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Enhancing Corporate Innovation Through Artificial Intelligence Adoption: A Study of Chinese Telecommunications Companies

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Abstract

This study explores the impact mechanism of artificial intelligence (AI) adoption intensity on corporate innovation performance within the context of the digital economy. Using a sample of Chinese telecommunications companies, the research investigates how AI adoption intensity influences innovation performance. Empirical analysis reveals a significant positive relationship between AI adoption intensity and innovation performance. Furthermore, AI availability, encompassing mobile, interactive, and autonomous aspects, is found to partially mediate this relationship. The study underscores the role of AI adoption in enhancing innovation efficiency and effectiveness, facilitating lean and agile product development, and supporting various stages of the innovation process. Despite its contributions, the research acknowledges limitations in sample representation and calls for future studies to broaden the scope and address potential negative impacts of AI adoption. This study provides insights into the transformative potential of AI in fostering corporate innovation.

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1. Introduction

1.1 Research background

The digital economy is propelling a new era of growth, with enterprises undergoing profound digital transformations. China's digital economy reached 50.2 trillion yuan in 2022, marking a 10.3% year-on-year growth and constituting 41.5% of the GDP (Füller et al., 2022). Artificial intelligence (AI), as a strategic technology, is driving a new technological revolution and industrial transformation, facilitating innovation across industries (Füller et al., 2022). In the telecommunications sector, AI enhances customer service, network management, and resource allocation, bolstering operators' competitiveness (Füller et al., 2022). It is projected that AI's value in the telecom market will soar to $38.8 billion by 2031, with a 41.4% annual growth rate (Füller et al., 2022). Telecom giants are increasingly investing in AI to innovate and modernize infrastructure. For instance, a British company aims to replace 10,000 roles with AI by 2030, while Japanese providers halved energy consumption in wireless networks using AI (Füller et al., 2022). Additionally, a US telecom firm slashed customer call abandonment rates by 62% through AI deployment (Füller et al., 2022). Chinese telecom companies demonstrate a robust adoption of AI, leveraging it to enhance innovation responsiveness and performance (Issa et al., 2022). However, academic research lacks cross-examination between AI and corporate innovation, hindering a comprehensive understanding of AI's impact on innovation performance (Pietronudo et al., 2022). Thus, there's a pressing need to innovate theoretical research on AI-empowered corporate innovation to guide Chinese telecom enterprises amid the new development paradigm (Pietronudo et al., 2022).

1.2 Problem statement

Scholars emphasize factors impacting innovation, particularly the role of digital technologies like AI (Hengstler et al., 2016). Recent findings highlight AI's unique impact on innovation (Hengstler et al., 2016; Usai et al., 2021). Scholars advocate for more research on how AI supports enterprise innovation (Appio et al., 2021; Johnson et al., 2022). AI adoption research is nascent, lacking a systematic understanding of its support for enterprise innovation (Prem, 2019; Yams et al., 2020). Scholarly focus is shifting to how AI influences innovation outcomes (Usai et al., 2021). Despite AI adoption studies, empirical research on AI's effects on innovation performance remains limited (Prem, 2019; Yams et al., 2020). Existing studies analyze AI adoption factors but overlook its outcomes (Braganza et al., 2021). Research explores AI's impact on organizational variables and performance (Chen et al., 2022; Lee et al., 2022). However, empirical studies on AI's effect on enterprise innovation performance are scarce (Mikalef et al., 2019). The theory of technological availability offers a lens to understand how AI adoption intensity affects innovation performance (Lehrer et al., 2018; Zeng et al., 2020). It considers technology's power, users, and goals, providing insights into AI's impact on innovation (Trocin et al., 2021; Parchoma, 2014). In conclusion, AI adoption intensity, influenced by various factors, can enhance enterprise innovation by providing technological availability. However, existing research lacks a comprehensive understanding of AI's impact on innovation performance, warranting further exploration.

1.3 Research question and objectives

This study focuses on the impact of AI adoption intensity on innovation performance in China's telecommunications industry, guided by the theory of technological availability. The research questions are:

(1) How does AI adoption intensity affect innovation performance in China's telecommunications?
(2) How does AI adoption intensity influence AI availability?
(3) How does AI availability affect innovation performance?

(4) Does AI availability mediate the relationship between AI adoption intensity and innovation performance?

The objectives are to validate:
(1) The influence of AI adoption intensity on innovation performance.
(2) The impact of AI adoption intensity on AI availability.
(3) The effect of AI availability on innovation performance.
(4) The mediating role of AI availability between AI adoption intensity and innovation performance.

