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Digital Technology Driving Exploratory Innovation in the Enterprise: A Mediated Model with Moderation

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Abstract: Emerging digital technologies, with their great advantages in resource convergence, opportunity identification, supply-demand docking and knowledge sharing, are breaking and subverting traditional business concepts and providing a new impetus and opportunities for enterprise innovation activities. Therefore, it is valuable to explore how digital technology affects exploratory innovation to gain a sustainable competitive advantage in a dynamic and changing market environment. Based on data from Chinese A-share high-tech manufacturing listed companies from 2012 to 2020, this paper empirically tests the impact of digital technology on enterprise exploratory innovation by using a fixed effects negative binomial regression model and further explores the intermediate mechanism and boundary conditions between the two. The results show that digital technology has a significant positive impact on enterprise exploratory innovation, and that knowledge breadth plays a mediating role; high network centrality can effectively strengthen the positive impact of digital technology on enterprise knowledge breadth, thus promoting enterprise exploratory innovation. The conclusion enriches and expands the theoretical and empirical research on the driving effect of digital technology innovation, and provides strong practical guidance for encouraging enterprises to achieve exploratory innovation.

Keywords: digital technology; knowledge breadth; network centrality; exploratory innovation

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Citation: Gao, J.-L.; Chen, Y.; Zhang, X.-Q. Digital Technology Driving Exploratory Innovation in the Enterprise: A Mediated Model with Moderation. *Systems* **2023**, *11*, 118. https://doi.org/10.3390/systems11030118

Academic Editors: Ikpe Justice Akpan, Bamidele Adebisi and Murali S. Shanker

Received: 27 January 2023
Revised: 16 February 2023
Accepted: 21 February 2023
Published: 24 February 2023

1. Introduction

In recent years, the wave of digitalization has swept across the world, prompting all fields of the global social economy to compete for change [1–3]. In addition, events such as the COVID-19 pandemic occur frequently, and the dynamic changes in the external production and operation environment continue to impact the survival and development of enterprises. How to meet the requirements of the digital paradigm revolution to achieve high-level scientific and technological innovation in enterprises has become an important issue that needs urgent attention. In addition, countries around the world have, in turn, issued relevant strategies and supporting policies for the development of the digital economy, and the development speed and impact of the digital economy have reached unprecedented heights, success that plays a key role in the restructuring of global resource elements and the reshaping of the global economic structure [3,4]. China has attached great importance to the digital economy in recent years and has successively formulated the outline for the Implementation of the Strategy of Network Power and the outline for the Development of Digital Economy to help the development of the digital economy from the top-level design level of the country. Digital technology, the first productive force of the digital economy, is deeply integrated with the real economy and rapidly penetrates all levels of the economy and society, providing new growth momentum for the traditional manufacturing industry, in order to achieve high-quality development [5,6].

Digital technology supports companies in making scientific innovation decisions by facilitating real-time processing of massive amounts of information and accurate identification of possible paths of technological evolution. By transforming organizational structures, business processes, and technological paradigms, digital technology applications fundamentally change innovation activities in companies [7]. Digital technology improves the efficiency of corporate innovation by reducing resource consumption and shortening R&D cycles while keeping the original resources intact [8]. The self-iterative nature of digital technology helps enterprises overlay new features after designing and producing related products or services [9]; it is conducive to the continuous innovation of products and services. In addition, digital technology can accurately simulate various parameters and reduce uncertainty in the R&D process by virtually simulating the design, production, and use of products [10]. The application of digital technology not only enhances the level of innovation within the organization but also promotes collaborative innovation outside the company [11]. Relying on the digital ecosystem, including digital infrastructure and digital platforms, enterprises achieve collaborative innovation in the interaction of symbiosis, competition, and cooperation by gathering knowledge and technology from different fields [12]. Therefore, the question of whether enterprises can grasp technological opportunities and effectively apply digital technology to promote enterprise innovation and development has become a hot topic of concern to scholars. Based on this, this paper asks the following questions: Can digital technology impact exploratory innovation in firms? What are the mechanisms and boundary conditions for digital technology to influence exploratory innovation in firms?

Exploratory innovation is a drastic and radical innovation behavior which requires enterprises to break away from the original knowledge structure, acquire and create new products or services through R & D activities, and form a sustainable competitive advantage [13]. It is of great significance for enterprises to achieve leapfrog development through transformation and upgrading. To gain a competitive advantage, enterprises need to continuously cultivate exploratory innovation capabilities, establish core technological advantages, and cope with the changing external environments. Due to the inherent complexity and technical difficulty of exploratory innovation, as well as the systematic and in-depth development of enterprises, it is difficult for enterprises to rely on traditional business concepts and their resources to obtain the success of exploratory innovation. In the context of the new technological revolution, external digital technology, which is considered to be highly versatile and disruptive, can fundamentally change consumer behavior and expectations, alter the basic shapes of products and business models, and even disrupt the competitive landscape of incumbents [14]. Exploratory innovation is regarded as an important component of the creative destruction process, and the changes in innovation activities triggered by digital technology provide a new impetus for the exploratory innovation of enterprises.

Through the literature review, it is found that the research on the impact and mechanism of digital technology on enterprise exploratory innovation is still in the exploratory stage, and that the existing research still has the following shortcomings: First, the existing literature on the impact of enterprise digital technology on enterprise innovation is mostly discussed from the perspective of single digital technology or integrated digital technologies. For example, based on a single digital technology perspective, some scholars believe that the deep combination of AI application capability and AI management capability based on AI can help enterprises enhance their willingness to innovate and improve their innovation performance [15]; widening broadband Internet access helps to increase the number of research and development personnel and improve the efficiency of innovation [16]. Based on the perspective of integrated digital technology, some scholars further explore the impact of digital technology on enterprise innovation by examining the extent to which enterprises apply a variety of digital technologies, such as using the dummy variable "0/1" to measure whether enterprises use digital technology [6]. However, measuring the level of digital technology application in enterprises by counting only a single digital technology or based on the decision whether to use digital technology at all cannot accurately measure the driving effect of digital technology on enterprise innovation; second, the existing literature mainly focuses on the overall empowering effects of digital technology on enterprise innovation, but does not deeply explore the mechanisms and effects of digital technology on exploratory innovation activities of enterprises. For example, enterprises can efficiently obtain useful information resources, reduce the risks of enterprise innovation and enhance enterprise innovation performance through the application of digital technology [5]. Third, the existing literature on exploratory innovation in firms mostly uses theoretical analysis and case studies, such as Xie et al. [17], who use a two-case comparative study to explore the impact of exploratory innovation on firms' strategic performance under different stages of hybrid integration, but lack a panel data-based empirical test of how digital technology facilitates exploratory innovation in firms.

