-factor model	9.311	0.574	0.548	0.116	0.128

Note: N = 511.

5.3. Descriptive statistics

Table 5 presents the means, standard deviations, and correlations of the variables in the model. The results show that the means and standard deviations of the variables are within reasonable ranges, indicating that the data distribution is relatively normal. Correlation analysis reveals significant positive correlations between AI adoption and perceived adaptability, social adaptability, and production adaptability ($r = 0.369^{**}$, $p < 0.01$; $r = 0.384^{**}$, $p < 0.01$; $r = 0.360^{**}$, $p < 0.01$). Additionally, perceived adaptability, social adaptability, and production adaptability are positively correlated with market perception ($r = 0.412^{**}$, $p < 0.01$; $r = 0.381^{**}$, $p < 0.01$; $r = 0.347^{**}$, $p < 0.01$), and market perception is positively correlated with firm innovation capability ($r = 0.384^{**}$, $p < 0.01$). These preliminary findings provide a solid data foundation for subsequent empirical analysis. They will aid in further exploring the specific relationships and mechanisms among variables in the proposed chain mediation model.

5.4. Hypothesis testing

Given the complexity of the model in this study, we utilized Amos 26.0 software to construct Model 1. The main fit indices for Model 1 are $\chi^2/df = 2.727$, RMSEA = 0.058, GFI = 0.904, CFI = 0.917, and AGFI = 0.879, indicating an excellent model fit. Fig. 2 illustrates the calculated path coefficients. AI adoption significantly enhances firm innovation capability ($\beta = 0.210$, SE = 0.059, $p < 0.001$), thus supporting Hypothesis 1. AI adoption also has significant positive effects on perceived adaptability, social adaptability, and production adaptability ($\beta = 0.476$, SE = 0.052, $p < 0.001$; $\beta = 0.501$, SE = 0.053, $p < 0.001$; $\beta = 0.467$, SE = 0.052, $p < 0.001$), supporting Hypotheses 2a, 2b, and 2c. Furthermore, AI adoption positively correlates with market perception ($\beta = 0.189$, SE = 0.064, $p < 0.01$), validating Hypothesis 5. Perceived adaptability, social adaptability, and production adaptability positively impact firm innovation capability ($\beta = 0.214$, SE = 0.054, $p < 0.001$; $\beta = 0.131$, SE = 0.054, $p < 0.05$; $\beta = 0.170$, SE = 0.055, $p < 0.01$), supporting Hypotheses 3a, 3b, and 3c. Additionally, perceived adaptability, social adaptability, and production adaptability have positive effects on market perception ($\beta = 0.252$, SE = 0.057, $p < 0.001$; $\beta = 0.191$, SE = 0.060, $p < 0.01$; $\beta = 0.143$, SE = 0.059, $p < 0.05$), confirming Hypotheses 8a, 8b, and 8c. Finally, market perception positively affects firm innovation capability ($\beta = 0.104$, SE = 0.048, $p < 0.05$), validating Hypothesis 6.

The mediation pathways for Model 1 reveals the following results (See in Table 6): 1. The indirect effect of AI adoption on firm innovation capability through perceived adaptability (ind-a) is 0.1016(SE = 0.0275, $p < 0.001$), with a 95% confidence interval of [0.0523, 0.1600]. 2. The indirect effect through social adaptability (ind-b) is 0.0656 (SE = 0.0286, $p < 0.05$), with a 95% confidence interval of [0.0115, 0.1244]. 3. The effect through production adaptability (ind-c) is 0.0796 (SE = 0.0288, $p < 0.01$), with a 95% confidence interval of [0.0274, 0.1417]. 4. The effect through market perception (ind-d) is 0.0197 (SE = 0.0121, $p < 0.01$), with a 95% confidence interval of [0.0026, 0.0524]. Since all confidence intervals exclude zero, these results support Hypotheses 4a, 4b, 4c, and 7.

Finally, to test the chain mediation effects in this study, we calculated the coefficients by multiplying the three-stage effects of two paths(Xiong et al., 2023): 5. The path coefficient for ind-e is 0.0125 (SE = 0.0069, $p < 0.01$), with a 95% confidence interval of [0.0016, 0.0297]; 6. The path coefficient for ind-f is 0.01 (SE = 0.0061, $p < 0.01$), with a 95% confidence interval of [0.0014, 0.0270]; 7. The path coefficient for ind-g is 0.0070 (SE = 0.0046, $p < 0.05$), with a 95% confidence interval of [0.0007, 0.0203]. These results support Hypotheses 9a, 9b, and 9c.