1.4 Research significance

This study investigates how AI adoption intensity influences innovation performance in China's telecommunications sector, using theories like technological availability, resource-based theory, and dynamic capability theory. It aims to validate the impact of AI adoption intensity on innovation performance, AI availability, and the mediating role of AI availability. Theoretical significance lies in advancing research on AI adoption by discussing factors at organizational levels (Lee et al., 2022). Moreover, it clarifies how AI adoption intensity affects innovation performance, bridging the gap between AI and innovation research (Baabdullah et al., 2021; Pietronudo et al., 2022). The study contributes practically by guiding Chinese telecom companies in AI adoption and inspiring innovation through AI technology (Chen et al., 2021; Paluch et al., 2019). It also offers insights for government support and industry collaboration to enhance AI integration and innovation-driven development.

2. Literature Review

2.1 Artificial intelligence adoption intensity

The adoption intensity of artificial intelligence has emerged as a significant focus in both academic and practical domains, reflecting a burgeoning area of research. Scholars such as Kaplan and Haenlein have transitioned from defining and categorizing artificial intelligence to exploring its transformative impacts in specific contexts. However, research on adoption intensity remains in its infancy, lacking comprehensive empirical studies and result-oriented discussions. Initially, while there's a consensus on the fundamental concepts and features of artificial intelligence, research predominantly focuses on its technical aspects, laying a groundwork for its managerial applications. Yet, investigations into artificial intelligence adoption intensity within innovation contexts are notably sparse. Despite its increasingly pivotal role in innovation practices, there's a gap between theoretical discourse and practical implementation. Consequently, there's a pressing need to bridge this disconnect by examining artificial intelligence adoption within innovation scenarios. Moreover, existing studies often prioritize the antecedents of artificial intelligence adoption, neglecting its outcomes. Few studies have concurrently explored both antecedents and outcomes, leading to a fragmented understanding. Additionally, the lack of configurational thinking in analyzing antecedent variables has further complicated the understanding of artificial intelligence adoption intensity. Consequently, this study aims to elucidate the impact mechanism of adoption intensity on innovation performance by investigating its driving factors and their effects within innovation contexts.

2.2 Artificial intelligence availability

Artificial intelligence availability stems from technological accessibility, defined as technology adopters' capacity to achieve organizational goals by employing AI technology (Volkoff & Strong, 2017; Du et al., 2019). This definition emphasizes achieving specific outcomes, portraying AI availability as the potential for enterprises to interact with AI technology to produce results (Marku & Silver, 2008). The concept encompasses subjective factors such as organizational capabilities, alongside technological characteristics, shaping a dynamic process influenced by both the technology itself and adopters' traits (Zammuto et al., 2007). AI availability is differentiated from AI capabilities and technological features, highlighting its situational, goal-oriented nature and its reflection of the adopters' actions and outputs (Xie Weihong et al., 2022). Trocin et al. (2021) introduced second-order and first-order availability dimensions for AI to support digital process and service innovation. They identified specific actions and outcomes within information collection and analysis stages, highlighting AI's role in promoting innovation. However, this qualitative study lacked empirical development and China-specific insights. To address this gap, this study proposes measurable dimensions of AI availability in innovation contexts, integrating mobile, interactive, and autonomous availability. These dimensions reflect AI's unique advantages in innovation and can be tested on a larger scale. AI availability is influenced by both subjective (e.g., cognitive factors) and technological factors. Subjective factors include adopters' goals and actions, while technological factors encompass AI's capabilities and functionalities (Liu Yi & Wang Wei, 2019; Trocin et al., 2021). However, these factors require empirical validation, especially in China-specific contexts. AI availability yields outcomes like enhanced fairness perception, improved communication, transparent feedback, less biased decision-making, and revenue growth, granting enterprises a competitive edge (Trocin et al., 2021). For instance, AI facilitates fair data processing, real-time communication, transparent analytics, unbiased decision-making, and expanded information utilization, thereby enhancing enterprise performance. Research on AI availability is still nascent, primarily due to limited empirical studies and a lack of distinction between potential actions and actual outcomes. While existing studies offer insights into AI's theoretical foundations, empirical testing and measurement remain inadequate, necessitating further research to establish clear dimensions and models for empirical validation.

