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How Does Applying Artificial Intelligence Influence Firms' Ambidextrous Innovation Performance? Evidence Obtained from Chinese A-Share Listed Firms

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Abstract

As a transformative technology, artificial intelligence (AI) is profoundly reshaping corporate innovation practices, creating new opportunities for ambidextrous (exploitative and exploratory) innovation and thereby advancing sustainable competitiveness. Drawing on ambidextrous theory and adopting a resource-based perspective, we employed panel data from Chinese A-share listed firms in the 2014–2023 period to examine the relationship between AI application and corporate exploitative and exploratory innovation performance as well as the mechanism behind AI's effects in this regard. We further explored the moderating effect of data resources. The findings reveal that AI application significantly enhances both exploitative and exploratory innovation performance. Improvement in corporate research and development efficiency and the optimization of labor structures play mediating roles in the relationship between AI application and both exploitative and exploratory innovation. Moreover, firms' data resources strengthen the positive impact of AI on exploitative innovation while weakening its effect on exploratory innovation. Overall, this study provides novel insights into how traditional enterprises can leverage AI to foster ambidextrous innovation and achieve sustainable competitive advantages. These findings offer practical guidance for corporate executives and policymakers on strategically implementing AI for innovation management.

Keywords: artificial intelligence; ambidextrous innovation; data resource; resource-based view; sustainable innovation

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1. Introduction

Artificial intelligence (AI), as one of the most prominent emerging technologies to reshape the global economic landscape, exerts a profound influence on the sustainable development of modern businesses [1]. In the context of firms, AI technology has significantly affected their strategic planning [2], organizational structures [3,4], business processes [5], and so on. Particularly for firms from non-digital-native industries, AI technology serves not only as a crucial strategic instrument for enhancing innovation capabilities but also as an important means of achieving effective digital transformation, adapting to the digital economy, and therefore developing sustainable competitive advantages.

The concept of ambidextrous innovation originates from organizational learning theory [6], which highlights the necessity of managing two distinct, yet often conflicting, categories of behavior: exploitation and exploration. Exploitation encompasses organizational activities such as refinement, production, efficiency, selection, implementation, and execution.

Conversely, exploration involves activities characterized by terms like searching, variation, risk-taking, experimentation, playing, flexibility, discovery, and innovation. The innovation activities derived from successfully integrating and balancing these two forms of organizational learning behavior are termed ambidextrous innovation. Exploitative innovation emphasizes the innovative activities focusing on the optimization of existing production processes and services [7], usually carried out by resource bricolage or orchestration based on their existing knowledge, information, and routines [8,9]. In contrast, exploratory innovation focuses on more long-range and disruptive changes, requiring firms to exceed the existing knowledge framework and develop new technologies and products for potential customers or future market demands [7]. The former usually enhances firms' short-term performances, helping them survive in the face of fierce market competition. The latter requires a firm to acquire new knowledge and develop new products to cope with future uncertainties [10]. Both are important guarantees of firms' sustainable development [11].

However, exploitative and exploratory innovation differ substantially in their resource requirements, knowledge bases, and strategic cycles [7,12]. While exploitative innovation provides firms with immediate competitive advantages, its dependence on refining and recombining existing knowledge may constrain its scope for radical breakthroughs, thereby exposing firms to heightened vulnerability when facing disruptive environmental shifts. Conversely, exploratory innovation enables firms to seize future opportunities, yet its high risk, uncertain returns, and substantial resource demands often divert critical assets away from current operations, undermining short-term competitiveness and placing firms under considerable pressure [7,12]. As a result, achieving ambidextrous innovation requires firms to develop core dynamic capabilities that enable them to adapt to environmental changes and sustain continuous innovation [13]; this, however, remains a challenging endeavor.

Recent advances in AI technology, including with respect to its diffusion, inference capabilities, and reinforcement learning, are attracting growing scholarly interest in its managerial implications. The literature generally recognizes that AI application enhances firms' innovation performance. Documented effects include the transformation and upgrading of human capital and labor structures [14,15], the optimization of research and development (R&D) resource allocation and management [16], the strengthening of organizational learning and knowledge management capabilities [17], and the creation of an innovation culture that combines leadership with resilience [18,19]. However, the literature still presents two critical research gaps: First, although studies have focused on a series of potential ways AI adoption influences firms' innovation performance, there is a lack of theoretical exploration from the ambidextrous innovation perspective. Given the significance of both exploitative and exploratory innovation for firms' sustainable development, addressing this gap can effectively fill the vacancy in the current research on AI and firm innovation. Second, the literature falls short in exploring the boundary conditions that affect the effectiveness of AI technology, particularly the influence of firms' data resources as a key boundary condition. Considering the general-purpose nature of AI technology, its application efficacy often hinges upon the level of critical complementary resources held. Since the essence of AI technology lies in the efficient and precise processing and deep mining of digitalized information, a firm's data resources are highly likely to significantly impact the effectiveness of its AI application. Nevertheless, this issue has not been explored in the literature.

Based on the information above, this study primarily investigates the following key research questions: How does the application of AI technology affect firms' exploitative and exploratory innovation performance? What is the mechanism through which this effect operates? Do firms' data resource characteristics moderate the influence of AI technology on both exploitative and exploratory innovation performance? Using unbalanced panel data from Chinese A-share listed firms during the 2014–2023 period, we employ fixed-

effects regression analysis to empirically examine the underlying relationships between these variables. Our findings provide theoretical insights and practical implications for firms seeking to strategically leverage AI technologies, optimize knowledge recombination strategies, and enhance sustainable innovation. This study makes three main contributions. First, it extends research on the economic consequences of AI adoption by examining its impact on firms' ambidextrous innovation through the lens of resources and capabilities. Whereas prior studies primarily focused on AI's influence on invention-oriented innovation [5,20], we adopt the perspective of ambidextrous innovation and analyze the role of AI adoption in firms, especially those that are not from digital-native industries. This approach broadens our understanding of how AI technologies reshape innovation outcomes with a view to promoting the sustainable development of firms in the digital era. Second, from the perspective of emerging technologies, this study enriches the literature on the determinants of ambidextrous innovation by explicating the degree to which and mechanisms through which AI contributes to firms' innovation performance. While prior research has emphasized that environmental characteristics [21,22], firms' resource structures [16], and leadership traits [18] significantly influence firms' ambidextrous innovation, this study casts the progress of AI technology as a promising opportunity for firms to achieve ambidexterity, revealing how firms can exploit AI to realize a balance between exploitative and exploratory activities. Finally, this study emphasizes the alignment between technology and organizational resources, clarifying the boundary conditions of AI's impact on ambidextrous innovation from a resource-based perspective. As a general-purpose technology, AI amplifies or attenuates the efficacy of organizational resources in value creation and competency development [23,24]. In particular, data, which are highly complementary to AI technology, profoundly influence firms' strategic choices and outcomes with respect to adopting AI. By incorporating firms' data resource characteristics into the analytical framework, we uncover the interaction mechanisms between AI technologies and complementary resources, offering a more contextual explanation of the relationship between AI applications and ambidextrous innovation. These insights help firms design innovation strategies that reconcile short-term goals with long-term performance, thereby providing theoretical guidance and practical implications for sustainable development in the digital era.

The structure of this study is as follows: Section 2 presents a literature review. Section 3 presents our theoretical analysis and research hypotheses. Section 4 presents the research data and methods. Section 5 provides the empirical results. The conclusions of our study are summarized in Section 6, followed by a series of recommendations and further research directions.

2. Literature Review

This literature review establishes the theoretical foundation for our study by synthesizing existing knowledge on key constructs and identifying the research gap concerning the complementary roles of AI and data resources. Section 2.1 reviews the primary factors that influence a firm's ability to balance exploitative and exploratory innovation. Section 2.2 defines AI technology and summarizes the established literature regarding its impact on corporate innovation performance. Finally, Section 2.3 examines the crucial, foundational role of data resources in maximizing the efficacy of AI applications, leading to our discussion of the moderating effects considered in this study.

2.1. Factors Influencing Firms' Ambidextrous Innovation

Ambidextrous innovation reflects an organization's ability to balance the exploration of new knowledge with the exploitation of existing knowledge [6]. Achieving ambidexterity requires firms to develop core dynamic capabilities that enable them to adapt to environ-

mental changes and sustainable innovation [13]. In essence, ambidextrous innovation represents the fundamental ability of firms to secure sustainable competitive advantages in complex environments.

