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The Relationship Between Data-Intelligence Empowerment, Knowledge Diversification, and Knowledge Recombinant Capabilities: Research on Sustainability of Chinese High-Tech Listed Firms

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Abstract: Based on resource orchestration theory, this paper examines the influence of data-intelligence empowerment on enterprise knowledge recombinant capabilities empirically, using A-share-listed high-technology enterprises from 2012 to 2021 as research examples. Research shows that data-intelligence empowerment can promote both enterprise knowledge recombinant reuse capability and knowledge recombinant creation capability. Furthermore, knowledge depth diversification acts as a mediator between data-intelligence empowerment and knowledge recombinant reuse capability, and knowledge breadth diversification plays a mediating role between data-intelligence empowerment and knowledge recombinant creation capability. The heterogeneity analysis demonstrates that the data-intelligence empowerment has a more promotive impact on knowledge recombinant reuse capability in non-state-owned enterprises and eastern region enterprises, and there is a promotion effect on the knowledge recombinant creation capability across enterprises with different ownership structures and regions. This study provides theoretical guidance as well as practical references for enterprises to take advantage of digital intelligence technology to empower themselves, match internal and external resources and capabilities, and ultimately accomplish sustainable recombinant innovation.

Keywords: data-intelligence empowerment; knowledge recombinant reuse capability; knowledge recombinant creation capability; knowledge diversification; resource orchestration theory

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1. Introduction

Data-intelligence empowerment refers to the process of enabling enterprises to realize value creation by providing them with three types of digital intelligence capabilities: connectivity, analytics, and intelligence [1]. Given how quickly digital intelligence technology is developing, large-scale digital economy enterprises have become the key force of digital technology innovation. Digital intelligence technology has brought profound changes to product type, production process, business model, and organizational structure and challenged the traditional innovation theory. Therefore, how to leverage data-intelligence empowerment to foster enterprise sustainable innovation has been widely recognized as a significant topic in recent years.

Although the role of digital intelligence technology in stimulating innovative knowledge generation has been widely demonstrated [2], existing research has centered more on the novelty of the innovative knowledge itself. Henderson and Clark (1990) proposed that

innovative knowledge is categorized into component knowledge and architectural knowledge [3]. Architectural innovation, an approach to innovation that recombines component knowledge without changing core knowledge, is often overlooked in research. From this point of knowledge recombination, innovation is a process whereby enterprises locate and integrate knowledge to develop novel goods, services, or commercial models to fuel innovation possibilities [4,5]. Carnabuci and Operti [6] believe that the ability of enterprises to recombinant existing technologies drives their innovation capabilities and categorize knowledge recombinant capabilities into knowledge recombinant reuse capability and knowledge recombinant creation capability based on whether new knowledge combinations are generated, which are manifested in the deepening and expansion of recombinant capabilities. Data-intelligence empowerment broadens the channels of resource acquisition, improves the absorptive capacity of enterprises [2], and promotes the cross-integration of diversified technologies. Through the implementation of technological diversification strategies, enterprises acquire complementary knowledge around core and non-core areas. In this way, they strengthen their core competence while developing new technological capabilities [7], which is demonstrated in the examination of the depth of knowledge and the cross-border search for the breadth of knowledge [8], laying the foundation for deepening and expanding knowledge recombinant capabilities.

One of an enterprise's most valuable resources is knowledge [9]. The process of recombining knowledge in an enterprise is a process of resource orchestration. The theory of resource orchestration opens the "black box" of the enterprise from resources to capabilities and then to the realization of competitive advantage. The resource orchestration theory claims that in order to create sustainable value, businesses combine both internal and external resources and skills through resource building, resource bundling, and resource leveraging [10]. On the one hand, the reinterpretation of digital resources allows enterprises to integrate digital resources with organizational culture and user needs [11], while sustainably delving deeper into related fields, finding new room and new contextual significance to enhance knowledge recombinant reuse capability. On the other hand, the availability of digital resources shortens the knowledge distance between intra-enterprise and inter-enterprise [11]. Through resource empowerment, enterprises can obtain heterogeneous knowledge sustainably, expand the knowledge base of recombination, accelerate the cross-disciplinary knowledge integration, and enhance knowledge recombinant creation capability. IT has been studied to improve the recombinant capabilities of enterprises [12], and the recombinant capabilities as part of the dynamic capabilities of enterprises can promote breakthrough innovation [13]. However, the process of formation of knowledge recombinant capabilities are given less attention, and the different mechanisms of the two kinds of knowledge recombinant capabilities are not distinguished. Enterprises are able to accumulate a wealth of knowledge and technology for sustainable innovation by applying digital intelligence technology to improve the efficiency of utilizing within knowledge resources as well as the capacity to identify and absorb knowledge from outside sources [2]. Since rational use of resources is a basis for capacity development [10], the knowledge recombinant capabilities of firms are enhanced through the effective and sustainable integration of technological knowledge. Knowledge diversification is a reflection of how well-versed in several sectors enterprises are. It can broaden and deepen the knowledge foundation for knowledge recombination [7]. Thus, different knowledge diversification strategies may lead to different knowledge recombination capabilities. There is room for this work to offer some minor contributions to the literature on the influence mechanism of data-intelligence empowerment on enterprise knowledge recombination, as empirical research from the standpoint of recombination has not been extensively studied in prior studies.

Specifically, this paper builds a theoretical analytical framework for resource orchestration under the recombinant perspective from the resource empowerment dimension of empowerment theory, uses high-technology companies listed on the A-share market between 2012 and 2021 as research cases, and uses a variety of measurement methods to research the influence mechanism of data-intelligence empowerment on enterprise knowledge recombinant capabilities. The results show that data-intelligence empowerment will promote enterprises' knowledge recombinant reuse capability and knowledge recombinant creation capability, and knowledge depth diversification and knowledge breadth diversification play an intermediary role in the two paths, respectively.

These are the paper's contributions. Firstly, this paper takes a recombination perspective rather than a single-resource, capability, or boundary perspective and discusses the fundamental problem of how data-intelligence empowerment sustainably affects enterprise knowledge recombinant capabilities under the unified framework of resource orchestration theory, which is a new application of resource orchestration theory in the context of digital innovation. Secondly, this paper focuses on the sources of firms' knowledge recombinant capabilities rather than their impact on firm performance and analyzes the differential effect of data-intelligence empowerment on the two kinds of knowledge recombinant capabilities. Thirdly, in order to clarify the mechanism of influence of the interaction between data-intelligence empowerment and enterprise knowledge recombination, knowledge diversification is incorporated into the research framework and different knowledge diversification strategies are distinguished.

The remaining research in this paper is divided into six parts. The Section 2 reviews the relevant literature and analyzes the current state of research in related fields. In the Section 3, the key theories are reviewed, the relationship between data-intelligence empowerment and enterprises knowledge recombinant capabilities is analyzed, the mediating effect of knowledge diversification is explored, research hypotheses are presented, and a research model is built. The Section 4 covers the research methodology, which includes sample selection, data collection, variable measurement, and regression modeling. The findings of the empirical analysis including statistics, baseline regression, robustness test, heterogeneity analysis, and endogeneity test are presented in the Section 5. The role mechanism analysis, which examines the mediating impacts of knowledge depth diversification and knowledge breadth diversification, respectively, is covered in the Section 6. Finally, the Section 7 includes conclusions, contributions, limitations, and future directions.

2. Literature Review

2.1. Data-Intelligence Empowerment

The notion of "Authorization Empowerment", which describes the decentralization of enterprises to subordinates in order to provide better customer service, is the source of what is known as "Empowerment" [14]. Empowerment includes three dimensions: structural empowerment, psychological empowerment and resource empowerment [15]. Removing structural barriers that prevent a subject from accessing resources is known as structural empowerment. Psychological empowerment refers to employees' acquisition of power and improvement of self-efficacy. The ability of the subject to access and manage resources is referred to as resource empowerment.