2.3 Enterprise innovation performance

Innovation stands as the cornerstone of a company's vitality, with innovation performance serving as a critical gauge of success. Existing research offers diverse perspectives on innovation performance, with scholars broadly categorizing it into narrow and broad definitions. Narrowly, innovation performance is viewed as the output of innovation efforts, exemplified by market success rates, product improvements, or technological advancements (Hagedoorn & Cloodt, 2003; Wang & Ahmed, 2004). Conversely, a broader perspective encompasses not just outcomes but also the process of innovation, acknowledging the journey from creativity to market entry (Ernst, 2001; Ari et al., 2005). Studies on enterprise innovation performance span various dimensions, including disruptive versus progressive innovation, product versus process innovation success, and digital era innovation facets (He & Wong, 2004; Gemünden et al., 1996; Chen et al., 2020). These dimensions provide a nuanced understanding of innovation's multifaceted impact on organizational success. Scholarly attention on enterprise innovation performance antecedents covers environmental, organizational, cross-organizational, and individual factors (Luo Feng et al., 2022; Chi Renyong et al., 2020; Yang Zhenning & Zhao Hong, 2020; Wu Fengqing & Fu Huixian, 2020). Notably, recent discussions emphasize the role of digital technology as a key influencer, urging a deeper examination of artificial intelligence's adoption intensity and its implications for innovation performance (Ciarli et al., 2021; Usai et al., 2021). While considerable research delves into enterprise innovation performance, consensus remains elusive regarding its definition, dimensions, and measurement. This study narrows down innovation performance to outcome-focused definitions, aiming to explore the impact of artificial intelligence adoption intensity on innovation performance, thereby contributing to a deeper understanding of innovation antecedents and guiding performance enhancement strategies.

2.4 Management theory

2.4.1 Technology availability theory

The technology availability theory offers a significant perspective on how digital innovations, notably artificial intelligence, influence enterprise innovation (Liu Yi et al., 2020). This theory, rooted in ecological psychology, explores the interplay between technology and human interaction in the digital realm (Robey et al., 2013). It integrates technology determinism and social determinism, elucidating the impact of digital tools on behavior (Majchrzak et al., 2016; Senyo et al., 2021). In its origin stage (1977-2006), availability theory emerged from ecological psychology, emphasizing the complementary relationship between entities in the environment and behavioral subjects (Gibson, 1986). This stage laid the groundwork for subsequent research on availability's transformative potential (Liu Yi et al., 2020). During the introduction phase (2007-2017), availability theory expanded into the realm of technology, particularly information systems, highlighting the potential actions enabled by technology adoption (Zammuto et al., 2007; Markus and Silver, 2008). In the current development stage (2018-present), availability theory has evolved with the digital revolution, encompassing dimensions like big data and artificial intelligence (DeLuca et al., 2021; Trocin et al., 2021). Research now spans individual, organizational, and ecological levels, examining the multifaceted impact of digital technologies (Autio et al., 2018). Availability theory is viewed through functional, relational, and behavioral lenses (Senyo et al., 2021; Xie Weihong et al., 2022). Scholars explore how technology design, interaction dynamics, and behavioral goals shape availability (Strong et al., 2014; Nambisan et al., 2017). Availability theory finds application across various domains, including information technology, big data, digital technology, and artificial intelligence (Liu Yi et al., 2020; Lehrer et al., 2018; Trocin et al., 2021). It informs research on organizational innovation, digital literacy, and entrepreneurial ecosystems (Austio et al., 2018; Kozanoglu and Abedin, 2021; Belitski et al., 2021). In this study, availability theory elucidates the impact of artificial intelligence adoption on innovation performance, underscoring the role of technology in organizational change (Liu Yi et al., 2020). By examining the interplay between technology and behavior, this framework offers insights into digital transformation dynamics (Leonardi and Vaast, 2017).

2.4.2 Resource-based theory

Penrose (1959) initially proposed the concept that an enterprise is a collection of resources, laying the foundation for the resource-based view (RBV). Wernerfelt (1984) formally introduced RBV, which was later advanced by Barney (1991). Significant contributions to RBV's conceptual and theoretical development have been made by Barney (2001), Barney et al. (2001), and Wang and Ahmed (2007). RBV underscores the importance of resources and capabilities as the source of competitive advantage. Resources, whether tangible or intangible, are valuable, rare, inimitable, and non-substitutable (Wernerfelt, 1984; Barney, 1991). The State Council of China (2020) recognized data as a key production factor, highlighting its significance in driving economic development and technological advancements. Data, from an RBV perspective, is valuable, scarce, immutable, and irreplaceable (Lin Xiaoyue et al., 2022). Research on RBV has evolved through three stages: traditional RBV, dynamic RBV, and RBV-action view (Zhang Lu et al., 2021). Traditional RBV focuses on heterogeneous resources and capabilities (Barney, 2001). Dynamic RBV emphasizes dynamic capabilities, leading to the dynamic capability theory (Zhang Lu et al., 2021). RBV-action view explores resource acquisition, integration, and allocation processes (Baker and Nelson, 2005; Simon et al., 2011). RBV has been integrated with various topics such as value creation, organizational practices, and strategic alliances (Zhang Lu et al., 2021), offering insights into resource utilization and management. Jordana et al. (2019) suggest that RBV is suitable for analyzing enterprise data resources' role, emphasizing their value and scarcity. Data quality moderates the relationship between artificial intelligence adoption intensity and AI availability, with higher data quality enhancing AI's effectiveness (Jordana et al., 2019). RBV thus provides a framework for studying AI adoption's impact on data quality and subsequent AI availability.

