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ARTICLE

Artificial Intelligence and Firm Technological Diversification: Unveiling the Distinctions Between Related and Unrelated Domains

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Abstract

Artificial intelligence (AI) is revolutionizing the way firms pursue technological diversification (TD), yet its distinct effects on related and unrelated diversification remain insufficiently explored. Based on the knowledge-based view, this study examines the distinct effects of AI on related and unrelated TD to elucidate AI's specific role in facilitating both the optimization of existing knowledge and the exploration of new domains. Using a multi-period difference-in-differences model and panel data from China's listed manufacturing firms (2013–2022), our empirical analysis demonstrates that AI significantly promotes firm TD, particularly in unrelated TD. Additionally, we identify that core-technology competence strengthens the positive effect of AI on unrelated TD, while knowledge stocks weaken it. These results contribute to the literature on TD by underscoring the role of AI. Practically, the study offers actionable insights for managers to harness AI in balancing exploration and exploitation within their TD strategies.

摘要

人工智能正在彻底改变企业追求技术多元化的方式,然而其对相关和非相关多元化的独特影响尚未得到充分探索。基于知识基础观，本研究考察了人工智能对相关和非相关技术多元化的独特影响,以阐明人工智能在促进现有知识优化和新领域探索方面的具体作用。通过使用多期双重差分模型和中国上市制造企业(2013 - 2022年)的面板数据，我们的实证分析表明，人工智能显著促进了企业技术多元化，特别是在非相关技术多元化方面。此外，我们发现核心技术能力加强了人工智能对非相关技术多元化的积极影响，而知识储备则削弱了这种影响。这些结果通过强调人工智能的作用,为技术多元化的文献做出了贡献。实际上,该研究为管理者在其技术多元化战略中利用人工智能平衡探索和开发提供了可行的见解。

Keywords: artificial intelligence; core-technology competence; knowledge stocks; related technological diversification; technological diversification; unrelated technological diversification

关键词: 人工智能; 技术多元化; 非相关技术多元化; 相关技术多元化; 核心技术能力; 知识储备

Introduction

In recent decades, we have witnessed the remarkable evolution and rapid iteration within the realm of artificial intelligence (AI). This progress, characterized by advancements in data collection, optimization, and breakthroughs in novel algorithms (Jarrahi, Askay, Eshraghi, & Smith, 2023; Townsend, Hunt, Rady, Manocha, & Jin, 2024), has not only enhanced convenience and spurred innovation but also significantly boosted profitability (Brem, Giones, & Werle, 2023; Füller, Hutter, Wahl, Bilgram, & Tekic, 2022; Raisch & Fomina, 2024). Consequently, it has also fueled the extensive adoption of AI by firms seeking to explore new frontiers and drive further innovation. Take, for instance, Midea, a Chinese private firm with over two decades of history, which has successfully transitioned from a domestic appliance manufacturer to a global technology powerhouse within the past decade by leveraging AI technologies. Its expanded technological landscape now includes natural language processing (NLP)-powered smart home interaction systems, computer vision-enabled industrial inspection robots, and deep learning-optimized medical imaging diagnostics. This case exemplifies the potential of AI to enhance firm technological diversification (TD).

TD, defined as the breadth of technological domains a firm spans (Choi & Lee, 2022), is a pivotal strategy for firms to gain a competitive edge and establish a dominant market position (Ceipek, Hautz, Mayer, & Matzler, 2019; Choi & Lee, 2021). It not only enhances a firm's average productivity but also serves to mitigate risks associated with technology investment (Belderbos, Leten, & Suzuki, 2023; Garcia-Vega, 2006). To better understand the nuances of TD, scholars have made a distinction between related technological diversification (RTD) and unrelated technological diversification (UTD). RTD refers to diversification within adjacent technological domains, while UTD involves broad diversification across distant technological domains (Choi & Lee, 2022; Kim, Lim, & Park, 2009). Although TD is widely recognized as a critical strategy for firms to achieve competitive advantage, the processes underlying RTD and UTD differ significantly. The distinction between RTD and UTD reflects a fundamental strategic dilemma: exploiting existing competencies versus exploring new domains. RTD enables firms to incrementally improve and leverage existing knowledge (exploitation), whereas UTD involves venturing into unfamiliar territories with higher risks but the potential for breakthrough innovation (exploration). These distinctions are particularly relevant in the context of AI, which functions both as a tool for exploiting existing knowledge and as an enabler for exploring new domains (Grimes, von Krogh, Feuerriegel, Rink, & Gruber, 2023; Haefner, Wincent, Parida, & Gassmann, 2021; Hutchinson, 2021). By formalizing tacit knowledge and identifying cross-domain synergies, AI uniquely addresses the challenges of knowledge distance and integration barriers. Consequently, AI disrupts traditional exploration costs and risks, enabling firms to pursue UTD more strategically while maintaining RTD efforts (Jarrahi, Askay, Eshraghi, & Smith, 2023; Raisch & Fomina, 2024). Understanding this dual role of AI is essential for firms seeking to balance stability in existing domains with innovation in new ones.

Previous studies have identified several factors that contribute to a firm's TD, including resource utilization (Ceccagnoli, Lee, & Walsh, 2024; Wang & Xiao, 2017), the diversity of firm innovation networks' partners, regional diversity (Zhang & Tang, 2018), innovation-oriented strategy formulation (Tang, Liu, & Xiao, 2023), and internal basic research (Ceccagnoli et al., 2024; Gupta, 1990). However, the inadequacy lies in the fact that these approaches do not inherently mitigate the complexities involved in capturing and integrating disparate knowledge. It overlooks the need for sophisticated mechanisms to overcome the challenges of operational barriers, such as decoding and integrating, which are posed by knowledge distance (Miller, 2006), which is defined as the difference between the external knowledge a firm acquires and its internal knowledge base (Zhu, Yang, Zhang, & Wang., 2024). However, the role of AI in TD remains unclear in existing research. Midea's strategic diversification provides a compelling example of how AI can influence the choice between RTD and UTD. Initially focused on home appliances, Midea used AI to develop intelligent products with voice control and user habit learning, a clear case of related diversification within its traditional domain. However, when the firm recognized the limitations of millimeter wave radar technology – characterized by market homogeneity and low commercial value – it leveraged AI to explore new opportunities in unrelated fields. Specifically, AI tools were used to analyze market trends and identify medical imaging as a high-growth area. Midea built on its existing expertise in imaging technologies but extended into the medical domain by developing a smart imaging platform driven by AI. This shift illustrates how AI can help firms cross knowledge distance by identifying synergies between existing capabilities and new technological fields, enabling informed decisions about diversification. Thus, AI served not only as a technical enabler but also as a strategic tool for navigating diversification choices.

Some scholars argue that AI technologies such as machine learning and knowledge graphs facilitate feature extraction and similarity calculation (Brem et al., 2023), which empowers firms to construct a proprietary knowledge base and foster RTD. This approach yields benefits such as learning, knowledge transfer, and accumulation (Chen, Shih, & Chang, 2012). Conversely, an alternative view holds that AI transcends boundaries, decoding and weakening knowledge silos across various technologies (Tian, Zhao, Yunfang, & Wang, 2023), enabling firms to explore novel technological domains and promoting UTD (Lou & Wu, 2021). Notably, UTD safeguards technical commonality while reducing innovation uncertainty and enhancing strategic flexibility (Chen et al., 2012; Chiu, Lai, Liaw, & Lee, 2009). Despite these insights, the broader impact of AI on overall TD remains an area ripe for exploration, particularly the nuanced differences between RTD and UTD, which remain to be explored and studied.

Based on the knowledge-based view (KBV), this study analyzes the relationship between AI and firm TD, including its two subtypes: RTD and UTD. Empirical testing utilizes panel data from China's publicly listed manufacturing firms over the decade from 2013 to 2022, employing a multi-period difference-in-differences (DID) model. Additionally, the study explores the moderating effects of core-technology competence and knowledge stocks.

The main contributions of this study are as follows: First, drawing on the KBV, this work explores the impact of AI on firm TD and finds that AI positively influences the level of firm TD, which not only enriches the academic research around AI's facilitation of diverse knowledge acquisition and integration in firms (Grimes et al., 2023; Hutchinson, 2021; Kakatkar, Bilgram, & Füller, 2020), but also supplements the antecedents of TD (Breschi, Lissoni, & Malerba, 2003; Ceccagnoli et al., 2024; Granstrand, Bohlin, Oskarsson, & Sjöberg, 2007; Tang et al., 2023). Second, to further explore the heterogeneous effect of AI in two subtypes of TD, we consider the different characteristics of explicit and tacit knowledge, and our findings reveal that AI significantly promotes UTD rather than RTD. This discovery underscores the ability of AI to identify and formalize tacit knowledge (Jang, Kim, & Yoon, 2023; McKinney et al., 2020; Yazici, Beyca, Gurcan, Zaim, Delen, & Zaim, 2020), which broadens a firm's technological scope in unrelated domains and highlights the practical utility of AI within firms (Babina, Fedyk, He, & Hodson, 2024; Lanzolla, Pesce, & Tucci, 2020; Li, Xu, Zheng, Han, & Zeng, 2023). Third, we focus our attention on the potential conditioning role of core-technology competence and knowledge stocks. Specifically, core-technology competence, a capacity for combining and architecting diverse knowledge (Henderson & Cockburn, 1994), enhances the relationship between AI adoption and TD, particularly in unrelated domains. Conversely, knowledge stocks, by reinforcing a focus on specialized knowledge and perpetuating learning inertia (Kang, Baek, & Lee, 2019), negatively moderate the AI-TD connection, notably for unrelated domains. These findings augment the existing literature on AI's strategic implications for firms under distinct conditions (Igna & Venturini, 2023; Lou & Wu, 2021).

The article is structured as follows: Section 2 carries on the theoretical analysis and research hypotheses; Section 3 introduces the data, variables, and model design; Section 4 presents empirical results, robustness tests, the moderating effects of core-technology competence and knowledge stocks, and their heterogeneous impact; and Section 5 summarizes the full text and offers pertinent recommendations.

Theory and Hypotheses

Technological Diversification

Early firm-level research framed TD as a matter of what a firm knows (Granstrand & Sjölander, 1990), reflecting the diversity and breadth of firm technical capabilities (Ceipek et al., 2019).

Subsequently, TD has been categorized into RTD and UTD based on the degree of commonality between technological domains. RTD involves diversification within or between narrow technological domains, rooted in the same fundamental knowledge and sharing common scientific principles. In contrast, UTD spans broad TD across distant technological domains (Kim et al., 2009). TD plays a pivotal role in enhancing firm financial and innovation performance, forming the cornerstone of its competitive advantage (Ceipek et al., 2019; Lee, Huang, & Chang, 2017). Due to its advantages, scholars have been deeply engaged in uncovering the antecedents of TD.

The firm's selection between deepening or narrowing the technology trajectory is significantly influenced by external communication channels (Estades & Ramani, 1998). Concurrently, internal resources play a crucial role (Lai & Weng, 2014). It has been proved that inventor collaboration networks broaden a firm's technological horizons through recombining innovative production factors (Li, Feng, Cao, & Shen, 2020). To capitalize on the advantages of their network positioning, firms must possess substantial internal resources (Lai, 2015). Firms can enhance external technology acquisition capabilities to boost their resource pools (Granstrand et al.., 2007). Simultaneously, effective utilization of unabsorbed idle resources can facilitate TD (Lai & Weng, 2014). Amidst these factors, scholars also highlight the paramount importance of knowledge synergy in driving TD. The coherence of a firm's internal knowledge structure (Breschi et al., 2003) coupled with proficient knowledge-sharing mechanisms (Tang et al., 2023) is essential in optimizing knowledge integration and restructuring processes, which, in turn, affects TD.