With the gradual penetration of digital intelligence technology into various fields and the promotion of social innovation and development, data-intelligence empowerment, which combines digital intelligence technology with empowerment theory, has become a research hotspot. The following four empowered subjects are the main focus of research on data-intelligence empowerment: digital intelligence technology can realize customer empowerment through demand collection and encouraging design for accurate production;

it can realize process empowerment through task decomposition and intelligent planning to ensure production efficiency; it can realize cooperation empowerment through cross-border synergy and matching of supply and demand resources; and it can realize employee empowerment through stimulation of their initiative and the provision of information feedback [16]. The inherent management and operation mode of enterprises has been altered by digital intelligence technology and platforms, which have also improved the efficiency of distributing resources, expanded the bounds of enterprises, and boosted innovative performance. From the single standpoint of resources, capabilities, and boundaries, the current research examines the influence mechanism and boundary conditions of data-intelligence empowerment on green process innovation [17], open innovation [18], and service innovation [19] from the perspective of resources, capabilities, and boundaries. Empirical research has gradually replaced case studies as the primary research methodology. It has been shown that digital intelligence technologies empower enterprises with richer knowledge resources and higher information processing capability, which provides the possibility for enterprises to effectively integrate knowledge to improve their innovation capability. However, few studies have delved into the relationship between data-intelligence empowerment and enterprise innovation capabilities from the perspective of recombination.

2.2. Knowledge Recombinant Capabilities

Knowledge recombinant capabilities is the process by which enterprises recombine existing knowledge and technology to achieve technological innovation and is divided into knowledge recombinant reuse capability and knowledge recombinant creation capability [6]. Knowledge recombinant reuse capability refers to the capability of an enterprise's experience-based in-depth exploration of existing knowledge portfolios to improve current solutions to adapt to market changes. Knowledge recombinant creation capability means the capability that enterprises transcend organizational boundaries, enrich their knowledge base, reorganize both inside and outside resources, and explore the potential for recombining existing knowledge and new knowledge, so as to form distinctive technological advantages [6]. Strumsky and Lobo [20] classified knowledge recombination according to the novelty of the knowledge elements and the combinations into enhanced combinations of old elements, new combinations containing only old elements, novel combinations containing both old and new elements, and initial combinations containing only new elements, the first of which belongs to knowledge recombination reuse, and the latter three belong to knowledge recombination creation.

It has been found that common knowledge provides the basis for knowledge recombination [21], and different resource characteristics [22] and the coupling of different domains of knowledge can have a differential impact on the diversity of recombination. Utilizing IT may expedite the spreading of inside knowledge and the incorporation from outside knowledge, boost the strength and diversity of knowledge recombination, thus promoting the number and quality of patents [12]. Knowledge recombinant capability has the potential to promote breakthrough innovation [13] and spur innovation quality [23]. The above studies show that the influencing factors of knowledge recombinant capabilities have been initially explored and the positive impact of knowledge recombinant capabilities on innovation has been confirmed, but the mechanism leading to different knowledge recombinant capabilities has not yet been fully clarified.

2.3. Knowledge Diversification

Knowledge diversification comes from Nelson's idea of "knowledge diversification", and Kodama put forward the concept. Knowledge diversification refers to the expansion of the technological boundaries of a company while maintaining its original core com-

petencies [24]. It reflects the extent to which firms seek linkages in knowledge networks and the diversity of knowledge domains in which firms are involved. Knowledge diversification is classified into knowledge depth diversification and knowledge breadth diversification based on the level of correlation between knowledge [8]. Knowledge depth diversification is the diversified knowledge related to the core technology field that the enterprise has, which is manifested as the knowledge depth of the enterprise in a certain field. Knowledge breadth diversification is the diversified knowledge that enterprises have in non-core technology fields, which is manifested in the breadth of knowledge in many fields. Knowledge diversification can be subdivided into four types: core, auxiliary, alternative, and exploratory [25]. Different types of knowledge diversification are associated with the innovation strategy of enterprises.

Research on knowledge diversification has focused more on knowledge breadth diversification and to some extent neglected knowledge depth diversification. Knowledge depth diversification can promote the replication, modification, and recombination of knowledge by enterprises [24], achieve synergy between core products and complementary changes [26], realize economies of scale, and eventually contribute to the improvement of innovation performance. Knowledge breadth diversification can overcome the limitations of local search [27], promote the cross-integration of cross-disciplinary knowledge, generate creative new features and applications [24], realize economies of scope, and reduce R&D risks [28]. However, beyond a certain extent, it will creates excessive communication and coordination costs and distract the attention of enterprise R&D investment, which will have an overkill impact on enterprise R&D productivity [29] and innovation performance [30]. Based on the above research, it can be found that different types of knowledge diversification can have different impacts on innovation. However, whether such differentiated impacts are equally applicable to the knowledge recombinant capabilities of firms in the context of digitization remains to be further explored.

2.4. Resource Orchestration Theory

The process by which an enterprise builds resources, groups resources to develop competencies, and then uses those competencies to create value is described by resource orchestration theory [10]. In the resource construction stage, it mainly involves the increase or decrease of the enterprise's resources. In the resource bundling stage, enterprises form capabilities by integrating resources that allows them to adjust to changes in the environment. Utilizing resources and capabilities to realize value creation is what is meant by the resource leveraging stage.

According to resource orchestration theory, enterprises can gain a competitive edge by combining their resources, competencies, and dynamic management. It has been argued that effective orchestration of resources is associated with higher innovation performance, which can improve firms' innovation efficiency [31] and enable process innovation [32]. Based on the theoretical framework of resource orchestration, Li and Jia [33] studied the digital innovation process of enterprises by analyzing the synergistic relationship between their resources. Resource orchestration theory explains the evolution from resources to capabilities and provides a theoretical basis for enterprises to realize value creation through the appropriate use of resources. This is an inspiration for clarifying the knowledge recombinant capabilities of enterprises through data-intelligence empowerment in acquiring and integrating knowledge resources.

3. Research Hypothesis

3.1. Data-Intelligence Empowerment and Knowledge Recombinant Reuse Capability

The resource orchestration theory emphasizes the adaptability of enterprises and the dynamics of resources. Resources themselves do not necessarily create value. Only by dynamically adjusting and optimizing the combination of resources to adapt to the internal and external environment can enterprises develop the ability to innovate and eventually produce sustainable competitive advantages [34]. According to the viewpoint of resource empowerment in the theory of empowerment, digital intelligence technology improves the three digital intelligence capabilities of enterprises, namely, connection, analysis, and intelligence, and empowers enterprises to possess and control resources [1], which is manifested in the increase of enterprises' knowledge resources and the improvement of their knowledge management capabilities. From the recombination point of view, the enterprise's ability to orchestrate knowledge resources to realize innovation reflects the enterprise's ability to manage knowledge. In other words, enterprises using digital intelligence technology can improve the efficiency of the use of existing knowledge resources and optimize the current knowledge management methods, thereby enhancing the ability for knowledge recombinant reuse capability.

First, the improved connectivity of enterprises through data-intelligence empowerment facilitates knowledge transfer and sharing, manifesting itself in opening up internal communication channels, which makes tacit knowledge explicit and thus promotes enterprises to improve their solutions based on the existing knowledge combinations. The enterprise's internal communication, information transmission, and solutions all comprise the knowledge elements [3], but they may be scattered throughout the organization and cannot be directly reorganized [35]. Prior research has demonstrated that the communication between inventors with different professional knowledge and team members in different departments can lead to the generation of knowledge recombination [9]. By introducing digital intelligence infrastructure, enterprises can eliminate the obstacles to obtaining information between different positions and promote the exchange of experiences and cross-sectoral synergies. Each of these advances the realization of employee empowerment, broadens the comprehension of current knowledge, and taps the potential use value of existing knowledge combinations for enterprises.