6. Discussion

6.1. Theoretical contributions

This study has two main theoretical contributions. Firstly, a chain mediation model of "artificial intelligence use digital adaptability market perception enterprise innovation capability" was constructed to explain how the use of artificial intelligence affects the innovation capability of enterprises through digital adaptability and market perception. Although previous studies have confirmed that digital technologies can promote innovation (Scuotto et al., 2017), on the one hand, they often categorize technologies such as big data and cloud computing for discussion, ignoring the fact that different digital technologies may have different impacts on enterprise innovation (Usai et al., 2021). On the other hand, research on artificial intelligence and innovation is often treated separately. Research on artificial intelligence in enterprise innovation often focuses on broader digital issues, with insufficient attention to specific technologies (Hutchinson, 2020), and research tends to explore causes rather than results (Baabdullah et al., 2021). Therefore, the

Table 5
Descriptive statistics and correlation analysis.

Variables	Mean	SD	1	2	3	4	5	6
1. Artificial intelligence adoption	4.380	1.441	1					
2. Perceived adaptability	4.409	1.420	0.369**	1				
3. Social adaptability	4.410	1.414	0.384**	0.418**	1			
4. Production adaptability	4.464	1.399	0.360**	0.403**	0.369**	1		
5. Market perception	4.325	1.380	0.376**	0.412**	0.381**	0.347**	1	
6. Innovation capability	4.466	1.401	0.422**	0.438**	0.396**	0.395**	0.384**	1

N = 511.

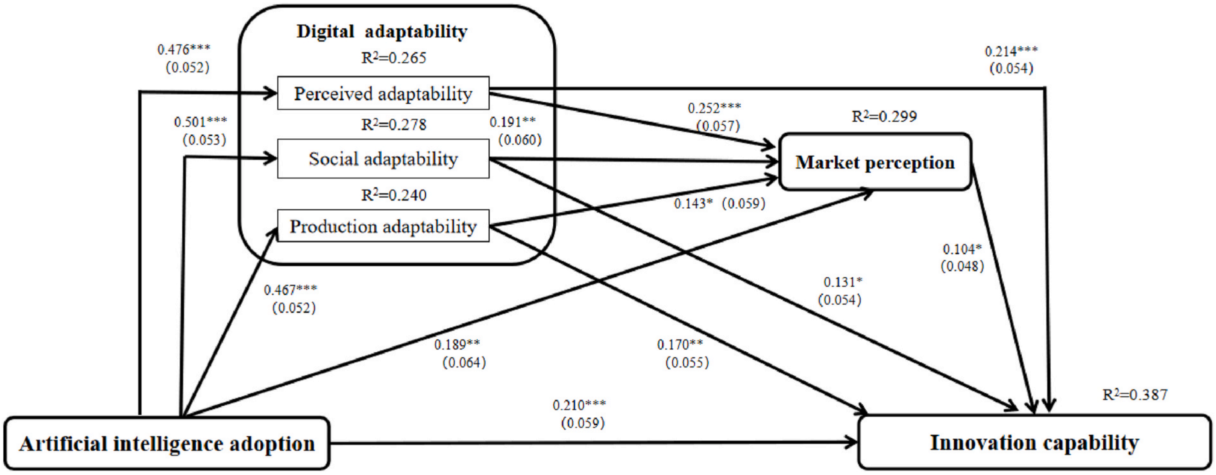

Fig. 2. Path analysis results for Model 1
Note: The path coefficients in the figure are unstandardized. The values in parentheses represent the standard errors and the 95% confidence intervals based on 8000 bootstrap samples. ***p < 0.001, **p < 0.01, *p < 0.05. Control variables are included in Model 1 but are omitted from the figure for brevity.

Table 6
Model 1 indirect effects analysis.

