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The Impact of Digital Technology Innovation Network Embedding on Firms' Innovation Performance: The Role of Knowledge Acquisition and Digital Transformation

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Abstract: In the digital economy context, enterprises' competitive environment is changing rapidly. Historically, enterprises rely on a solitary fight to occupy the market. Now, enterprises should actively embed into digital technology innovation networks to maximize access to external digital technology knowledge resources through organizational cooperation and achieve the absorption of digital resources and technologies. However, the relationship between digital technology innovation network embedding and innovation performance still needs to be clarified. Therefore, this study adopts the "structure–behavior–performance" research paradigm to extend innovation network research to the digital technology innovation network context, aiming to explore the impact of digital technology innovation network embedding on enterprise innovation performance and to analyze the mediating effect of knowledge acquisition and the moderating effect of digital transformation. This study conducts an empirical study based on Chinese A-share listed firms that undertook digital technology innovation from 2010–2021. The findings show that digital technology innovation networks' relational and structural embedding positively affects firm innovation performance. Knowledge acquisition mediates digital technology innovation network embedding and innovation performance. Digital transformation has a moderating role between digital technology innovation network embedding and innovation performance, and different levels of digital transformation will have different effects on firms' innovation performance. Overall, the relational and structural embedding of digital technology innovation networks can encourage enterprises to acquire more social capital and tacit knowledge and reduce R&D costs, thus improving their innovation performance. Firms should focus on building external cooperation networks, actively establishing an excellent corporate image, strengthening communication and cooperation with network members, establishing mutually beneficial cooperation beliefs, and promoting digital transformation. The present results will help companies understand the impact of digital technology innovation networks and provide a reference for companies to utilize in digital transformation to improve their innovation performance.

Keywords: digital technology innovation; network embedding; digital transformation; innovation performance; knowledge acquisition

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1. Introduction

In today's information era, China's economy has moved closer to innovation-driven transformation and upgrading. In recent years, with the rapid development of digital technology, enterprises have begun to realize the importance of digital technology and actively invest in digital technology innovation [1]. Therefore, enterprise digital technology innovation has become an indispensable part of enterprise development and a key factor in the competitive advantage of modern enterprises [2]. Through the application of digital technology, the production and management of enterprises becomes more efficient and convenient and also enhances the competitiveness of enterprises [3]. Enterprises must actively explore the application of digital technology and continuously promote the innovation of digital technology in order to better respond to market changes and development trends. Only in this way can enterprises gain advantages in the fierce market competition and achieve sustainable development. Therefore, how to effectively use digital technology innovation to enhance corporate performance has become a hot industry research topic.

Enterprise digital technology innovation is not only a matter of technological innovation but also one of organizational change [4,5]. Enterprises need to make organizational changes in the process of digital technology innovation in order to adapt to the needs of the digital era. Digital technology innovation requires cooperation and communication between enterprises and other organizations to facilitate the sharing of knowledge and resources and improve the performance of enterprises. Therefore, it is essential to study the impact of network embedding in the digital technology innovation of enterprises on innovation performance, as well as the mediating effect of knowledge acquisition and the moderating effect of digital transformation. Although many scholars have studied the relationship between network embedding and corporate innovation [6–8], overall, these studies have not considered digital contextual factors. On the one hand, digital technology innovation network embedding can help firms access external innovation resources and knowledge to improve their innovation performance [9–11]. On the other hand, too much digital technology innovation network embedding may lead firms to face problems, such as knowledge reuse and innovation inertia, thus reducing their innovation performance [12,13]. The relationship between digital technology innovation network embedding and different levels of innovation performance still lacks in-depth exploration.

In addition, knowledge acquisition is an essential process for enterprises to acquire external knowledge, experience, technology, and other resources in the embedding of the digital technology innovation network [14,15]. Through knowledge acquisition, enterprises can obtain more innovation resources and promote technological upgrading and innovation capability [16]. Therefore, it is essential to investigate whether there is a mediating effect of knowledge acquisition on the impact of digital technology innovation network embedding on innovation performance in order to deeply understand the mechanism of digital technology innovation network embedding with respect to the innovation performance of enterprises. Digital transformation, as one of the essential paths for enterprises to achieve innovation and development, can promote enterprises' innovation capability and competitiveness [17,18]. Digital transformation can help companies better utilize digital technologies to improve their productivity, product quality, and service levels, increasing their market share and profitability [19]. Therefore, whether digital transformation can moderate the effect of digital technology innovation network embedding on innovation performance is also an essential question in this study.