As it is a key driver of firms' sustainable competitiveness [25], ambidextrous innovation's mechanisms and determinants have been a key issue in both academic research and practice [6]. Prior studies have suggested that both organizational attributes and environmental characteristics play critical roles in shaping firms' ambidextrous innovation strategies. At the organizational level, structural and leadership factors constitute critical conditions influencing firms' ambidextrous innovation. Structural separation enables different organizational units to concentrate on either exploitation or exploration [7]. As for firms' ambidextrous leadership [26,27], innovative organization culture [28,29], and technology capabilities [25], at the environmental level, external conditions and dynamics determine whether firms need ambidextrous innovation and which type of innovation is more effective [21,30]. Favorable government policies [31,32] and environmental uncertainty [33] can stimulate firms' ambidextrous innovation. Industry competition, by contrast, tends to weaken the motivation for exploratory innovation [34], while it reinforces exploitative innovation [35]. In addition, an advanced technological environment and a supportive business context have also been shown to enhance firms' ambidextrous innovation performance [36].

In summary, firms' ability to achieve ambidextrous innovation, a long-standing research focus, is dependent upon how they choose to reasonably and efficiently allocate their finite resources between the two innovation activities to achieve sustainable development. Whether through changes in firm-level internal characteristics or external environmental shifts, the core mechanism affecting ambidextrous innovation is the impact on organizational resource allocation efficiency under various conditions. AI technology simultaneously creates a critical external technological environment that firms must face and constitutes a technology that shapes their internal characteristics. Thus, AI is likely to influence firms' ambidextrous innovation behavior by altering their existing resource allocation modes and efficiency. This relationship has not been explored from this specific theoretical perspective.

2.2. AI Technologies: Essence and Influence on Firms' Innovation

As an emerging technology at the forefront of a new wave of technological revolution and industrial transformation, AI is attracting a growing amount of attention concerning its implications for innovation management research [1,37]. Although prior studies conceptualized AI from diverse perspectives, such as its instrumental, agentic [38,39], and ecological attributes [40], a shared view is that AI essentially constitutes a data-driven process of human–machine interaction [3,41], lacking human beliefs [4,42]. Consequently, the value of AI for firms, including organizational learning [43], entrepreneurial decision-making [44], and resource allocation improvement [45–47], relies highly on human–AI collaboration and the scale, quality, and structure of organizational data [40].

Researchers have generally found that there is a positive relationship between AI application and firms' innovation performance, wherein AI influences the latter through enabling and enhancing firms' innovation abilities [5]. AI can be a powerful tool that enables managers to explore and select valuable problems and solutions [48]. AI adoption significantly reshapes firms' production and operational processes [49], as well as their business models [50], while also substantially transforming the characteristics of workforce structures. AI adoption also enhances firms' ability to access and integrate knowledge [51], accelerating technology spillover [52] and thus further fostering firms' innovation performance.

2.3. The Role of Data in AI Application

The essence of modern AI technology—particularly machine learning and deep learning—lies in algorithms that autonomously identify patterns, extract regularities, and generate predictions or outputs based on various data [53,54], implying that data constitute the fundamental factors of production for AI. As Felin and Holweg (2024) [41] highlighted, AI functions as a data-driven prediction tool whose capability boundaries are determined by the breadth and depth of training data, but it also lacks the capacity for forward-looking causal reasoning grounded in human beliefs. Hence, data resources provide the foundational basis for AI applications, which may therefore significantly influence innovation outcomes.

Data are also crucial to the efficacy of AI applications. As it is inherently data-driven and lacks human beliefs, applying AI entails a number of risks, including algorithmic bias, decision opacity, trust crises, and accountability ambiguities [39]. These risks often trace back to the data perspectives [55], as biased or unrepresentative datasets may directly reproduce or even amplify existing decision-making and inference errors [56]. Therefore, ensuring effective and sustainable AI-enabled innovation requires addressing the quality, representativeness, and governance of data resources [24].

The main findings from the literature about our topic of study are summarized in Table 1.

Table 1. Summary of our literature review.

Research Topic	Representative Studies	Key Findings
Factors Influencing Firms' Ambidextrous Innovation	Oluwafemi et al., (2020) [26]; Waseel et al., (2024) [25]	Organizational characteristics such as leadership style, strategic orientation, and technological capabilities influence firms' ambidextrous innovation performance.
	Gao et al., (2021, 2023) [31,32]; Kim et al., (2025) [33]; Auh & Menguc, (2005) [34]	Favorable environments and situations, such as instances wherein governmental subsidies are received, foster firms' ambidextrous innovation; severe competition weakens firms' exploratory innovation practices.
Influences of AI Application on Innovation	Brem et al., (2023) [49]; Gama & Magistretti, (2025) [5]; Kakatkar et al., (2020) [48]; Rammer et al., (2022) [50]; Sun et al., (2025) [51]	AI application fundamentally reshapes firms' existing operation processes, business models, and labor structures in a positive way, boosting their capacity for knowledge integration and technology spillover.
Data in AI Application	Boussioux et al., (2024) [53]; Felin et al., (2024) [41]; Kemp, (2024) [43]; Lebovitz et al., (2022) [55]	Data constitute the fundamental factor of production and the capability boundary for modern AI technology, particularly machine learning and deep learning. Their scale, depth, quality, representativeness, and governance directly determine the effectiveness and sustainability of AI applications.

In summary, the literature suggests that as an emerging technology, AI is profoundly reshaping the internal structures and capability bases of firms, thereby providing opportunities for achieving both exploitative and exploratory innovation. From a resource-based view, AI serves as a dynamic enabler that enhances firms' capacity for knowledge integration, resource allocation, and organizational learning—capabilities that are essential for balancing exploitation and exploration. However, AI itself—as a general-purpose technology with pervasiveness and accessibility—is not the sole source of sustainable innovation. Its efficacy also depends on the complementarity effect with firms' heterogeneous resource endowments. In particular, data have become a pivotal productive resource, serving as the foundation that determines the efficiency and reliability of AI-driven knowledge discovery and decision-making. Scale, quality, and structure are likely to play a crucial synergistic and moderating role in linking AI adoption with ambidextrous innovation. This implies

that whether firms can effectively leverage AI to foster ambidextrous innovation hinges not only on the technology itself but also on whether firms possess the data resource base necessary for enabling their deployment and value appropriation. Clarifying this interplay can offer theoretical and practical insights into how non-digital-native firms can develop sustainable innovation advantages through the co-evolution of technological capabilities and data assets.

3. Theoretical Analysis and Research Hypotheses

As discussed in the literature review, both exploitative and exploratory innovation are resource—and knowledge-intensive activities, demanding a high level of resource commitment from a firm. A core dilemma in balancing ambidextrous innovation lies in the fact that it is often difficult for a firm's finite resources to meet the resource demands of both types of innovation activities simultaneously under different circumstances [6]. However, a key impact of AI technology on firms is its potential to fundamentally alter their conventional resource allocation methods. This shift may, in turn, profoundly affect a firm's ambidextrous innovation performance by influencing their R&D efficiency and labor structure. Furthermore, as a prerequisite directly determining the effectiveness of AI adoption, a firm's data resources are likely to either reinforce or weaken the effect of AI technology on both exploitative and exploratory innovation performance. Based on this information, Section 3.1 analyzes the potential impact of AI application on ambidextrous innovation performance and the mechanism of this impact. Section 3.2 will then treat data resources as a crucial contingency forming a synergistic effect with AI technology, further analyzing how the heterogeneity in firm-level data resource endowment affects the efficacy of AI application.

3.1. The Impact of Artificial Intelligence on Firms' Ambidextrous Innovation

From a resource-based theoretical perspective, firms are heterogeneous bundles of resources, and their sustainable competitive advantages stem from their strategic resources that are valuable, rare, inimitable, and non-substitutable [57]. A firm's inherent resource constraints determine its strategic choices, while the quantity of resources it possesses and how they are allocated dictate the intensity and scope of its strategic behaviors. As an emerging general-purpose technology [58], AI is characterized by its accessibility [45], making it difficult for AI to constitute an exclusive advantage on its own [43]. Instead, its value lies in serving as an enabler that reconfigures and amplifies firms' existing resources and capabilities, thereby fostering new sources of competitive advantage. Exploitative innovation deepens, optimizes, and extends existing knowledge, technologies, and markets, emphasizing efficiency, reliability, and immediate returns. By contrast, in exploratory innovation, firms seek new knowledge, venture into emerging markets, and experiment with disruptive technologies, processes characterized by risk-taking, experimentation, and a long-term orientation. Although the objectives and processes of the two types of innovation activities differ, both typically require firms to make stable investments in both material and knowledge resources. Exploitative innovation often begins with a firm's evaluation of existing operations and the collection of external environmental information to identify potential avenues for optimization, subsequently allocating R&D personnel to carry out the innovation. In contrast, exploratory innovation necessitates the proactive commitment of various resources to search for previously non-existent technologies, markets, business processes, and strategic concepts in untouched domains. Following this search, R&D personnel are dedicated to experimentation and trial-and-error activities, ultimately leading to the generation of innovative outcomes. The application of AI technologies offers firms new possibilities for overcoming the paradox of ambidextrous innovation stemming from limited resource constraints. AI facilitates ambidexterity primarily

through two key mechanisms: enhancing R&D efficiency and optimizing firms' labor structures. These mechanisms illustrate how AI reshapes firms' resource and capability bases, thereby fostering both exploitative and exploratory innovation. Innovation is a process of knowledge transformation and creation [59]. Traditional innovation activities, however, rely heavily on R&D personnel's experience, intuition, and trial-and-error efforts, making these activities costly, time-consuming, and uncertain [30]. By contrast, AI fundamentally alters this paradigm by improving cost efficiency and knowledge acquisition.