Second, the improved analytical capability of companies through data-intelligence empowerment enables the discovery of new applications for old knowledge portfolios, as evidenced by the ability to leverage the reinterpretability of digital resources to enable enterprises to rapidly transform the context of utilization of the knowledge combinations involved in a product or service. The scene specificity of knowledge elements requires the combination of knowledge and scene [36]. Since it is difficult to be imitated by other enterprises, it has formed a unique strategic advantage of the enterprise. By introducing digital intelligence infrastructure, enterprises create digital channels for communication with their customers, quickly identify application scenarios for their products or services from multi-dimensional data analysis, and correlate them with the corresponding customer needs. All of them contribute to empowering customers and increase the flexibility and adaptability of innovation outcomes.

Third, the improved intelligent capability of enterprises through data-intelligence empowerment helps to optimize the allocation of innovation-related resources of enterprises, which is manifested in the ability of digital intelligence technology to improve the way of R&D and operation of enterprises, thus enhancing their core competencies. By applying digital intelligence technology, companies are able to automate routine tasks, free up limited attention resources for product details and personalized services, gain a deeper grasp of its core technologies, and make it easier to explore optimization directions within

the current technology space [18]. Enterprises can lower innovation costs and increase fault tolerance space by utilizing digital twins, digital simulation, and other auxiliary design technologies. As the Internet of Things has grown, it has allowed enterprises to improve product performance based on captured and stored business data. They all support the achievement of process empowerment and raise the efficiency of knowledge recombinant reuse. Therefore, we put forward the following hypothesis:

Hypothesis 1a. *Data-intelligence empowerment has a positive impact on enterprise knowledge recombinant reuse capability.*

3.2. Data-Intelligence Empowerment and Knowledge Recombinant Creation Capability

By utilizing digital intelligence infrastructure, enterprises can enhance their current competencies and improve recognition, absorption, and transformation of new knowledge. New knowledge implies new recombination spaces and new ways of thinking, which open up new ideas for companies to develop new technologies and solve new problems, encourage enterprises to veer off the original technical path [37], increase the novelty of knowledge and knowledge combination, and thus enhance the knowledge recombinant creation capacity.

First, digital intelligence technology gives enterprises the capability to connect, so that enterprises can continuously scan the internal and external environment, quickly identify the use of resources, and absorb new knowledge for recombination. Applying digital intelligence technology improves network connectivity and lowers the cost of information search [19], so that heterogeneous resources can flow across ambiguous enterprise boundaries. Enterprises rely on common data standards to access the ecosystem, bridge corporate processes with the supplier chain and the client, and are able to obtain a wealth of complementary knowledge from external sources at a lower cost, enhancing the pooled knowledge, achieving cooperative empowerment, and laying the foundation for knowledge recombinant creation capability.

Second, digital intelligence technology gives enterprises the capability to analyze, which enables them to delve deeper based on the varied needs of customers and to find out more about the interdependence of knowledge. Innovative technology is derived from the combination of new knowledge components as well as a creative combination of preexisting knowledge components [38]. By arranging and grouping the gathered data, enterprises can convert implicit information into general and complementary knowledge and create structured knowledge for big data analysis, in which they continuously deepen their comprehension of present knowledge and knowledge combinations, find the possibilities of multidisciplinary cross-integration and recombining sleeping patents, use the linkage between knowledge and update the application of knowledge to realize process empowerment, and provide direction for the improvement of knowledge recombinant creation capability.

Third, digital intelligence technology gives enterprises the capability to be intelligent, allowing them to modify their research and development strategies, so that enterprises can continuously explore new ways to effectively integrate knowledge. There is no longer a definite beginning and finish to innovation. The three distinct phases of new idea generation, product development, and commercialization that were part of an organization's traditional innovation process have evolved into a dynamic process [39]. Enterprises utilize crowdsourcing platforms to find excellent workforces, merge professional and digital talent dynamically, and maximize human capital through knowledge recombinant creation to expand the knowledge base. By predicting future demand trends based on preliminary big data analysis, finding the optimal strategy from multiple solutions, piecing together knowledge in new ways based on new demands, and using machine learning to con-

tinuously iterate, enterprises realize process empowerment and identify opportunities to enhance knowledge recombinant creation capability. Therefore, we put forward the following hypothesis:

Hypothesis 1b. *Data-intelligence empowerment has a positive impact on enterprise knowledge recombinant creation capability.*

3.3. Data-Intelligence Empowerment and Knowledge Diversification

Data-intelligence empowerment improves the enterprise's knowledge search capability and overcomes the limitations of its knowledge processing capability, increasing the availability of knowledge resources [16], which facilitates the enterprise's access to more complementary knowledge, thus completing resource construction. This process involves enterprises re-examining their existing resources and improving their current knowledge system around their core domains to promote the migration of knowledge related to their core domains, and it also includes enterprises absorbing external knowledge and expanding their technological domains to integrate cross-domain expertise.

By embedding digital intelligence technology, enterprises deeply integrate digital resources with organizational management and R&D methods, improve connection ability and analysis ability, optimize knowledge management system and resource allocation efficiency related to core competence [1], and continue to strengthen the existing knowledge to gain knowledge appreciation constantly. Improvement of connection capabilities enables enterprises to break the knowledge island and to promote the two-way communication and one-way transmission of internal knowledge among inventors [12], which is helpful to realize deep sharing of relevant knowledge, to reduce the duration of the product life cycle and, in the end, to maximize resource utilization. Improved analytical capabilities assist enterprises in knowledge retrieval and storage, enabling them to quickly locate the knowledge with the highest relevance to their core technological capabilities and improve the efficiency of information processing. It also supports enterprises in deep learning of existing knowledge systems, splitting and reorganizing unstructured and semi-structured knowledge into structured knowledge. This helps to reduce the subjective influence of manual judgment, and improve R&D efficiency.

The utilization of digital intelligence technology expedites the exchange of resource components between enterprises, improves the level of knowledge spillover, continuously expands the boundary of enterprises [18], and increases the marginal effect of innovative knowledge, which is conducive to enterprises to obtain more irrelevant knowledge in core areas from the outside. By using intelligent technologies such as intelligent search engines, enterprises can broaden their knowledge acquisition channels [40], enhance their ability to perceive external changes [41] and search for useful resources, enrich the knowledge base of cross-domain technologies, and achieve dynamic matching of inside and outside resources. The formation of the digital platform shortens the knowledge distance between the innovation subjects, connects the stakeholders both within and without the enterprise [42], increases the depth and intensity of the enterprise's embedding in the social network. In this way, firms are able to absorb and utilize more heterogeneous knowledge, which provides the possibility for the deep integration and transformation of cross-disciplinary knowledge. Therefore, we put forward the following hypotheses:

Hypothesis 2a. *Data-intelligence empowerment has a positive impact on knowledge depth diversification.*

Hypothesis 2b. *Data-intelligence empowerment has a positive impact on knowledge breadth diversification.*

3.4. The Mediating Role of Knowledge Diversification

Knowledge diversification can expand the scope of knowledge integration. Knowledge depth diversification and knowledge breadth diversification are important factors in promoting both the amount and quality of corporate innovation [22]. Since resources are the basis of capabilities and capabilities are the evolutionary direction of resources [43], the knowledge recombination capabilities of enterprises come from the effective integration of diversified knowledge. In the process of data-intelligence empowerment, enterprises are facing transformation pressure and external competition pressure. Knowledge diversification is the key factor for enterprises to adapt to environmental uncertainty and maintain competitive advantage. In the process of enterprises' data-intelligence empowerment, enterprises not only need to use digital intelligence technology to improve operational efficiency, but also need to explore new competitive advantages under digital conditions [44]. Data-intelligence empowerment facilitates enterprises to continuously strengthen their knowledge recombinant reuse capability based on their experience in integrating core domain knowledge, and it also encourages enterprises to proactively explore external resources for cross-domain knowledge recombinant creation and to achieve leapfrogging of the technology track.