Therefore, the main questions to be answered in this study are as follows:

(1). How do the relational and structural embedding of digital technology innovation network embedding affect firm innovation performance?

(2). What is the role of a firm's knowledge acquisition capability in digital technology innovation network embedding and the firm's innovation performance?

(3). How does digital transformation moderate the impact of digital technology innovation network embedding on innovation performance?

In this context, this study is based on social network, resource base, and firm innovation theories [6]. Taking Chinese A-share listed enterprises that have conducted digital technology innovation as examples, we explore the impact of network embedding of digital technology innovation on innovation performance, as well as the mediating effect of knowledge acquisition and the moderating effect of digital transformation. This study adopts the social network analysis method [8], based on the patent data of enterprises, and uses tools such as Python to calculate network embedding indicators and innovation performance indicators of target enterprises. It also combines the financial data of enterprises to calculate the degree of digital transformation of different enterprises. It conducts an empirical study on the effect of digital technology innovation network embedding on the innovation performance of enterprises. Meanwhile, the analysis of mediating and moderating effects is used to reveal the mechanism further and the factors contributing to the impact of digital technology innovation network embedding on innovation performance.

The contributions of this study are as follows: First, this paper empirically investigates the impact of digital technology innovation network embedding on the innovation performance of enterprises. Through the social network analysis method, we explore the degree and direction of the impact of digital technology innovation network embedding on the innovation performance of enterprises, which provides an essential theoretical and practical reference for the digital transformation of enterprises [20]. Second, this paper reveals the mediating effect of knowledge acquisition. Exploring the mechanism of digital technology innovation network embedding on innovation performance further reveals the path of digital technology innovation network embedding affecting innovation performance, which provides an essential reference for enterprises to acquire external innovation resources and knowledge in digital transformation effectively [21]. Finally, this paper analyzes the moderating effect of digital transformation. Exploring the moderating effect of digital transformation on the relationship between digital technology innovation network embedding and innovation performance, it provides essential guidance for formulating enterprises' digital transformation strategies. The findings of this paper have important practical implications for how companies can better use digital technology innovation network embedding to improve innovation performance in the digital transformation process [22]. At the same time, the findings of this paper also provide a new idea and theoretical basis for academics to deeply explore the relationship between digital technology innovation network embedding and enterprise innovation performance.

The rest of this paper is structured as follows: In the second part, we review the existing relevant studies and propose the research hypothesis of this paper. In the third part, we design the research regarding data source and acquisition, indicator selection, and the model. In the fourth part, we explore the impact mechanisms of digital technology innovation network embedding, knowledge acquisition, digital transformation, and innovation performance from theoretical and empirical perspectives. In the fifth part, we discuss the research results and summarize this study's main findings and future research directions.

2. Review and Theoretical Hypotheses

2.1. Digital Technology Innovation Network Embedding and Firm Innovation Performance

In recent years, with the massive application and implementation of digital technologies in the innovation process of enterprises, scholars have started to emphasize the necessity of digital technologies in the field of management and innovation and to analyze in depth the application of digital technologies in order to improve innovation in enterprises [23–25]. Scholars have now explored sustainable strategies for the digitalization of enterprises [26], how to integrate information resources with organizational capabilities and thus develop digital capabilities [27,28], and how to create and capture new competitive opportunities through digital technologies [29].

In the process of digital technology innovation, companies in the digital technology innovation network cannot establish cooperative relationships with all other companies. There may be a break in the connection between companies and specific business entities. However, enterprises can be indirectly connected through the connection of third-party "intermediaries." Suppose a company wants to access the resources and information of indirectly connected companies. In that case, it must access them through companies in other locations in the network [30]. Firms in different structural positions have different abilities to access and control resources [31]. In digital technology innovation networks, on the one hand, firms with higher centrality (occupying core positions) have access to other partners who are not associated with each other, connecting subjects with inconsistent technical knowledge and reducing information asymmetry [32,33]. Therefore, compared with other positioned firms in the network, firms with the advantage of centrality can quickly and efficiently reach extensive and rich knowledge and technologies and analyze, absorb, and transform them [34,35].