2.4.3 Dynamic capability theory

In response to the dynamic business landscape of the 1990s, scholars introduced dynamic capability theory as an extension of RBV, addressing the need for enterprises to adapt to changing markets (Eisenhardt & Martin, 2000). Unlike RBV's static perspective, dynamic capability theory emphasizes an enterprise's ability to update, integrate, and restructure resources (Teece & Pisano, 1994). This enables firms to cope with evolving environments and maintain competitive advantages (Wang & Ahmed, 2007). Dynamic capabilities are multidimensional and involve complex interactions among resources (Barreto, 2010), including search, selection, and configuration capabilities (Helfat et al., 2007). Dynamic capability theory is a prominent topic in strategic management research, explored from three perspectives: element, process, and hierarchical (Jiao Hao et al., 2021). Elements of dynamic capabilities encompass various dimensions such as perception, learning, and coordination (Pavlou & ElSawy, 2011). From a process perspective, dynamic capabilities are nested within organizational processes like new product development (Eisenhardt & Martin, 2000). Hierarchically, dynamic capability is considered a higher-order capability enabling firms to adapt to change (Helfat & Winter, 2011). Dynamic capability theory underscores the importance of organizational flexibility in navigating uncertain environments (Teece et al., 1997). Organizational flexibility enables firms to reconfigure resources and processes swiftly (Eisenhardt & Martin, 2000), essential for responding to market dynamics (Xiao et al., 2021). By leveraging organizational flexibility, firms can adjust resource allocation effectively, enhancing innovation performance and decision-making (Teece et al., 1997). Thus, dynamic capability theory provides a theoretical framework for understanding the role of organizational flexibility.

2.5 Research framework

Existing research emphasizes innovation as vital for businesses' survival and growth in competitive markets (Rosenbusch et al., 2011). The adoption of artificial intelligence (AI) has enhanced innovation efficiency and outcomes for many enterprises (Davenport et al., 2020; Paschen et al., 2020; Keding & Meissner, 2021). However, little research delves into how AI adoption intensity affects innovation performance, and its underlying mechanisms remain unclear. The theory of technological availability offers a perspective on the interaction between technology and behavior, avoiding deterministic views of technology's impact (Rosenbusch et al., 2011). This theory provides a fresh lens for understanding technology's role in enterprises.

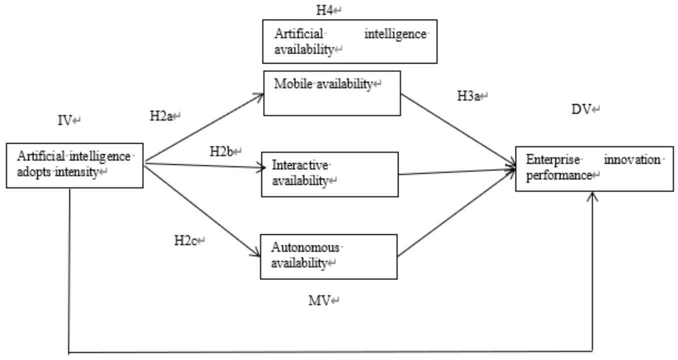

Figure 2-1 Research Framework

This study adopts the theoretical framework of technological availability, combining resource-based theory and dynamic capability theory to explore the impact of AI adoption intensity on innovation performance. Figure 2.2 illustrates the theoretical model. The section explores the main effects of AI adoption intensity on innovation performance and investigates the mediating effects of AI availability.

2.6 Hypotheses

Based on the theoretical framework, the following hypotheses are proposed:
H1: The adoption intensity of artificial intelligence positively influences enterprise innovation performance.
H2: The adoption intensity of artificial intelligence positively influences the availability of artificial intelligence.
H2a: AI adoption intensity positively impacts mobile availability.
H2b: AI adoption intensity positively impacts interactive availability.
H2c: AI adoption intensity positively impacts autonomous availability.
H3: The availability of artificial intelligence positively influences enterprise innovation performance.
H3a: Mobile availability positively impacts corporate innovation performance.
H3b: Interactive availability positively impacts firm innovation performance.
H3c: Autonomous availability positively impacts enterprise innovation performance.
H4: The availability of artificial intelligence mediates the relationship between AI adoption intensity and innovation performance.
H4a: Mobile availability mediates the relationship between AI adoption intensity and enterprise innovation performance.
H4b: Interactive availability mediates the relationship between AI adoption intensity and firm innovation performance.
H4c: Autonomous availability mediates the relationship between AI adoption intensity and firm innovation performance.