Given the above shortcomings, this study attempts to contribute to the relevant literature from the following perspectives. First, by using the text analysis method, digging out the keywords related to digital technology in enterprises' annual reports, and calculating the number of their appearances to scientifically and systematically measure the application degree of digital technology in enterprises. Second, by focusing on China's Shanghai-Shenzhen A-share listed high-tech manufacturing enterprises from 2012 to 2020, with the help of Stata, version 16.0; Software for data statistics; William Gould Research: Computer Resource Center, USA, 1985, to examine empirically the relationship between digital technology and enterprise exploratory innovation, and investigate the intermediate mechanism and boundary conditions of digital technology affecting enterprise exploratory innovation in depth, which is of great theoretical and practical significance for the promotion of the digital development of manufacturing enterprises and the reshaping of their innovation advantages.

2. Theory and Hypothesis

2.1. Digital Technology and Exploratory Innovation

With the rapid development of new digital technologies such as artificial intelligence and big data, digital technology has become the core path for enterprises to establish competitive advantages in order to achieve exploratory innovation. First, in the context of digitalization, enterprises are changing from the traditional vertical, hierarchical pyramid structure to a flat and networked organizational structure [18]. While eliminating the redundant levels of the organization, managers are impelled to flexibly adjust the innovation scheme in the dynamic market environment to improve the decision-making efficiency of enterprise exploratory innovation. Second, by embedding digital technology, enterprises can effectively strengthen data sharing among innovators and accurately identify front-end and terminal needs by involving suppliers, customers and other stakeholders in the innovation process [19], all in the process of carrying out targeted innovation. For example, by using digital technology to build a user innovation platform, Haier encourages users to participate in product design and development based on their own needs, which not only improves user satisfaction but also provides new possibilities for enterprises to explore and develop targeted products. Third, digital technology digitizes the production factors of the enterprise design, R&D, production, and other processes, accurately grasps the flow of resources in each link, and visualizes R&D data [10], and thus improves the allocation efficiency of resources. For example, various cloud computing deployment models, such as public and private clouds, not only help enterprises obtain elastic resources on demand but also save the time cost of technicians in managing and maintaining systems, which helps technicians devote more time to innovation activities. Thus,

H1: *digital technology can promote the exploratory innovation of enterprises*.

2.2. Digital Technology and Breadth of Knowledge

The concept of "knowledge base" was first proposed by Cohen and Levinthal [20] in their study of "absorptive capacity"; it refers to the collection of knowledge elements in various fields accumulated by enterprises in the course of long-term business development, and largely determines the integration and absorption capacity of enterprises relative to external resources. Based on the different characteristics of the knowledge base, Katila and

Ahuja [21] further divided it into knowledge breadth and knowledge depth. Knowledge breadth is based on the horizontal coverage of knowledge and measures the types and quantities of knowledge elements possessed by an enterprise; the greater the knowledge breadth, the wider the range of the enterprise's knowledge domain and the more diversified the knowledge. Knowledge depth is based on the vertical depth of knowledge and measures the proficiency of an enterprise in the knowledge elements in a specific field; the greater the knowledge depth, the more specialized the knowledge. In this regard, this paper focuses on the more diversified knowledge breadth.

In the era of Industry 4.0, the pace of comprehensive digitization has been accelerating, and the changes and applications of digital technology have had a profound impact on the production and operation of enterprises and information-based interactions. First, in the increasingly symbiotic digital ecosystem, the computability and computational efficiency of digital technology helps enterprises break the barrier of geographic space to knowledge acquisition [22], and helps enterprises learn more knowledge and technologies from other regions, continuously expanding the geographic scope of enterprise knowledge sources. Secondly, digital technology has gradually penetrated various aspects of design, manufacturing, and R&D, which helps to promote the cross-border integration and collaborative R&D of enterprises. Some studies have shown that cooperative R&D is an important channel for the realization of knowledge spillover [23]. Different R&D subjects have different levels of knowledge accumulation [24], and the cooperation and communication among multiple subjects such as enterprises, universities, and research institutes helps to realize the cross-organizational transfer of knowledge and accelerate the collision and integration of heterogeneous knowledge, and thus expand the knowledge base of enterprises. Again, the digital platform and digital infrastructure owned by digital technology effectively connect enterprises and employees [25], and reduce information asymmetry through the transparency of enterprise development, which helps employees clarify their learning development direction and lay the foundation for enterprise knowledge diversification. In addition, the wide application of digital technology builds bridges for communication between employees [6], facilitates knowledge sharing and collision among employees, and helps to tap more invisible knowledge to achieve knowledge accumulation. Thus,