Moreover, this extensive and rich knowledge and these technologies are the basis of enterprise innovation. Firms can select and construct different combinations of knowledge and technologies and transform them into a large number of innovations. Thus, firms improve their innovation performance [36].

On the other hand, firms with high centrality have the advantage of controlling the flow of technological resources and information in the innovation network [37,38]. This control advantage can broaden access to heterogeneous information, help firms quickly reach heterogeneous resources that are dynamic and time-sensitive, and accelerate the speed of resource absorption and accumulation [39,40]. Firms can select and integrate novel and heterogeneous technologies according to their needs, form more good innovation ideas, and rely on their rich experience and knowledge to design and execute them, thus improving their innovation performance. Therefore, the following hypothesis is proposed in this study:

Hypothesis 1a. *Digital technology innovation network structure embedding positively affects firm innovation performance.*

Relational embeddedness refers to the relationships that actors within a network establish based on mutual willingness, such as cooperation, trust, and relational tightness, emphasizing the characteristics of relationships between firms and other network members [41]. Relational embeddedness is usually measured in terms of relationship strength. On the one hand, partners with strong relationships are more stable with each other due to frequent transactions, which can save transaction costs due to repeated contracting and bidding. They are more likely to generate economies of scale [42]. On the other hand, the trust mechanism generated by strong relationships determines a higher cost for firms to violate network practices. This is because such violations would lead to the loss of a large number of orders from stable partners, which could discourage opportunistic behavior and reduce the possibility of moral hazard [43]. Under this solid relational contract, the cost of acquiring knowledge resources between firms and uncertainty is lower, and the transfer of firms' knowledge resources can be achieved smoothly. Moreover, as the sources of information and resources that enterprises can reach become more and more extensive, they can quickly access the frontier technological knowledge in the innovation network and reduce the search costs and transaction costs of the organization [44], and the more resources and information spillover they receive, which is conducive to the improvement of their technological innovation performance. Therefore, this study proposes the following hypothesis:

Hypothesis 1b. *Digital technology innovation network relationship embedding positively affects firm innovation performance.*

2.2. The Mediating Role of Knowledge Acquisition

Knowledge acquisition is an essential way for enterprises to acquire innovation resources [45], and the level of network embedding in digital technology innovation will affect the ability of enterprises to acquire knowledge. In the process of digital technology innovation, enterprises often need to acquire more external digital technology knowledge through network embedding to achieve their internal innovation and enhance their competitive advantage to reduce the drawbacks of only having a single expertise [46]. In the process of acquiring knowledge, the degree of network embedding can significantly increase the exposure area and the depth of an enterprise's access to external knowledge [35], especially the ability to gain more access to the heterogeneous knowledge that is crucial to its innovation. By introducing these knowledge resources into their enterprises, enterprises can improve their knowledge systems so that their internal knowledge reserves can be improved in depth and breadth, which is very beneficial for enterprises, enabling them to avoid risks and improve their performance [47]. Moreover, enterprises with high levels of network embedding form favorable interactions with each other and thus have a higher possibility of sharing knowledge resources, which is also more conducive to acquiring enterprise knowledge [6].

In addition, with the increasing accessibility of knowledge in today's enterprises, competition among enterprises is becoming increasingly fierce. In order to achieve innovation, enterprises must have sufficient knowledge accumulation, and only then can they lay the foundation for improving innovation performance. Peng (2012) argues that firms play a significant role in driving their innovation strength, performance, and market competitiveness through external learning [48]. Dyer and Hatch (1998) argue that knowledge acquisition accelerates firms' product development and improves their ability to adapt to the market, customers, and the environment [49]. At the same time, knowledge acquisition enables firms to acquire new ideas or perspectives, which can also increase the motivation and incentive among the firm's employees to participate in and achieve innovation [50]. The amount of adequate knowledge reserved within a firm is undoubtedly essential, and knowledge acquisition can drive its innovation performance by applying it to the firm's innovation after absorption and transformation. Therefore, differences in the degree of firms' embedding in the innovation network will lead to differences in the knowledge acquired between firms, which will further affect firms' innovation performance. The following hypotheses are proposed in this study:

Hypothesis 2. *Knowledge acquisition mediates the relationship between digital technology innovation network embedding and firms' innovation performance.*