From the resource-based view, AI can be said to integrate data as a novel production factor with computational power and algorithms, profoundly transforming firms' technological environment. First, AI-enabled data resources endow firms with the ability to rapidly and effectively acquire and integrate critical internal and external knowledge, thereby reducing the costs of information searching and learning in the early stages of R&D. Second, AI enhances firms' predictive and simulation capabilities in innovation, lowering development costs. For instance, generative adversarial networks (GANs) allow firms to achieve near-realistic simulations based on limited data and experiments in a cost-efficient manner [60]. Finally, AI improves the allocation of R&D resources by identifying key factors that drive success and directing resources toward projects with higher probabilities of success and greater value.

From the perspective of organizational ambidexterity, exploitative and exploratory activities require distinct knowledge bases and cognitive logics [61]. As a skill-biased technology, AI alters firms' labor structures in non-neutral ways. Emerging digital technologies have reshaped labor demand, income distribution, and workforce composition, providing new opportunities for cultivating the knowledge and capabilities required for ambidexterity. On the one hand, AI substitutes for low-skill routine tasks, releasing critical resources and managerial attention needed for innovation. Both exploitative and exploratory innovation are knowledge-intensive, relying heavily on firms' cognitive resources and skilled talent. In traditional settings, however, highly educated R&D and managerial staff often remain trapped carrying out repetitive data processing and routine tasks, limiting their creative potential. AI's automation capabilities allow firms to redeploy these resources toward domains requiring human judgment, creativity, and strategic thinking, thereby enhancing ambidexterity. On the other hand, the effectiveness of AI depends on human–machine collaboration [46]. The experience and capabilities of AI users determine the extent to which this technology creates value, requiring firms to employ talent with technical capabilities and the capacity to learn. In exploitative innovation, such collaboration takes the form of AI-driven solution searches complemented by human decision-making, ensuring alignment with strategic priorities and efficiency maximization [42]. In exploratory innovation, AI extends the search frontier, while human decision-makers break existing frames of reference, leveraging AI's insights for higher-order creativity.

Accordingly, we propose the following hypotheses:

H1a. *AI applications bolster firms' exploitative innovation performance.*

H1b. *AI applications bolster firms' exploratory innovation performance.*

3.2. The Moderating Role of Firms' Data Resources

From a resource-based perspective, data have become a critical strategic resource in the digital economy, playing a decisive role in shaping firms' competitiveness [57]. Data resources are extensible, developmental, non-consumable, and co-productive in use [40,54] while also embodying firms' unique histories and knowledge bases [43]. Accordingly, data that generate expected economic returns constitute a valuable, rare, inimitable, and non-

substitutable strategic resource. Considering that exploitative innovation and exploratory innovation rely on distinct knowledge bases, the disparity in firms' data resource levels may profoundly affect how the application of Artificial Intelligence (AI) technology facilitates these two types of innovation activities.

Exploitative innovation emphasizes the deep searches for and recombination of existing knowledge and resources [61]. When supported by abundant and accurately recorded data, AI can further enhance firms' exploitative innovation performance. Data resources enable AI to accelerate the scanning and recognition of exploitative opportunities, shifting innovation activities from being experience-driven to data-driven. Rich data resources also provide a foundation for automated and large-scale opportunity identification, allowing firms to uncover potential optimization directions from existing knowledge. Moreover, they support the development of digital twins and predictive models that improve innovation processes [38]. By enabling the more precise identification of deficiencies in current processes or services, abundant data resources ensure that scarce innovation inputs (e.g., R&D investment and managerial attention) are allocated with greater efficiency and focus.

However, the value of any resource is not static. Abilities built on specific resources can become rigid over time, thereby constraining innovation [13]. Accordingly, while data resources enhance firms' ability to leverage AI for exploitative innovation, they can simultaneously reinforce path dependence and generate knowledge rigidities, thus inhibiting exploratory innovation. On the one hand, data resources are prone to degenerating from flexible to rigid assets over time, weakening AI's potential to support exploration. Once firms build efficient systems around particular data types and AI technologies, the sunk costs and asset-specific investments make it prohibitively costly to pivot toward new untested data sources or technological paths. In this case, the more extensively firms exploit existing data through AI, the more they gravitate toward incremental rather than radical innovation. On the other hand, both data and AI exhibit strong feedback loops and self-reinforcing tendencies [3,47], which can entrench behavioral patterns and further limit exploration. Because AI outputs are trained on existing datasets and lack interpretability, AI-driven exploration tends to favor options with abundant data support, generating algorithmic bias [44]. Moreover, firms pursuing breakthrough innovation often have to deal with a scarcity of data in the early stages, where the absence of relevant datasets prevents AI from reliably evaluating opportunities and risks, leading to systematic underestimation or rejection of exploratory initiatives.

Accordingly, we propose the following hypotheses:

H2a. *Data resources strengthen the positive effect of AI applications on exploitative innovation.*

H2b. *Data resources weaken the positive effect of AI applications on exploratory innovation.*

Figure 1 shows the theoretical model of this study.

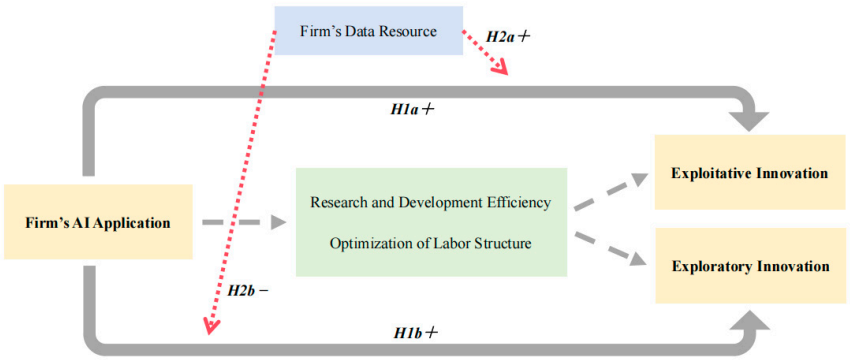

Figure 1. Theoretical model.

4. Data and Methods

4.1. Data Source and Sample Selection

To test the relationship between firms' application of AI, ambidextrous innovation, and the moderating role of data resources, we selected unbalanced panel data of China's A-share listed firms from traditional industries during the 2014–2023 period. Firm-level innovation data were obtained from the Chinese Patent Data Project (CPDP) database [62], while firms' information and financial data were collected from the China Stock Market and Accounting Research (CSMAR) database [63]. Based on the research context for this study, the sample was further refined as follows: (1) Firms designated as "special treatment (ST)" by the stock exchange during the sample period were excluded. Special treatment indicates that the listed firm has an abnormal financial status and is at risk of being delisted, usually with a high suspicion of financial fraud. (2) Firms classified under Sector I (Information Transmission, Software, and Information Technology Services Industry) and Sector J (Financial Industry), according to China's National Industry Classification for 2017, were removed. We excluded samples under Sector I because, in these sectors, AI technology is often an integral part of the products and services offered rather than an emerging, externally adopted technology [64]. This premise is inconsistent with our theoretical analysis, which is grounded in the resource-based view of AI's impact. Furthermore, we excluded samples under Sector J due to fundamental differences in the structure and substance of their financial statements relative to non-financial firms. For instance, the primary sources of income for the financial sector are interest income, fees, and commissions, whereas non-financial firms generate revenue from the provision of products or services. These systemic distinctions lead to significant discrepancies in key control variables used in this study, such as return on assets (ROA) and the debt-to-asset ratio (leverage). Excluding these samples is necessary to ensure the robustness of the entire empirical model. (3) Firms with missing values regarding key variables were excluded. This procedure resulted in the exclusion of 773 firm-year observations from the initial dataset. Since the excluded sample constitutes less than 5% of the total observations, it is unlikely that it introduced any significant bias into the model estimation results for this study. (4) To avoid the effect of extreme values from the sample on the results, we decreased the dependent and independent variables in the sample by 1% and 99%. After these steps, the final dataset consisted of 20,998 firm-year observations, covering 3139 listed firms.