H2: *digital technology can promote the breadth of enterprise knowledge.*

2.3. Knowledge Breadth and Exploratory Innovation

The resource-based theory holds that the innovative activities of enterprises cannot be solely created by resources. As an internal resource, the knowledge and information continuously acquired and deposited during the production and operation of an enterprise is an important support for the evolution of the organization and the successful realization of exploratory innovation [26]. First of all, for the existing knowledge within an enterprise, the use of the same set of knowledge elements can produce limited innovation value. When a set of knowledge elements is repeatedly used, its combined potential is continuously depleted until it is exhausted [27]. The more heterogeneous knowledge a firm has, the more likely it is to tap into new useful combinations [21,28], and thereby to reduce the path dependence that occurs in the innovation process of the firm. Second, according to organizational learning theory, knowledge breadth can improve the absorptive capacity of a firm [20]. An enterprise with diversified knowledge has a more complete knowledge system and can quickly digest and absorb more new knowledge and technology. The positive cycle of knowledge accumulation can effectively enhance the willingness of enterprises to expand new business fields and provide inexhaustible power for exploratory innovation. Again, companies with diverse knowledge are more likely to identify and perceive changes in the market environment within the industry [29]. The greater the breadth of knowledge, the more knowledgeable the firm's managers and technology developers are about their competitors, upstream and downstream partners, and other stakeholders [30]. It is easier to identify new issues in a dynamic market environment, which enables a better grasp of the direction and timing of innovation. Thus,

H3: *knowledge breadth can promote the exploratory innovation of enterprises.*

2.4. The Mediating Role of Knowledge Breadth

Apart from the direct impact of digital technology on exploratory innovation, a large part of the reason for this digital innovation is that digital technology helps enterprises break through their knowledge limitations, realize the relevant links and possible integration of resources, and then promote enterprise-wide exploratory innovation. Firstly, based on knowledge acquisition theory, the wide application of digital technology provides enterprises with a convenient information-sharing platform [8]. Internally, it can effectively weaken the boundaries of departments, and excavate the tacit knowledge of enterprises by promoting communication among employees of various departments, to speed up the transformation of achievements from new knowledge to new technologies, and lay a solid foundation for enterprises to achieve exploratory innovation. Externally, it can accelerate the information flow between enterprises and external network subjects such as upstream and downstream partners and customers [31], continuously expand the scope of knowledge acquisition, and promote the collision and integration of heterogeneous knowledge, to increase the possibility of successfully realizing exploratory innovation. Secondly, the information resources brought by digital technology can provide employees with more efficient knowledge learning and development opportunities [6], stimulate employees' work potential, and enhance their willingness to participate in decision-making, thus providing intellectual support for enterprises seeking to realize exploratory innovation. In addition, digital technology, with its powerful data mining and analysis capabilities [32], can help companies reduce environmental uncertainty while quickly grasping valuable market information and identifying innovation opportunities, providing a good opportunity for companies to realize exploratory innovation. Thus,

H4: *digital technologies and exploratory innovation are mediated by knowledge breadth.*

2.5. The Moderating Effect of Network Centrality

At present, the relationship between organizational networks is increasingly close and their boundaries are gradually blurred. How to use digital technology to expand the breadth of enterprise knowledge to enhance the competitiveness of enterprises in an increasingly competitive environment deserves our further exploration. Based on the social network theory, a network location can reflect an enterprise's ability to obtain and control resources from other enterprises [33]. Differences in a network's location can bring different information resources and opportunities for companies to access [34]. In this paper, network centrality is an important indicator for measuring the network location of a firm. First, firms with high network centrality act as a central hub in the network [35] and can establish connections with more subjects and have access to more market information and the current status of partners as well as competitors, thus enhancing the ability to access heterogeneous knowledge and resources [36]. On this basis, the use of digital technology by enterprises can further broaden the transmission channels of information, accelerate the integration and utilization of resources, and thus achieve the accumulation of a knowledge base within the enterprise. Second, compared with enterprises with low network centrality, enterprises with high network centrality have stronger industry influence, hold the dominant and controlling power of information transmission, and can allocate resources and coordinate more effectively [37]. On this basis, the deep application of digital technology can facilitate the deployment and reorganization of enterprise resources, thus expanding the breadth of enterprise knowledge elements. In addition, enterprises in a network intermediary position can participate more effectively in higher quality innovation networks and maintain their own diversity and flexibility in accessing knowledge elements in technology, markets and design, thereby driving exploratory innovation [34,38]. Thus,

H5: *the network centrality positively regulates the relationship between digital technology and knowledge breadth, i.e., when the enterprise network centrality is high, the positive effect of digital technology on enterprise knowledge breadth is stronger; while when the enterprise network centrality is low, the positive effect of digital technology on enterprise knowledge breadth is weaker*.

In summary, the theoretical model is shown in Figure 1.

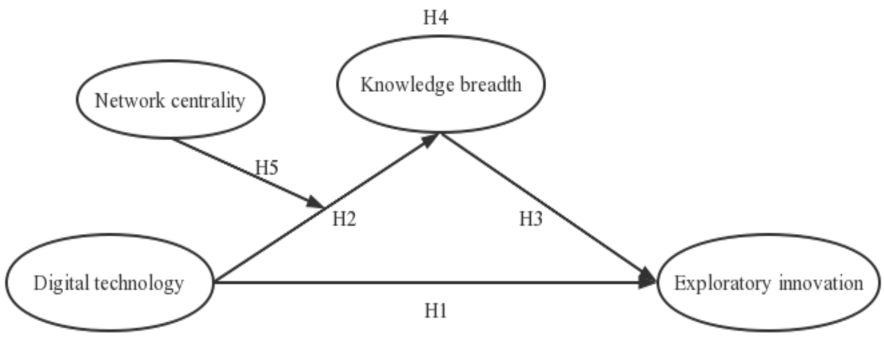

Figure 1. Theoretical framework.