Hypothesis 2a. *Knowledge acquisition mediates the relationship between embedding digital technology innovation network relationships and firms' innovation performance.*

Hypothesis 2b. *Knowledge acquisition mediates the relationship between embedding digital technology innovation network structures and firms' innovation performance.*

2.3. The Moderating Role of Digital Transformation

Digital transformation is an essential initiative for companies to use new digital technologies to improve business processes, create business models, rethink investment measurements, and thus make changes in the broader ecosystem and learn from interactions with stakeholders to maintain a competitive advantage in the digital era [51]. Currently, there is no consensus on the impact of digital transformation on corporate innovation. On the one hand, some scholars argue that digital transformation can enhance innovation performance by improving the efficiency of information sharing and facilitating knowledge accumulation [52,53]. For example, Jin (2022) demonstrated the contribution of digital transformation to the level of corporate innovation based on a technological innovation perspective [53]. On the other hand, it has also been argued that during the transitional phase of digital transformation, firms will increase the exploitation of resources to increase production, which may lead to a reduction in innovation activities [54]. For example, Ghasemaghaei (2020) found that the development of big data can harm the efficiency of corporate innovation [55].

Digital transformation transforms corporate innovation from being experience-driven to being data-driven by building digital platforms, optimizing resource allocation, and using big data and the Internet of Things to access customers' consumption habits, laying the foundation for improving corporate innovation performance [23]. Thus, digital transformation can significantly impact firms in networks that perform innovation activities in digital technologies. Specifically, on the one hand, digitization will bring information resources to firms that can help them identify valuable information resources within the innovation network faster and at the lowest cost and improve the efficiency of resource allocation and innovation performance [56]. On the other hand, the data-processing capability of enterprises also has an essential role in supporting the absorption and integration of network resources [57]. In the absorption and integration stage of network resources, digitization can help enterprises remove redundant and irrelevant information, effectively screen the knowledge resources needed by enterprises, and then classify, transform, and integrate these resources to increase the integration and profound transformation of resources and lay a good foundation for subsequent technological innovation. Therefore, digital transformation success will help enterprises utilize digital technology tools to improve innovation performance. This study proposes the following hypotheses:

Hypothesis 3. *Digital transformation has a moderating effect on the relationship between digital technology innovation network embedding and firm innovation performance.*

Hypothesis 3a. *Digital transformation positively moderates digital technology innovation network relationship embedding and firm innovation performance.*

Hypothesis 3b. *Digital transformation positively moderates digital technology innovation network structure embedding and firm innovation performance.*

The conceptual framework of this study is shown in Figure 1:

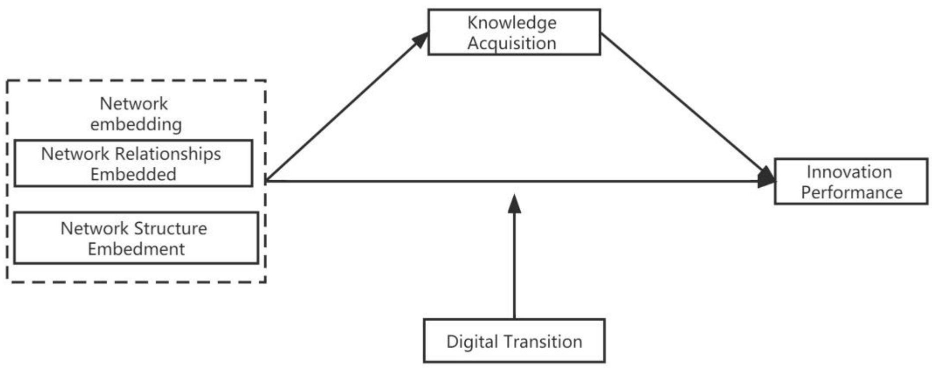

Figure 1. Research framework diagram.

3. Research Design

3.1. Sample Selection and Data Sources

China's A-share market is one of the world's largest stock markets, with many listed companies. With the rapid development of China's economy, Chinese A-share listed companies have become an essential part of China's economic development. Studying these companies can help us understand the trends and prospects of China's economic development. Therefore, this study presents empirical research on Chinese A-share listed enterprises that conduct digital technology innovation. To identify patented digital technologies, this study referred to the "Digital Economy Core Industry Classification and International Patent Classification Reference Relationship Table (2023)" issued by the State Intellectual Property Office of China, which specifies the patents related to the digital economy core industry.