4.2. Description of Variables

4.2.1. Dependent Variables

The dependent variables are exploitative innovation (Exploit) and exploratory innovation (Explore). Given that firms' innovation output is largely reflected in their patenting activities [65], we identified firms' ambidextrous innovation performance based on the classification information pertaining to their annual patent applications. Following prior studies [66], we distinguish between exploitative and exploratory innovation based on firms' patent applications. Specifically, if the first four digits of the International Patent Classification (IPC) code of a patent application appeared at least once in the past five years, then the patent was classified as exploitative innovation; otherwise, it was classified as exploratory innovation. Accordingly, if a firm applied for patents in the current year and the IPC codes match those in the preceding five-year window, then these patents were classified as exploitative innovation. By contrast, if a firm applied for patents in IPC classes not observed in the prior five years, then these patents were classified as exploratory innovation. Finally, the annual counts of exploitative and exploratory patents were log-transformed after adding 1, and the resulting values were used to measure firms' exploitative and exploratory innovation levels, respectively.

4.2.2. Independent Variable

The independent variable is AI application (AIapp). Prior studies commonly employed textual data from a firm's Management Discussion and Analysis (MD&A) to operationalize its strategic behavior [67,68]. The text-based metrics are supported by the following compelling reasons: First, the MD&A content intuitively captures the cognitive framework of a firm's top management team; this framework is a crucial antecedent to the firm's execution of concrete strategic actions [69]. Second, since the MD&A provides a summary of a firm's strategic activities in the preceding year and its future strategic outlook, conducting a text analysis on this document can reasonably reflect the firm's strategic engagement over the past year [70]. Finally, textual analysis can capture information that is inaccessible through financial data and survey-based scales [71]. Following prior research, we evaluated firms' application of AI using textual analysis of their annual reports. Specifically, drawing upon established AI-related keyword lists [51,68], we calculated the frequency of these keywords within the MD&A section for each firm-year observation. Finally, the firm's AI application level was quantified as the natural logarithm of one plus the keyword frequency. Since firms may exaggerate or hide their application of AI in the MD&A for strategic reasons, following approaches used in the literature [72], we also employed firms' investment in intellectual-technology-related properties. Specifically, we manually searched through firms' financial statements for their investments. Then, we screened firms' asset investments for items containing keywords such as "electronic," "computer," "software," and "information". Finally, we added the total end-of-year value of the firms' related investments.

The final keyword list for the firms' application of AI is presented in Table 2.

Table 2. AI application keyword list.

AI Application Keywords
pattern recognition, robotic process automation, predictive analytics, data pipelines, speech recognition, robotic, cognitive framework, OCR, robot, handwriting recognition, artificial intelligence, machine learning model, facial recognition, deep learning, machine learning framework, tensor, natural language processing, neural network, model training, tensor processing unit, natural language understanding, artificial neural network, customer segmentation, TPU, intent classification, convolutional neural network, personalization engines, cuda, slot filling, recurrent neural network, inferencing, dialogflow, entity recognition, generative adversarial network, embedding, Word2Vec, semantic translation, feedforward network, algorithm, Doc2Vec, machine translation, machine learning, automation, GloVe, Chatbot, supervised, machine learning, data science, universal sentence encoding, autonomous agent, unsupervised machine learning, data acquisition, embeddings from language models, language identification, supervised learning, data processing, neural network language model, named entity extraction, unsupervised learning, modelling, latent semantic analysis, named entity recognition, reinforcement learning, AI operations, vector space models, relationship extraction, Model registry, AIOps, deep averaging network, terminology extraction, model manifestation, machine learning, Ops, prediction, semantic web, model servicing, MLOps, clustering engine, computer vision, model monitoring, machine learning ontologies, topic modelling, object recognition, model validation, AI ethics, RapidMiner, intelligent word recognition, transfer learning, machine learning bias, KNIME, intelligent image analysis, oneshot learning, machine bias, Alteryx, image processing, pooling, training data, SAS (Version 9.4).

4.2.3. Moderating Variable

The moderating variable is firms' data resources (Data). Researchers have taken a dichotomous approach to measuring firms' data resources based on whether keywords related to data assets appear in their annual reports [73]. However, this approach may overlook the intensity differences between firms regarding their data resources. To address this issue, we developed a keyword list based on China's Data Management Capability Maturity Assessment Model (DCMM) [74]. Issued in 2018, the DCMM was the first government-issued national standard measuring organizations' data management capabil-

ity. The DCMM contains eight major building blocks on data management, namely, "data strategy," "data governance," "data framework," "data standard," "data quality," "data safety," "data application," and "data life cycle," providing a comprehensive means of measuring firms' data management. Therefore, we used the frequency with which these phrases appear in a firm's annual report to measure its data resources. To avoid missing related keywords, we employed the Word2Vec natural-language-processing method to capture all data-related keywords [75]. The Word2Vec method represents words and phrases in natural languages as dense, real-valued vectors based on their contextual information, thereby constructing a word-embedding space in which the geometric distance between vectors reflects the semantic similarity between words. A smaller distance indicates a higher degree of semantic and syntactic similarity. In this study, we set the phrases of the eight major building blocks mentioned above as the seed words, employed the "Skip-Gram" model to predict the potential targeted words, and used the cosine distance to measure the semantic similarity based on the MD&A texts of sample firms. Finally, we took the natural logarithm of one plus the keyword frequency and employed the results as the extent of the firms' data resources.

The final keyword list for data resources is presented in Table 3.

Table 3. Data resource keyword list.

Seed Word	Extended Word
Data strategy	cloud, data infrastructure, data connection
Data governance	data management, data hub, data middleware, data middle platform, business intelligence, informatization, computility, algorithm
Data framework	parallel processing, data model, data sharing, data interflow, service-oriented architecture, database, AutoML, sampling, PyTorch, TensorFlow, visualization, open edge computing, metadata, product data management, distributed computation, data modeling
Data standard	data warehouse, data exchange, data fabric, data retrieval, data coding, security orchestration, automation and response, data closed loop, network video recorder, enterprise resource planning, DevOps, data model, decision support system
Data quality	internet safety, password, information safety, data validation, sensitive data, data provenance, data lineage, data monitoring, data reconciliation, data collection
Data safety	information security, local area network, private data, data protection
Data application	data analysis, data mining, intellectual algorithm, data business, software development, data silo, data modeling, data service, data sensing
Data life cycle	data maintenance, intelligent fault diagnose, data retire, data destruction

4.2.4. Control Variable

Following prior studies [46,51], we controlled for a set of variables that may affect firms' innovation performance: (1) firm size (Size)—this is measured by taking the logarithm of total assets at the end of the year; (2) age of the firm (Age)—this is measured by subtracting the year a firm was established from the year of the statistic and then taking the logarithm of the resulting value; (3) return on assets (Roa)—this is measured using the ratio of a firm's net profit to its total assets; (4) leverage (Leverage)—this is measured using the ratio of a firm's total liabilities to its total assets; (5) R&D intensity (R&D)—this is measured by determining the ratio of annual research and development expenses to total assets; (6) board scale (Board)—this is measured using the logarithm of the number of people on a firm's board; (7) firm's governance structure (Independent)—this is measured by determining the proportion of independent directors on the board; and (8) ownership

concentration (Top5)—this is measured using the Herfindahl–Hirschman Index (HHI) of the shareholding ratio of the top five shareholders. Specifically, the HHI is calculated by squaring the shareholding proportion of each shareholder of the top 5 shareholders and then summing the resulting numbers. Additionally, firm- and year-fixed effects were controlled to account for unobservable factors related to individual firms and specific years.

Table 4 provides summary descriptions of the variables.

Table 4. Variable descriptions.

Variable Types	Variable	Description	Measurement
Dependent Variable	Exploit	Exploitative Innovation	Exploitative patent applications: A patent is classified as exploitative if the first four digits of the IPC code appeared at least once in the past five years.
	Explore	Exploratory Innovation	Exploratory patent applications: A patent is classified as exploitative if the first four digits of the IPC code did not appear in the past five years.
Independent Variable	AIapp	AI Application	The frequency of AI-related keywords in the MD&A part of the annual report.
Moderating Variable	Data	Data Resources	Information from the annual report obtained by using a keyword list (expanded via Word2Vec) based on the eight major building blocks of the DCMM.
Control Variables	Size	Firm Size	Natural logarithm of the total assets at the end of the year.
	Age	Firm Age	Natural logarithm of the difference between the static year and the firm's establishment year.
	Roa	Return on Assets	Ratio of net profit to total assets.
	Leverage	Debt Ratio	Ratio of total liabilities to total assets.
	R&D	Research and Development Intensity	Ratio of annual research and development expenses to total assets
	Board	Board Scale	Natural logarithm of the number of people on the board.
	Independent	Governance Structure	Proportion of independent directors on the board.
	Top5	Ownership Concentration	HHI of the shareholding ratio of the top five shareholders.