In conclusion, TD has substantial strategic and practical significance for firms. Scholars have extensively investigated its determinants, including internal and external networks (Estades & Ramani, 1998; Li et al., 2020), technology acquisition capabilities (Granstrand et al., 2007), knowledge base characteristics (Tang et al., 2023), and resource utilization (Gupta, 1990). While prior approaches to enhancing TD have been valuable, they fall short in providing comprehensive solutions to bridge the knowledge distance. Concurrently, conventional technologies are constrained by the physical limitation of recoding and reinterpreting various technologies (Brem et al., 2023). However, AI emerges as a transformative force in the new generation of technological revolutions (Babina et al., 2024; Igna & Venturini, 2023; Townsend et al., 2024). AI offers the potential to decode and share various types of data (Brem et al., 2023), which may have unforeseen implications on the established technology strategic direction of the firm and its practical utility (Brem et al., 2023; Lou & Wu, 2021; Muhlroth & Grottke, 2022). This emerging landscape provides a novel research direction for further advancing firm TD.

In addition, as firms strive for higher levels of TD, they inevitably encounter elevated coordination and integration costs (Lee et al., 2017). During this phase, the firm's core-technology competence and knowledge stocks may play a regulatory role in the relationship between AI and firm TD. Core-technology competence not only signifies proficiency in applying existing skills but also encompasses the capacity to assimilate new technologies and foster novel knowledge development (Henderson & Cockburn, 1994; Leonard-Barton, 1992). Promoting TD necessitates the effective management of diverse knowledge. Core-technology competence enhances a firm's ability to absorb diverse knowledge and mitigate the complexities associated with managing multi-technology portfolios (Choi & Lee, 2021). Meanwhile, knowledge stocks reflect the knowledge characteristics of the firm. Deep knowledge stocks often signify technical specialization (Teece, Pisano, & Shuen, 1997), whereas achieving TD requires firms to span multiple technological domains. Technical specialization results in learning inertia and path dependence, which, in turn, heightens the difficulty of knowledge acquisition and recombination (Kang et al., 2019).

Accordingly, we propose a moderating effect model to reveal the influence and boundary conditions of AI on firm TD, as shown in Fig. 1.

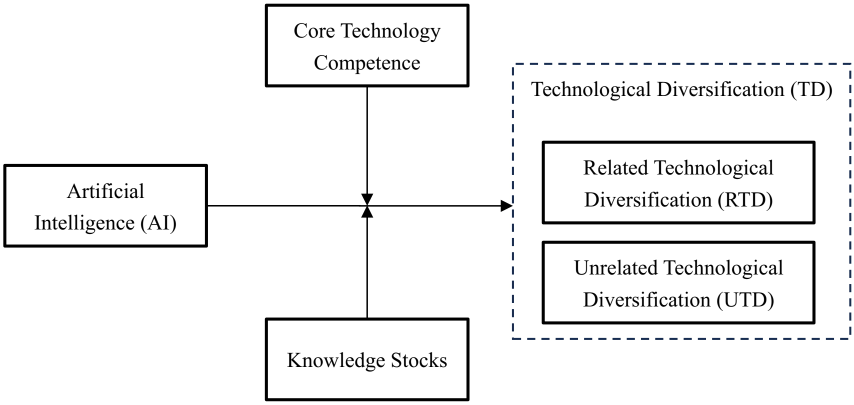

Figure 1. Research model

AI and TD

AI is a technique based on the continuous processing and analysis of multiple data sources to develop new products and services or generate more solutions (Hutchinson, 2021). AI exerts a profound impact on the training of skilled talents within firms (Apell & Eriksson, 2021), organizational structures (Benassi, Grinza, Rentocchini, & Rondi, 2022), and innovation strategies (Jarrahi et al., 2023). In these contexts, AI extends, complements, and potentially supersedes human capabilities, thereby enabling effective and systematic innovation development and facilitation, revealing promising opportunities – a process also known as AI-driven innovation. The incorporation of AI-driven innovation management may herald the seventh paradigm of innovation management (Füller et al., 2022). The adoption of AI by firms can enhance decision-making and achieve higher levels of innovation (Mercier-Laurent, 2020; Yablonsky, 2020). Simultaneously, TD remains a vital strategy for achieving long-term technological progress within organizations (van Rijnsoever, van den Berg, Koch, & Hekkert, 2015). Consequently, further research is required to elucidate AI's role in facilitating cross-domain knowledge acquisition and integration (Grimes et al., 2023).

According to the KBV, firms can cultivate diverse knowledge bases through knowledge accumulation, diffusion, and recombination of both old and new knowledge (Ceipek et al., 2019; Grant, 1996). Among these processes, knowledge recombination stands out as a critical mechanism. It involves firms reshaping internally generated and externally acquired knowledge elements in novel ways, thereby facilitating the discovery of fresh technological opportunities (Zahra & George, 2002). Therefore, firm TD encompasses two essential processes. First, firms effectively acquire diverse knowledge from external sources. Second, they recombine existing and newly acquired knowledge (Kogut & Zander, 1992; Nag & Gioia, 2012). The impact of AI on firm TD manifests primarily in the following ways.

First, in external knowledge acquisition, AI, particularly through machine learning approaches, offers cost advantages and untapped potential in information collection and processing (Haefner et al., 2021). Not only can AI swiftly gather and organize information from consumers, suppliers, and competitors (Haefner et al., 2021), but it also accelerates the process of value extraction from complex, multi-sourced data (Kakatkar et al., 2020). Alibaba, the world's largest online commerce platform, exemplifies how AI drives TD within the firm. Notably, its expansion into autonomous driving and medical imaging stems from AI's capacity to reconfigure knowledge absorption processes. Since 2015, AI has empowered Alibaba to decode market demands for intelligent connected vehicles and identify autonomous driving opportunities (Nylund, Ferras-Hernandez, & Brem, 2018). The implementation of multimodal learning architecture allows systematic processing of unstructured road-testing videos and vehicle malfunction reports, facilitating domain-specific expertise acquisition. In medical imaging, where conventional analytics rely on statistical pattern recognition, AI achieves superior precision in automated anomaly detection (e.g., tumor localization in CT scans) through advanced feature extraction (Babina et al., 2024; Hussain et al., 2021). This capability enables Alibaba to derive clinically actionable insights from medical images, thereby accessing previously inaccessible technical domains (Cockburn, Henderson, & Stern, 2019). Therefore, AI enriches a firm's existing knowledge base by expanding the search and efficient processing of external information from various domains, transforming it into absorbed knowledge to explore new techniques.

Second, in terms of knowledge recombination, AI, leveraging neural networks, calculates the correlations, characteristics, and similarities among existing knowledge elements (Brem et al., 2023). It can identify associations between technologies by learning from vast amounts of patent data and review reports, which help firms discover potential novel technologies (Jang et al., 2023; Lu et al., 2020; Zhang et al., 2016). The clustering and grouping results serve as the foundation for firms to further explore cross-fertilization across different knowledge categories (Kakatkar et al., 2020). This process enables firms to recombine knowledge effectively, fostering the emergence of cross-disciplinary technologies (Raisch & Fomina, 2024; Tsouri, Hansen, Hanson, & Steen, 2022).

In conclusion, AI improves the TD of firms by facilitating the acquisition and recombination of diverse knowledge.

Hypothesis 1 (H1): AI has a positive effect on firm TD.

Separate Effects of AI on UTD and RTD

AI can improve the knowledge acquisition and recombination ability of firms, but the driving effect generated by AI may be different in the two subtypes of TD. According to the KBV, knowledge can be categorized into two types: explicit and tacit (Grant, 1996; Spender, 2014). Explicit knowledge is revealed through communication, enabling it to be acquired by others at a marginal cost approaching zero. Tacit knowledge, on the other hand, becomes apparent through the application of tacit knowledge and, if not externalized, can only be attained through practice (Duan, Deng, Liu, Yang, Liu, & Wang, 2022; Grant, 1996; Kucharska & Erickson, 2023). From the perspective of knowledge management (Alavi & Leidner, 2001; Galunic & Rodan, 1998), we posit that firms entering knowledge domains closely aligned with existing knowledge demonstrate higher tacit-to-explicit knowledge conversion efficiency, enabled by accumulated domain-specific experience and organizational learning mechanisms. As a supplementary learning accelerator, AI not only extracts latent patterns from unstructured data via NLP architectures (e.g., BERT and GPT) but also engineers explicit knowledge by formalizing tacit associations (Liebowitz, 2001; Ma & Fan, 2024; Zaoui Seghroucheni, Lazaar, & Al Achhab, 2025). For example, high-tech firms leverage AI's pattern recognition to extract radiologists' experiential intuition in mammography interpretation (Ebel, Söllner, Leimeister, Crowston, & de Vreede, 2021; McKinney et al., 2020). However, if the organizational learning mechanisms are highly efficient, the residual tacit knowledge available for AI extraction diminishes, thereby differentiating AI's roles in UTD and RTD.

In related technological domains, much tacit knowledge has been partially formalized into explicit forms or internalized through path-dependent learning mechanisms, thereby diminishing the amount of remaining tacit knowledge readily available for AI to extract. Specifically, firms have developed mature organizational learning mechanisms, such as formalized processes, procedural routines, and IT infrastructures (Kucharska & Erickson, 2023), facilitating the conversion of tacit into explicit knowledge. The residual tacit knowledge is predominantly embedded in highly contextual practices, like emergent clinical decision-making or specific production line adjustments, characterized by high specificity and discreteness, thus constraining AI extraction. Moreover, much of the new tacit knowledge from related technical domains obtained through AI tends to overlap with the existing knowledge within firms, leading to increased redundancy and suboptimal value creation (Kretschmer & Symeou, 2024). Consequently, AI's incremental contribution to RTD advancement is substantially diluted by the efficiency of path-dependent organizational learning systems.

In contrast, within unrelated technological domains, path-dependent organizational learning mechanisms are less efficient, leaving much explicit knowledge not acquired and the majority of tacit knowledge not explicit (Nooteboom, Van Haverbeke & Duysters et al., 2007). Consequently, a rich reservoir of explicit and tacit knowledge from unrelated technological domains remains accessible for AI extraction. Before AI adoption, firms encountered dual challenges in knowledge transformation: (1) the absence of foundational cognitive frameworks for unrelated domains, which hinders the identification of tacit knowledge (Prusak, 1997), and (2) the lack of practical trial-and-error learning, which limits the efficiency of tacit-to-explicit knowledge conversion (Prusak, 1997). These limitations constrain the efficiency of path-dependent learning mechanisms in obtaining tacit knowledge from unrelated domains but also signify substantial potential for AI to extract such knowledge. Given AI's higher returns and innovative problem-solving capabilities, firms exhibit greater demand for AI technologies when new technological opportunities emerge, aiming to pursue diverse technological advancements through varied recombination strategies (Babina et al., 2024; Boussioux, Lane, Zhang, Jacimovic, & Lakhani, 2024; Wu, Hitt, & Lou, 2020). First, firms can leverage eXplainable AI to analyze technical themes in patent documents from unrelated technological domains (Jang et al., 2023), thereby quickly gaining explicit knowledge in those areas. Meanwhile, AI technologies based on feature selection methods can identify and extract critical tacit knowledge (Yazici et al., 2020), constructing cross-modal knowledge networks for the systematic mining of tacit knowledge. Second, drawing on Nonaka's SECI model, AI accelerates the socialization and externalization of tacit knowledge (Ahamad & Mishra, 2024), facilitating knowledge integration and cross-technological recombination from unrelated domains (Tsouri et al., 2022; Wu, Lou, & Hitt, 2024). This promotes connections and complementarities among different types of technologies (Brem et al., 2023), enhancing firms' adaptability across various technological domains (Grashof & Kopka, 2022).