Knowledge depth diversification reflects the richness of complementary knowledge related to the core domains constructed by the firm. The related knowledge has the characteristics of small difference and high correlation between knowledge. Knowledge depth diversification can promote the exploration of the depth of knowledge by enterprises, reduce the cost and uncertainty of knowledge fusion in related fields by generating cumulative effects and economies of scale [29], and contribute to the improvement of knowledge recombinant reuse capability. On the one hand, the knowledge recombination of related knowledge along the existing technical route can replicate experience and practice, effectively exert the cumulative effect of innovation, accelerate the R&D process, and achieve the diversification of innovation results with lower innovation costs. On the other hand, there is a high correlation between related knowledge, which can reduce the uncertainty of knowledge transfer and the cost of knowledge fusion [30] and improve the flexibility of knowledge recombinant reuse. Enterprises realize scenario-based innovation by matching innovations with diverse scenarios.

Knowledge breadth diversification reflects the richness of complementary knowledge that firms build around non-core areas. Unrelated knowledge has the characteristics of a high degree of heterogeneity between knowledge and belonging to different scientific foundations. Knowledge breadth diversification can identify innovation opportunities by broadening knowledge base of enterprises, promote cross-fertilization of knowledge in different fields, and facilitate knowledge recombinant creation capability. On the one hand, the continuous combination of finite resources will gradually exhaust the recombination space, resulting in the marginal cost of innovation gradually exceeding the marginal income. A broader knowledge base strengthens an enterprise's grasp of cutting-edge knowledge and the exploration of new opportunities [45], thus facilitating the discovery of the potential value of cross-domain knowledge recombination and enhancing knowledge recombinant creation capability. On the other hand, technological transition theory states that the integration of cross-domain knowledge and highly differentiated knowledge can break through the constraints of the original knowledge structure [38] and promote the old technology track to a higher level of a new technology track. Unrelated knowledge diversification can overcome the "local search limitations" [29]. By embedding knowledge with low correlation or cross-cognitive fields into each other, knowledge recombinant creation capability can be enhanced.

The previous paragraph has proved that data-intelligence empowerment will have an impact on knowledge diversification. Further inference leads to the conclusion that knowledge diversification acts as a mediator between data-intelligence empowerment and enterprise knowledge recombination. The application of digital intelligence technology empowers enterprises to acquire the three digital intelligence capabilities of connectivity, analytics and intelligence, as well as to assimilate rich knowledge resources and improve knowledge management capabilities. By exploring new knowledge in current fields and cross-border search, enterprises can deepen their understanding of existing knowledge combinations and open up new technical routes, so as to better accomplish the process from building diversified knowledge resources to bundling knowledge resources to form knowledge recombinant reuse capability and knowledge recombinant creation capability. Drawing from the aforementioned analysis, we put forward the following hypotheses:

Hypothesis 3a. *Knowledge depth diversification plays a mediating role between data-intelligence empowerment and knowledge recombinant reuse capability.*

Hypothesis 3b. *Knowledge breadth diversification plays a mediating role between data-intelligence empowerment and knowledge recombinant creation capability.*

The theoretical model is shown in Figure 1.

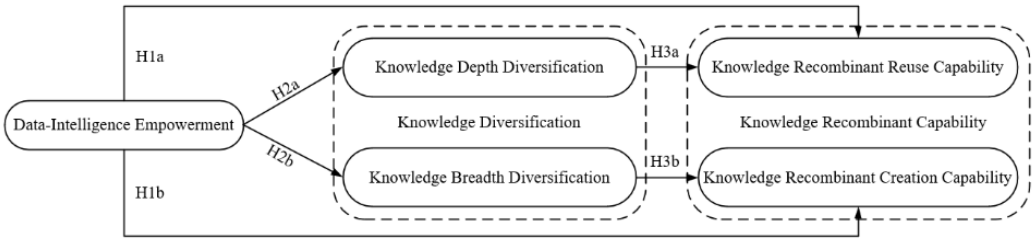


Figure 1. Theoretical model.

4. Methods

4.1. Data and Sample

The present tendency in development is to accelerate the deep integration of manufacturing and information technology, driven by the rapid pace of the global digitalization process and the promotion of intelligent manufacturing. High-tech companies are knowledge-intensive. They are the principal force of innovation and the key strength to break through the technological blockade. Facing the opportunity window of data-intelligence empowerment, they play an important role in realizing key core technology breakthroughs through knowledge recombination, promoting industrial transformation and upgrading, and driving national innovation and development. Therefore, this paper conducts an empirical analysis based on the data from high-technology companies listed on A-shares between 2012 and 2021.

Firstly, from the CSMAR database, we obtain the names, stock codes, industry codes, province codes, and financial data of every A-share-listed company from 2012 to 2021, eliminating ST and *ST enterprises. Then, drawing on the Classification Catalogue of Strategic and Emerging Industries, the Classification of Strategic and Emerging Industries (2012) (Trial), and relevant documents of the Organization for Economic Cooperation and Development (OECD) and comparing with the Guidelines for the Industrial Classification of Listed Companies (2012 Revision), we determine 19 subcategories in three categories of manufacturing, information industry, and scientific research and technology services as high-tech industries, and screen listed 1735 companies belonging to high-tech industries according to industry codes. Subsequently, we collect the annual reports of these listed

companies from 2012 to 2021 for textual analysis and the data of enterprise invention patents from 2007 to 2021 in the patent retrieval and analysis system of the State Intellectual Property Office, including patent number, patent type, application date, international patent classification number, etc. Finally, the necessary variables are computed, and panel data are created by matching financial, digital transformation, patent, and pertinent data from provincial statistics yearbooks. The continuous variables are winsorized at the 1% and 99% quantiles to reduce the impact of anomalous data on the results.

4.2. Measurements

4.2.1. Dependent Variables: Knowledge Recombinant Reuse Capability (RR), Knowledge Recombinant Creation Capability (RC)

Patent classifications are often chosen to characterize knowledge combinations [46]. Using the method proposed by Carnabuci and Operti [6,47] to measure the two kinds of knowledge recombinant capabilities, namely knowledge recombinant reuse capability and knowledge recombinant creation capability: ① The knowledge elements are constructed according to the part before the patent IPC classification number '/'. ② In the control group, the pairwise combination of different types of knowledge elements in the patents applied by the focus enterprise i during the period of t-6 to t-1 was counted. In the observation group, the pairwise combination of different types of knowledge elements in the patents applied by the focus enterprise i during the period of t was counted. ③ When the combination of knowledge elements (a, b) appears simultaneously in the control group and the observation group, it is knowledge recombinant reuse, and the total number of occurrences in the control group and the observation group is recorded as C_{RR}. When the knowledge element combination (a, b) only appears in the observation group and does not appear in the control group, it is knowledge recombinant creation, and the number of occurrences in the observation group is recorded as C_{RC}. ④ The natural logarithm of C_{RC} and C_{RR} plus one is used to measure knowledge recombinant reuse capability and knowledge recombinant creation capability of high-tech enterprises.