4.3. Model Specification

To verify the hypotheses, we constructed the following models:

$$\text{Exploit}_{i,t} = c + \alpha \text{AIapp}_{i,t} + \beta_i X_{i,t} + \sum \text{Firm} + \sum \text{Year} + \tau_{it}, \quad (1)$$

$$\text{Explore}_{i,t} = c + \alpha \text{AIapp}_{i,t} + \beta_i X_{i,t} + \sum \text{Firm} + \sum \text{Year} + \tau_{it}, \quad (2)$$

$$\text{Exploit}_{i,t} = c + \alpha \text{AIapp}_{i,t} \times \text{Data}_{i,t} + \theta \text{AI}_{i,t} + \epsilon \text{Data}_{i,t} + \beta_i X_{i,t} + \sum \text{Firm} + \sum \text{Year} + \tau_{it}, \quad (3)$$

$$\text{Explore}_{i,t} = c + \alpha \text{AIapp}_{i,t} \times \text{Data}_{i,t} + \theta \text{AI}_{i,t} + \epsilon \text{Data}_{i,t} + \beta_i X_{i,t} + \sum \text{Firm} + \sum \text{Year} + \tau_{it} \quad (4)$$

Models (1) and (2) test the effects of AI application on exploitative innovation and exploratory innovation, respectively, in which i denotes the firm; t denotes the year;

α denotes the estimated coefficient of the core explanatory variable (AIapp); ε represents the random error; Exploit and Explore denote firms' exploitative and exploratory innovation performances, respectively; X is a vector of all firm-level control variables; Firm denotes the firm-fixed effects; and Year denotes the year-fixed effects.

To further test the moderating effect of firms' data resources, Models (3) and (4) extend the prior models by including the extent of data resources (Data) and this variable's interaction term with respect to AI application. In the empirical analysis, we focus on the indications and significance of α across the four models. As per our hypotheses, we expected α to be positive in Models (1), (2), and (3) and negative in Model (4).

5. Empirical Results and Analysis

5.1. Descriptive Statistics and Correlation Analysis

Table 5 presents the descriptive statistics pertaining to the variables. The mean value of the firms' AIapp is 0.739, with a standard deviation of 0.966, indicating substantial variation in the extent of AI adoption among different firms. The mean, median, and maximum values of exploitative innovation (Exploit) are all higher than those of exploratory innovation (Explore), suggesting that the sample firms are generally more inclined toward exploitative innovation but also exhibit notable heterogeneity in different types of innovation activities. The ranges of the other control variables are consistent with prior studies, confirming the validity and representativeness of the sample.

Table 5. Descriptive statistics of the variables.

Variable Name	Variable Expression	Obs	Mean	Std	Min	Max
Firms' exploitative innovation performance	Exploit	20,998	2.730	1.899	0.000	7.372
Firms' exploratory innovation performance	Explore	20,998	1.461	1.133	0.000	4.060
Firms' AI application	AIapp	20,998	0.739	0.966	0.000	3.989
Firms' size	Size	20,998	22.589	1.309	17.641	28.644
Firms' age	Age	20,998	3.090	0.261	1.792	4.290
Return on firms' total assets	Roa	20,998	0.462	0.207	0.008	1.957
Firms' liability	Leverage	20,998	0.023	0.089	−2.646	0.786
R&D investment intensity	R&D	20,998	0.017	0.021	0.000	1.455
Firms' board scale	Board	20,998	2.123	0.200	0.000	2.890
Firms' governance structure	Independent	20,998	0.377	0.057	0.000	0.800
Firms' share concentrationTOP5	Top5	20,998	0.145	0.110	0.001	0.810

Obs represents number of observations, Mean represents the average of samples, Std represents the standard error of the samples, Min represents the minimum number of the samples, and Max represents the maximum number of samples.

Table 6 reports the results of the correlation analysis and the variance inflation factor (VIF) tests. The correlation between the variables shows that firms' AIapp is significantly and positively correlated with both exploitative innovation (Exploit) and exploratory innovation (Explore), providing preliminary evidence that AI adoption facilitates ambidextrous innovation. Furthermore, the absolute values of the correlation coefficients for the correlations between the main variables are relatively small (with the maximum being 0.464), and all the VIF values are below 2 (with the maximum being 1.525)—far lower than the conventional threshold of 10. These results indicate that multicollinearity is not a serious concern in the regression models.

Table 6. Correlations and variance inflation factors.

Variables	Exploit	Explore	AIapp	Size	Age	Leverage	Roa	R&D	Board	Independent	Top5
Exploit	1.000										
Explore	0.705 ***	1.000									
AIapp	0.176 ***	0.106 ***	1.000								
Size	0.357 ***	0.301 ***	0.082 ***	1.000							
Age	−0.113 ***	−0.130 ***	0.025 **	0.054 ***	1.000						
Leverage	0.067 ***	0.055 ***	0.018 *	0.404 ***	0.103 ***	1.000					
Roa	0.103 ***	0.095 ***	−0.011	0.147 ***	−0.010	−0.288 ***	1.000				
R&D	0.464 ***	0.286 ***	0.154 ***	−0.117 ***	−0.101 ***	−0.096 ***	0.044 ***	1.000			
Board	0.111 ***	0.108 ***	−0.037 ***	0.241 ***	0.009	0.101 ***	0.043 ***	−0.042 ***	1.000		
Independent	−0.005	−0.018 *	0.038 ***	0.026 ***	−0.014	−0.007	0.000	−0.030 ***	−0.525 ***	1.000	
TOP5	0.075 ***	0.093 ***	−0.026 ***	0.324 ***	−0.091 ***	0.059 ***	0.148 ***	−0.090 ***	0.096 ***	0.041 ***	1.000
VIF	—	—	1.087	1.525	1.028	1.456	1.240	1.119	1.558	1.451	1.131

***, **, and * indicate passing significance tests at 1%, 5%, and 10% significance levels, respectively.

5.2. Benchmark Regression Results and Analysis

Table 7 presents the baseline regression results. Columns (1) and (2), without the control variables, show that the coefficients of firms' AI application (AIapp) are 0.116 and 0.058, with both being significant at the 1% level. After firm-level control variables were added in Columns (3) and (4), the coefficients of AI remain positive and significant, at least at the 5% level (0.075 and 0.033), suggesting that AI adoption enhances both exploitative and exploratory innovation among firms. Columns (5) and (6) further incorporate firms' data resources (Data) and their interaction with AI. The coefficients of the interaction terms are 0.041 and −0.042, with both being significant at least at the 5% level, indicating that having a greater quantity of data resources strengthens the positive effect of AI on exploitative innovation, while it constrains AI's effect on exploratory innovation. Overall, these results provide empirical support for all the proposed hypotheses.

Table 7. Benchmark regression results for artificial intelligence influencing ambidextrous innovation.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Exploit**	**Explore**	**Exploit**	**Explore**	**Exploit**	**Explore**
AIapp	0.116 ***	0.058 ***	0.075 ***	0.033 **	0.071 ***	0.047 ***
	(0.015)	(0.014)	(0.015)	(0.013)	(0.015)	(0.014)
Data					−0.031	0.046
					(0.030)	(0.030)
AIapp×Data					0.037 **	−0.051 ***
					(0.018)	(0.016)
Size			0.464 ***	0.293 ***	0.487 ***	0.312 ***
			(0.032)	(0.025)	(0.033)	(0.026)
Age			−0.378	−0.960 ***	−0.437	−1.11 ***
			(0.343)	(0.278)	(0.331)	(0.280)
Roa			−0.170 **	−0.263 **	−0.189 *	−0.254 ***
			(0.101)	(0.084)	(0.101)	(0.088)
Leverage			0.050	0.126	0.010	0.143
			(0.103)	(0.097)	(0.105)	(0.102)

Table 7. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Exploit**	**Explore**	**Exploit**	**Explore**	**Exploit**	**Explore**
R&D			4.814 *	1.891	5.06 *	1.99
			(2.672)	(1.193)	(2.76)	(1.23)
Board			0.217 **	0.030	0.209 **	0.038
			(0.103)	(0.089)	(0.103)	(0.089)
Independent			0.359	−0.312	0.313	−0.461 *
			(0.292)	(0.242)	(0.292)	(0.247)
Top5			0.247	0.299	0.344	0.617 ***
			(0.269)	(0.206)	(0.283)	(0.233)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observation	20,998	20,998	20,998	20,998	20,998	20,998
Adj.R square	0.815	0.456	0.824	0.466	0.834	0.465

* Robust standard errors in ( ). ***, **, and * indicate passing significance tests at the 1%, 5%, and 10% significance levels, respectively. Y represents the control.