3. Methodology

3.1 Research method

The research methodology of this study adopts a mixed-method approach, integrating qualitative and quantitative methods to explore the impact of artificial intelligence (AI) adoption intensity on enterprise innovation performance. Through practical problem formulation, literature review, and empirical analysis, the study examines the driving factors of AI adoption intensity and its mechanism on innovation performance. The questionnaire survey method is employed to gather data from Chinese telecommunications companies in major cities known for high AI adoption rates, followed by analysis using SPSS, Amos, and Mplus software. Additionally, semi-structured interviews are conducted with IT management personnel to gain insights into AI usage in innovation. These interviews aim to refine questionnaire items and uncover the nuances of variables, enhancing the validity of the study (Law et al., 2019; Sun & Zuo, 2022; Sun et al., 2024).

3.2 Questionnaire design

The questionnaire design section of this study outlines a systematic approach to utilizing the classic quantitative research method in management. Adhering to principles of applicability, logic, clarity, convenience, and neutrality, the process involves six sequential steps, including clarifying purpose and content, selecting validated scales based on existing research, designing a questionnaire layout with opening remarks, personal and company information sections, variable items, and feedback requests. Prior to formal research, a preliminary survey is conducted with assistance from the China Telecom Industry Association to ensure the reliability and validity of the scale. Formal research involves distributing questionnaires to senior managers of eligible telecommunications companies, followed by hypothesis validation through data analysis (Wang, 2020; Law et al., 2019; Sun & Zuo, 2022).

3.3 Variable measurement

The variable measurement section of this study delineates the operationalization of key constructs: artificial intelligence (AI) adoption intensity, AI availability, and enterprise innovation performance. Drawing upon established scales, the study employs a 7-point Likert scale to gauge the frequency and extent of AI adoption, referencing Lee et al. (2022) for question items and scoring methods. Likewise, AI availability is assessed using mobility, interactivity, and autonomy scales adapted from Issa et al. (2022). For enterprise innovation performance, subjective measurement methods are adopted, with five indicators including new product development speed and market recognition, informed by Peng Zhenzhen et al. (2020). Additionally, control variables such as company age and size are considered to enhance the study's scientific rigor, aligning with previous research suggesting their influence on innovation (Coad et al., 2016; Baer & Oldham, 2006). Company age is measured using the natural logarithm of establishment years, while company size is categorized based on employee count, with specific thresholds for each category (Sun & Zuo, 2022; Sun & Zuo, 2023; Law et al., 2019; Peng et al., 2020).

3.4 Pre-survey

Before commencing large-scale sampling, a pre-survey was undertaken to bolster the scale's reliability and validity. Initial interviews with two senior managers from Chinese telecommunications firms and three IT department senior managers informed question refinement and overall questionnaire consistency. Leveraging the China Telecom Industry Association's assistance, 156 questionnaires were distributed to eligible telecom managers, yielding 102 valid responses. Among the sampled enterprises, 45.10% were under 30 years old, with 41.18% having employee counts ranging from 1001 to 4990. Exploratory factor analysis of pre-survey data guided scale revisions. SPSS 26.0 verified the data's suitability for factor analysis, with a KMO of 0.765 and Bartlett's test significance ($p = 0.000$). Nine factors, with a cumulative explained variance of 72.683%, underwent rotation and analysis. Results indicated satisfactory reliability and validity across constructs, with Cronbach's alphas and factor loadings exceeding 0.7 and 0.5, respectively. Adjustments were made to questionnaire language based on respondent feedback. For instance, "In enterprises, artificial intelligence can independently decide which applications are designed or tasks are completed" was refined to "Artificial intelligence can enable products and innovation activities to independently decide which applications are designed or tasks are completed."

3.5 Data collection

For data collection, this study employs stratified random sampling, facilitated by the China Telecommunications Industry Association (CTEIA), targeting telecom firms in AI-forward regions: Shanghai, Beijing, Guangzhou, Shenzhen, and Chengdu. A total of 578 questionnaires were distributed, yielding 396 valid responses after filtering out irregularities (e.g., all 3-point scores), achieving a recovery rate of 68.51%. Utilizing the WJX.CN platform, a questionnaire link or QR code was generated. From September to October 2023, CTEIA Secretariat staff used WeChat to distribute questionnaires to senior telecom managers, ensuring ongoing communication to capture AI adoption strategies and progress accurately.

3.6 Data analysis

The sample analysis includes respondent and enterprise characteristics. In terms of respondent characteristics, 60.1% were male, and 39.9% were female. Regarding job positions, 2.0% were CEOs, 3.8% were directors, 13.9% were supervisors, and 53.0% were managers. For enterprise characteristics, 35.4% had been in existence for ≤ 19 years, 38.9% for 20-29 years, 17.2% for 30-39 years, and 8.6% for ≥ 40 years. In terms of size, 16.4% had ≤ 100 employees, 47.2% had 1001-4990 employees, 24.7% had 5000-9990 employees, and 11.6% had ≥ 10000 employees. Common method bias was controlled by collecting data in two stages while ensuring questionnaire confidentiality and reasonable question order. The Harman univariate test indicated no significant common method bias issues, with the first factor explaining 22.683% of the variance.