Therefore, in related technical domains, much of the tacit knowledge can be effectively captured through path-dependent organizational learning mechanisms, rendering it explicit. Conversely, in unrelated technical domains, the path-dependent learning mechanisms are inefficient, leaving a substantial reservoir of tacit knowledge available for AI extraction. This underscores the more pronounced role of AI in promoting firm UTD.

Hypothesis 1a: (H1a) AI has a positive effect on firm UTD.

Hypothesis 1b (H1b): AI does not have a positive effect on firm RTD.

Moderation Effect

The moderating effect of core-technology competence

Core-technology competence shows the importance of performing R&D outside the current technical domain for firms (Choi & Lee, 2021). The core-technology competence of firms includes 'combination capabilities' and 'architecture capabilities' (Henderson & Cockburn, 1994). The former pertains to the mastery and practical application of existing technologies, enabling firms to address commonly related challenges. The latter refers to the absorption, comprehension, and innovative application of new technologies, fostering the development of new knowledge (Grant, 1996; Henderson & Cockburn, 1994). This multifaceted capability equips firms to cope with new technologies while maintaining existing skills (Kim, Lee, & Cho, 2016).

First, firms with strong core-technology competence have established a solid R&D foundation and are adept at leveraging their existing technological expertise to create novel combinations of technologies, which means they can more effectively absorb knowledge from multiple domains obtained through AI (Henderson & Cockburn, 1994). Simultaneously, these firms often attract talent with high-caliber R&D management skills (Leonard-Barton, 1992), who excel in identifying and comprehending diverse technical knowledge that can be integrated into their existing technological frameworks. Empowered by AI, they possess the foresight to facilitate the fusion of foundational and cutting-edge technologies, promoting profound restructuring within innovation systems (Liu & Ali, 2022), thereby enhancing the efficiency of acquiring and recombining various types of knowledge. This expansion of knowledge boundaries significantly contributes to TD.

Second, RTD, focusing on the extension of existing related technological domains, necessitates the efficient restructuring of explicit knowledge. Firms with high core-technology competence are adept at systematically capturing and structuring explicit knowledge through their current technologies, integrating it into their firm technology management systems (Grant, 1996), which not only increases the internal diversity of related technologies but also accelerates the role of AI in recombining explicit knowledge, thereby fostering RTD. In contrast, UTD emphasizes the acquisition of tacit knowledge and the recombination of both tacit and explicit knowledge. Firms with less advanced core-technology competence struggle to identify and manage diversified knowledge in remote and unrelated domains, which are typically characterized by higher uncertainty (Kim et al., 2016). Their architectural capabilities come into play in more innovatively applying new technologies to attain and manage new knowledge, augmenting AI's effectiveness in unrelated technological domains (Grant, 1996; Henderson & Cockburn, 1994). Furthermore, when a firm endeavors to broaden its technological footprint, it inevitably faces the increasing complexity and heightened coordination demands of its technology portfolio (Lee et al., 2017). Firms with superior core-technology competence leverage their combinatorial capabilities to harmonize and integrate disparate knowledge categories (Choi & Lee, 2021).

Hypothesis 2 (H2): Core-technology competence positively moderates the relationship between AI and firm TD.

Hypothesis 2a (H2a): Core-technology competence positively moderates the relationship between AI and firm UTD.

Hypothesis 2b (H2b): Core-technology competence positively moderates the relationship between AI and firm RTD.

The moderating effect of knowledge stocks

Knowledge stocks are the set of explicit knowledge and tacit knowledge that firms accumulate over time (Teece et al., 1997). According to the KBV, knowledge stock represents a strategic asset accumulated over the long term by a firm. To develop a diversified knowledge base, firms need to consider the influence of existing knowledge characteristics (Grant, 1996). While long-term knowledge accumulation implies that the firm is less susceptible to being overtaken by short-term rivals, it also signifies a deepening of experience within specific knowledge domains (Kang et al., 2019). Therefore, we introduce knowledge stocks to examine the boundary issues concerning the relationship between AI and firm TD, including UTD and RTD.

Deep knowledge stocks often reflect the specialization of knowledge in a certain technical domain, resulting in higher similarity and a narrower gap between knowledge elements (Breschi et al., 2003; Chen, Lin, Lin, & Hsiao, 2018). However, improving TD necessitates that firms possess diverse knowledge and skills to achieve breadth. Paradoxically, the knowledge dependence and learning inertia stemming from specialization can diminish firms' motivation to fully harness AI in acquiring diverse knowledge (Kang et al., 2019). This can stifle creative thinking and innovative behavior, as the comfort of existing expertise might overshadow the pursuit of novel, diverse insights

(Kang et al., 2019; Teece et al., 1997). Therefore, deep knowledge stocks will weaken the positive impact of AI on TD.

Regarding RTD, deep knowledge stocks often lead firms to focus their resources on specific technological domains while potentially neglecting the importance of related domains. However, the gains of a particular knowledge domain show a decreasing pattern (Klette & Kortum, 2004). Even with AI, under conditions of high specialization and improper resource allocation, AI's ability to innovatively recombine related explicit knowledge is constrained (Galunic & Rodan, 1998), resulting in diminishing returns and thereby inhibiting the promotion of AI in RTD within firms. Simultaneously, as for UTD, firms need to internalize the tacit knowledge they acquire. The transformation of tacit knowledge into explicit knowledge is a prevailing trend in knowledge integration within modern firms (Spender, 2014). However, the incremental new knowledge introduced by AI and the deeply specialized knowledge from a firm's internal knowledge base amplify the incompatibility of knowledge structures, making knowledge integration more difficult (Capaldo, Lavie, & Messeni Petruzzelli, 2016). Consequently, knowledge stocks negatively influence the relationship between AI and firm UTD.

Hypothesis 3 (H3): Knowledge stocks negatively moderate the relationship between AI and firm TD.

Hypothesis 3a (H3a): Knowledge stocks negatively moderate the relationship between AI and firm UTD.

Hypothesis 3b (H3b): Knowledge stocks negatively moderate the relationship between AI and firm RTD.

Research Design

Sample Selection and Data Source

According to *The Global AI Index* published by the UK's Tortoise Media, the United States and China rank first and second, respectively, in the global AI landscape. While the United States maintains a clear lead in terms of technological iterations, China, as the world's manufacturing hub, boasts a more comprehensive industrial system and a broader category of sectors. This diversity in its industrial portfolio fosters a wider variety of application scenarios for AI, thereby providing a rich research context for both UTD and RTD studies in the AI domain.

Therefore, this study selects 2,054 manufacturing firms listed on the Shanghai and Shenzhen stock exchanges from 2013 to 2022 as the sample. Because the annual reports of listed firms are relatively complete, they offer comprehensive financial and patent data. According to the *China Artificial Intelligence Development Report 2020* released by Tsinghua University, AI technologies made breakthrough progress in deep learning in 2013. Since then, AI has been broadly applied across a variety of industries. Therefore, I have chosen 2013 as the starting point for my research. We divide Chinese manufacturing firms into two categories: the first category is manufacturing firms engaged in AI research or AI product manufacturing, that is AI developers; the second category is manufacturing firms that apply typical AI products, technologies, or solutions to their business management processes, including R&D, production, marketing, operation, and maintenance (Xie, Ding, Xia, Guo, Pan, & Wang, 2021). Given the research focus on AI's impact on firm TD, this study concentrates on the latter category. Because the former category firms are engaged in AI research and development from the beginning to the end, there are more complex mechanisms between AI and firm TD. Specifically, the following criteria were applied to screen and select data: (1) There are 67 AI-based manufacturing firms whose main business is the research and development of AI technology or the manufacture of AI products; (2) firms that have been delisted, suspended, or terminated; (3) ST and *ST firms; and (4) firms with serious missing of important data during the survey period. After excluding the firms under these rules, this article takes the remaining 1,987 manufacturing firms as research samples.

The AI data used in this paper aresourced from annual reports publicly disclosed by firms through content analysis. Additionally, patent data are obtained from the State Intellectual Property Office of China (CNIPA), while financial data are derived from the China Securities Market Accounting Research Database (CSMAR). To mitigate the impact of outliers on the results, we winsorize all continuous variables at the 1% level separately by calendar year in this research (Jäger, Schoefer & Heining, 2021).

Variable Description

Independent variable: AI

AI has penetrated many industries, yet the measurement of AI has not reached a consensus in the academic community. Previous studies mainly measure AI based on two primary sources: data related to industrial robots within firms (Wang, Zhou, & Chiao, 2023) and the frequency of AI-related words in firm annual reports (Li et al., 2023; Wang, Sun, & Xu, 2022; Xie et al., 2021). Nevertheless, the former approach tends to underestimate the diverse application scenarios of AI in manufacturing firms, whereas the latter is more comprehensive. Consequently, we argue that the latter approach is more appropriate for our research. It is noteworthy, however, that previous research employing text analysis mistakenly includes AI-related vocabulary extracted from the industry overview sections of the firm's annual reports, leading to measurement errors. To refine this approach, in this study, we harness text analysis in conjunction with residual analysis to scrutinize the distribution characteristics of AI-related word frequencies in the annual reports of 1,987 listed manufacturing firms in China, aiming to ascertain whether these firms have adopted AI and identify the initial year of AI adoption.

First, we establish a dictionary of AI-related terms based on previous research. Wang and scholars utilized a set of AI-related terms in the *China Artificial Intelligence Development Report 2018* released by Tsinghua University as the key dictionary (Wang et al., 2022). Building upon this, our study leverages the top 20 feature words extracted from AI patents (Miric, Jia, & Huang, 2022) and considers the cooperation density of AI technology outlined in *China's New Generation of AI Industry Development Report 2023* released by the China Artificial Intelligence Development Strategy Research Institute. Consequently, we update the original key dictionary with the following 25 AI keywords: Internet of Things (IoT), autonomous driving, virtual reality, intelligent recommendation, blockchain, biometrics, human-computer interaction, knowledge graph, machine translation, pattern recognition, neural networks, image matching, recognition systems, information processing, big data, cloud computing, intelligent robotics, machine learning, computer vision, space technology, learning algorithms, speech recognition, augmented reality, smart chips, and natural language processing.

Then, this article extracts the above 25 keyword frequencies from the annual reports disclosed by listed firms to find out all AI-related keyword frequencies. However, it is noteworthy that the market background section of a firm's annual reports often references the application of AI within the industry. To mitigate the impact of this section on the final research outcomes, we analyze the regression residual. Specifically, we regress the AI-related word frequency obtained from firms against the industry's average value. Subsequently, we analyze the residuals. If the residuals remain positive for three consecutive years, we consider the year of the initial positive residual as the time when the firm first adopted AI. If the residual is positive and negative alternately, or only two consecutive years of positive, we combine this information with the firm's word frequency data for the corresponding years. In such cases, a manual examination of the firm's annual report is conducted to ascertain whether AI adoption occurred and to determine the specific timing at which the firm adopts AI.

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According to the above rules, if a firm adopts AI, $Treat_{it}$ is 1, otherwise 0. If AI is adopted in year t, $Post_{it}$ is 0 before year t and $Post_{it}$ is 1 after (and including) year t. The independent variable, DID_{it}, is the cross term of the dummy variables for $Treat_{it}$ and $Post_{it}$.