5.3. Robustness Checks

5.3.1. Test of Omitted Variable Bias

The determinants of firms' ambidextrous innovation are rather complex, which may raise concerns about endogeneity caused by omitted variables. Following Altonji et al.'s approach (2005) [76], we measured the potential bias attributable to unobservable factors and inferred the extent to which omitted variables may affect the baseline results. Specifically, we calculated the ratio of coefficient differences after conditioning on a limited set of observable covariates and used this ratio to assess the likelihood of omitted-variable bias. A higher ratio indicates that the estimates are less sensitive to selection with respect to observables, implying that unobserved factors would need to be substantially stronger than observed ones to fully account for the estimated effects.

Table 8 reports the results of the test of omitted bias. When no control variables or fixed effects are included, the ratio is below 1, much smaller than that under other specifications, suggesting that omitted-variable bias is more pronounced in this case. This finding indicates the necessity of incorporating control variables and fixed effects in the baseline models. Moreover, when only firm- and year-fixed effects are included without other controls, or when firm-level covariates are controlled alongside firm-fixed effects, the ratios of the coefficients for AI application with respect to ambidextrous innovation fall between 1.270 and 3.125. This indicates that self-selection with respect to unobservable factors would need to be at least 1.270 times stronger than that regarding observable factors to fully explain away the baseline results. Hence, the probability that unobserved variables substantially bias our estimates is relatively low.

Table 8. Omission bias test.

	Exploit			Explore		
	(1)	(2)	(3)	(4)	(5)	(6)
Groups of Controls	Coefficient of Limited Controls	Coefficient of All Controls	Ratio Difference	Coefficient of Limited Controls	Coefficient of All Controls	Ratio Difference
No Controls	0.513	0.075	0.171	0.180	0.033	0.224
Only Control Firm- and Year-Fixed Effects	0.116	0.075	1.830	0.058	0.033	1.320
Only Control Firm-Specific Variables	0.099	0.075	3.125	0.059	0.033	1.270

5.3.2. Test of Sample Selection Bias

To address potential concerns regarding sample selection bias, we employed the propensity score matching (PSM) approach to evaluate the robustness of our results. Specifically, we divided the sample into two groups—high- and low-AI-application groups—using the median value of firms' AI application as the cutoff point. Next, we estimated the propensity scores for all firms based on the control variables using a logit model. We then performed one-to-one nearest matching and re-estimated the regressions with the matched sample.

Columns (1) and (2) of Table 9 present the results based on the PSM-matched sample. The findings reveal that firms' AI application remains positively associated with both exploitative and exploratory innovation, with coefficients that are statistically significant at least at the 5% level. These results indicate that our benchmark conclusions remain robust even after endogeneity concerns arising from potential sample selection bias are mitigated.

Table 9. Results of propensity score matching and instrumental variable estimation.

	(1)	(2)	(3)	(4)	(5)
Variables	**Exploit**	**Explore**	**AIapp**	**Exploit**	**Explore**
AIapp	0.028 **	0.069 **			
	(0.013)	(0.015)			
IV			0.038 ***		
			(0.011)		
AI_IV				2.10 ***	0.968 ***
				(0.671)	(0.338)
Controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observation	19,884	19,884	18,788	18,788	18,788
Adj.R square	0.818	0.456	0.323	0.224	0.167

Robust standard errors in ( ). ***, **, and * indicate passing significance tests at the 1%, 5%, and 10% significance levels, respectively. Y represents the control.

5.3.3. Test of the Instrumental Variable

We further employed an instrumental variable to address other potential endogeneity concerns. Specifically, we selected historical, region-level data related to information and communication infrastructure as the instrumental variable. On the one hand, the history of the adoption of postal and telecommunication services in a city reflects local social preferences and the extent of technological development, which, in turn, shape firms' current adoption and application of information technologies, including AI. On the other hand, such communication facilities have become largely obsolete in modern business operations and thus do not directly affect firms' current innovation performance. Based on this logic, we used the number of post offices in the city in which a firm is based in 1984 (per 100 units) as the instrument variable. Since the 1984 city-level post office data are cross-sectional and therefore not suitable for panel regression carried out directly, we followed the approach used in previous research: constructing a panel instrument variable. Specifically, we combined the number of post offices in 1984 with the proportion of total households with internet access in a firm's city headquarters in the previous year, denoted as IV.

Columns (3)–(5) of Table 6 report the results of the two-stage least squares (2SLS) estimation. The first-stage regression shows that the instrument variable (IV) is positively and significantly associated with firms' AI application. Moreover, the Cragg–Donald Wald F-statistic substantially exceeds the Stock–Yogo critical values, indicating that the selected variable is not a weak instrument. The second-stage results demonstrate that the instrumented AI application (AI_IV) remains positively and significantly related to both

exploitative and exploratory innovation. These findings further reinforce the robustness of our baseline results.

5.3.4. Additional Robustness Checks

To further ensure the reliability of our findings, we conducted several robustness checks by considering lagged effects, adopting alternative measures of key variables, adjusting the fixed effects specification, and refining the sample selection. Table 10 reports the results of these tests.

Table 10. Other robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**Exploit**	**Explore**	**Exploit**	**Explore**	**Exploit**	**Explore**	**Exploit**	**Explore**
AIapp	0.079 *** (0.016)	0.030 * (0.015)			0.070 *** (0.015)	0.042 *** (0.013)	0.086 *** (0.023)	0.051 ** (0.021)
Invest			0.007 ** (0.003)	0.006 *** (0.002)				
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Year-Industry FE	N	N	N	N	Y	Y	N	N
Observation	17,398	17,398	20,998	20,998	20,998	20,998	9942	9942
Adj.R square	0.840	0.474	0.822	0.466	0.834	0.482	0.835	0.490

Robust standard errors in ( ). ***, **, and * indicate passing significance tests at the 1%, 5%, and 10% significance levels, respectively. Y represents the control, N represents not controlling the corresponding variable.

First, given that the effect of digital technology application on firms' ambidextrous innovation may exhibit time-lagging effects, we used firms' time-lagged exploitative innovation performance (Lag_Exploit) and exploratory innovation performance (Lag_Explore) as dependent variables to conduct robustness checks. Columns (1) and (2) of Table 10 present the estimation results. The coefficients of AI application on both time-lagged exploitative and exploratory innovation are positive, with the former and latter being significant at the 1% and 10% levels, respectively. This result indicates that even when lagged effects are accounted for, AI application continues to significantly enhance firms' ambidextrous innovation, bolstering the robustness of our baseline results.

Second, as mentioned previously, annual reports may contain strategic disclosure behaviors, particularly concerning emerging technologies, as firms may overstate adoption to gain potential benefits. To address this concern, we used financial information as an alternative proxy for AI application. Following prior studies [72], we employed firms' investment in digital-related assets as a proxy measure, denoted as Invest. Columns (3) and (4) show that such investment is positively and significantly associated with both exploitative and exploratory innovation, at least at the 1% level. This finding further validates the robustness of our results.

Third, since industry characteristics may also influence firms' ambidextrous innovation, we re-estimated the model by replacing firm- and year-fixed effects with firm- and industry-year-fixed effects. Columns (5) and (6) report the estimation results obtained by using alternative fixed-effect models. The coefficients of AI application (AI) remain positive and statistically significant at the 1% level, indicating that our findings are not sensitive to alternative fixed-effects specifications.

Finally, for non-digital-native firms, the adoption of emerging digital technologies often involves a two-stage process: deciding whether to adopt and determining the extent of adoption [77]. These two dimensions may have different marginal effects on innovation.

To address this issue, following the approach taken in Chen and Roth (2023)'s study [78], we excluded firms that did not disclose AI application from the sample and re-estimated the benchmark models. Columns (7) and (8) show that the coefficients of AI application remain positive and significant (at least at the 5% level), thereby providing further support for the robustness of our main findings.

5.4. Mechanism Testing

The preceding theoretical analyses suggest that the application of AI primarily promotes ambidextrous innovation by enhancing firms' R&D efficiency and optimizing labor structure. To further validate these mechanisms, we constructed the following models to examine how AI application influences ambidextrous innovation through these channels:

$$\text{Mechanism}_{i,t} = c + \alpha \text{AIapp}_{i,t} + \beta_i X_{i,t} + \sum \text{Firm} + \sum \text{Year} + \tau_{it} \quad (5)$$

$$\text{Exploit}_{i,t}/\text{Explore}_{i,t} = c + \alpha \text{AIapp}_{i,t} + \theta \text{Mechanism}_{i,t} + \beta_i X_{i,t} + \sum \text{Firm} + \sum \text{Year} + \tau_{it} \quad (6)$$

The mediating variables we sought to test are firms' R&D efficiency (Efficiency) and labor force structure (Graduate). In this study, we measure R&D efficiency by the number of patent applications generated per unit of R&D investment and measure labor force structure by the proportion of employees holding a master's degree or above in total employment.