The data for this study mainly come from the WIND and IncoPat patent databases. The WIND database contains data and information on global financial markets, including stocks, bonds, futures, foreign exchange, funds, indices, warrants, macro industries, and other varieties, providing financial institutions, government organizations, enterprises, and the media with accurate, timely, and complete financial data information 7 × 24 × 365 without interruption. IncoPat, as a critical Clarivate patent database, currently contains more than 170 million patent documents from 158 countries, organizations, or regions around the world, integrating multiple functional modules, such as patent search, a thematic library, analysis and surveillance, and early warnings, providing comprehensive, accurate, and timely innovation intelligence. Its data are procured from official and commercial data providers. It provides deeply processed and integrated patent entry information, as well as legal, operational, homologation, citation, and other information, and can realize 24 h dynamic data updates. The specific process of data collection and processing in this study is as follows:

In the first step, we performed an advanced search in the Incopat patent database with the search formula "((Applicant = (Company Name)) AND (Patent Type = (Invention Patent)) AND (IPC = (A61B5) OR IPC = (A61N5) OR IPC = (A63F13) OR IPC = (A63H30) OR IPC = (B08B) OR IPC = (B22F) OR IPC = (B23K) OR IPC = (B25H) OR IPC = (B25J) OR IPC = (B29C64) OR IPC = (B29C64) OR IPC = (B33Y) OR IPC = (B41J2) OR IPC = (B60S) OR IPC = (B61L) OR IPC = (B64D) OR IPC = (B81B) OR IPC = (B81C) OR IPC = (C03B) OR IPC = (C22C) OR IPC = (E04B1) OR IPC = (F16L11/127) OR IPC = (F26B) OR IPC = (G01C) OR IPC = (G01D) OR IPC = (G01J) OR IPC = (G01N) OR IPC = (G01S) OR IPC = (G02B) OR IPC = (G02F) OR IPC = (G03B21) OR IPC = (G03C) OR IPC = (G06) OR IPC = (G07D) OR IPC = (G07F) OR IPC = (G07G) OR IPC = (G08G1) OR IPC = (G09F9) OR IPC = (G09G) OR IPC = (G10L15) OR IPC = (G11B) OR IPC = (G11C) OR IPC = (H01) OR IPC = (H02J7) OR IPC = (H02M) OR IPC = (H04) OR IPC = (H05B) OR IPC = (H05H) OR IPC = (H05K)) AND ((AD = [20100101 TO 20211231])))". The data on invention patents related to digital technology applied by each A-share listed company from 2010–2021 were searched. Information, such as title, applicant, application number, application date, patent type, IPC classification number, and emerging industry classification number, on these invention patents was obtained. A total of 159,374 invention patents were obtained.

In the second step, data matching, Python was used to split the applicants represented in the data for the 159,374 patents obtained and match them with the names and stock codes of listed companies in the WIND database for subsequent index matching and fusion processing.

In the third step, data cleaning was performed to exclude companies that did not match the stock code and companies that did not submit patent applications in the observation period. Moreover, in order to obtain more reliable and comprehensive data, this study (1) excluded samples of companies in the financial industry and (2) excluded samples of companies with missing data values and abnormal data values for relevant indicators, and it was found that there were 1426 companies in total that have carried out digital technology innovation through cooperation among Chinese A-share listed companies from 2010–2021.

In the fourth step, the metrics were calculated by using the pandas and network packages in Python to construct the relevant networks or models and referring to the degree of centrality calculation used by scholars such as Phelps (2010) [58] to go about calculating the degree of centrality in each enterprise's structural embedding and the frequency of cooperation between enterprises and partners within the network in the relationship embedding. In such studies, when constructing networks, scholars have found that inter-firm partnerships generally last 3–5 years [59]. Therefore, this study used a 3-year rolling time window to split the innovation network of listed firms engaged in digital technology innovation from 2010–2021 into ten periods (2010–2012, 2011–2013, 2012–2014, . . . , 2019–2021). The indicators of independent, dependent, moderating, and mediating variables were further calculated using tools such as Python. The cooperative network of enterprises conducting digital technology innovation from 2010–2021 is shown in Figure 2. The enterprises were very closely connected, which provided an essential basis for the subsequent calculation of network embedding indicators.