Dependent variable: TD

TD. As defined earlier, TD represents the degree to which a firm's knowledge is dispersed across various technical domains. Meanwhile, the patent IPC classification number is widely used in the research of patent scope (Huang & Chen, 2010). Patents categorized by technical levels are segmented into sections (e.g., A), classes (e.g., A01), subclasses (e.g., A01B), and groups (e.g., A01B33/00). Following the research of Bolli, Seliger, and Woerter (2019; Duan, Deng, et al., 2022), the four-digit IPC subclass is used to distinguish technological domains. Therefore, this article uses the entropy index method to measure firm TD (Aldieri, Makkonen, & Paolo Vinci, 2020; Carnabuci & Operti, 2013):

$$\textit{Technological diversification}\,(TD) = \sum_{j=1}^{n} P_j \times \ln\left(\frac{1}{P_j}\right) \tag{1}$$

P_j is the share of firms that have filed at least one patent as an inventor in the technological domain j in the last three years, and $\ln\left(\frac{1}{P_j}\right)$ is the weight of each four-digit IPC subclass, which is calculated as the reciprocal natural logarithm of the number of patents as a share. The sum of the shares of all technology categories is the degree of firm TD. If a firm is only engaged in research in a specific technology area, the index is 0. And if it specializes in different technology areas, the index is close to $\ln(N)$.

The entropy index measure can be divided into related and unrelated categories, which have higher consistency in the discriminant and prediction tests. So, it is useful for evaluating the variance within the group. We utilize the entropy measure to divide TD into RTD and UTD (Liu et al., 2020).

UTD. As defined by Chatterjee and Blocher, UTD represents the degree to which a firm is diversified in unrelated technology areas, which is measured as the entropy of the distribution of patents over first-level-patent categories (Chatterjee & Blocher, 1992; Chen et al., 2012; Zabala-Iturriagagoitia, Gómez, & Larracoechea, 2020):

$$\textit{Unrelated technological diversification}\,(UTD) = \sum_{k=1}^{n} P_k \times \ln\left(\frac{1}{P_k}\right) \tag{2}$$

P_k is the share of firms that have filed at least one patent as an inventor in the technological domain k in the previous three years.

RTD. Because TD is composed of RTD and UTD. TD is the union of UTD and RTD. RTD is calculated as follows (Chen et al., 2012):

$$\textit{Related technological diversification}\,(\mathrm{RTD}) = TD - UTD \tag{3}$$

Moderators: core-technology competence and knowledge stocks

Core-technology competence. There are two main measures at present. The first is to use the technological domain with the highest volume of patent applications. However, this method overlooks the cross-technology patent tendency exhibited by certain firms and fails to account for industry-specific variations in relative strength among firms. The second approach is to use the revealed technology advantage (RTA) index. The RTA index is often used to study a firm's technical depth and technical advantages in the industry (Choi & Lee, 2021; Kim et al., 2016), which can overcome the shortcomings of the first measure. In year t, the RTA index of firm i in the technological domain j is calculated as follows:

$$RTA_{ijt} = \frac{P_{ijt}/P_{it}}{P_{jt}/P_t} \tag{4}$$

P_{ijt} is the number of patent applications for the firm i in the technological domain j at time t. P_{it} is the total number of patent applications by the firm i at time t ($P_{it} = \sum_{j}^{n} P_{ijt}$). P_{jt} is the total number of patent applications by the entire sample firms in the technological domain j at time t ($P_{jt} = \sum_{i}^{n} P_{ijt}$). P_t is the total number of patent applications by all firms in the technological domain j at time t ($P_t = \sum_{i}^{n} \sum_{j}^{n} P_{i,jt}$).

As seen from the above formula, the RTA index calculates the ratio of the patent share of firm i in the technological domain j (P_{ijt}/P_{it}) to the total patent application share of all firms in the technological domain j (P_{jt}/P_t), which reflects the comparative advantage of firm i in the technological domain j in the whole industry. When the RTA index is greater than 1, it indicates that the firm's level in the technological domain j is higher than the industry average level; when the RTA index is less than 1, it indicates that the firm's level in the technological domain j is lower than the industry level.

Either interpretation indicates that the RTA index represents firm i's comparative advantage in technological field j. As the measure of firm-specific core-technology competence, we use the maximum value among the RTA indexes (i.e., relative strength) multiplied by the number of patent applications for the corresponding technological domain (i.e., absolute strength) (Choi & Lee, 2021; Kim et al., 2016; Patel & Pavitt, 1997). The calculation formula is as follows:

$$CORETECH_{it} = \ln\left[max\left\{RTA_{ijt} \cdot P_{ijt}\right\}\right] \tag{5}$$

Knowledge stocks. Patent stock serves as a metric for quantifying a firm's knowledge reservoir. This reservoir encapsulates the innovative accomplishments attained by the firm (Bolívar-Ramos, 2017). To explore how historical knowledge accumulation moderates the relationship between AI and firm TD, this article examines the total number of patents granted by firms in the past three years (in thousands of records) to measure the knowledge stocks by firms (Chenet al., 2018).

$$PreStore_{it} = \sum_{t-1}^{t-3} store_{it} \tag{6}$$

Control variables

Given that the adoption and implementation of technology within a firm are influenced by multifaceted factors, including organizational resources and profitability, this study selects the following control variables based on prior research (Li et al., 2023; Tian et al., 2023; Yayavaram & Chen, 2014): (1) *Firm age (AGE)* – the logarithm of the time interval from the year of firm establishment to the study year (Kim et al., 2016); (2) *Firm growth (TOBINQ)* – measured by Tobin's *Q* value, which reflects the market value of a firm relative to its assets; (3) *Firm profitability (ROA)* – measured by the return on total assets, providing insights into financial performance; (4) *Firm quick-freezing ratio (Quickratio)* – the ratio of quick-freezing assets and current liabilities; (5) *Firm asset-liability ratio (LEV)* – the ratio of total liabilities and total assets of the firm; (6) *Firm R&D intensity (RDratio*) – the ratio of R&D expenditure to total operating income; (7) *Influence of major shareholders (Sharehold*) – the shareholding ratio between the first and second largest shareholders; and (8) *CEO duality (DUAL*) – a dummy variable, if the chairman and the general manager are the same one, the value is 1, and otherwise, it is 0.

Variable definitions and summary statistics are presented in Tables 1 and 2, respectively. Table 3 presents the correlation coefficients between all variables. Furthermore, Fig. 2 depicts the adoption rate of AI among Chinese manufacturing firms from 2013 to 2022. Notably, between 2017 and 2019, significant advancements in AI technologies were observed, including the introduction of deep learning frameworks such as TensorFlow 1.0 and the emergence of edge computing (Grzybowski, Pawlikowska-Lagod, & Lambert, 2024). These developments have been instrumental in

Table 1. Variable definitions

Variable	Definition
Treat	AI dummy: 1 if the firm adopts AI, 0 otherwise
Post	AI adoption year dummy: 1 for all years after (and including) the year of AI adoption, 0 otherwise
DID	Interactions of treat and post
TD	Technological diversification measured by the methods of Aldieri et al. (2020); Carnabuci and Operti (2013); and Chen et al. (2012)
UTD	Unrelated technological diversification measured by the methods of Chen et al. (2012) and Zabala-Iturriagagoitia et al. (2020)
RTD	Related technological diversification measured by the method of Chen et al. (2012)
AGE	The logarithm of the elapsed years since the firm's establishment measured by the method of Choi and Lee (2022)
ROA	Return on Assets
DUAL	Management power dummy: 1 if the chairman and the general manager are the same person, 0 otherwise
TOBINQ	Firm growth measured by Tobin's *Q*
RDratio	The ratio of R&D expenses to total revenue
LEV	The ratio of total liabilities to total assets
Quickratio	The ratio of liquid assets to current liabilities
Sharehold	The shareholding ratio of the first- and second-largest shareholders.
CORETECH	Core-technology competence measured by the method of Kim et al. (2016)
PreStore	Knowledge stocks measured by the method of Chen et al. (2018)

facilitating efficient production management and real-time decision-making in manufacturing firms. Consequently, the period from 2017 to 2019 witnessed a notable increase in the application of AI within firms' operations. Moreover, Table 2 reveals a pronounced variation in firm TD, with a standard deviation of 1.209. This indicates that many firms have considerable scope for TD improvement. These observations highlight the importance of investigating the potential of AI to bolster TD within firms.

Model Design

The main purpose of this article is to assess the influence of AI on firm TD and its subtypes, RTD and UTD. Additionally, we explore the moderating effect of core-technology competence and knowledge stocks in the process. The DID method can accurately estimate the causal effect of an event on special groups based on the time of the event and the presence or absence of individual-specific trends (Ashenfelter & Card, 1985; Xie et al., 2021). Referring to the relevant research, AI is selected as a quasi-natural experiment (Li et al., 2023; Tian et al., 2023; Zhou, Luo, Ye, & Tao, 2022). Since the traditional DID model is only applicable to the simultaneous occurrence of quasi-natural experiments, we adopt a multi-period DID model to account for varying adoption times across firms. Specifically, we designate manufacturing firms that have adopted AI as the experimental group, contrasting them with manufacturing firms that have not adopted AI, serving as the control group.

Baseline model

First, we construct a baseline regression model to explore the impact of AI on firm TD, including RTD and UTD:

$$TD_{it} = \alpha_0 + \beta_0 DID_{it} + X_{it} + \sigma_t + \gamma_j + \delta_k + \zeta_i + \varepsilon_{ijt} \tag{7}$$

Table 2. Summary statistics for variables

	Mean	SD	Min	Max
DID	0.297	0.457	0.000	1.000
TD	2.662	1.209	0.000	5.497
UTD	1.393	0.720	0.000	2.942
RTD	1.267	0.721	0.000	3.050
AGE	2.919	0.313	1.609	3.584
ROA	0.045	0.057	−0.224	0.234
DUAL	0.287	0.452	0.000	1.000
TOBINQ	1.995	1.194	0.786	9.797
RDratio	4.146	3.026	0.050	19.630
LEV	0.412	0.182	0.052	0.896
Quickrate	1.780	1.597	0.155	14.614
Sharehold	7.767	11.909	1.001	120.200
PreStore	0.172	0.355	0.001	3.312
CORETECH	6.799	1.256	3.967	10.338

$$UTD_{it} = \alpha_0 + \beta_0 DID_{it} + X_{it} + \sigma_t + \gamma_j + \delta_k + \zeta_i + \varepsilon_{ijt} \tag{8}$$

$$RTD_{it} = \alpha_0 + \beta_0 DID_{it} + X_{it} + \sigma_t + \gamma_j + \delta_k + \zeta_i + \varepsilon_{ijt} \tag{9}$$

$$DID_{it} = Treat_{it} \times Post_{it} \tag{10}$$

In the model, the subscripts i, t, and j represent the firm, year, and industry, respectively. α is an intercept. σ_t represents firm fixed effect. γ_j represents the year fixed effect, and δ_k represents industry fixed effects. ζ_i represents the province fixed effect. And ε_{ijt} is a random error term. The core explanatory, DID_{it}, is the cross term of dummy variables for $Treat_{it}$ and $Post_{it}$. Its coefficient β is the focus of this paper. A positively significant coefficient indicates that AI promotes TD in firms, whereas a negatively significant coefficient suggests otherwise.