4.2.2. Independent Variable: Data-Intelligence Empowerment (DIE)

It is generally believed that the annual report of enterprises, as an information disclosure tool, can effectively reflect the degree of digital transformation, strategic planning, and future vision of enterprises. Textual analysis method commonly uses the natural logarithm of the number of word frequencies of digitally transformed feature words [48] or the percentage of feature word frequencies to the total length of the text of the annual report [49] as proxy variables for data-intelligence empowerment. Drawing from existing studies, the annual reports of listed companies are collected, and the digital transformation feature words related to "artificial intelligence technology", "big data technology", "cloud computing technology", "block chain technology" and "digital technology application" are extracted [48,50]. The natural logarithm of total word frequency plus one is used as the proxy variable of data-intelligence empowerment.

4.2.3. Mediator Variables: Knowledge Depth Diversification (KDD), Knowledge Breadth Diversification (KBD)

There are currently three methods of measuring knowledge diversification: variety measurement, index measurement, and discrepancy measurement. Variety measurement measures the number of knowledge categories covered by an enterprise's knowledge portfolio, which only reflects the number of knowledge domains an enterprise is involved in but ignores the enterprise's performance in each knowledge domain. Index measurement is to reflect the number of knowledge categories possessed by the enterprise and the distribution of the categories by utilizing indicators such as entropy index, Herfindahl index, and Blau

index. Discrepancy measurement is to reflect the diversified knowledge possessed by the enterprise by measuring the knowledge distance between the technology portfolio of the focus enterprise and the reference point [7]. Compared with other measurement methods, the entropy index method can decompose the indicator into two indicators of knowledge depth diversification and knowledge breadth diversification. Thus, according to the IPC classification number, the technical fields involved in the enterprise are determined, and the level of knowledge diversification of the enterprise is measured by the entropy index method [29]. The overall knowledge diversification (KD) is measured by the subcategory (top 4) of the main classification number of the t year invention patent. The knowledge breadth diversification is measured by the category (top 3) of the main classification number of the t year invention patent. The knowledge depth diversification is measured by the difference between the two. The calculation formulas are:

$$KD_{i,t} = \sum_{j=1}^{n_1} \left(P_{i,j,t} \times \ln \frac{1}{P_{i,j,t}} \right) \quad (1)$$

$$KBD_{i,t} = \sum_{j=1}^{n_2} \left(P_{i,j,t} \times \ln \frac{1}{P_{i,j,t}} \right) \quad (2)$$

$$KDD_{i,t} = TD_{i,t} - KBD_{i,t} \quad (3)$$

Among them, $P_{i,j,t}$ is the ratio of the number of invention patents belonging to category j in the t year of enterprise i to all patents, n_1 is the total number of subcategories of invention patents applied by enterprises in the t year, and n_2 is the total number of categories of invention patents applied by enterprises in the t year.

4.2.4. Control Variable

Referring to the existing research, the variables that may affect the knowledge recombinant capabilities of enterprises are selected as the control variables. The selection and measurement of variables are shown in Table 1.

Table 1. Measurement of variables.

Type	Name	Sign	Measurement
Dependent Variables	Knowledge recombinant reuse capability	RR	Natural logarithm of total number of knowledge element combinations (a, b) in the patents of both control group and observation group plus one
	Knowledge recombinant creation capability	RC	Natural logarithm of number of knowledge element combination (a, b) in the patents of observation group plus one
Independent Variable	Data-intelligence empowerment	DIE	Natural logarithm of annual report digital word frequency plus one
Mediator Variables	Knowledge depth diversification	KDD	The overall difference between knowledge diversification and knowledge breadth diversification
	Knowledge breadth diversification	KBD	The entropy index of the ratio of the number of invention patents belonging to category j to all patents in year t of enterprise i

Table 1. *Cont.*

Type	Name	Sign	Measurement
Control Variables	Corporate performance	Roa	Return on total assets
	Growth	Grow	Increase rate of main business revenue
	Asset liability ratio	Lev	Ratio of total liabilities to total assets
	Free Cash Flow	Cfr	Ratio of net cash flow of operating activities to total assets
	Tobin's Q	Tobins	Ratio of market value to total assets
	Number of Years since Listing	Firmage	Logarithm of the difference between the observation year and the listing year
	Double-hatting	Duality	Whether the chairman serves as CEO
	Shareholding Concentration	Top1	Shareholding ratio of the largest shareholder

4.3. Model Construction

To examine the impact of data-intelligence empowerment on knowledge recombinant capabilities, we set the following model:

$$RR_{i,t} = \alpha_0 + \alpha_1 DIE_{i,t} + \alpha_2 Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (4)$$

$$RC_{i,t} = \beta_0 + \beta_1 DIE_{i,t} + \beta_2 Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (5)$$

In the above model, the dependent variables in the regression are knowledge recombinant reuse capability (*RR*) and knowledge recombinant creation capability (*RC*). The core independent variable is data-intelligence empowerment (*DIE*). *Year* and *Industry* represent year fixed effect and industry fixed effect, respectively. *Controls* is the control variable and ε is the random error term of the model.

To examine the mechanism of knowledge diversification, the following model is constructed:

$$KDD_{i,t} = \gamma_0 + \gamma_1 DIE_{i,t} + \gamma_2 Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (6)$$

$$KBD_{i,t} = \lambda_0 + \lambda_1 DIE_{i,t} + \lambda_2 Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (7)$$

$$RR_{i,t} = \alpha_0{}' + \alpha_1{}' DIE_{i,t} + \alpha_2{}' KDD_{i,t} + \alpha_3{}' Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (8)$$

$$RC_{i,t} = \beta_0{}' + \beta_1{}' DIE_{i,t} + \beta_2{}' KBD_{i,t} + \beta_3{}' Controls_{i,t} + Year + Industry + \varepsilon_{i,t} \quad (9)$$

Among them, *KDD* represents the knowledge depth diversification, and *KBD* represents the knowledge breadth diversification.

5. Results

5.1. Descriptive Statistics and Correlation Analysis

5.1.1. Descriptive Statistics

Table 2 displays the descriptive statistical findings for the primary variables. The value of enterprise knowledge recombinant reuse capability ranges from 0 to 7.55. The value of knowledge recombinant creation capability ranges from 0 at the minimum to 5.85 at the maximum. The lowest and maximum values for data-intelligence empowerment are 0 and 4.23, respectively. It shows that when it comes to knowledge recombinant reuse capability, knowledge recombinant creation capability, and data-intelligence empowerment, there are notable differences among the sample enterprises. Knowledge breadth diversification exhibits a higher mean value than knowledge depth diversification, suggesting a stronger

activity of the former. All control variables' results do not differ appreciably from those found in current literature.

Table 2. Descriptive statistics of the main variables.

Variable	N	Mean	SD	Min	p50	Max
RR	6240	1.94	1.91	0	1.61	7.55
RC	6240	2.45	1.31	0	2.4	5.85
DIE	6240	1.47	1.11	0	1.39	4.23
KDD	6240	0.28	0.31	0	0.2	1.15
KBD	6240	1.01	0.66	0	1.02	2.57
Roa	6240	0.05	0.06	−0.2	0.04	0.21
Grow	6240	0.25	0.44	−0.48	0.16	2.36
Lev	6240	0.39	0.18	0.06	0.38	0.8
Cfr	6240	0.05	0.06	−0.11	0.05	0.23
Tobins	6240	2.23	1.33	0.9	1.82	8.2
Firmage	6240	1.95	0.77	0	1.95	3.26
Duality	6240	0.35	0.48	0	0	1
Top1	6240	31.87	13.97	7.95	29.77	68.45

5.1.2. Correlation Analysis

Table 3 displays the correlation coefficients for the primary factors. The correlations between data-intelligence empowerment and knowledge recombinant reuse capability and knowledge recombinant creation capability have passed the 1% significance level test, indicating that there are significant correlations between them. Furthermore, all of the variables' correlation coefficients are less than 0.7. Additionally, none of the variables in this research have a significant multicollinearity issue because their VIF values are all less than 2.