Table 11 reports the results of the mechanism tests. Column (1) shows that AI application significantly improves firms' R&D efficiency, as reflected by the increase in the number of patent applications per unit of R&D input. Columns (2) and (3) further indicate that higher R&D efficiency significantly enhances ambidextrous innovation. Column (4) shows that AI application significantly increases the share of highly educated employees within firms. Columns (5) and (6) further demonstrate that the structural shift in the workforce, driven by a higher proportion of highly educated employees, significantly promotes ambidextrous innovation. In sum, the mechanism test results confirm that AI application fosters ambidextrous innovation by enhancing firms' R&D efficiency and reshaping their labor force structure.

Table 11. Estimation results regarding the mediation mechanism with respect to R&D efficiency and optimization of the labor structure.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**Efficiency**	**Exploit**	**Explore**	**Graduate**	**Exploit**	**Explore**
AIapp	0.004 ***	0.041 ***	0.005 **	0.382 ***	0.073 ***	0.031 **
	(0.001)	(0.010)	(0.002)	(0.135)	(0.015)	(0.013)
Efficiency		8.866 ***	7.188 ***			
		(0.189)	(0.156)			
Graduate					0.005 ***	0.004 ***
					(0.001)	(0.001)
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observation	20,998	20,998	20,998	20,998	20,998	20,998
Adj.R square	0.730	0.897	0.602	0.836	0.824	0.467

Robust standard errors in ( ). ***, **, and * indicate passing significance tests at the 1%, 5%, and 10% significance levels, respectively. Y represents the control.

5.5. Heterogeneity Test

5.5.1. Slack Resource Heterogeneity

Organizational slack, as a discretionary buffer resource, provides financial support for innovation activities and is a critical determinant of firms' innovation performance [79,80]. When firms face major technological transformations, abundant slack resources allow firms to absorb risks and tolerate failures, enabling them to allocate resources more flexibly between exploring future opportunities and refining existing businesses. Conversely, firms constrained by limited slack resources tend to adopt more conservative strategies, concentrating their scarce resources on short-term activities that can quickly generate cash flow. Thus, differences in slack resource levels may systematically shape the pathways through which AI applications affect ambidextrous innovation. Given that absorbed slack resources are characterized by low liquidity, high specificity, and weak visibility, this study focuses on the heterogeneity of unabsorbed slack resources in conditioning the AI–innovation relationship. We classify sample firms into high-slack and low-slack groups, using the median of the sum of the debt-to-asset ratio and the current ratio as the threshold.

Table 12 presents the results. For the firms in the high-slack group, AI application significantly promotes both exploitative and exploratory innovation. By contrast, for the firms in the low-slack group, AI application exerts a significant positive effect only on exploitative innovation, while its effect on exploratory innovation is not significant. These findings suggest that firms' resource endowments are a key contingency in shaping the innovation outcomes of AI adoption. Ample slack resources can effectively mitigate the uncertainty and high failure costs inherent in exploratory innovation, enabling managers to overcome short-term survival pressures and achieve balanced support for both exploitative and exploratory innovation. Conversely, for firms lacking slack resources, stringent resource constraints force them to prioritize low-risk, quick-return innovation activities. As a result, applications of AI are channeled toward exploitative innovation, improving efficiency, reducing costs, and optimizing existing operations, while high-risk and long-cycle exploratory innovation is strategically postponed beyond firms' immediate risk-bearing capacity.

Table 12. Estimated results regarding firms' slack resource heterogeneity.

	(1)	(2)	(3)	(4)
Variables	**High Slack Resource**		**Low Slack Resource**	
	Exploit	**Explore**	**Exploit**	**Explore**
AIapp	0.072 ***	0.026 *	0.062 ***	0.034
	(0.018)	(0.013)	(0.023)	(0.020)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observation	10,453	10,453	10,545	10,545
Adj.R square	0.837	0.458	0.829	0.501

* Robust standard errors in ( ). ***, **, and * indicate passing significance tests at the 1%, 5%, and 10% significance levels, respectively. Y represents the control.

5.5.2. Firms' AI Foundation Heterogeneity

AI increasingly exhibits the characteristics of a general-purpose technology [5,54]. However, general-purpose technologies themselves do not provide firms with sustainable competitive advantages [43]. Accordingly, the innovation-enhancing effect of AI may be more pronounced during the initial stage of adoption, i.e., when firms move from "absence" to "presence" in regard to AI usage. For firms that already possess a mature AI foundation, innovation performance and competitive advantage are more likely to stem from the deep

integration of AI with other firm-specific resources and special organizational structures. We divided sample firms into high-AI-foundation and low-AI-foundation groups based on whether they have been granted invention patents related to AI technologies.

Table 13 reports the results of the heterogeneity analysis based on firms' technological foundation regarding AI. For the high-AI-foundation group, AI application has no significant effect on either exploitative or exploratory innovation, suggesting that for firms with strong AI foundations, AI per se does not directly enhance ambidextrous innovation. In contrast, for the low-AI-foundation group, AI application significantly promotes both exploitative and exploratory innovation. These findings corroborate the general-purpose technology nature of AI: its adoption—i.e., whether and how firms use it—matters more for innovation outcomes than the extent of use.

Table 13. Estimated results regarding firms' AI foundation heterogeneity.

	(1)	(2)	(3)	(4)
Variables	**High AI Foundation**		**Low AI Foundation**	
	Exploit	**Explore**	**Exploit**	**Explore**
AIapp	0.034	−0.041	0.087 ***	0.041 **
	(0.021)	(0.033)	(0.016)	(0.014)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observation	2042	2042	18,956	18,956
Adj.R square	0.828	0.466	0.812	0.465

* Robust standard errors in ( ). ***, **, and * indicate passing significance tests at the 1%, 5%, and 10% significance levels, respectively. Y represents the control.

5.5.3. Industrial Competitiveness Heterogeneity

The intensity of industry competition substantially shapes firms' innovation strategies [30]. Competition levels influence firms' strategic decision-making horizons, resource conditions, and the speed of strategic iteration, thereby affecting how firms deploy AI technologies [38,43]. Consequently, the effect of AI adoption on ambidextrous innovation is likely to vary across industries with different competition intensities.

As in prior studies, we divided sample firms into high-competition and low-competition groups. Specifically, if an industry's Herfindahl–Hirschman Index (HHI) is below the median HHI across all industries in 2012, the industry is classified as high competition. Table 14 presents the results of the heterogeneity analysis. For firms in highly competitive industries, AI application significantly enhances exploitative innovation but has no significant effect on exploratory innovation. In contrast, for firms in less competitive industries, AI application significantly promotes both exploitative and exploratory innovation. These findings indicate that under high competitive pressure, firms tend to concentrate their strategic focus on short-term efficiency gains. Accordingly, AI is deployed in a more instrumental and utilitarian manner, with exploratory innovation—characterized by high risk, long horizons, and uncertain outcomes—being strategically sacrificed or marginalized due to misalignment with urgent survival goals. Conversely, in less competitive industries, firms typically enjoy monopoly rents or a more relaxed survival environment, so they face fewer short-term pressures. Managers in such contexts are more inclined to pursue long-term orientations, enabling firms to use AI in a more comprehensive and diversified manner—i.e., not only as a means of deepening existing advantages but also as an effective tool for disruptive experimentation, new product development, and market exploration.

Table 14. Estimated results regarding industrial competition intensity heterogeneity.

Variables	(1)	(2)	(3)	(4)
	High Competition Intensity		Low Competition Intensity	
	Exploit	Explore	Exploit	Explore
AIapp	0.055 ***	−0.001	0.085 ***	0.056 **
	(0.019)	(0.018)	(0.02)	(0.020)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observation	10,459	10,459	10,539	10,539
Adj.R square	0.822	0.447	0.833	0.504

* Robust standard errors in ( ). ***, **, and * indicate passing significance tests at the 1%, 5%, and 10% significance levels, respectively. Y represents the control.

6. Conclusions and Implications

This section summarizes this study's key findings, discusses the theoretical and practical implications for governments and firms, and, finally, acknowledges the limitations of this research while suggesting avenues for future investigation.

6.1. Main Research Conclusions

Based on data from Chinese A-share listed companies spanning 2014 to 2023, this study explores the relationship between AI application and firms' exploitative and exploratory innovation performance, along with the underlying mechanisms and boundary conditions, providing a practical basis upon which firms can achieve sustainable development in the digital era. The key findings are as follows.