Moderation model

Through the theoretical analysis in the previous section, we will further discuss the moderating effect on the relationship between AI and TD, considering the core-technology competence and knowledge stocks of firms. The specific model settings are as follows:

(1) The moderating effect of core-technology competence:

$$\begin{aligned} TD_{it} = {} & \alpha_1 + \beta_2 DID_{it} + \eta_1 CORETECH_{it} + \eta_2 DID_{it} \times CORETECH_{it} \\ & + X_{it} + \sigma_t + \gamma_j + \delta_k + \zeta_i + \varepsilon_{ijt} \end{aligned} \tag{11}$$

To assess the effectiveness of the moderating effect, we focus on the coefficient of DID_{it} and the interactive items $DID_{it} \times CORETECH_{it}$, considering both their sign consistency and statistical significance. Specifically, if η_2 exhibits statistical significance and aligns with the sign of β_2 (either positive or negative), it indicates that the core-technology competence of firms reinforces AI's role in promoting TD.

Table 3. Correlation coefficients

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. *DID*	1												
2. *TD*	0.230***	1											
3. *UTD*	0.206***	0.839***	1										
4. *RTD*	0.179***	0.840***	0.411***	1									
5. *AGE*	0.111***	0.148***	0.150***	0.098***	1								
6. *ROA*	−0.024***	−0.022**	−0.033***	−0.004	−0.065***	1							
7. *DUAL*	0.013	−0.081***	−0.085***	−0.051***	−0.097***	0.065***	1						
8. *TOBINQ*	−0.027**	−0.174***	−0.164***	−0.129***	−0.038***	0.244***	0.049***	1					
9. *RDratio*	0.160***	0.138***	0.089***	0.143**	−0.043***	−0.022**	0.074***	0.160***	1				
10. *LEV*	0.106***	0.320***	0.307***	0.230***	0.117***	−0.403***	−0.108***	−0.276***	−0.189***	1			
11. *Quickratio*	−0.062***	−0.233***	−0.226***	−0.165***	−0.102***	0.291***	0.096***	0.226***	0.224***	−0.692***	1		
12. *Sharehold*	−0.043***	−0.006	−0.008	−0.002	0.009	−0.046***	−0.080***	−0.028***	−0.080***	0.069***	−0.040***	1	
13. *CORETECH*	0.087***	0.181***	0.154***	0.151***	0.021**	0.064***	−0.001	−0.008	0.002	0.028***	−0.048***	−0.055***	1
14. *PreStore*	0.204***	0.493***	0.463***	0.370***	0.100***	−0.027***	−0.028***	−0.130***	0.103***	0.251***	−0.138***	−0.026***	0.241***

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

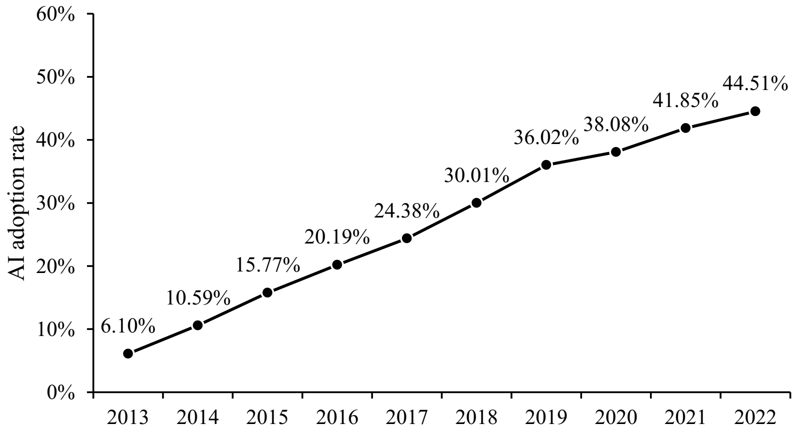


Figure 2. AI adoption rate during 2013–2022

(2) The moderating effect of knowledge stocks:

$$TD_{it} = \alpha_1 + \beta_2 DID_{it} + \eta_3 PreStore_{it} + \eta_4 DID_{it} \times PreStore_{it} + X_{it} + \sigma_t + \gamma_j + \delta_k + \zeta_i + \varepsilon_{ijt} \tag{12}$$

To assess the effectiveness of the moderating effect, we focus on the coefficient of DID_{it} and the interactive items $DID_{it} \times PreStore_{it}$, considering both their sign consistency and statistical significance. Specifically, if η_4 exhibits statistical significance and diverges from the sign of β_2 (particularly if it is negative), it indicates that the knowledge stocks of firms attenuate the promotional impact of AI on TD.

Empirical Test and Analysis

The Impact of AI on TD

Since the data in this study are observational rather than experimental, employing the multi-period DID model for demonstration is prone to the problem of 'selection bias' (Zhou et al., 2022). Specifically, before the firm adopts AI, there is no guarantee that there will be similar individuals in the control group and the experimental group. Since the research object of this article is Chinese manufacturing firms, inherent individual differences are inevitable. To mitigate the potential selectivity bias in our empirical results, we use the propensity score matching (PSM) method. Individual characteristics used for identification include all control variables and the industry to which a firm belongs. We implement one-to-three nearest-neighbor matching and construct a Logit model to estimate propensity scores (Liet al., 2023). In the matching balance test, the PSM method significantly reduces the deviation between the treatment firms and the control firms, and no significant difference is found in the mean of covariates between the treatment group and the control group at a significance level of 5%, suggesting that the matching effect is satisfactory.

This article uses the fixed effects method to examine the relationship between AI and firm TD by constructing a multi-period DID model. In addition, we apply VIF for testing before regression to avoid multicollinearity between variables. The experimental results show that the VIF value of each variable is less than 10, and the highest value across all models and variables was less than 2.26, indicating that the problem of multicollinearity is not significant among the independent and control variables. Therefore, the variables can be regressed. The results of the baseline regression are reported in Table 4. Notably, regardless of whether control variables are added, AI significantly promotes firm TD. AI facilitates large-scale data mining and knowledge recombination, enabling firms to transcend

Table 4. Impact of AI on TD and its two types

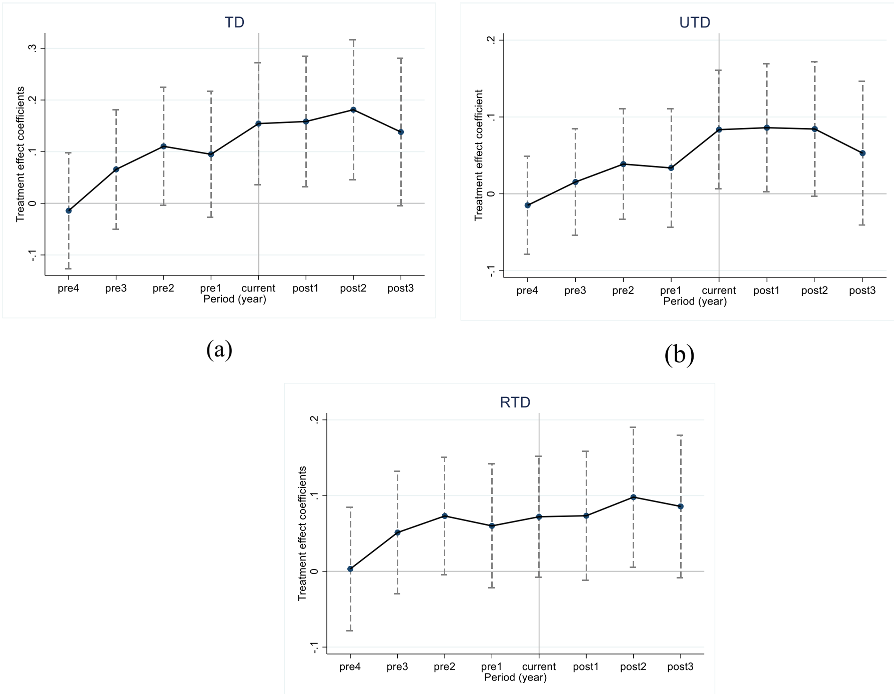
	(1) TD	(2) TD	(3) UTD	(4) UTD	(5) RTD	(6) RTD
DID	0.083**	0.076**	0.062***	0.058***	0.022	0.019
	(0.034)	(0.034)	(0.022)	(0.022)	(0.025)	(0.025)
AGE		0.390*		0.338**		0.048
		(0.209)		(0.142)		(0.143)
ROA		1.023***		0.465***		0.572***
		(0.245)		(0.140)		(0.168)
DUAL		0.061*		0.023		0.038*
		(0.032)		(0.020)		(0.023)
TOBINQ		−0.012		−0.006		−0.006
		(0.011)		(0.007)		(0.008)
RDratio		0.034***		0.019***		0.015***
		(0.008)		(0.005)		(0.005)
LEV		0.670***		0.371***		0.305***
		(0.135)		(0.085)		(0.093)
Quickratio		−0.003		−0.0005		−0.003
		(0.011)		(0.007)		(0.007)
Sharehold		−0.002		−0.001		−0.001
		(0.001)		(0.001)		(0.001)
Constant	2.645***	1.073*	1.378***	0.155	1.265***	0.923**
	(0.010)	(0.609)	(0.007)	(0.415)	(0.007)	(0.419)
Observations	11,175	11,175	11,175	11,175	11,175	11,175
Adjusted R^2	0.630	0.633	0.667	0.670	0.413	0.415
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

the constraints of a single technology and expand into multiple technological domains. Furthermore, to enhance the robustness of our findings, we control for individual, year, province, and industry fixed effects. Even after accounting for these factors, the results remain statistically significant at the 5% level. Consequently, we accept H1.

The Impact of AI on Two Types of TD

To further study the heterogeneous impact of AI on two types of TD, this article categorizes TD into UTD and RTD. Employing a benchmark regression approach, the empirical results can be seen in Table 4. In models (3) and (4), regardless of whether the control variables are added or not, AI can significantly contribute to UTD. Even after controlling for the individual, year, province, and industry fixed effects, the core explanatory variable DID remains positively significant at the 1% level. However, when examining the impact of AI on RTD, we find that it does not influence the diversification patterns within firms. Therefore, H1a and H1b are verified.



(a) (b) (c)

Figure 3. Dynamic trend test
Notes: The *x*-axis represents the adoption year of AI by the firm. The *y*-axis represents the coefficient value of treatment effect. The vertical dashed line in the graph represents the 95% confidence interval.

Robustness Test

Dynamic trend test

The prerequisite for the use of multi-period DID is that the experimental group and the control group met the parallel trend beforehand, indicating that the two groups showed similar trends in TD before adopting AI. We conducted a parallel trend test to ensure the validity of the DID model (Wu & Huo, 2023). In (a), (b) and (c) from Fig. 3, we can see that before adopting AI, TD, UTD, and RTD were not significant at the 95% confidence interval over the four years, which indicated that the experimental and control groups showed a consistent trend before adopting AI. Simultaneously, the promoting effect of AI adoption on firm TD is significant at the 5% level and persists until the third period. Its influence on UTD within firms is significant within the first two years following adoption. In contrast, the effect on RTD exhibits a notable lag, only becoming significant by the third period, and overall, its effect on RTD is not significant. Hence, the dynamic trends further substantiate that AI is the driver of improvements in TD and UTD.

Placebo test

To test the influence of AI on TD and its subtypes, we address the potential influence of random factors or unobserved variables. Specifically, our objective is to ascertain whether observed changes indeed result from the adoption of AI by firms. Our core explanatory variable, DID, was randomly sampled 500 times (Ferrara, Chong & Duryea, 2012).