Reliability Testing: Cronbach's α coefficients were computed, ranging from 0.809 to 0.878, indicating good reliability for the scale.

Validity Testing: Confirmatory factor analysis was conducted, showing factor loadings > 0.6, CR > 0.7, and AVE > 0.5 for all variables, ensuring good construct validity.

4. Results and Discussion

4.1 Profile of respondents

Descriptive statistical analysis using SPSS 26.0 revealed key insights into the respondent profile. Pearson correlation analysis displayed correlations between variables. Results showed that correlations between dimensions of AI availability were highest, consistent with its second-order factor structure. Pairwise correlations between AI adoption, market intelligence response, and enterprise innovation performance indicated significant positive relationships, supporting hypothesis testing. Moderating variables like data quality and organizational flexibility showed significant positive correlations with other variables, supporting moderating effects. Correlation coefficients < 0.7 indicated no serious multicollinearity. Overall, sample data met analysis requirements and supported research hypotheses, describing variable relationships effectively.

4.2 The effect of artificial intelligence adoption intensity on enterprise innovation performance

The study tested the impact of artificial intelligence (AI) adoption intensity on enterprise innovation performance. Results indicated a significant positive effect ($\beta = 0.404$, $p < 0.001$), supporting hypothesis H1. This finding suggests that AI adoption intensity is crucial for enhancing innovation performance. Although literature on AI and innovation is limited, scholars acknowledge AI's potential to enhance innovation by improving rationality and creativity. Existing qualitative research supports this notion, but empirical evidence is scarce.

Table 4-1 Direct Impact of AI Adoption Intensity on Enterprise Innovation Performance

Non standardized path coefficient	Standard error	P-value	Standardized path coefficient	Fit indicators				
				$\chi 2/df$	RMSEA	CFI	TLI	SRMR
0.404	0.055	0.000	0.455	2.358	0.059	0.970	0.954	0.033

The study's findings align with existing research. Scholars have found that AI adoption positively influences corporate performance by streamlining tasks, reducing errors, and identifying new opportunities. Moreover, AI's impact on performance has been validated in various contexts, including B2B small and medium-sized enterprises. Scholars have also highlighted AI's significance in innovation scenarios, emphasizing its role in digital innovation availability and supporting innovation activities at different stages. The study extends existing research by refining enterprise performance into innovation performance and empirically verifying the positive relationship between AI adoption intensity and innovation performance.

Specifically, high AI adoption supports lean and agile product development methods, shortens innovation cycles, and enhances innovative knowledge and abilities. Throughout the innovation process, AI aids in opportunity identification, idea generation, concept development, and implementation. Furthermore, the study underscores the broader relationship between digital technology and enterprise innovation. While digital technology is recognized as a key innovation driver, its disruptive challenges remain underexplored. This study identifies AI as a core digital technology driving innovation in telecommunications enterprises.

4.3 The impact of the adoption intensity of artificial intelligence on its availability

The study investigated the impact of artificial intelligence (AI) adoption intensity on AI availability and its three dimensions: mobile, interactive, and autonomous availability. Results from direct effect path analysis supported the hypotheses (H2, H2a, H2b, and H2c), indicating significant positive effects of AI adoption intensity on AI availability and its dimensions.
Firstly, AI adoption intensity positively influenced mobile availability ($\beta = 0.375$, $p < 0.001$). AI adoption facilitates effective data processing, learning, and integration, enhancing enterprises' ability to perceive and respond to opportunities and threats in the environment (Pavlou & ElSawy, 2011). Additionally, AI's capabilities in data processing enable enterprises to analyze complex data and extract insights, supporting timely decision-making (Huang et al., 2014). AI's dual agent collaborative learning enhances enterprises' learning abilities, further improving mobile availability (Wu et al., 2022).

Table 4-2 Direct Impact of AI Adoption Intensity on AI Availability

Variable relationships	NSPC	SE	P	SPC	Fit indicators				
					$\chi2/df$	RMSEA	CFI	TLI	SRMR
Artificial intelligence adopts strength mobility availability	0.375	0.051	0.000	0.475	1.377	0.031	0.990	0.984	0.025
Artificial intelligence adopts intensity interaction availability	0.584	0.071	0.000	0.534	2.602	0.064	0.971	0.943	0.037
Artificial intelligence adoption intensity - autonomous availability	0.397	0.065	0.000	0.379	2.765	0.067	0.972	0.944	0.034
AI adoption intensity - AI availability	0.359	0.045	0.000	0.561	2.476	0.063	0.945	0.926	0.044