Table 3. Correlation coefficient.

	RR	RC	DIE	KDD	KBD	Roa	Grow	Lev	Cfr	Tobins	Firmage	Duality	Top1
RR	1												
RC	0.606 ***	1											
DIE	0.044 ***	0.054 ***	1										
KDD	0.311 ***	0.441 ***	0.178 ***	1									
KBD	0.303 ***	0.585 ***	0.00600	0.290 ***	1								
Roa	0.059 ***	0.054 ***	−0.0110	0.00600	−0.00300	1							
Grow	−0.052 ***	−0.026 **	0.110 ***	0.087 ***	−0.038 ***	0.112 ***	1						
Lev	0.192 ***	0.198 ***	−0.048 ***	0.094 ***	0.235 ***	−0.354 ***	−0.025 **	1					
Cfr	0.103 ***	0.064 ***	−0.028 **	−0.00700	0.0200	0.434 ***	−0.065 ***	−0.129 ***	1				
Tobins	−0.053 ***	−0.094 ***	0.077 ***	−0.022 *	−0.129 ***	0.303 ***	0.084 ***	−0.300 ***	0.150 ***	1			
Firmage	0.228 ***	0.119 ***	0.026 **	0.083 ***	0.137 ***	−0.198 ***	−0.102 ***	0.338 ***	0.00400	−0.115 ***	1		
Duality	−0.046 ***	−0.041 ***	0.048 ***	−0.0160	−0.074 ***	0.0200	0.024 *	−0.117 ***	−0.0130	0.057 ***	−0.236 ***	1	
Top1	0.031 **	0.058 ***	−0.094 ***	−0.00400	0.102 ***	0.111 ***	−0.047 ***	0.048 ***	0.074 ***	−0.058 ***	−0.113 ***	0.0110	1

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2. Baseline Regression

This paper chooses the fixed-effect model, which can better control the influence of year and industry characteristics and prevent estimation error resulting from the exclusion of critical factors. Table 4 displays the results of the regression.

In Column (1) and Column (2), the regression coefficients of data-intelligence empowerment on knowledge recombinant reuse capability and knowledge recombinant creation capability are 0.1420 and 0.1349, respectively, which are significant at the level of 1%. This suggests that the higher the degree of data-intelligence empowerment, the greater the knowledge recombinant reuse capability and knowledge recombinant creation capability are. The core hypotheses 1a and 1b are verified.

Table 4. Baseline regression.

	(1)	(2)
	RR	**RC**
DIE	0.1420 ***	0.1349 ***
	(0.0383)	(0.0220)
Roa	4.4684 ***	3.5551 ***
	(0.6427)	(0.4065)
Grow	−0.1216 *	−0.0519
	(0.0739)	(0.0468)
Lev	1.8482 ***	1.3695 ***
	(0.2669)	(0.1607)
Cfr	1.2085 **	0.0372
	(0.5555)	(0.3468)
Tobins	−0.0573 **	−0.0558 ***
	(0.0292)	(0.0182)
Firmage	0.4058 ***	0.0829 **
	(0.0623)	(0.0361)
Duality	0.0632	−0.0100
	(0.0847)	(0.0492)
Top1	0.0033	0.0034 *
	(0.0033)	(0.0019)
Year	Yes	Yes
Industry	Yes	Yes
_cons	−0.0031	1.4305 ***
	(0.2067)	(0.1213)
N	6240	6240
adj. R^2	0.1642	0.1297

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered to the enterprise level in parentheses. Same below.

5.3. Supplementary Analyses

5.3.1. Robustness

1. Replacement of key variable

The data-intelligence empowerment, as measured by DIE2, is remeasured using the ratio of the total frequency of the characteristic words of the digital transformation to the total number of words in the enterprise annual report due to the difference in word count. As can be seen from Table 5, the regression results support the validity of the study findings presented in this work.

Table 5. Replacement of independent variable.

	(1)	(2)
	RR	**RC**
DIE2	0.1425 ***	0.1353 ***
	(0.0385)	(0.0220)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
_cons	0.0053	1.4231 ***
	(0.2074)	(0.1222)
N	6159	6159
adj. R2	0.1645	0.1299

*** $p < 0.01$.

2. Replacement of the regression model

The explained variables in this paper are enterprise knowledge recombinant reuse capability and enterprise knowledge recombinant creation capability. The result based on

the formula is non-negative with an abundance of zero values. To avoid the "left truncation" problem, this paper uses the Tobit model to regress again, and the results are displayed in Table 6. The statistical results show that there has been little to no change from the original model, suggesting that the study findings presented in this paper are essentially reliable.

Table 6. Tobit model.

	(1)	(2)
	RR	**RC**
DIE	0.2116 ***	0.1394 ***
	(0.0529)	(0.0225)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
_cons	−4.3352 ***	0.4400
	(1.1523)	(0.3910)
N	6240	6240
Pseudo R^2	0.0439	0.0409

*** $p < 0.01$.

5.3.2. Endogenous

1. Instrumental variable method

Since the data-intelligence empowerment is likely to be affected by the enterprise knowledge recombinant capabilities. In order to reduce the endogenous problem caused by the mutual causality between the data-intelligence empowerment and the enterprise knowledge recombinant capabilities, this paper takes the data-intelligence empowerment with one lag as its own instrumental variable (DIE_IV), and uses the two-stage least squares method for regression estimation. Table 7 presents the findings. Since the lag variable of data-intelligence empowerment is related to itself and the current enterprise knowledge recombinant capabilities cannot impact the previous data-intelligence empowerment of enterprise, DIE_IV satisfies the requirements for the use of instrumental variables. The weak instrumental variable test confirms the instrumental variables' validity in the first stage of regression when the Cragg–Donald Wald F statistic exceeds the 10% level's crucial value. The predicted value of the data-intelligence empowerment obtained in the first stage is used as the independent variable in the second stage. Column (1) (2) (3) shows the results. The estimated DIE_EST coefficients in columns (2) and (3) are in line with the baseline regression's estimation results, which are both strongly positive. The results of this study remain robust since the predicted coefficients and significance for every key variable are essentially compatible with the benchmark regression.

Table 7. Instrumental variable method.

	(1)	(2)	(3)
	DIE	**RR**	**RC**
DIE_IV	0.817 ***		
	(0.010)		
DIE_EST		0.157 **	0.160 ***
		(0.058)	(0.032)
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Cragg-Donald Wald		7446.10	
N		3797	
F	6589.0	10.39	14.65

*** $p < 0.01$, ** $p < 0.05$.

2. Propensity score matching

Re-measure the index of data-intelligence empowerment with "whether to carry out data-intelligence empowerment". According to the median of the original data-intelligence empowerment index (DIE_M), the "0-1" dummy variable is set, and the data-intelligence empowerment index (DIE_DUM) is replaced according to the following formula:

$$DIE_DUM = \begin{cases} 1, DIE \geq DIE_M \\ 0, DIE < DIE_M \end{cases} \quad (10)$$

Table 8 displays the regression results. The statistical findings for H1a and H1b are essentially in line with the original model. After taking into account the endogenous problem, the results demonstrate that the statistical findings of this work are quite robust.

Table 8. Propensity score matching.

	(1)	(2)
	RR	**RC**
DIE_DUM	0.1426 ***	0.1349 ***
	(0.0383)	(0.0220)
Controls	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
_cons	−0.0040	1.4348 ***
	(0.2070)	(0.1214)
N	6234	6234
adj. R^2	0.1642	0.1299

*** $p < 0.01$.

5.4. Heterogeneity

Even though the aforementioned analysis reveals that data-intelligence empowerment affects enterprise knowledge recombinant capabilities, more research is required to determine whether the ownership structure and geographic location of various enterprises differ.