Path	Unstandardized β	SE	95%Confidence Interval
1.ind-a	0.1016***	0.0275	[0.0523, 0.1600]
2.ind-b	0.0656*	0.0286	[0.0115, 0.1244]
3.ind-c	0.0796**	0.0288	[0.0274, 0.1417]
4.ind-d	0.0197**	0.0121	[0.0026, 0.0524]
5.ind-e	0.0125**	0.0069	[0.0016, 0.0297]
6.ind-f	0.0100**	0.0061	[0.0014, 0.0270]
7.ind-g	0.0070*	0.0046	[0.0007, 0.0203]
Total	0.5059***	0.0488	[0.4145, 0.6046]

Note.
Ind-a: AI adoption → Perceived adaptability → Firm innovation capability.
Ind-b: AI adoption → Social adaptability → Firm innovation capability.
Ind-c: AI adoption → Production adaptability → Firm innovation capability.
Ind-d: AI adoption → Market perception → Firm innovation capability.
Ind-e: AI adoption → Perceived adaptability → Market perception → Firm innovation capability.
Ind-f: AI adoption → Social adaptability → Market perception → Firm innovation capability.
Ind-g: AI adoption → Production adaptability → Market perception → Firm innovation capability.

connection between the use of artificial intelligence and the innovation capability of enterprises has not been fully explored. This study constructs a chain mediation model of "artificial intelligence use digital adaptability market perception enterprise innovation capability", using digital adaptability and market intelligence response as mediating variables, revealing how enterprises can utilize the potential of artificial intelligence to respond to market changes through intelligent decision-making, thereby promoting innovation capability enhancement. This discovery enriches the theoretical framework regarding the impact of artificial intelligence usage on corporate innovation capabilities. It expands the application scope of artificial intelligence in management disciplines, responding to Pietranudo et al.'s (2022) call for strengthening interdisciplinary research between artificial intelligence and innovation.

Secondly, this study explores the impact of artificial intelligence on the innovation capability of enterprises. Based on the dynamic capability theory focuses on defining three key dimensions of digital adaptability: perceptual adaptability, social adaptability, and production adaptability. Based on the theory of dynamic capabilities, this study suggests that enterprises can better unleash the potential of artificial intelligence in enhancing their innovation capabilities by matching their abilities in sensing, seizing opportunities, and reconfiguring resources with the dimensions of digital adaptability (Teece, 2007). Specifically, perceptual adaptability corresponds to the perceptual link in the dynamic capabilities of enterprises, helping them discover technological trends and innovation opportunities; Social adaptability emphasizes the ability to seize opportunities and promote efficient collaboration and resource integration within internal and external networks of enterprises; Production adaptability focuses on resource restructuring, optimizing production processes and business models to achieve comprehensive transformation of technological value. This perspective provides new ideas for the theoretical construction of artificial intelligence in enterprise innovation while expanding the applicability of dynamic capability theory in the digital context (Chirumalla, 2021a, 2021b; Ghosh et al., 2022). Moreover, this study explores the roles of perceptual adaptability, social adaptability, and production adaptability in using artificial intelligence and verifies their mediating effects in enhancing corporate innovation capabilities. These findings also provide a new perspective for understanding the practical application of artificial intelligence in enterprises and also provide direction for subsequent research.

6.2. Management implications

The conclusion of this study has a profound impact on enterprise management practices, emphasizing the key role of artificial intelligence technology in enhancing enterprise innovation capabilities and market competitiveness. This study points out that artificial intelligence can improve production efficiency and help companies redefine their innovation paths. In addition, applying artificial intelligence in market forecasting, competitive analysis, and other areas can help companies seize opportunities in complex market environments and achieve more efficient innovation (Al Dhaheri et al., 2024; Sullivan & Wamba, 2024). Based on this, the study proposes that enterprises consider artificial intelligence as their core competitiveness, emphasizing the establishment of support mechanisms within the organization, the cultivation of professional talents, the strengthening of technology research and development, and investment (Carayanis et al., 2006; Malik et al., 2012), and exploring the application of artificial intelligence in different business scenarios to maximize its role in promoting innovation. In short, research provides clear direction for enterprises to embed artificial intelligence into innovation strategies, capture market opportunities, and create higher innovation value.