Figure 4 shows the estimated coefficients and *P*-value density distribution of core explanatory variables obtained through random sampling. As seen (a), (b) and (c) from Fig. 4, under the random

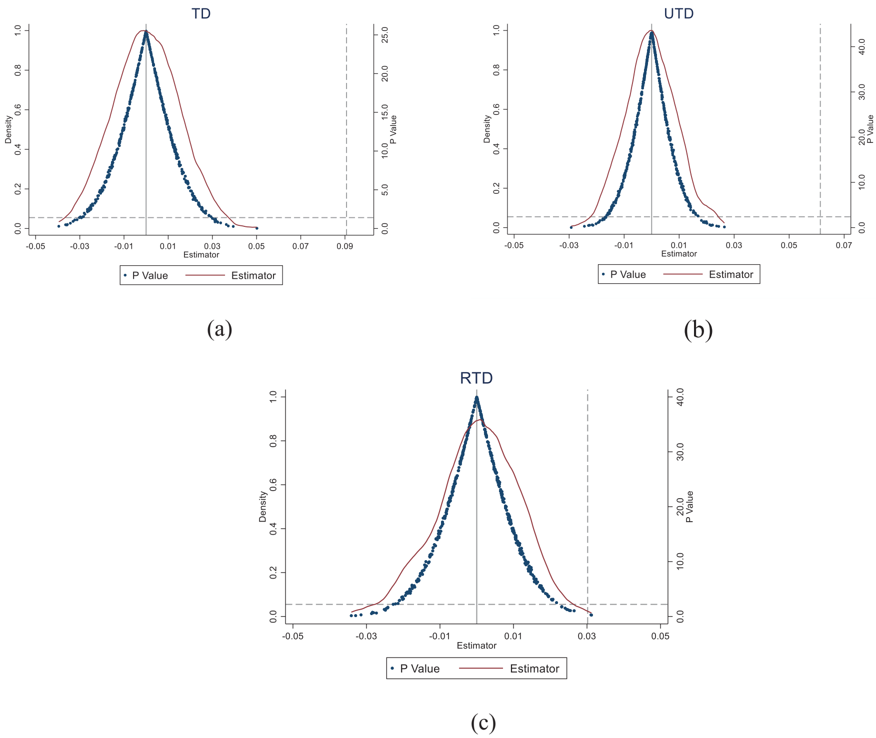


Figure 4. Placebo test

sampling of 800 times, the coefficients obey a normal distribution around the zero value. Moreover, the coefficients are far away from our baseline regression estimate. Therefore, it is proved that the influence of AI on firm TD and its classification is robust and not accidental.

Change PSM method

We replaced the matching method used in the PSM analysis. This approach is intended to ensure that our primary findings are not influenced by the specific choice of matching technique. Specifically, we substituted the original nearest neighbor matching with radius matching (Li et al., 2023). This substitution enables us to verify the consistency and reliability of our results across different matching methods. Table 4 reports the DID results for the sample matched using the radius matching method.

In Table 5, the sample matching method does not change the conclusion of this article. AI significantly improves the TD in firms, including UTD. However, the impact of AI on RTD remains statistically insignificant. Thus, our previous empirical findings are still robust when considering the sample selectivity bias.

Replace the independent variable

Measuring the adoption of AI technologies crucially involves constructing a lexicon. In our benchmark regression, we compiled a list of 25 AI-related terms based on previous research (Li et al., 2023; Miric et al., 2022; Wang & Qiu, 2023). To provide a more comprehensive assessment of AI characteristics and their impact on firms, we employed the AI dictionary constructed by Yao, Zhang, Guo, and Feng (2024). The construction method for this dictionary was as follows: First, drawing upon industry reports on AI and the AI vocabulary provided by the World Intellectual Property Organization, we selected 52 seed words. Subsequently, utilizing the Word2Vec method and

Table 5. PSM regression by radius matching

	(7) TD	(8) TD	(9) UTD	(10) UTD	(11) RTD	(12) RTD
DID	0.099*** (0.032)	0.091*** (0.032)	0.066*** (0.021)	0.061*** (0.021)	0.034 (0.023)	0.030 (0.023)
AGE		0.428** (0.198)		0.340*** (0.131)		0.083 (0.135)
ROA		0.858*** (0.227)		0.368*** (0.131)		0.505*** (0.154)
DUAL		0.050* (0.030)		0.014 (0.019)		0.037* (0.021)
TOBINQ		−0.022** (0.010)		−0.012* (0.007)		−0.009 (0.007)
RDratio		0.031*** (0.008)		0.017*** (0.005)		0.015*** (0.005)
LEV		0.605*** (0.128)		0.331*** (0.079)		0.281*** (0.087)
Quickratio		−0.005 (0.010)		−0.0003 (0.007)		−0.005 (0.007)
Sharehold		−0.002 (0.001)		−0.001 (0.001)		−0.001 (0.001)
Constant	2.632*** (0.010)	1.018* (0.580)	1.374*** (0.006)	0.186 (0.385)	1.257*** (0.007)	0.840** (0.397)
Observations	12,610	12,610	12,610	12,610	12,610	12,610
Adjusted R^2	0.629	0.632	0.664	0.667	0.416	0.418
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Skip-gram model, we trained the corpus using text materials from annual reports and patent documents. Based on the cosine similarity between the seed words and output words, we identified the 10 most semantically similar words for each seed term. Next, we eliminated duplicate words, those unrelated to AI, and those with excessively low frequency. This process culminated in a final set of 73 words constituting our AI lexicon for this study, which is detailed in the Appendix.

According to this AI dictionary, we use the natural logarithm of AI keywords plus 1 (lAIwords) as a proxy for AI drawing on the listed firm's annual report. Regression results are shown in Table 6. After changing the core explanatory variable, AI remains statistically significant at the 1% level on TD and UTD, whereas its impact on RTD is insignificant. These results attest to the robustness of our previous findings.

Replace the dependent variable

The Herfindahl index is commonly used to measure the TD. So we use the Garcia-Vega method to replace the original measure with the adjusted Herfindahl index (***aHHI***) (Garcia-Vega, 2006). The

Table 6. Replace the independent variable

	(13) TD	(14) UTD	(15) RTD
lAIwords	0.101***	0.069***	0.032
	(0.029)	(0.018)	(0.022)
AGE	0.393*	0.342**	0.047
	(0.208)	(0.141)	(0.143)
ROA	1.013***	0.455***	0.572***
	(0.245)	(0.140)	(0.169)
DUAL	0.059*	0.022	0.037
	(0.032)	(0.020)	(0.023)
TOBINQ	−0.012	−0.006	−0.005
	(0.011)	(0.007)	(0.008)
RDratio	0.034***	0.019***	0.015***
	(0.008)	(0.005)	(0.005)
LEV	0.659***	0.366***	0.300***
	(0.135)	(0.085)	(0.093)
Quickratio	−0.004	−0.001	−0.003
	(0.011)	(0.007)	(0.007)
Sharehold	−0.002	−0.001	−0.001
	(0.001)	(0.001)	(0.001)
Constant	1.050*	0.136	0.920**
	(0.608)	(0.413)	(0.420)
Observations	11,160	11,160	11,160
Adjusted R^2	0.634	0.670	0.416
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

calculation formula is as follows:

$$adjusted\ diversity = \left(1 - \sum_{j=1}^{n} \left(\frac{N_{ij}}{N_i}\right)^2\right) \left(\frac{N_i}{N_i - 1}\right) \tag{13}$$

N_{ij} refers to the number of patents authorized by i in the technical domain j, and N_i refers to the number of all patents authorized by the firm. Similarly, we distinguish patent scope by IPC classification number, the four-digit IPC number is used to calculate the whole firm TD. UTD is measured by the first digit IPC number, and RTD is the difference between TD and UTD. Compared to the traditional Herfindahl index, the estimate can reflect the true diversification of a firm with a limited number of patents (Garcia-Vega, 2006). Using this value as the explained variable, benchmark regression results are shown in Table 7, Models (16–18). Notably, AI contributes to UTD rather than RTD. These findings underscore the robustness of our previous results.

To more accurately measure RTD in firms, we calculate it by a three-digit IPC number, which means these patents belong to the same class. The regression result shown in Table 7, Model (19), indicates that the core independent variable is not statistically significant, which is consistent with our previous findings.

Table 7. Replace the dependent variable

	(16) aHHI-TD	(17) aHHI-UTD	(18) aHHI-RTD	(19) RTD_3-digit IPC
DID	0.008*	0.013**	−0.005	−0.0056
	(0.005)	(0.007)	(0.006)	(0.0042)
AGE	0.034	0.038	−0.007	−0.0412
	(0.026)	(0.037)	(0.034)	(0.0256)
ROA	0.023	0.0001	0.022	−0.0446
	(0.031)	(0.045)	(0.042)	(0.0296)
DUAL	0.008*	0.010	−0.002	−0.0014
	(0.004)	(0.006)	(0.006)	(0.0041)
TOBINQ	0.0001	0.002	−0.002	0.0022
	(0.002)	(0.002)	(0.002)	(0.0015)
RDratio	0.002**	0.003**	−0.001	−0.0007
	(0.001)	(0.001)	(0.001)	(0.0009)
LEV	0.064***	0.103***	−0.037*	−0.0371**
	(0.017)	(0.024)	(0.022)	(0.0167)
Quickratio	0.0004	0.003	−0.003	−0.0008
	(0.002)	(0.002)	(0.002)	(0.0015)
Sharehold	0.0001	−0.0002	0.0003	−0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	0.740***	0.375***	0.360***	0.3256***
	(0.075)	(0.109)	(0.100)	(0.0747)
Observations	10,950	10,950	10,950	11,175
Adjusted R^2	0.424	0.403	0.341	0.2373
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Change the sample period

Long-term datasets may be subject to influences from various factors, such as economic fluctuations across different periods and changes in the pace of technological advancements, which can potentially lead to instability in the results. According to the *China Artificial Intelligence Development Report 2020*, released by Tsinghua University, China hit a high in AI patent applications in 2018, indicating an intense focus on AI technology among Chinese firms that increasingly adopted AI in their operations. This study addresses this issue by shortening the sample period to investigate the relationship between AI and firm TD during the timeframe of 2018 to 2022, thereby reducing the potential confounding effects of non-research variables. The regression results, as shown in Table 8, indicate that the promoting effect of AI on firm TD is statistically significant at the 5% level without adding control variables. After considering control variables, AI's impact on UTD is significant at the 5% level. However, its impact on RTD is not statistically significant. Thus, our previous findings are robust.

Table 8. Change the sample period: 2018–2022

	(20) TD	(21) TD	(22) UTD	(23) UTD	(24) RTD	(25) RTD
DID	0.108**	0.096*	0.078***	0.071**	0.035	0.029
	(0.053)	(0.053)	(0.030)	(0.030)	(0.041)	(0.041)
AGE		0.052		0.326		−0.246
		(0.505)		(0.306)		(0.384)
ROA		0.324		0.072		0.271
		(0.310)		(0.165)		(0.236)
DUAL		0.009		−0.002		0.013
		(0.046)		(0.028)		(0.036)
TOBINQ		−0.024		−0.006		−0.018*
		(0.015)		(0.009)		(0.011)
RDratio		0.015		0.011**		0.004
		(0.010)		(0.005)		(0.008)
LEV		0.657***		0.285**		0.377**
		(0.212)		(0.113)		(0.158)
Quickratio		−0.015		−0.006		−0.010
		(0.020)		(0.011)		(0.014)
Sharehold		−0.003		−0.001		−0.002
		(0.002)		(0.001)		(0.002)
Constant	2.860***	2.442	1.491***	0.372	1.366***	1.983*
	(0.021)	(1.519)	(0.012)	(0.916)	(0.016)	(1.156)
Observations	6,686	6,686	6,686	6,686	6,686	6,686
Adjusted R^2	0.627	0.629	0.704	0.705	0.391	0.391
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Moderation Analysis

Table 9 reports the results of the moderation analysis. We incorporate the moderator , the core explanatory variable, and their interaction term into the regression model. We then assess the statistical significance of the interaction term's coefficient to test the morderation effect.