Secondly, AI adoption intensity positively impacted interactive availability ($\beta = 0.584$, $p < 0.001$). AI adoption promotes the development of intelligent products, enabling seamless interaction between users and products (Qi Jiayin et al., 2021). Intelligent products respond to user needs, enhancing interaction quality and quantity (Du & Xie, 2021). Moreover, AI facilitates communication between enterprises and users by analyzing multi-source data and identifying patterns (Kaplan & Haenlein, 2020). Thirdly, AI adoption intensity positively influenced autonomous availability ($\beta = 0.397$, $p < 0.001$). Strong AI enables products to operate independently, interact with other entities, and achieve goals autonomously (Huang Minxue & Lv Linxiang, 2022). In innovation processes, AI's autonomous completion of tasks accelerates innovation trends, with AI systems increasingly undertaking complex tasks autonomously (Braganzad et al., 2021). However, despite AI's autonomy, enterprises need to maintain control and supervision to mitigate risks (Fjeldstad et al., 2012; Leyer & Schneider, 2021). Overall, AI adoption intensity significantly influences AI availability and its dimensions, underscoring AI's transformative potential in enhancing enterprise capabilities and innovation processes.

4.4 The impact of the availability of artificial intelligence on the innovation performance of enterprises

The study investigated the impact of artificial intelligence (AI) availability and its dimensions on firm innovation performance. Results from direct effect path analysis supported the hypotheses (H3, H3a, H3b, and H3c), indicating significant positive effects of AI availability and its dimensions on innovation performance. Mobile availability positively influenced firm innovation performance ($\beta = 0.555$, $p < 0.001$). It supports innovation management by enhancing idea generation, problem identification, evaluation, and creativity (Haefner et al., 2021). Additionally, it facilitates internal communication and knowledge sharing, fostering a culture of teamwork and innovation (Moye & Langfred, 2004).

Table 4-3 Impact of AI Availability on Enterprise Innovation

Variable relationships	NSPC	SE	P	SPC	Fit indicators				
					$\chi 2/df$	RMSEA	CFI	TLI	SRMR
Mobile availability - enterprise innovation performance	0.555	0.073	0.000	0.500	2.329	0.058	0.965	0.950	0.038
Interactive availability - enterprise innovation performance	0.501	0.065	0.000	0.505	1.854	0.046	0.981	0.970	0.031
Autonomous availability - enterprise innovation performance	0.383	0.050	0.000	0.468	2.445	0.063	0.968	0.950	0.036
Artificial Intelligence Availability - Enterprise Innovation Performance	1.057	0.125	0.000	0.652	2.892	0.069	0.923	0.905	0.041

Interactive availability also positively impacted firm innovation performance ($\beta = 0.501$, $p < 0.001$). It promotes value co-creation between enterprises and users, facilitating collaboration and knowledge sharing (Vargo & Lusch, 2017). Interactive availability enables real-time interaction with users, leading to product customization and enhanced creativity (Rahikka et al., 2011). Autonomous availability positively influenced firm innovation performance ($\beta = 0.383$, $p < 0.001$). It enhances innovation performance by combining AI's speed of information processing with human intuitive judgments (Jarrahi, 2021). AI's collaboration with employees frees up time for creative activities, improving overall analytical decision-making ability and creativity (Wilson & Daugherty, 2018). Considering AI availability as a second-order latent variable, its impact on firm innovation performance was significant ($\beta = 1.057$, $p < 0.001$). This underscores the transformative potential of AI availability in enhancing innovation performance.

4.5 The mediating role of testing the commonality of artificial intelligence

The study examined the mediating role of artificial intelligence (AI) availability dimensions (mobile, interactive, and autonomous) on the relationship between AI adoption intensity and firm innovation performance. Using Mplus 7.4 software, path analysis revealed significant direct and mediating effects.

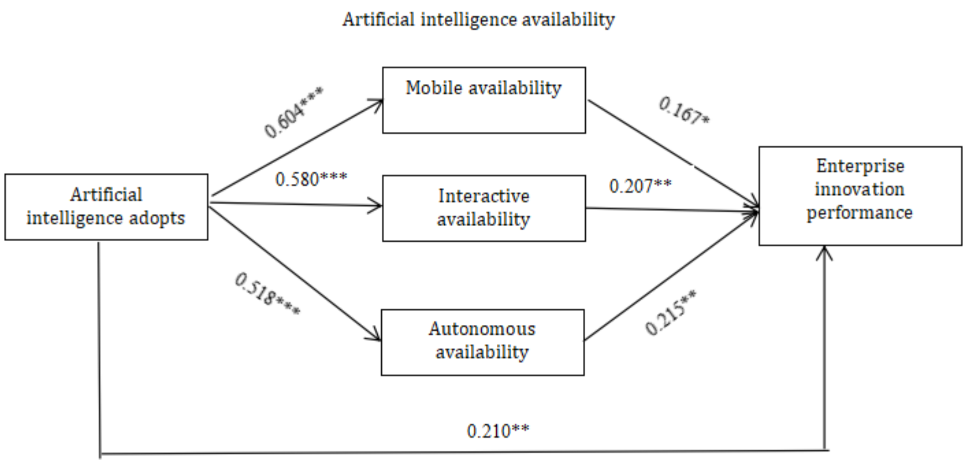

Figure 4-1 Path Analysis of AI Adoption Intensity, Availability, and Innovation Performance in Enterprises