3. Methodology

3.1. Data and Samples

Based on the text analysis method and the negative binomial regression method, this paper selects listed enterprises of the computer and office equipment manufacturing industry in China's Shanghai and Shenzhen with listed A-shares from 2012 to 2020 as the research sample for empirical study. According to a recent survey released by the global credit insurance leader Yuliyasoft, China is the fastest growing country in terms of digitalization, while many countries' economies have stagnated in the past two years due to the COVID-19 epidemic and the consequent lack of new breakthroughs in digitalization. Therefore, the study can provide a constructive reference and an inspiration for other countries and regions. Considering that the state released information technology development planning documents successively in 2011, more and more entrepreneurs then recognized the importance of digital technology, and there is a certain lag between the annual reports and the patent data of enterprises, the year interval of this paper is set from 2012 to 2020. Since the independent variable of this paper is digital technology, and listed enterprises in the computer and office equipment manufacturing industry are more widely versed in digital technology, the selection of this type of enterprise is somewhat representative. Considering the different calculation methods of market value of B shares and H shares, only A-share listed enterprises are selected as samples in this paper. The listed enterprises in the financial and insurance category, ST category and *ST category will have missing financial data due to various abnormal situations, so they are excluded from the original sample of this paper. Finally, 322 enterprises with a total of 2130 observations were obtained. All research data was obtained from the CSMAR database, Juchao Information Network, the Patent Technology Search Engine, etc. Stata 16.0 software was used to conduct an unbalanced panel data regression analysis.

3.2. Measurements

3.2.1. Dependent Variable: Exploratory Innovation (EI)

Existing studies on the measures of exploratory innovation of enterprises mainly include the cost expenditure of R&D activities of enterprises [39], the ratio of the number of newly cited invention patents to the total number of patents [40] and the number of invention patent applications of the enterprises in the corresponding year [41]. Considering that R&D expenses are prone to be inconsistent with the actual situation as considered in the statistical process, due to certain incentives, as well as the small number of patent citations in China's corporate patents, the third measure was chosen to measure exploratory innovation by taking the number of corporate invention patent applications.

3.2.2. Independent Variable: Digital Technology (DT)

The current measurement method for "digital technology" mainly includes: (a) constructing a scale to interview the core personnel of the company, including asking whether the business processes and operation processes involve digital technology [42]; (b) manual compilation annual reports of listed companiesto construct 0–1 dummy variables [12]; (c) the text analysis method, using software to capture multiple keywords in the annual reports of listed companies, using keyword word frequency summation [4]; and (d) construction of quantitative values based on the investment amount for digital technology-related projects and the year-end share of total intangible assets [43]. Among the above digital technology measurement methods, the questionnaire method has a small sample size and is difficult to implement, and reckoning the number of digital technology project investments encounters difficulties in covering the actual implementation in enterprise operation. Therefore, it was feasible and scientific to choose the textual analysis method to measure the degree of digital technology application by mining the frequency of keywords related to "digital technology" through an in-depth search of public annual reports of listed enterprises.

The specific steps were as follows: First, we used Python crawler technology to download the 2012–2020 annual reports of listed enterprises in the computer and office equipment manufacturing industry in Shanghai and Shenzhen A-shares from the Juchao information website and convert the pdf format of the annual reports into a readable txt format, which is then used as a database for subsequent keyword screening. Second, concerning the thesaurus selection by Wu et al. [4], a team of experts was invited to further screen the keywords in the thesaurus based on specific contexts, and 50 keywords including digital technology, artificial intelligence, Internet, big data, blockchain, cloud computing, etc. were finally identified. Thirdly, we used Python software to write code to realize the acquisition of keywords and aggregate the number of occurrences of all keywords to arrive at the total digital technology index.

3.2.3. Intermediary Variable: Knowledge Breadth (KB)

Based on the method of Liu & Feng [44], the number of successful patent classification numbers applied by enterprises was used to measure the knowledge breadth based on the IPC classification standard. The "classification number by major category" was used as the main measure, and the "classification number by minor category" was used for robustness testing, and the larger the value was, the wider the knowledge was.

3.2.4. Moderator Variable: Network Centrality (NC)

There are three standard measures of network centrality, namely, degree centrality, mediation centrality, and proximity centrality [45]; among these, mediation centrality measures the extent to which an individual in the network controls the linkage paths of other individuals in the network and it is the most widely used, so it is used as an indicator of network centrality in this paper. Based on the CSMAR data related to whether a director of a firm is also a director in other firms (1 if he/she is also a director, 0 otherwise), we constructed a network location relationship matrix of firms, calculated the intermediation centrality of each director, took the average of intermediation centrality of all directors as the main research variable, and took the maximum value for robustness testing. Where g denotes the number of firms in the chain director network, and gjk is the number of paths that firm j must pass through to connect with firm k,

$$\mathrm{NC_i} = \frac{\frac{\sum_{j<k} g_{jk(n_i)}}{g_{jk}}}{(g-1)(g-2)}$$

3.2.5. Control Variables

Firm size (SIZE) reflects to a certain extent the risk resistance of the enterprise and the level of enterprise development. We therefore used the logarithm of operating income to measure firm size. Firm age (AGE) reflects a company's technological reserves and is measured by adding 1 to the logarithm of the difference between the sample observation year and the company's listing year. Gearing ratio (LEV) is an important indicator for assessing financial health. The ratio of total liabilities to total assets was calculated. As for nature of ownership (SOE), state-owned companies are secured by the strength of the state and cooperation with other research institutions makes more sense for them. State-owned enterprises were 1, and non-state-owned enterprises were 0. Finally, the percentage of independent directors (INDRATIO) reflects the decision-making behavior of companies to carry out innovation. The ratio of the number of independent directors to the total number of directors was calculated. The names and measures of the main variables are shown in Table 1.

Table 1. Variable names and measures.