5.4.1. Heterogeneity of Ownership Structure

Due to the variations in the resource base, market environment, and organizational structure of enterprises with different ownership structures, this article divides the sample enterprises into state-owned and non-state-owned enterprises and examines them respectively. Table 9 presents the findings. In the sample group of non-state-owned enterprises, the regression coefficients of data-intelligence empowerment on knowledge recombinant reuse capability and knowledge recombinant creation capability are significantly positive. In the sample group of state-owned enterprises, the regression coefficient of data-intelligence empowerment on knowledge recombinant reuse capability does not pass the test, and the regression coefficient of data-intelligence empowerment on knowledge recombinant creation capability is significantly positive. The aforementioned findings indicate that knowledge recombinant reuse capability and data-intelligence empowerment are more clearly correlated in non-state-owned enterprises, and knowledge recombinant creation capability is positively impacted by data-intelligence empowerment in different ownership structures. The reasoning behind this is that non-state-owned companies need to take an increased proactive approach to innovation and are driven by consumer demand in order to obtain a competitive edge as they face increasingly intense market competition. Through data-intelligence empowerment, non-state-owned enterprises can overcome the ability trap, gain a deeper grasp of their current knowledge base, access more external resources, improve existing products continuously, and develop new products in the min-

ing of customer needs. In contrast, due to the intricate internal structure, state-owned enterprises take longer to adjust their strategies and incur higher conversion costs when transforming their R&D models and organizational management with digital intelligence technology. As a result, the role that data-intelligence empowerment plays in advancing enterprise knowledge recombinant reuse capability is more behind schedule. In addition, state-owned enterprises are more likely to obtain policy support, and thus have an advantage in resource acquisition. They can improve knowledge recombinant creation capability by continuously expanding the knowledge base.

Table 9. Heterogeneity analysis of ownership structure.

	State-Owned Enterprises		**Non-State-Owned Enterprises**	
	RR	**RC**	**RR**	**RC**
DIE	0.1237	0.1133 **	0.1314 ***	0.1432 ***
	(0.1031)	(0.0561)	(0.0383)	(0.0234)
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
_cons	0.1941	1.8104 ***	−0.1872	1.4733 ***
	(0.5575)	(0.3295)	(0.2279)	(0.1374)
N	1453	1453	4586	4586
adj. R^2	0.1617	0.1760	0.1827	0.1104

*** $p < 0.01$, ** $p < 0.05$.

5.4.2. Heterogeneity of Region

The 30 provinces in China to which the sample firms belong are categorized into three regions based on National Bureau of Statistics standards: east, central, and west. This is done because different regions have different resources and development phases. The purpose of this is to test whether there is heterogeneity in the influence of data-intelligence empowerment on enterprise knowledge recombinant reuse capability and knowledge recombinant creation capability in different regions. Table 10 displays the results of the grouping test. The results show that data-intelligence empowerment and knowledge recombinant reuse capability have a significant positive regression coefficient in the enterprises of the eastern region. The regression coefficients of data-intelligence empowerment on knowledge recombinant creation capability of enterprises in all regions are significant. The findings indicate that, while data-intelligence empowerment positively affects knowledge recombinant creation capability in companies across all areas, the association between data-intelligence empowerment and enterprise knowledge recombinant reuse capability is more pronounced in the eastern region. The rationale is that the application of digital intelligence infrastructure shortens the knowledge distance between regions, improves the knowledge spillover level between innovation subjects, reduces the cost of acquiring innovative knowledge, and enables enterprises to combine internal and external resources in a more novel way to develop new core competencies. The process of enterprise data-intelligence empowerment requires a strong resource base and technical talents. The eastern region has a strong industrial foundation, a high level of digitization and intelligence, and a natural geographical and demographic advantage over the central and western regions. It is conducive for enterprises to realize how to fully integrate digital intelligence technology into their initial commercial procedures and organizational structures, maximize the empowering role of digital intelligence technology, explore the potential use value of the existing knowledge combination, and continuously strengthen the competitive advantage.

Table 10. Heterogeneity analysis of region.

	Eastern Region		Central Region		Western Region	
	RR	**RC**	**RR**	**RC**	**RR**	**RC**
DIE	0.1458 ***	0.1380 ***	0.1992	0.1882 *	0.0393	0.1123 **
	(0.0426)	(0.0244)	(0.1536)	(0.1050)	(0.0858)	(0.0533)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−0.0351	1.4331 ***	1.1869	1.9327 ***	−0.3664	1.1901 ***
	(0.2285)	(0.1369)	(0.7425)	(0.4726)	(0.6030)	(0.3220)
N	4842	4842	565	565	817	817
adj. R^2	0.1858	0.1324	0.1411	0.1121	0.2252	0.1858

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6. Mechanisms

6.1. Knowledge Depth Diversification

The channel mechanism test of knowledge depth diversification and knowledge breadth diversification is shown in Table 11. First, Column (1) is the benchmark regression result, indicating that data-intelligence empowerment significantly promotes the knowledge recombinant reuse capability (β = 0.1420, $p < 0.01$). Column (3) shows an estimated considerably positive relationship (β = 0.0362, $p < 0.01$) between data-intelligence empowerment and knowledge depth diversification, suggesting that data-intelligence empowerment strongly encourages knowledge depth diversification, and H2a is verified. Second, in Column (5), the estimated coefficients of data-intelligence empowerment and knowledge depth diversification are significantly positive. Compared with Column (1), the coefficient value of data-intelligence empowerment is reduced, indicating that the influence of data-intelligence empowerment on knowledge recombinant reuse capability is partially mediated by knowledge depth diversification, and H3a is verified. The Sobel test and Bootstrap method are used to test the mediating path. The Sobel test Z value is 5.735 ($p < 0.01$), and the 95% Bootstrap test confidence interval is [0.059, 0.090], suggesting that the intermediary role of knowledge depth diversification is still robust. Therefore, the knowledge depth diversification acts as an intermediary between data-intelligence empowerment and knowledge recombinant reuse capability.

Table 11. Main effects and mechanism.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	RR	**RC**	**KDD**	**KBD**	**RR**	**RC**
DIE	0.1420 ***	0.1349 ***	0.0362 ***	0.0507 ***	0.0670 *	0.0758 ***
	(0.0383)	(0.0220)	(0.0059)	(0.0112)	(0.0353)	(0.0171)
KDD					2.0762 ***	
					(0.1284)	
KBD						1.1667 ***
						(0.0294)
Sobel test Z value					5.735 ***	4.502 ***
					(0.013)	(0.013)
Bootstrap confidence interval					[0.059, 0.090]	[0.042, 0.076]
					(0.008)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−0.0031	1.4305 ***	0.0809 **	0.5098 ***	−0.1710	0.8357 ***
	(0.2067)	(0.1213)	(0.0322)	(0.0598)	(0.1876)	(0.0968)
N	6240	6240	6240	6240	6240	6240
adj. R^2	0.1642	0.1297	0.1052	0.1802	0.2627	0.4075

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.2. Knowledge Breadth Diversification

First, Column (2) is the benchmark regression result, indicating that data-intelligence empowerment significantly promotes knowledge recombinant creation capability ($\beta = 0.1349$, $p < 0.01$). In Column (4), the estimated coefficient of data-intelligence empowerment on knowledge breadth diversification is significantly positive ($\beta = 0.0507$, $p < 0.01$), suggesting that data-intelligence empowerment strongly encourages knowledge breadth diversification, and H2b is verified. Second, in column (6), the regression coefficients of data-intelligence empowerment and knowledge breadth diversification are significantly positive. Compared with column (2), the coefficient value of data-intelligence empowerment is lower, indicating that the influence of data-intelligence empowerment on knowledge recombinant creation capability is partially mediated by knowledge breadth diversification, and H3b is verified. The Sobel test and Bootstrap method are used to test the mediating path. The Sobel test Z value is 4.502 ($p < 0.01$), and the 95% Bootstrap test confidence interval is [0.042, 0.076], suggesting that the intermediary role of knowledge breadth diversification is still robust. Therefore, knowledge breadth diversification acts as an intermediary between data-intelligence empowerment and knowledge recombinant creation capability.