First, the coefficient of DID × CORETECH is positive, statistically significant, and consistent with the coefficient of DID, indicating that the core-technology competence positively moderates AI and TD. Notably, this effect effectively influences UTD rather than RTD. Thus, we accept H2 and H2a, while rejecting H2b.

Second, the coefficient for the interaction term DID × PreStore is significantly negative in the relationship of AI and TD, including UTD. This finding suggests that knowledge stocks weaken AI's role in promoting UTD within firms. Consequently, we accept H3 and H3a, while rejecting H3b.

Heterogeneity Analysis

To further study the relationship between AI and firm TD, this article conducts a heterogeneity analysis from three aspects: firm size, region, and firm ownership types.

Table 9. Regression results of the moderating effect

	(26) TD	(27) TD	(28) UTD	(29) UTD	(30) RTD	(31) RTD
DID	0.068** (0.029)	0.090** (0.038)	0.053** (0.022)	0.058** (0.024)	0.015 (0.024)	0.032 (0.029)
CORETECH	0.071*** (0.011)		0.020*** (0.007)		0.051*** (0.008)	
DID × *CORETECH*	**0.032**** **(0.016)**		**0.025**** **(0.011)**		**0.008** **(0.013)**	
PreStore		−0.107 (0.069)		0.138*** (0.051)		−0.239*** (0.061)
DID × *PreStore*		**−0.131**** **(0.066)**		**−0.157***** **(0.045)**		**0.033** **(0.060)**
AGE	0.378** (0.165)	0.537** (0.265)	0.329** (0.141)	0.436** (0.172)	0.044 (0.142)	0.097 (0.197)
ROA	1.010*** (0.200)	0.736*** (0.259)	0.463*** (0.140)	0.320** (0.145)	0.561*** (0.167)	0.435** (0.182)
DUAL	0.057** (0.028)	0.065* (0.035)	0.021 (0.020)	0.016 (0.022)	0.036 (0.022)	0.048* (0.026)
TOBINQ	−0.015 (0.010)	−0.011 (0.011)	−0.007 (0.007)	−0.008 (0.007)	−0.007 (0.008)	−0.003 (0.008)
RDratio	0.034*** (0.006)	0.032*** (0.008)	0.019*** (0.005)	0.019*** (0.005)	0.015*** (0.005)	0.013** (0.006)
LEV	0.650*** (0.107)	0.542*** (0.153)	0.365*** (0.084)	0.335*** (0.093)	0.292*** (0.092)	0.211* (0.110)
Quickratio	−0.005 (0.010)	−0.015 (0.014)	−0.001 (0.007)	−0.004 (0.009)	−0.004 (0.007)	−0.011 (0.010)
Sharehold	−0.002 (0.001)	−0.003* (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.002** (0.001)
Constant	1.129* (0.484)	0.827 (0.782)	0.186 (0.413)	−0.057 (0.507)	0.950** (0.415)	0.890 (0.582)
Observations	11,175	9,536	11,175	9,536	11,175	9,536
Adjusted R^2	0.637	0.623	0.671	0.671	0.419	0.400
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Firm size is pertinent to a firm's technological capabilities and financial capacity to invest in emerging AI technologies (Li et al., 2023). Moreover, geographically, firms located in pilot zones for the new generation of AI enjoy unique policy incentives, access to advanced facilities, and a concentration of AI talent (Li et al., 2023). Lastly, firms with differing ownership exhibit variations in their culture, strategic decisions, and risk appetites (Tian et al., 2023). Consequently, examining these dimensions of heterogeneity sheds light on the subtle differences in how AI influences TD, including its subtypes, across firms with distinct profiles.

Table 10. Heterogeneity regression results of firm size

	Small scale			Large scale		
	(32) TD	(33) UTD	(34) RTD	(35) TD	(36) UTD	(37) RTD
DID	0.098*	0.069**	0.031	0.021	0.015	0.007
	(0.053)	(0.032)	(0.037)	(0.040)	(0.030)	(0.036)
AGE	0.940***	0.626***	0.330	−0.221	−0.007	−0.233
	(0.345)	(0.211)	(0.237)	(0.238)	(0.190)	(0.213)
ROA	0.561	0.308	0.253	0.745**	0.142	0.617**
	(0.354)	(0.201)	(0.246)	(0.305)	(0.193)	(0.264)
DUAL	0.028	0.018	0.011	0.070	0.013	0.055
	(0.042)	(0.027)	(0.030)	(0.042)	(0.028)	(0.038)
TOBINQ	0.005	−0.003	0.007	−0.026	−0.007	−0.018
	(0.014)	(0.008)	(0.010)	(0.017)	(0.013)	(0.013)
RDratio	0.028***	0.012**	0.015**	0.022**	0.016**	0.007
	(0.010)	(0.006)	(0.007)	(0.009)	(0.006)	(0.009)
LEV	0.651***	0.295**	0.369***	0.238	0.073	0.162
	(0.201)	(0.118)	(0.131)	(0.174)	(0.137)	(0.166)
Quickratio	−0.006	−0.008	0.002	−0.036	−0.015	−0.023
	(0.013)	(0.008)	(0.009)	(0.022)	(0.013)	(0.016)
Sharehold	−0.005**	−0.003***	−0.002	−0.001	−0.001	−0.0001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−0.884	−0.831	−0.105	3.651***	1.626***	2.081***
	(0.986)	(0.604)	(0.681)	(0.710)	(0.567)	(0.632)
Observations	5,419	5,419	5,419	5,584	5,584	5,584
Adjusted R^2	0.467	0.585	0.306	0.641	0.662	0.407
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Firm size

To assess whether firm size has an impact on the relationship between AI and TD, we categorize firms into large firms and small firms according to the median firm size within our sample (Li et al., 2023). As seen in Table 10, small firms gain more benefits from AI on UTD. It may be because of the agility of small firms, enabling them to swiftly adapt to market-driven technological shifts. Despite their relatively limited resources compared to large firms, small firms strategically harness AI to expand their technological horizons and foster diversification.

Region

To investigate whether the geographic region of a firm matters in the effect of AI, this study conducts a regional heterogeneity test. China's Ministry of Science and Technology has set up 17 new-generation AI innovation and development pilot areas, including Beijing, Shanghai, Tianjin, Shenzhen, Hangzhou, Hefei, Deqing County, Chongqing, Chengdu, Xi'an, Jinan, Guangzhou, Wuhan, Suzhou, Changsha, Zhengzhou, and Shenyang.

As seen from Table 11, AI has a significant effect on the promotion of firm TD, including UTD and RTD, for those in these innovation and development pilot areas. The successful application of AI in

Table 11. Heterogeneity regression results of region

	No AI pilot area			AI pilot area		
	(38) TD	(39) UTD	(40) RTD	(41) TD	(42) UTD	(43) RTD
DID	0.035	0.050**	−0.014	0.145***	0.070**	0.077**
	(0.036)	(0.020)	(0.027)	(0.052)	(0.029)	(0.039)
AGE	0.120	0.125	−0.009	0.829***	0.725***	0.099
	(0.206)	(0.117)	(0.156)	(0.282)	(0.158)	(0.212)
ROA	1.203***	0.525***	0.693***	0.605*	0.296	0.319
	(0.242)	(0.137)	(0.184)	(0.360)	(0.202)	(0.270)
DUAL	0.059*	0.021	0.037	0.071	0.030	0.042
	(0.034)	(0.019)	(0.026)	(0.049)	(0.028)	(0.037)
TOBINQ	−0.026**	−0.007	−0.019**	0.005	−0.010	0.015
	(0.012)	(0.007)	(0.009)	(0.017)	(0.009)	(0.013)
RDratio	0.029***	0.020***	0.009	0.038***	0.017***	0.021***
	(0.008)	(0.004)	(0.006)	(0.009)	(0.005)	(0.007)
LEV	0.539***	0.296***	0.248**	1.012***	0.574***	0.449***
	(0.127)	(0.072)	(0.096)	(0.205)	(0.115)	(0.154)
Quickratio	−0.001	−0.002	0.001	−0.012	0.002	−0.014
	(0.012)	(0.007)	(0.009)	(0.018)	(0.010)	(0.014)
Sharehold	−0.001	−0.001	−0.0005	−0.003	−0.001	−0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Constant	1.915***	0.789**	1.130**	−0.283	−0.998**	0.721
	(0.605)	(0.344)	(0.459)	(0.817)	(0.459)	(0.613)
Observations	7,764	7,764	7,764	3,411	3,411	3,411
Adjusted R^2	0.635	0.669	0.409	0.634	0.676	0.434
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

these regions can be attributed to the favorable policy environment, financial backing, and collaborative resource-sharing among firms. By leveraging cross-technology exchange and application, firms radiate their technological expertise into unrelated domains while maintaining their competitive advantages. Notably, even in non-AI pilot areas, AI continues to drive and become more significant in UTD within firms, which may be because they have to rely on self-exploration to develop areas that are further away from existing domains, and AI serves as a good tool for that.

Ownership

To investigate whether the ownership of a firm matters in the effect of AI, we divide the whole sample into two subsamples: state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). We conduct regression for these two types of ownership, and the results are shown in Table 12. We find that the promotion effect of AI on firm TD and firm RTD is significant in SOEs, while the promotion of AI on UTD is significant in non-SOEs. It may be because SOEs have more abundant capital and policy support, firms' culture focuses on stable management, and they tend to integrate AI with the present technology systems to improve RTD. Non-SOEs have a short decision-making chain, an agile

Table 12. Heterogeneity regression results of ownership

	Non-SOEs			SOEs		
	(44) TD	(45) UTD	(46) RTD	(47) TD	(48) UTD	(49) RTD
DID	0.053	0.064***	−0.010	0.116**	0.039	0.079**
	(0.037)	(0.021)	(0.028)	(0.049)	(0.028)	(0.037)
AGE	0.639***	0.477***	0.159	−0.166	−0.182	0.027
	(0.198)	(0.111)	(0.150)	(0.332)	(0.190)	(0.252)
ROA	1.022***	0.522***	0.512***	0.901**	0.327	0.594**
	(0.240)	(0.135)	(0.182)	(0.367)	(0.211)	(0.278)
DUAL	0.037	0.026	0.011	0.106**	0.009	0.096**
	(0.034)	(0.019)	(0.025)	(0.050)	(0.028)	(0.038)
TOBINQ	0.005	0.002	0.004	−0.050***	−0.027***	−0.023*
	(0.012)	(0.007)	(0.009)	(0.018)	(0.010)	(0.014)
RDratio	0.047***	0.028***	0.018***	0.003	−0.005	0.009
	(0.007)	(0.004)	(0.005)	(0.011)	(0.006)	(0.008)
LEV	0.709***	0.379***	0.336***	0.542***	0.263**	0.287**
	(0.134)	(0.075)	(0.101)	(0.185)	(0.106)	(0.140)
Quickratio	0.001	0.005	−0.004	−0.032	−0.029**	−0.003
	(0.011)	(0.006)	(0.008)	(0.023)	(0.013)	(0.018)
Sharehold	0.00001	0.0001	−0.0002	−0.003**	−0.001*	−0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.122	−0.399	0.528	3.282***	2.101***	1.139
	(0.573)	(0.322)	(0.433)	(1.001)	(0.574)	(0.759)
Observations	7,435	7,435	7,435	3,740	3,740	3,740
Adjusted R^2	0.594	0.651	0.378	0.667	0.670	0.454
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

market response, and a higher willingness to take risks. They tend to use AI to explore new areas, find new growth points, and promote UTD.