6.3. Limitations and future research directions

Although this study provides important theoretical contributions and practical insights in the field of artificial intelligence and enterprise innovation capabilities, there are still some limitations. First of all, in the sample collection stage, this study selected nine provinces and cities with different gradients in the regional competitiveness of the AI technology industry as the research objects. It limited the industry scope to the Internet, finance, manufacturing and telecommunications fields. Although this sample selection has a certain representativeness, it may also limit the broad applicability of the research results. Therefore, future research should consider expanding the sample size, such as emerging industries such as healthcare and education, which have gradually become important areas for artificial intelligence applications in recent years (Dwivedi et al., 2021; Zhang & Lu, 2021). Future research can cover more regions and industries to verify the universality of the conclusions of this study. Secondly, in terms of digital adaptability research, although this study is based on the theory of dynamic capabilities and clarifies the three main dimensions of digital adaptability, digital adaptability may not be limited to these three dimensions. Data sharing, intelligence level, and data security have important impacts on artificial intelligence technology (Car et al., 2019; Mühlhoff, 2023). Future research should further explore and explore new adaptive dimensions and analyze the causes and impacts of these dimensions, as well as their interactions and dynamic changes, which will help to have a more comprehensive understanding of the mechanism of artificial intelligence in the process of enterprise innovation.

7. Result

This study is based on the theory of dynamic capabilities. It deeply explores the impact of artificial intelligence use on enterprise innovation capabilities, revealing the importance and influence of artificial intelligence technology in modern enterprise innovation management. The study aims to analyze the relationship between the level of artificial intelligence technology enterprises use in their actual operations and their innovation capabilities through questionnaire surveys from multiple time periods and sources. The research results indicate that the higher the degree to which enterprises use artificial intelligence, the stronger their innovation capabilities. This discovery highlights the necessity and urgency for companies to enhance their innovation capabilities by introducing artificial intelligence technology in today's highly competitive market environment (Huang et al., 2019). Secondly, the study revealed the mediating role of the three core dimensions of digital adaptability - perceptual adaptability, social adaptability, and production adaptability - between the use of artificial intelligence and corporate innovation capabilities. Perceived adaptability refers to the sensitivity of an enterprise to external environmental and market changes; Social adaptability reflects a company's ability to obtain key information and resources through social networks and partner relationships, helping the company effectively integrate external resources; Production adaptability refers to how enterprises can fully utilize artificial intelligence technology to optimize processes and improve production efficiency in actual production and service processes, thereby achieving the transformation of innovative achievements. These three dimensions affect the innovation process of enterprises, enabling artificial intelligence to directly drive technological progress and indirectly promote the improvement of innovation capabilities by enhancing the ability of enterprises in these dimensions. Thirdly, market perception plays an important mediating role between the use of artificial intelligence and the innovation capabilities of enterprises. The use of artificial intelligence can significantly enhance a company's perception of market changes and consumer demand, helping it more accurately capture market opportunities and develop more effective innovation strategies. Fourthly, digital adaptability and market perception have a chain-mediated effect between the use of artificial intelligence and the innovation capability of enterprises, indicating that digital adaptability provides the possibility for enterprises to achieve high-level innovation results on the one hand and ultimately promotes the output of innovation results by influencing the external actual actions of enterprises on the other hand.

This study refers to Lin's (2023) framework based on technology availability theory in theoretical background, which proposes a logical model of "technology factors or subject factors - potential capabilities provided by technology (availability dimension) - actual actions - outcome output". In Lin's theory, technological factors or subject factors influence the actual actions of enterprises through technological availability (such as technological capabilities, resources, and environmental support), ultimately affecting the output of innovative results. In this study, digital adaptability, as a key mediating variable affecting a company's innovation capability, provides a potential capability dimension similar to technological availability. Specifically, digital adaptability helps companies utilize artificial intelligence technology to better adapt to market changes, optimize innovation processes, and promote the generation of innovative results through three dimensions: perceptual adaptability, social adaptability, and production adaptability. Therefore, although this study did not directly apply the theory of technology availability, there is a mutually reinforcing dialogue between its theoretical ideas and the framework of technology availability, which further enriches the understanding of the relationship between technology and innovation capabilities and provides a new perspective for future research. By revealing the positive impact mechanism of artificial intelligence usage on enterprise innovation capability, this study provides a new perspective for understanding how enterprises can enhance their innovation capability through technological means, and also clarifies the role of the three key dimensions of digital adaptability in this process. This discovery provides a potential research path that combines technology availability theory and dynamic capability theory for future academic research, promoting further exploration in related fields.

Author contributions

Conceptualization, Y.G. and L.Y.; methodology, Y.G.; data curation, S.L. and Y.G.; formal analysis, Y.G. and S.L.; Writing— original draft preparation, Y.G. and L.Y.; Writing—review& editing, L.Y. All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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