7. Conclusions and Discussions

7.1. Discussions of Results

First of all, data-intelligence empowerment facilitates knowledge recombinant reuse capability and knowledge recombinant creation capability of enterprises. Digital intelligence technology can strengthen the ability to manage knowledge and innovate by empowering enterprises with three kinds of digital intelligence capabilities: connection, analysis, and intelligence. This finding is almost consistent with the idea that IT use can increase the intensity and diversity of knowledge recombination of enterprises [12], suggesting that enterprises can take advantage of the characteristics of digital resources to achieve architectural innovation through the application of digital intelligence technology. On the one hand, data-intelligence empowerment can sustainably facilitate internal knowledge transfer and sharing, discover new application scenarios for knowledge recombination, improve R&D methods, and enhance knowledge recombinant reuse capability. On the other hand, data-intelligence empowerment can promote the formation of new thinking logic in enterprises and improve knowledge recombinant creation capability by absorbing new knowledge, discovering dependencies between knowledge, and sustainably exploring new combination methods.

Secondly, this paper also considers the mechanism of the relationship between data-intelligence empowerment and knowledge recombinant capabilities. First, there is a significant positive relationship between data-intelligence empowerment and knowledge diversification. This suggests that companies have access to richer knowledge resources through data-intelligence empowerment. Data-intelligence empowerment facilitates enterprises to acquire more complementary knowledge for resource construction, which not only optimizes the efficiency of knowledge management system and resource allocation [1], and thus sustainably obtains knowledge value-added, but also blurs the boundaries of the enterprise, improves the level of knowledge overflow [12], and continuously expands the knowledge base of the enterprise. Second, knowledge depth diversification acts as an intermediary between data-intelligence empowerment and knowledge recombinant reuse capability, and knowledge breadth diversification acts as an intermediary between data-intelligence empowerment and knowledge recombinant creation capability. This finding suggests that enterprises have developed knowledge recombinant capabilities by effectively integrating diverse knowledge resources using digital intelligence technology. This shows

that the viewpoint of "enterprise capability originates from the rational use of resources" emphasized by resource orchestration theory [34] is still valid in the context of digital intelligence. Digital intelligence technology deepens the core competence of enterprises in the relevant field, forms the cumulative effect of enterprise knowledge recombinant reuse, and improves the flexibility of knowledge transfer, so as to sustainably improve the existing technology. Digital intelligence technology deepens the embeddedness of enterprises in social networks, improves the absorptive capacity of enterprises' cross-domain knowledge, and promotes enterprises to break through the existing knowledge structure in order to enhance knowledge recombinant creation capability.

Finally, ownership structure heterogeneity and regional heterogeneity all play a role in how data-intelligence empowerment affects enterprise knowledge recombinant capabilities. Particularly, non-state-owned enterprises and eastern region enterprises exhibit a more pronounced promotion effect of data-intelligence empowerment on knowledge recombinant reuse capability, and there is a promotion effect on the knowledge recombinant creation capability in various contexts.

7.2. Contributions

7.2.1. Theoretical Contributions

First, the perspective of recombination is introduced into the analytical framework of digital innovation. Distinguished from analyzing the mechanism of the role of digital intelligence technology in influencing firms' innovations from a single perspective of resources, capabilities, processes, and boundaries [18], based on resource orchestration theory, this paper clarifies the impact of data-intelligence empowerment on the sustainable innovation capabilities of high-tech enterprises from the recombination perspective, which is a new application of empowerment theory and resource orchestration theory in the field of digital innovation research, and extends the relevant theoretical perspectives.

Second, it enriches the influencing factors of knowledge recombinant capabilities. Different from previous studies, which pay more attention to how knowledge recombination affects enterprise innovation and enterprise performance [13], this paper discusses the differentiated influences of data-intelligence empowerment on the two kinds of knowledge recombinant capabilities, which is a supplement to the source of enterprise recombinant capabilities [6]. The empirical findings presented in this research demonstrate that data-intelligence empowerment can promote knowledge recombinant reuse capability and knowledge recombinant creation capability. The conclusion of the study provides empirical support for the sustainable beneficial effects of data-intelligence empowerment on different kinds of knowledge recombinant capabilities, which contributes to a fuller comprehension of the process.

Third, there is a clearer understanding of the mechanism behind the link between data-intelligence empowerment and enterprise knowledge recombinant capabilities. This paper introduces knowledge diversification into the research framework of data-intelligence empowerment and enterprise knowledge recombinant capabilities. On the basis of knowledge diversification promoting enterprise innovation [8], this paper goes on to distinguish the different knowledge recombinant capabilities caused by different knowledge diversification strategies, analyzes the intermediary role of knowledge depth diversification and knowledge breadth diversification between data-intelligence empowerment and knowledge recombinant reuse capability and knowledge recombinant creation capability, delves deeper into the mechanism that influence these processes, and expands on research ideas in related fields.

7.2.2. Management Insights

First, expedite the improvement of the digital innovation system and pay attention to the application of the concept of digital intelligence at the strategic level sustainably. Enterprises should seize the opportunity window of data-intelligence empowerment for enterprise innovation and promote the thorough integration of digital intelligence technology with organizational management, manufacturing, marketing, etc. A digital strategy is customized to optimize the empowering role of digital intelligence transformation based on its own basis and needs, as well as the features of different ownership structures and geographical conditions.

Second, formulate a knowledge diversification strategy that considers both the fortification of core competencies and the augmentation of capacity boundaries. Establishing an internal and external two-way driven empowering mechanism, utilizing the digital intelligence platform to delve deeply into existing knowledge and fully absorb heterogeneous knowledge, reexamining internal and external resources, optimizing internal resource allocation, and flexibly grasping changes in the external market are all expected of enterprises. They should also seek the balance between data-intelligence empowerment and two kinds of knowledge recombinant capabilities, tap new opportunities and create new value, while maintaining sustainable competitive advantage.

Third, further develop and put into practice pertinent incentive programs to direct enterprises in releasing the vitality of innovation through the digital intelligence transformation. The risk of enterprise transformation can be reduced and an environment conducive to innovation can be fostered via institutional guarantee. Given the variances across enterprises, policy support ought to be skewed toward the central and western areas. Through tax breaks, R&D subsidies, and other means, enterprises can be assisted in resolving financing issues of sustainable innovation and smoothly transitioning through the transformation stage.

7.3. Limitations and Future Directions

First, the research scope is restricted to high-tech listed companies. Problems with self-selection could arise from the small sample size. In the future, we can analyze the industrial heterogeneity of the influence of data-intelligence empowerment on knowledge recombinant capabilities and explore the universality of the research conclusions.

Second, the boundary of the effect of data-intelligence empowerment on knowledge recombinant capabilities is not clear. Future research can delve deeper into the moderating variables that impact the connection between data-intelligence empowerment and knowledge recombinant capabilities, as well as enrich the effects of data-intelligence empowerment on enterprise knowledge recombinant capabilities under different scenarios.

Finally, this study solely focuses on how knowledge diversification mediates the relationship between data-intelligence empowerment and enterprise knowledge recombinant capabilities. In the future, we can further study other mechanisms of the influence of data-intelligence empowerment on enterprise knowledge recombinant capabilities.

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