Conclusion

Research Conclusion

The competitiveness and survival of firms increasingly depend on the development of diversified technological capabilities, which, in turn, are limited by knowledge distance and direction (Miller, 2006). As an emerging technology, AI is reshaping firm landscapes. With the ability to analyze multi-source data (Kakatkar et al., 2020) and decode various technologies (Brem et al., 2023), AI opens novel avenues for firms to explore new technological domains. Therefore, based on the KBV, this paper discusses the impact of AI on firm TD and its two subtypes. Treating firm AI adoption as a quasi-natural experiment, we employ panel data from China's listed manufacturing firms spanning 2013 to 2022. Our findings are as follows.

First, by evaluating the direct effect of AI on firm TD, it is found that China's listed manufacturing firms adopting AI have significantly improved their TD. We further subdivide TD into RTD and

UTD, confirming that AI can significantly promote UTD, while the improvement of firm RTD is significant only for those located in the new generation of AI pilot areas.

Second, the moderating effects of core-technology competence and knowledge stocks are tested empirically. The results show that core-technology competence positively moderates the relationship between AI and TD, which is primarily observed in the UTD. Additionally, knowledge stocks weaken the relationship between AI and UTD.

Third, it further analyzes the heterogeneous effect of AI on firm TD and its subtypes from three aspects: firm size, ownership types, and region. At the firm level, the results show that AI significantly facilitates UTD in small firms and non-SOEs. Also, AI improves TD and RTD in SOEs. At the regional level, AI plays a more pronounced role in promoting firm TD, including UTD and RTD, in the AI pilot area.

Theoretical Contribution

This study aims to provide a new understanding of how AI promotes firm TD and its subtypes based on the KBV, and how core-technology competence and knowledge stocks moderate the relationship between AI and TD. The study's key contributions are as follows.

First, this research is grounded in the KBV, elucidating how AI extends the boundaries of knowledge acquisition for firms and facilitates the recombination of new and existing knowledge. This aids firms in transforming information into diversified technological knowledge that can be assimilated, thus providing micro-level evidence for the role of AI in enhancing TD within firms. This finding not only supplements Agrawal et al.'s assertion that 'AI in knowledge creation is characterized by the capability to leverage the information one possesses to generate information one did not have before' (Agrawal, Gans, & Goldfarb, 2017), but also contributes to the literature on the antecedents of TD. Prior research on the antecedents of TD has predominantly centered on firm resources (Gupta, 1990; Lai, 2015), network positioning (Estades & Ramani, 1998), knowledge attributes (Tang et al., 2023), and merger and acquisition strategies (Granstrand et al., 2007). Despite these contributions, there has been an oversight regarding the impact of new technology on firms' exploration of novel technological domains (Brem et al., 2023; Muhlroth & Grottke, 2022). By underscoring the role of AI in this context, we fill this research gap and further apply the KBV within the realm of AI-driven knowledge management (Grimes et al., 2023; Jarrahi et al., 2023).

Second, we identify the heterogeneous impact of AI on UTD and RTD based on the differing challenges in acquiring and transferring explicit and tacit knowledge. Due to the accessibility of explicit knowledge (Grant, 1996), firms can accumulate sufficient expertise within related domains, whereas the difficulty in identifying and formalizing tacit knowledge leaves more room for optimization in unrelated technical domains (Duan, Yang, et al., 2022). The capability to acquire new information, which is already somewhat present in a similar form within the firm, varies with different types of diversification (Kretschmer & Symeou, 2024). That is one of the reasons why AI is a tool for enhancing UTD, but ineffective in related domains. Simultaneously, AI technologies such as machine learning enhance the firm's ability to decipher tacit knowledge from other domains and manage different levels of knowledge, effectively aiding in the exploration of unrelated technical domains (Yazici et al., 2020; Zhang et al., 2016). This resonates with the findings by Lou and Wu that 'AI has limitations in incremental drug development but is effectively pronounced for new drug-target pairs' (Lou & Wu, 2021), and we extend this to the manufacturing industry. Consequently, this study broadens the research frontier at the intersection of AI and firm technology management (Hutchinson, 2021; Kakatkar et al., 2020), aiming to reveal the unique capabilities of AI in UTD in firms.

Finally, we explore the boundary conditions between AI and firm TD. We find that the core-technology competence of a firm, which represents its ability to integrate and build various forms of knowledge (Cockburn et al., 2019; Henderson & Cockburn, 1994; Kim et al., 2016), enhances the relationship between AI adoption and firm TD, particularly in UTD. Conversely, knowledge reserves, reinforcing a focus on specialized expertise and maintaining a learning inertia (Kang et al., 2019; Teece et al., 1997), negatively moderate the AI-TD connection, especially in UTD. These findings deepen our understanding of how AI influences a firm's strategic choices under certain conditions (Igna & Venturini, 2023).

Managerial Implications

By framing RTD and UTD within the KBV, this study highlights how AI enables firms to address the distinct challenges of each strategy. This dual role of AI – enhancing efficiency in related domains and enabling exploration in unrelated domains – provides new insights into AI's strategic implications for firms seeking to achieve sustainable innovation and competitive advantage. The study offers some implications for technology diversification-related strategic decision-making and AI practitioners.

This study confirms the significant impact of AI on firm TD, especially in UTD. This underscores the pivotal role of AI in facilitating diverse knowledge acquisition and recombination, ultimately bolstering TD. In general, firms pursuing TD strategies should seize the opportunities brought by emerging technologies, accelerating the adoption of AI, especially small-scale listed firms. Those technology-focused firms should judiciously align their strategic trajectories with their geographical context, making well-informed decisions about the adoption of AI. To effectively embed and leverage AI, firms must continually strengthen their core-technology competence, foster interdisciplinary talent, and enhance their capacity to manage and absorb knowledge from unrelated technological domains. At the same time, although knowledge stocks have a negative moderating effect on AI's impact, it does not mean that knowledge stocks are not important. Instead, firms should cultivate flexible and open knowledge management systems to encourage the continuous updating and iteration of their existing knowledge base. They are supposed to advocate an innovation-oriented organizational culture that encourages employees to jump out of the path-dependent thinking paradigms. By mitigating path dependence and strategically combining existing knowledge with emerging AI, a firm can expand its technology horizons.

In practice, firms must strike a balance between UTD and RTD by considering their resource availability and risk tolerance to determine the optimal diversification strategy. After adopting AI, firms should prevent an excessive concentration on UTD to the detriment of RTD. First, firms should make a reasonable resource management prioritization. Assess the firm's available resources and market trends to prioritize investment in key technology areas. If resources are feasible, aim to pursue both RTD and UTD realms, but establish clear priorities. Allocate more resources to enhancing the internal AI ecosystem for UTD, but ensure that the strategic shift does not weaken the firm's competence in existing technologies. Second, firms should manage TD risk promptly. Conduct thorough risk assessments and formulate risk management plans for both RTD and UTD. Implement pilot projects to gradually enter new domains while monitoring potential risks in existing technological domains. Utilize AI algorithms to assess prospective risks and identify the optimal combination of technologies to minimize overall risk.

Policymakers must proactively adapt to the rapidly evolving AI landscape. Acknowledging AI's pivotal role in advancing TD within firms, policymakers should facilitate the seamless integration of AI into manufacturing firms. Simultaneously, we find that AI significantly promotes both UTD and RTD within firms located in AI pilot areas. Conversely, firms situated outside AI pilot areas experience no significant impact on RTD. This divergence likely stems from varying AI maturity levels across regions. To address this, the government can expand AI pilot areas based on the successful experiences of existing pilot areas. Additionally, special subsidies can be offered to incentivize firms outside the pilot areas to embrace AI adoption. Such measures would not only catalyze cross-technology exploration but also level the playing field, ensuring broader participation in the AI-driven technological revolution.

Limitations and Future Research

This article empirically tests the relationship between AI and firm TD, enriching the existing research on the antecedents of TD and the utility of AI. But there remains scope for further improvement and discussion.

First, due to the availability of data, this study focuses on China's publicly listed manufacturing firms as the research context. The practical implications of our findings are significant within this specific domain. Nevertheless, it is essential to acknowledge that listed firms often operate on a large scale. Consequently, the adoption of AI and TD may yield different outcomes and boundaries in other countries, industries, or smaller-scale firms. Factors such as industry structure, geographic market dynamics, and regulatory frameworks may alter the mechanisms through which AI impacts diversification strategies. Future research should explore these contextual variations to further refine our understanding of AI's contributions.

Second, based on the KBV, this article discusses the action mechanism of AI on firm TD from the perspective of diverse knowledge acquisition and recombination. There may be other mechanisms that exist. Future research could explore this issue from various theoretical lenses, including the resource-based view, dynamic capability theory, and learning theory.

Third, this study acknowledges the need to explore how firms strike a balance between RTD and UTD after adopting AI, and identifying the equilibrium and boundary points between UTD and RTD remains a direction for future research. Meanwhile, further exploration regarding the specific impact of AI on organizational performance after the promotion of firm TD is necessary. Scholars are encouraged to delve into the tangible contributions of AI post-implementation, shedding light on its role in enhancing organizational outcomes.

Finally, given the rapid evolution of AI and its multifaceted application within the firm environment, there are currently lacking unified standards for measuring the degree of firm adoption of AI. This study uses word frequency methods and residual analysis to identify possible biases in AI patterns. However, a more comprehensive understanding necessitates qualitative approaches, such as case studies, which can illuminate the diverse facets of AI across different technological contexts. Meanwhile, distinguishing technological domains based on IPC classification numbers may introduce some measurement errors. Future research could explore more refined measures to better address these nuances.

Data availability statement. The data supporting the findings of this study are openly available on the Open Science Framework (OSF) at https://osf.io/9txru/?view_only=d83127834bdd420fb99c5b76f41c9133.

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Appendix:
AI dictionary in English

A–E	F–M	N–W
AI Chips	Face Recognition	Natural Language Processing (NLP)
AI Products	Feature Detection	Neural Networks
Artificial Intelligence (AI)	Feature Extraction	Pattern Recognition
Artificial Intelligence Chips	Fintech	Question-Answering System
Augmented Reality (AR)	Human-Computer Collaboration	Recurrent Neural Networks (RNN)
Autonomous Driving	Human-Computer Interaction	Reinforcement Learning
Big Data Analytics	Human-Machine Dialogue	Robo-Advisors
Big Data Management	Image Recognition	Robotic Process Automation (RPA)
Big Data Marketing	Intelligent Agents	Smart Agriculture
Big Data Operations	Intelligent Computing	Smart Banking
Big Data Platforms	Intelligent Customer Service	Smart Governance
Big Data Processing	Intelligent Education	Smart Healthcare
Big Data Risk Control	Intelligent Elderly Care	Smart Homes
Biometric Identification	Intelligent Environmental Protection	Smart Insurance
Business Intelligence	Intelligent Regulation	Smart Retail
Cloud Computing	Intelligent Search	Smart Speaker
Computer Vision	Intelligent Sensors	Speech Recognition
Convolutional Neural Network (CNN)	Intelligent Transportation	Speech Synthesis
Data Mining	Intelligent Voice	Support Vector Machine (SVM)
Deep Learning	Internet of Things (IoT)	Unmanned Vehicles
Deep Neural Networks	Knowledge Graph	Virtual Reality (VR)
Distributed Computing	Knowledge Representation	Voice Interaction
Edge Computing	Long Short-Term Memory (LSTM)	Voiceprint Recognition
Enhanced Intelligence	Machine Learning	Wearable Devices
	Machine Translation	

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