Variable Type	Variable	Variable Measurement
Dependent Variable	Exploratory innovation (EI)	Number of corporate invention patent applications.
Independent Variable	Digital technology (DT)	Related keywords word frequency based on text analysis
Intermediary Variable	Knowledge breadth (KB)	Classification number by number of major categories
Moderator Variable	Network centrality (NC)	Average of intermediation centrality
Control Variable	Firm size (SIZE)	Logarithm of operating income
	Firm age (AGE)	Adding 1 to the logarithm of the difference between the sample observation year and the company's listing year
	Gearing ratio (LEV)	Ratio of total liabilities to total assets
	Nature of ownership (SOE)	State-owned enterprises are 1, and non-state-owned enterprises are 0
	Percentage of independent directors (INDRATIO)	Ratio of the number of independent directors to the total number of directors

3.3. Model Setting

In this paper, the number of patents as the dependent variable is a count variable with non-negative value and discrete distribution. If linear regression is used for this variable, the coefficient estimates obtained are inconsistent and biased, at which point Poisson regression and negative binomial regression are more desirable. However, the constraint that the mean value of the Poisson model is equal to the variance is difficult to satisfy. Therefore, this paper uses the negative binomial regression model for more accurate estimation (rejecting the Poisson model at the $p < 0.001$ significance level). Using the Hausman test, the negative binomial regression model with fixed effects was further determined (the random effects model was rejected at the $p < 0.001$ significance level). To test the research hypothesis, the following model was set in this paper.

$$EI_{i,t} = \beta_0 + \sum \beta_k Control + \sum Year + \varepsilon_{i,t} \quad (1)$$

$$EI_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \sum \beta_k Control + \sum Year + \varepsilon_{i,t} \quad (2)$$

$$EI_{i,t} = \beta_0 + \beta_1 KB_{i,t} + \sum \beta_k Control + \sum Year + \varepsilon_{i,t} \quad (3)$$

$$KB_{i,t} = \beta_0 + \sum \beta_k Control + \sum Year + \varepsilon_{i,t} \quad (4)$$

$$KB_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \sum \beta_k Control + \sum Year + \varepsilon_{i,t} \quad (5)$$

$$KB_{i,t} = \beta_0 + \beta_1 DT_{i,t} + \beta_2 DR_{i,t} + \beta_3 DT_{i,t} DR_{i,t} + \sum \beta_k Control + \sum Year + \varepsilon_{i,t} \quad (6)$$

In the above model, i denotes firm, t denotes time, EI denotes firm exploratory innovation, DT denotes digital technology, KB denotes knowledge breadth, DR denotes network centrality, Control is the aforementioned control variable, Year is the time fixed effect, and ε is the model random error term. In addition, to make the regression results more robust in the empirical analysis, the firm-level clustering robust standard errors are used. Among them, Equation (1) tests the effect of control variables on the exploratory innovation of enterprises. Equation (2) examines the effect of digital technology on the exploratory innovation of enterprises. Equation (3) examines the effect of knowledge breadth on exploratory innovation; Equation (4) tests the effect of control variables on knowledge breadth. Equation (5) examines the effect of digital technology on knowledge breadth of enterprises. Equation (6) adds an interaction term to test the moderating effect of network centrality in digital technology and knowledge breadth of enterprises.

4. Empiric Analysis

4.1. Descriptive Statistics

The results of descriptive statistics and correlation analysis of the variables in this paper are shown in Table 2. Among them, the standard deviation of the dependent variable EI is 387.511, indicating that the degree of exploratory innovation varies significantly among the sample enterprises. Additionally, digital technology, knowledge breadth, network centrality, and each control variable are significantly correlated with the exploratory innovation of enterprises, which initially supports the research hypothesis of this paper. In addition, the mean value of the variance inflation factor (VIF) is 1.35 and the maximum value is 1.93, which is much less than 10, indicating that there is no serious problem of multicollinearity in this study. However, regression analysis is needed to obtain more accurate validation results.

Table 2. Descriptive Statistics and Correlation Analysis.

Variable	M	SD	EI	DT	KB	DR	SIZE	AGE	LEV	SOE	INDRATIO
EI	80.192	387.511	1								
DT	50.790	70.263	0.150 *	1							
KB	5.113	4.631	0.347 *	0.271 *	1						
DR	0.000	0.001	0.161 *	−0.037	0.135 *	1					
SIZE	21.095	1.313	0.376 *	0.124 *	0.427 *	0.144 *	1				
AGE	1.759	0.892	0.169 *	0.099 *	0.169 *	0.187 *	0.414 *	1			
LEV	0.349	0.185	0.212 *	0.025	0.197 *	0.141 *	0.576 *	0.354 *	1		
SOE	0.229	0.420	0.118 *	0.093 *	0.204 *	0.146 *	0.284 *	0.433 *	0.133 *	1	
INDRATIO	0.386	0.059	−0.047 *	0.051 *	−0.011 *	0.012	−0.057 *	0.044 *	−0.007	−0.076 *	1

Note: Sample size: 322; * means $p < 0.1$.

4.2. Results of Regression Analysis

The regression test results of digital technology and knowledge breadth affecting firms' exploratory innovation are shown in Table 3. Model 1 is the baseline model, including all the control variables, indicating that the larger the size of a firm (SIZE), the younger its firm age (AGE), which is more conducive to exploratory innovation (EI). This is consistent with Schumpeter's innovation hypothesis that the larger a firm is, the greater its investment in innovation and the more capable it is of engaging in innovative activities. In addition, the younger the age of the firm, the more innovative the management is and the more willing to engage in innovative activities. Model 2 introduces digital technology into Model 1 and analyzes the relationship between digital technology (DT) and enterprise exploratory innovation (EI), and the results show that the regression coefficient is significantly positive ($\beta = 0.003$, $p < 0.01$), indicating that digital technology has a positive promotion effect on enterprise exploratory innovation, and that the research results support H1. In the context of digitalization, the widespread use of digital technologies has largely changed the organizational structure and business processes of companies, thus fundamentally transforming the implementation of innovation activities. Model 3 shows that the regression coefficient of knowledge breadth (KB) and enterprise exploratory innovation (EI) is significantly positive ($\beta = 0.063$, $p < 0.01$), indicating that expanding the knowledge breadth of enterprises is beneficial for them to achieve exploratory innovation, and the findings support H3. Companies with diversified knowledge have a more complete knowledge system and are more likely to identify and perceive changes in the market environment within the industry, thereby grasping innovation opportunities more quickly. Model 4 examines the effects of control variables on enterprises' knowledge breadth, and the results indicate that the larger the size of the enterprise (SIZE), the older their age (AGE), the higher their asset and liability ratio (LEV), and the greater their knowledge breadth (KB). Model 5 shows that the regression coefficient of digital technology (DT) on enterprise knowledge breadth (KB) is significantly positive (β = 0.001, $p < 0.01$), indicating that along with the continuous integration of digital technology into the production and operation activities of enterprises, its powerful information mining ability, and data analysis capability can effectively integrate business data and broaden the enterprise knowledge breadth, and therefore, the research results support H2. To ensure the robustness of the intermediate mechanism, this paper uses the Sobel test to examine the intermediary effect; the results show that the direct effect Z value between digital technology (DT), knowledge breadth (KB) and enterprise exploratory innovation (EI) is 9.614 ($p = 0.000$) and the indirect effect Z value is 2.823 ($p = 0.005$), both of which are greater than the critical value of 1.960, and the intermediary effect is further verified.