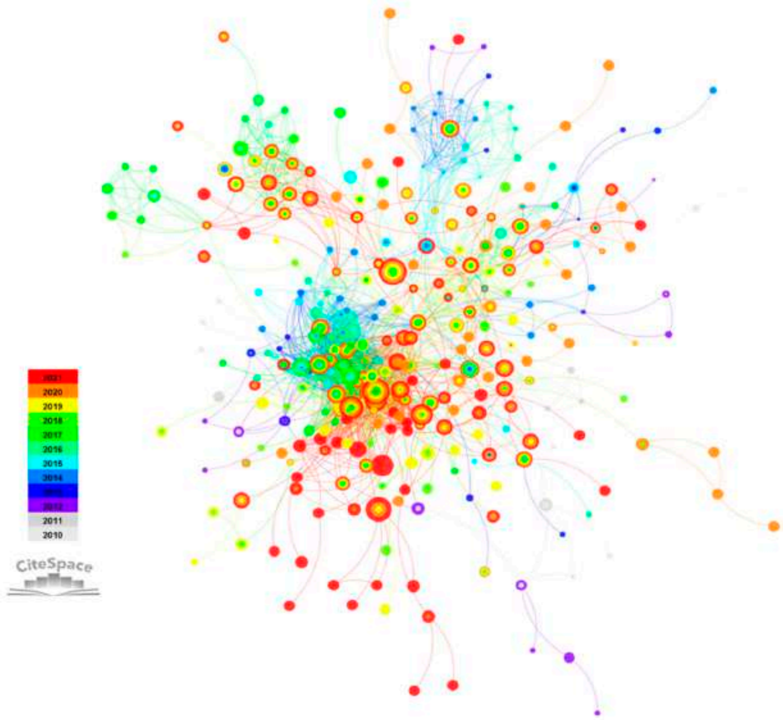

Figure 2. Collaboration network mapping of Chinese listed companies that have engaged in digital technology innovation, 2010–2021.

3.2. Variable Explanations

3.2.1. Independent Variable—Network Embedding

The digital technology innovation network embedding of firms in this study was mainly measured in terms of tight relational embedding and structural embedding. Determining the relational embedding (Nr) of digital technology innovation networks mainly involves examining the degree of trust and reciprocity among interlinked firms within the digital technology innovation network, which is usually measured by relationship strength. Strong relationships imply more opportunities for information exchange and cooperation among network members. To a certain extent, they have an essential impact on information search and exchange, knowledge sharing and acquisition, and collaborative development among network members [31]. Relational embedding focuses on the characteristics of the relationships between the cluster network in which firms are embedded and other firms and characterizes the strength of inter-firm relationships that support the interconnections within the digital technology innovation network. In this study, the strength of innovation network relationships among firms conducting digital technology innovation was measured using the "number of collaborations between target firms and partners in the network", as has been used in studies by Phelps (2010) [58] and others [60]. Specifically, the natural logarithm of the number of collaborations between the target firm and its partners plus one was used to measure the firm's relational embeddedness.

Structural embedding (Ns) is the impact of the relative position of digital technology innovation firms in the innovation network on the firm. This study referred to Liu (2022) [61] and other studies to measure the structural embeddedness of firms using the degree of centrality index in the network index. The higher the degree of centrality index of a firm, the greater the extent to which the firm is in the core position in the relevant network. This value is calculated as $C(ni) = d(ni)/n - 1$, where n is the total number of nodes and $d(ni) = j\ Xij$: when nodes ni and nj are not adjacent, $Xij = 0$; when nodes ni and nj are not adjacent, $Xij = 1$.

3.2.2. Dependent Variable—Innovation Performance

Invention patents are high-level innovations, and considering their quantity has the advantages of objectivity and consistency, on the one hand, reflecting the level of innovation of the firm at that time [62]. On the other hand, the number of invention patents is the most relevant and direct performance output of a firm's innovation process [63]. This study draws on Liang (2022) [64] in using the number of invention patent applications as the measure of a firm's innovation performance. The natural logarithm of the number of invention patent applications plus one is used as a measure of the firm's innovation performance. The firm's innovation performance in year t is the natural logarithm of the number of invention patents it applied for in year t plus one.