The standardized path coefficients indicated that AI adoption intensity positively influenced mobile (β = 0.604, p < 0.001), interactive (β = 0.580, p < 0.001), and autonomous (β = 0.518, p < 0.001) availability, which in turn positively affected firm innovation performance. Incorporating AI availability as a second-order latent variable strengthened the relationship between AI adoption intensity and firm innovation performance (β = 0.576, p < 0.001).
Bootstrap resampling confirmed the mediating effects of mobile (β = 0.124, p = 0.045), interactive (β = 0.146, p = 0.026), and autonomous (β = 0.136, p = 0.014) availability on the relationship between AI adoption intensity and firm innovation performance. The total mediating effect was significant (β = 0.406, p < 0.001), indicating partial mediation.

Table 4-4 Mediating Effects of Mobile, Interactive, and Autonomous Availability

					Bootstrap (5000x) 95% CI			
	PE (NS)	CPT			DC		Pctl	
Direct effects								
D1	0.257	0.108	2.382	0.017	0.051	0.481	0.048	0.479
Indirect effects								
M1	0.124	0.062	2.007	0.045	0.018	0.265	0.015	0.260
M2	0.146	0.066	2.229	0.026	0.029	0.289	0.031	0.294
M3	0.136	0.055	2.466	0.014	0.045	0.266	0.034	0.254
Total mediating effect	0.406	0.093	4.386	0.000	0.259	0.636	0.250	0.620
Total effect								
Total effect	0.663	0.088	7.529	0.000	0.520	0.859	0.521	0.859

The findings suggest that AI adoption intensity significantly influences firm innovation performance, with AI availability dimensions mediating this relationship. Telecommunications companies leverage AI to enhance innovation processes, promote communication, interaction with users, and support autonomous operation, thereby improving innovation performance.

4.6 Summary

This section surveyed telecommunications companies in major cities in China regarding AI adoption and innovation performance. 396 valid responses were collected and analyzed using SPSS 26.0, Amos 26.0, and Mplus 7.4. Results confirm all hypotheses. These include the positive impact of AI adoption intensity on innovation performance (H1), AI availability (H2), and its dimensions (H2a, H2b, H2c), as well as the positive impact of AI availability on innovation performance (H3, H3a, H3b, H3c), and the mediating role of AI availability between adoption intensity and innovation performance (H4, H4a, H4b, H4c).

5. Conclusion and Prospects

This study investigates the impact mechanism of artificial intelligence (AI) adoption intensity on corporate innovation performance in the context of the digital economy. It focuses on Chinese telecommunications companies to understand how AI adoption intensity influences innovation performance. Through empirical analysis, it is found that AI adoption intensity significantly and positively affects innovation performance. Moreover, AI availability, including mobile, interactive, and autonomous aspects, partially mediates this relationship. This suggests that AI adoption intensity not only directly impacts innovation performance but also indirectly influences it through AI availability. The study aligns with previous research indicating that digital technologies like AI enhance a company's innovation capability and performance. It emphasizes the importance of AI adoption for achieving faster and more effective innovation, particularly in enhancing innovation efficiency and effectiveness. AI adoption facilitates lean and agile product development methods, accelerates innovation cycles, and improves creative processes through knowledge creation, learning, and decision-making support. Additionally, AI supports various stages of the innovation process, enhancing both efficiency and effectiveness. The integration of AI into telecommunications brings significant benefits, including improved customer service, operational efficiency, and network security. AI-driven solutions enhance customer interactions, optimize network performance, and enable accurate predictive analysis. However, challenges such as resource allocation, ethical considerations, and skill development need to be addressed to fully leverage AI's potential. Despite its contributions, this study has limitations. The sample's industry focus and geographical scope may limit generalizability. Future research could broaden the sample and employ longitudinal studies to further validate findings. Additionally, exploring new dimensions of AI availability and investigating its impact in different industries and scenarios can enhance understanding. Furthermore, research should address potential negative impacts of AI adoption, such as ethical concerns and unintended consequences. Continuous exploration of AI's evolving landscape, including developments like ChatGPT, is essential for refining theoretical frameworks and guiding future research.

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