Table 3. Regression test results.

Variable	EI			KB		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
DT		0.003 ***			0.001 ***	0.001 ***
		(0.000)			(0.000)	(0.000)
KB			0.063 ***			
			(0.004)			
DR						18.800
						(34.350)
DT×DR						1.282 ***
						(0.442)
SIZE	0.263 ***	0.274 ***	0.232 ***	0.082 ***	0.072 **	0.067 **
	(0.027)	(0.026)	(0.027)	(0.029)	(0.029)	(0.029)
AGE	−0.083 **	−0.085 **	−0.106 **	0.103 **	0.102 **	0.103 **
	(0.041)	(0.041)	(0.041)	(0.044)	(0.044)	(0.044)
LEV	−0.234	−0.341 **	−0.250	0.349 **	0.302 **	0.299 *
	(0.168)	(0.169)	(0.168)	(0.152)	(0.153)	(0.153)
SOE	0.415 ***	0.375 ***	0.344 ***	−0.287 ***	−0.266 ***	−0.269 ***
	(0.077)	(0.077)	(0.078)	(0.097)	(0.098)	(0.097)
INDRATIO	−0.558	−0.523	−0.508	0.139	0.158	0.160
	(0.412)	(0.407)	(0.387)	(0.335)	(0.335)	(0.336)
YEAR FE	YES	YES	YES	YES	YES	YES
N	322	322	322	318	318	318

Note: Sample size: 322; * means $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The results of the moderating effect test of network centrality are shown in Model 6 of Table 3. The coefficient of the cross-product term between network centrality (DR) and digital technology (DT) is significantly positive at the 1% level, which shows that network centrality (DR) has a positive moderating effect on the relationship between digital technology (DT) and enterprise knowledge breadth (KB), and the research results therefore support H5. The moderating effect is shown in Figure 2. Under different levels of network centrality, there are differences in the effect of digital technology on enterprise knowledge breadth; specifically, enterprises have a stronger positive effect of digital technology on enterprise knowledge breadth under high network centrality, and a weaker positive effect of digital technology on enterprise knowledge breadth under low network centrality.

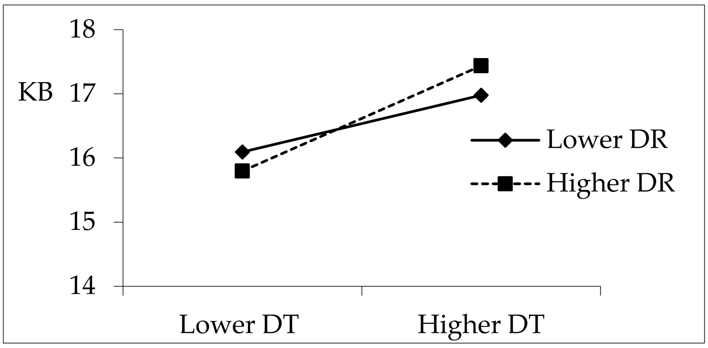

Figure 2. Moderating effect of network centrality.

4.3. Tests of Robustness

The issue of endogeneity arises due to the possible bidirectional causal relationship between the degree of digital technology adoption and firms' exploratory innovation. To avoid the influence of endogeneity on the findings, the independent variables are treated with a one-period lag as the instrumental variables, and the endogeneity issue is further analyzed using a two-stage panel data negative binomial regression; the reason for setting the instrumental variables in this way is that the one-period lagged level of digital technology adoption may significantly affect the extent to which the firms themselves value digital technology, but has no direct impact on the firm's achievement of exploratory innovation in the future, and thus fits the instrumental variable selection requirements better. Among them, statistics such as Kleibergen-Paaprk LM and Cragg-Donald Wald F reject the original hypotheses of the unidentifiable test and the weak instrumental variable test at the 1% significance level, reflecting the correlation between instrumental variables and independent variables. The results of the second-stage regression are shown in columns 1, 2, and 3 in Table 4, and are generally consistent with the previous findings.

Table 4. Robustness test estimation results.

Variable	EI		KB	EI		KB	KB	EI	KB
	1	2	3	4	5	6	7	8	9
DT	0.002 ***	0.001 ***	0.001 ***	0.003 ***	0.001 ***	0.001 **	0.002 ***	0.001 ***	0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
KB		0.601 ***			0.056 ***		0.041 ***		
		(0.075)			(0.005)		(0.003)		
DR			17.595			4.161		67.831 *	1.469
			(34.682)			(40.378)		(34.961)	(5.556)
DT×DR			0.993 ***			1.072 **		1.022 **	0.199 ***
			(0.365)			(0.545)		(0.486)	(0.077)
SIZE	0.275 ***	0.737 ***	0.071 **	0.271 ***	0.248 ***	0.047	0.516 ***	0.139 ***	0.068 **
	(0.026)	(0.052)	(0.029)	(0.031)	(0.032)	(0.039)	(0.055)	(0.028)	(0.029)
AGE	−0.080 **	0.072	0.104 **	−0.069	−0.089 *	0.132 **	0.133	0.094 **	0.104 **
	(0.041)	(0.073)	(0.044)	(0.048)	(0.048)	(0.059)	(0.088)	(0.043)	(0.044)
LEV	−0.347 **	0.164	0.298 *	−0.516 ***	−0.533 ***	0.408 **	0.299	0.013	0.300 **
	(0.169)	(0.149)	(0.153)	(0.200)	(0.199)	(0.192)	(0.205)	(0.153)	(0.153)
SOE	0.410 ***	0.571 *	−0.261 ***	0.382 ***	0.326 ***	−0.221	1.202 ***	−0.139	−0.271 ***
	(0.077)	(0.302)	(0.097)	(0.092)	(0.094)	(0.139)	(0.393)	(0.090)	(0.097)
INDRATIO	−0.440	0.055	0.271	−0.363	−0.495	0.614	0.364	0.303	0.160
	(0.407)	(0.223)	(0.339)	(0.455)	(0.431)	(0.398)	(0.271)	(0.347)	(0.335)
YEAR FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	322	322	318	296	296	291	322	318	318