3.2.3. Mediating Variable—Knowledge Acquisition

In the context of the marketization of the global technology economy, knowledge has become an increasingly important strategic resource in enterprise competition. In order to improve their innovation capability, enterprises must not only make rational use of existing knowledge but also continuously acquire new external knowledge. Schenker argued that tacit knowledge, such as advanced knowledge and technology in the industry and experience of previous successful innovations, plays an essential role in improving enterprises' innovation performance [33]. In this study, the number of patents cited in the annual patent application was used to represent enterprises' technological knowledge acquisition capability, based on the study by Wang (2020) [65]. The natural logarithm of the number of citations plus one of the numbers of patents filed by an enterprise each year was used to measure the enterprise's technological knowledge acquisition capability.

3.2.4. Moderating Variable—Digital Transformation

Digital transformation is a systematic process that empowers companies with new dynamics of development. In measuring the digital transformation process of corporate enterprises, scholars have proposed using different methods, such as questionnaire surveys and text mining of annual reports using Python [66]. Regarding text mining of annual reports using Python, scholars argue that corporate annual reports contain strategic features and development plans of enterprises, and digital transformation is an essential development strategy of enterprises at present. The relevant information is often reflected in the annual reports of enterprises [66]. In this study, we used Python to mine the text of the annual reports of listed enterprises in the high-end equipment manufacturing industry with the help of Wu Fei (2021) [67]. The terms "intelligent", "cloud platform", "cloud service", "data analysis", "cloud computing", "digital technology", "blockchain", "big data", "5G", "digital transformation", "artificial intelligence", "digitalization", and other words were used to measure the frequency of digital transformation among enterprises. The natural logarithm of the frequency of keywords related to "digital transformation" plus one per year was used to measure digital transformation.

3.2.5. Control Variables

In this study, we controlled for the effects of firm size, firm age, firm industry, healthy operating margin, number of R&D personnel, and firm nature on firm innovation performance. Enterprise size is the natural logarithm of the total number of employees; enterprise age is the difference between the year of establishment and the year of observation; enterprise industry is the type of industry the enterprise belongs to; enterprise operating profit ratio is the ratio of operating profit to total operating revenue; the number of R&D personnel is the logarithm of the total number of R&D personnel per year; and enterprise nature is the type of enterprise. The nature of the enterprise was recorded as 1 for state-controlled enterprises, 2 for private enterprises, and 3 for foreign investors.

The measurement of variables is shown in Table 1:

Table 1. Measurement of variables.

Variable Type	Variable Name	Variable Symbols
Dependent variable	Enterprise Innovation Performance	Eip
Independent variable	Network Structure Embedding	Ns
	Network Relationship Embedding	Nr
Intermediate variable	Knowledge Acquisition	Ka
Adjustment variable	Digital Transformation	Dig
Control variables	Enterprise Size	Es
	Enterprise Age	Ea
	Enterprise Operating Profit Margin	Eop
	Number of R&D Personnel	Rd
	Enterprise Nature	En
	Year Attribute	Year
	Industry of the Enterprise	Ind

3.3. Model Design

This study used an OLS mixed-effects model to analyze the relationship between innovation network embedding [61], knowledge acquisition [62], digital transformation [63], and corporate innovation performance of Chinese A-share listed firms that conduct digital technology innovation based on panel data. Specifically, the following empirical model was constructed to test the hypotheses, using innovation network embedding as the independent variable, corporate innovation performance as the dependent variable, knowledge acquisition as the mediating variable, and digital transformation as the moderating variable.

First, consider the impact of digital technology innovation network embedding on firms' innovation performance, i.e., hypotheses H1a and H1b. The specific models are:

$$\mathrm{EIP}_{\mathrm{i,t}} = \alpha_0 + \alpha_1\mathrm{INE}_{\mathrm{i,t}} + \gamma 1\mathrm{Controls} + \gamma 1\mathrm{Year} + \gamma 1\mathrm{Industry} + \varepsilon_{\mathrm{i,t}} \tag{1}$$

where EIP is firm innovation performance; INE is the independent variable, including network relationship embedding and network structure embedding; controls are control variables, including firm size, firm age, firm nature, healthy operating margin, and number of R&D personnel; and i and t represent firm and year, respectively. $\varepsilon_{i,t}$ is the residual term.