Firstly, AI application significantly promotes firms' exploitative and exploratory performance. A key tension between exploitative and exploratory innovation lies in how firms allocate limited innovation resources and managerial attention to two activities that place mutually exclusive demands on resources. The adoption of AI enhances firms' overall efficiency and reduces financing constraints associated with pursuing both types of innovation simultaneously, thereby creating a critical opportunity for firms to balance the two innovation activities.

Secondly, improvements in R&D efficiency and the optimization of firms' labor structures serve as mediating mechanisms through which AI application simultaneously enhances firms' ambidextrous innovation performance. Both exploratory and exploitative innovation are knowledge-intensive activities that also rely on material resources. On the one hand, AI can partially replace less knowledge-intensive and repetitive tasks, enabling firms to increase the proportion of highly educated laborers in their workforce. On the other hand, the intelligentization of decision-making and innovation management improves the output efficiency of firms' R&D investments. Together, these mechanisms inject vitality into firms' innovation activities, providing a critical pathway for balancing ambidextrous innovation and achieving sustainable development.

Finally, a firm's data resources positively moderate the relationship between AI application and exploitative innovation performance, while they negatively moderate the relationship between AI application and exploratory innovation performance. Since the efficacy of AI application is highly dependent on data input [43,55], firms with abundant data resources are likely to more effectively apply AI in investigating a firm's existing knowledge, thereby bolstering exploitative innovation performance. However, given the strong dependence of AI outputs on input data, abundant data resources may paradoxically

constrain firms' knowledge exploration in unfamiliar domains, thereby hampering their exploratory innovation performance.

Moreover, our heterogeneity analysis reveals that AI application has a stronger promotive effect on firms with weaker AI technology foundations. This finding suggests that once AI technologies have become deeply embedded in organizational routines, their marginal effect on enhancing ambidextrous innovation diminishes, and firms' sustainable competitiveness depends more on the integration of AI with unique resources and organizational capabilities. In contrast, for firms with a weaker AI foundation, AI application significantly promotes both exploitative and exploratory innovation, underscoring the fact that the adoption of AI from scratch generates substantial innovation dividends. Additionally, the positive impact of AI adoption on exploratory innovation is more pronounced for firms with higher levels of organizational slack, as such firms possess sufficient risk-bearing capacity and flexibility to support long-term and uncertain exploration activities. Conversely, for firms with lower levels of slack, AI adoption primarily enhances exploitative innovation, as resource constraints force managers to prioritize short-term efficiency gains and incremental improvements. Lastly, in highly competitive industries, AI adoption significantly promotes exploitative innovation but has no significant effect on exploratory innovation. This finding reflects firms' tendency to concentrate limited resources on short-term efficiency gains when facing strong competitive pressure. By contrast, in less competitive industries, AI adoption significantly promotes both exploitative and exploratory innovation, as firms enjoy more strategic leeway for engaging in long-term, high-risk exploration while also optimizing existing activities.

Overall, AI application promotes both exploitative and exploratory innovation by enhancing R&D efficiency and optimizing firms' labor structures. This process is shaped by the characteristics of firms' data resources and exhibits heterogeneity depending on a firm's AI technological foundations, its quantity of slack resources, and the intensity of industrial competition.

6.2. Theoretical Contributions

This study enriches the literature on AI's economic consequences and organizational ambidexterity in three ways. First, by empirically confirming that AI application positively influences both exploitative and exploratory innovation, we extend March's theory of organizational ambidexterity [6], demonstrating that AI acts as a technology enabler that helps firms overcome the inherent dilemma by increasing efficiency and resource capacity. Second, adopting the firm resource-based view [57], we contribute to the literature by identifying R&D efficiency and labor structure optimization as key mechanisms, thereby providing a fine-grained explanation of how a general-purpose technology like AI transforms the innovation production function. Finally, by introducing data resources as a critical boundary condition with a dual moderating effect—amplifying exploitation while constraining exploration—we refine the understanding of AI as a complementary resource and its context-dependent nature, highlighting that having more data is not always unilaterally beneficial for all types of innovation.

6.3. Practical Implementations

6.3.1. Implications for Government

Governments should adopt a differentiated yet precise policy approach to foster the integration of AI with the traditional economy to ensure sustainable development. First, given the strong contextual dependence of AI's effects on firms' ambidextrous innovation, policies should provide niche targeting support. For firms in highly competitive industries with restricted slack resources, policies should prioritize guiding AI applications toward

exploitative innovation, helping firms reduce costs, improving efficiency, and accumulating AI-related capabilities during transition. For firms with stronger technological foundations and abundant slack resources, governments should promote exploratory innovation in frontier and cross-disciplinary fields through subsidies and knowledge-sharing platforms, thereby helping the firms secure future technological advantages.

Second, governments should accelerate the establishment of the data exchange market to enable efficient circulation and compliant use of data resources. Since data are a critical complementary resource for AI, policy efforts should focus on dismantling data silos and enabling the value realization of diverse data types. On the one hand, institutions related to data property rights, circulation, and revenue distribution should be improved, and mechanisms for data ownership and rights allocation should be clarified to regulate the traded-data market, lowering the cost and risk of acquiring external heterogeneous data. On the other hand, governments should support industry- and region-level data spaces and open-source platforms, encouraging firms to share non-sensitive, internally generated data under secure conditions, thereby facilitating cross-sector data integration and mitigating innovation path dependence.

Finally, governments should optimize the innovation environment by fostering a regulatory framework that is tolerant of experimentation and failure. This would include strengthening competition policy to prevent dominant platforms from engaging in monopolistic practices, ensuring small and medium-sized enterprises and new entrants have fair opportunities to engage in exploratory innovation. Additionally, a more forgiving trial-and-error mechanism should be established in areas such as pilot programs, granting firms greater autonomy and reducing concerns about the risks associated with breakthrough innovation.

6.3.2. Implications for Firms

At the firm level, managers should increase their technological alignment with and long-term orientation toward AI adoption to ensure sustainable innovation outcomes are attained. First, firms should formulate AI and data strategies that dynamically align technology, resources, and innovation goals. AI adoption is a strategic investment rather than merely technology acquisition. For exploitative innovation, firms should prioritize high-quality governance of internally generated data, invest in precise algorithms, and embed AI into existing R&D processes. For exploratory innovation, firms should deliberately incorporate diverse external data, strengthen governance mechanisms, and establish dedicated data governance committees to avoid over-reliance on existing data structures and unlock new knowledge and opportunities.

Second, firms should reinforce organizational resilience by maintaining sufficient slack to buffer risks associated with exploratory activities. Where resources are constrained, firms tend to retreat to short-term, efficiency-focused innovation. To counter this, firms may adopt structurally separate organizational units with flexible evaluation standards to create space for exploratory efforts.

Finally, firms should develop context-specific human–AI collaborative innovation capabilities. The true value of AI lies in augmenting rather than replacing human capabilities. This requires cultivating hybrid talent proficient in both AI technologies and business processes, enabling the precise application of AI to diverse innovation scenarios. Simultaneously, firms should redesign workflows and decision-making mechanisms to foster mutual learning between humans and AI systems, thereby establishing new forms of agency and co-creation that drive ambidextrous innovation and shape distinctive competitive advantages in the AI era.

6.4. Limitations and Future Research Directions

This study provides empirical evidence on the effects of AI adoption on ambidextrous innovation, but further research could extend these insights in three directions. First, a limitation of this study is that it does not explicitly examine the role of data governance mechanisms, which may moderate the AI–innovation relationship. Future studies could investigate the governance mechanisms of data resources under different institutional arrangements, paying particular attention to how firms' internal data governance practices influence ambidextrous innovation. Secondly, this study lacks a case-based perspective on the dynamic evolution of AI adoption and its impact on firms' innovation strategies. As time progresses, the maturity, diffusion, and cost of AI technologies continue to change, which may alter the ways in which firms integrate AI into their innovation processes. Therefore, future research could adopt a case-based perspective to examine how firms combine AI technologies with their innovation strategies at different stages of AI evolution. Third, this study lacks an examination of how employee–AI interactions shape innovation outcomes from a more micro-level perspective. Micro-level studies could further explore the human–AI interaction processes within firms, focusing on how patterns of collaboration, trust-building, and responsibility allocation between employees and AI systems shape the outcomes of ambidextrous innovation.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
R&D	Research and development
GAN	Generative adversarial networks
CPDP	Chinese Patent Data Project
CSMAR	China Stock Market and Accounting Research
ST	Special treatment
IPC	International patent classification
AIapp	Artificial intelligence application
MD&A	Management discussion and analysis
DCMM	Management capability maturity assessment model
HHI	Herfindahl–Hirschman index
PSM	Propensity score matching
2SLS	Two-stage least squares
IV	Instrument variable

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