Note: Sample size: 322; * means $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Considering the posterior interference of relevant digital economy policies, the sample time is adjusted to 2013–2019 and the regression is re-run, and the robustness results of this item are shown in columns 4, 5, and 6 in Table 4, which are generally consistent with the previous findings. The t variable with a one-period lag is considered an instrumental variable and the analysis uses a two-stage panel data negative binomial regression to further analyze the endogeneity issue. For this reason, the mediating variable measures were changed from the original classification number by major category (first three digits of IPC classification number) to classification number by minor category (first four digits of IPC classification number) and regressed again, and the results obtained are shown in columns 7 and 8 in Table 4, which are consistent with the previous findings.

The moderating variable measure was changed from the mean of the original mediated centrality to the maximum of the mediated centrality and re-regressed; the obtained results are shown in column 9, and are consistent with the previous findings.

5. Discussion

In the new wave of technological revolution, manufacturing companies can seize market opportunities and easily achieve "innovation reversal" based on the disruptive innovation effect brought by digital technology. This study examines the importance of digital technology for exploratory innovation and proposes five hypotheses to test the effects of digital technology, knowledge breadth, and network centrality on exploratory innovation. H1 of this study shows a direct link between digital technology and exploratory innovation. The empirical test results of H1 suggest that digital technology plays a positive and critical role in promoting exploratory innovation in firms. The findings of H1 support previous research that digital technology makes it easier for organizations to access the resources and information needed to improve firm innovation performance [46]. The application of digital technology updates the processes of consumer demand acquisition, innovative thinking development, resource integration and allocation, product manufacturing and production, and after-sales adjustment and optimization, reconfiguring the established innovation system [19] and driving exploratory innovation in firms. The results of H1 are consistent with the previous literature, indicating that digital technology is an important force driving exploratory innovation in firms.

H2 of this study shows that digital technology expands the breadth of knowledge of firms. Previous studies also indicate that the continuous penetration of digital technologies and the ability of firms to draw on valuable information resources using online platforms facilitates the expansion of organizational communication and enables resource sharing among external innovation agents [31]. For example, smart devices launched by manufacturing companies rely on internal chips that can not only quickly sense changes in the external environment, but also collect relevant data through interaction with users and transmit them to the platform. Enterprises analyze the collected data intelligently to obtain users' usage of products and changes in demand promptly and expand their knowledge.

H3 of this study shows that knowledge breadth drives exploratory innovation in firms. Previous research has also shown that the broader a firm's knowledge and the more technological areas it covers, the more diverse its knowledge becomes. Those firms with diverse knowledge are more likely to dynamically identify the frontier technology areas that are developing within the industry, quickly perceive changes in the external environment [29], and thus make timely and accurate adjustments.

This study's H4 proposes that knowledge breadth acts as a bridge between digital technologies and exploratory innovation in firms. Firms use digital technology applications to break through their knowledge limitations and expand their knowledge acquisition. In turn, diverse knowledge can help enterprises explore innovation combinations to promote exploratory innovation. For example, Haier has created the Crowdsourcing platform to connect users on the demand side with designers on the design side, so that users can participate in the whole process of product design and R&D through information exchange and knowledge sharing, and realize the customized innovation mode of "reservation and pre-sale". This initiative can help enterprises respond to market changes promptly and improve their willingness to innovate by developing targeted R&D programs. Previous research has revealed the role of network centrality in facilitating knowledge breadth in the firm [35], but has not delved into how it affects the relationship between digital technology and knowledge breadth.

The H5 of our study adds the position of enterprises in the enterprise network, that is, how the network centrality mediates the relationship between digital technology and knowledge breadth. The findings support the idea that network centrality has the key ability to help firms expand their knowledge breadth. The findings show that firms with high network centrality occupy a central hub position and can establish connections with more subjects, thereby gaining access to a wider range of market information and laying the foundation for exploratory innovation. For example, Haier uses digital modules to extend its innovation system to external networks, gathering global module suppliers to participate in module development and supply, which facilitates heterogeneous technology and knowledge acquisition and builds an organizational ecosystem of collaborative innovation to meet user needs. In addition, Haier incorporates partners such as universities and research institutions into the collaborative innovation network, which helps to acquire new knowledge, improve R&D capability and innovation level, and thus reduce the risk and cost of new technology development.

After empirical analysis, the hypothesis test results proposed in this paper are set forth in Table 5.

Table 5. Summary of hypotheses tests.

H1: Digital technology can promote the exploratory innovation of enterprises.	YES
H2: Digital technology can promote the breadth of enterprise knowledge.	YES
H3: Knowledge breadth can promote the exploratory innovation of enterprises.	YES
H4: Digital technologies and exploratory innovation is mediated by knowledge breadth.	YES
H5: The network centrality positively regulates the relationship between digital technology and knowledge breadth, i.e., when the enterprise network centrality is high, the stronger the positive effect of digital technology on enterprise knowledge breadth; while when the enterprise network centrality is low, the weaker the positive effect of digital technology on enterprise knowledge breadth.	YES

6. Conclusions

6.1. Conclusions

Based on the resource-based view and social network theory, this paper analyzes the relationship between digital technology, network centrality, knowledge breadth, and enterprise exploratory innovation using the data of listed computer and office equipment manufacturing enterprises in Shanghai and Shenzhen listing A-shares in China from 2012 to 2020, and obtains the following research conclusions: First, the use of digital technology positively promotes the enterprises' realizing of exploratory innovations. With the continuous improvement of digitalization, enterprises can use digital technology to accelerate the flow and sharing of resources among regional enterprises and promote the realization of exploratory innovation. Second, knowledge breadth is an important transmission mechanism for digital technology in influencing enterprise exploratory innovation. By acquiring digital technology, enterprises can realize the acquisition of external heterogeneous knowledge and data and broaden their knowledge breadth, thus laying an important resource foundation for exploratory innovation activities. Third, enterprise network centrality positively regulates the mechanism of digital technology's effect on knowledge breadth. As the network centrality of enterprises increases, the role of digital technology in promoting the breadth of knowledge can be effectively enhanced, thus promoting the exploratory innovation of enterprises.

6.2. Theoretical Contributions

The conclusions of this study make the following theoretical contributions to the existing literature.

First, based on a resource-based view, this paper empirically tests the impact of digital technology on exploratory innovation in firms. On the one hand, the findings of this paper are consistent with the conclusions drawn by Pan [47] through a questionnaire survey, but this paper uses more objective panel data, which can effectively address the possible common methodological bias of the questionnaire data. On the other hand, this paper enriches and expands the research results in the fields related to digital technology and corporate exploratory innovation.

Second, with the knowledge element as the starting point, digital technology as the driving element, and enterprise exploratory innovation as the influence effect, we construct a research framework of digital technology, knowledge breadth, and enterprise exploratory innovation to examine the transmission role of knowledge breadth between digital technology and enterprise exploratory innovation. It has been shown that knowledge breadth is influenced by organizational environment, etc. [25], and that knowledge breadth affects enterprise' path dependence in the innovation process [21,28]. This paper focuses on digital technology's contribution to exploratory innovation by expanding knowledge breadth, which is explained by organizational learning theory and the resource-based view, in order to enrich the research on digital technology, knowledge breadth, and exploratory innovation in the digital context on the one hand, and expand the inner connection and application of organizational learning theory and the resource-based view on the other.

Third, based on the important role of network centrality in maintaining the competitive advantage of enterprises in a dynamic environment, this paper embeds it into the research framework to explore the moderating role of network centrality between digital technology and enterprise knowledge breadth, which not only helps to elucidate the influence mechanism of digital technology on knowledge breadth, but also inspires subsequent research to integrate internal factors of enterprises such as digital technology and external environmental factors to explore the influence of their interaction on enterprise exploratory innovation.

6.3. Managerial Implications

This study provides some implications and enlightenment for the policy development of business managers.

First, enterprises should accelerate the pace of digital technology application according to their resource conditions and promote the realization of exploratory innovation by accumulating more knowledge elements. For enterprises that have started to use digital technology, they should continuously increase investment in R&D and raise the proportion of technical personnel to help them quickly acquire and absorb external digital technology, enrich the breadth of knowledge sources, and provide a good opportunity for them to realize exploratory innovation. For enterprises that have not yet used digital technology, they should follow the new trend of digital era development, change their innovation strategy, consciously guide them to learn and use external digital technology, and strengthen cooperation and communication with external supply chain subjects to promote knowledge resource endowment, to help them improve their advantages and achieve innovation development.

Second, enterprises should grasp the advantages of their network location and continuously improve their network centrality. In the era of win-win cooperation, being located in the center of the network can effectively help enterprises obtain and control more external resources to maintain a sustainable competitive advantage. Therefore, enterprises with high network centrality should further use digital technologies such as artificial intelligence and big data to communicate and interact with other subjects in the network to, based on their advantages, accelerate the control of market information, enrich their knowledge base and realize information-driven R&D innovation, which can effectively reduce R&D risks and R&D costs and guarantee the smooth implementation of exploratory innovation. Enterprises with low network centrality should learn from the management and operation mode of enterprises located in the main position of the network, integrate and absorb valuable knowledge elements, and enhance their competitive advantages. At the same time, enterprises can also use the Internet and other digital technology applications to understand the shortcomings of other enterprises, constantly update their existing knowledge base, provide inexhaustible power for enterprise innovation activities, and promote the sustainable development of enterprises.

6.4. Prospect

There are still certain shortcomings in this study, which are subject to further research in the future. First, this paper uses Chinese Shanghai and Shenzhen A-share listed manufacturing enterprises, and future research can further examine enterprises in other countries, other industries, or other segments of the manufacturing industry to improve the generalizability of the research findings. Second, based on the knowledge base view, this paper explores the mechanism of the role of digital technology on firms' exploratory innovation, and future research can further explore whether there are other mediating variables to reveal the black box between digital technology and firms' exploratory innovation. Third, this paper only focuses on the antecedent influences of exploratory innovation, and the posterior influences of this innovative behavior can be further explored in the future to build a more complete theoretical model.

Author Contributions: Conceptualization, J.-L.G.; methodology, J.-L.G.; software, Y.C.; validation, J.-L.G. and Y.C.; formal analysis, J.-L.G.; investigation, J.-L.G. and Y.C.; resources, J.-L.G. and Y.C.; data curation, J.-L.G. and Y.C.; writing—original draft preparation, J.-L.G. and Y.C.; writing—review and editing, J.-L.G., Y.C. and X.-Q.Z.; visualization, X.-Q.Z.; supervision, X.-Q.Z.; project administration, Y.C.; funding acquisition, J.-L.G. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by National Social Science Planning Foundation in China to Jian-Li Gao [NO.21BRK010].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Research data available upon request.

Conflicts of Interest: The authors declare no conflict of interest.

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