Second, in exploring the mediating effect of knowledge acquisition, i.e., hypotheses H2a and H2b, this study used a three-step approach to test the mediating effect of knowledge acquisition, as modeled by:

$$\mathrm{EIP}_{\mathrm{i,t}} = \alpha_2 + \alpha_3\mathrm{INE}_{\mathrm{i,t}} + \gamma 2\mathrm{Controls} + \gamma 2\mathrm{Year} + \gamma 2\mathrm{Industry} + \varepsilon_{\mathrm{i,t}} \tag{2}$$

$$\mathrm{KA}_{\mathrm{i,t}} = \alpha_4 + \alpha_5\mathrm{INE}_{\mathrm{i,t}} + \gamma 3\mathrm{Controls} + \gamma 3\mathrm{Year} + \gamma 3\mathrm{Industry} + \varepsilon_{\mathrm{i,t}} \tag{3}$$

$$\mathrm{EIP}_{\mathrm{i,t}} = \alpha_6 + \alpha_7\mathrm{INE}_{\mathrm{i,t}} + \alpha_8\mathrm{KA}_{\mathrm{i,t}} + \gamma 4\mathrm{Controls} + \gamma 4\mathrm{Year} + \gamma 4\mathrm{Industry} + \varepsilon_{\mathrm{i,t}} \tag{4}$$

where KA is mediated variable knowledge acquisition; IP is firm innovation performance; INE is the independent variable, including network relationship embedding and network structure embedding; controls are control variables, including firm size, firm age, firm nature, healthy operating margin, and the number of R&D personnel; and i and t represent firm and year, respectively. $\varepsilon_{i,t}$ is the residual term.

Third, the moderating effect of digital transformation between digital technology innovation network embedding and innovation performance, i.e., hypothesis H3, was explored. The specific model is as follows:

$$\mathrm{EIP}_{\mathrm{i,t}} = \alpha_9 + \alpha_{10}\mathrm{INE}_{\mathrm{i,t}} + \alpha_{11}\mathrm{INE} * \mathrm{Dig}_{\mathrm{i,t}} + \gamma 5\mathrm{Controls} + \gamma 5\mathrm{Yeary} + \gamma 5\mathrm{Industry} + \varepsilon_{i,t} \quad (5)$$

where Dig is the moderating variable of digital transformation, INE*Dig is an interactive term for web embedding and digital transformation, and the other variables are as above.

4. Research Results

4.1. Descriptive Statistics and Correlation Analysis

The descriptive statistics table for the variables of interest reports the results of descriptive statistics for the main variables in this study (Table 2). The results of the descriptive statistics for the data in the sample of listed companies that performed digital technology innovation showed that the standard deviations of the main variables were within the normal range and that each variable was less affected by extreme values. The mean value of enterprise innovation performance was 2.735, the minimum value was 0.693, and the maximum value was 9.031, which indicates that the innovation performance of the enterprises conducting digital technology innovation varies widely among them. The mean value of the relational embedding of the enterprise digital technology innovation network was 1.813, the minimum value was 0.693, and the maximum value was 9.028. The mean value of the structural embedding of the enterprise digital technology innovation network was 0.144, the minimum value was 0.020, and the maximum value was 5.006, indicating that there is a significant difference in the level of network embedding in the innovation network of the listed enterprises that conduct digital technology innovation. In addition, we found that these variables were suitable for Pearson correlation analysis and subsequent regression analysis based on the distribution characteristics of the main variables. The mean value of knowledge acquisition was 1.747, with a minimum value of 0.000 and a maximum value of 9.971; the mean value of digital transformation was 0.609, with a minimum value of 0.000 and a maximum value of 4.745, indicating that there are significant differences in the opposite aspects of knowledge acquisition and digital transformation among the listed companies that perform digital technology innovation. In terms of the correlation between the variables and the dependent variable innovation performance (Table 3), there was a significant negative correlation between the firm's operating profitability, the nature of the firm, and innovation performance. The rest of the variables had a significant positive correlation with innovation performance. Moreover, the variance inflation factor (VIF) of the variables was tested in this study. The minimum value was 1.01, the maximum value was 2.65, and the mean value was 1.53. The VIF values of each variable were much less than 10, indicating that there was no problem of multicollinearity and that they were suitable for regression analysis.

Table 2. Descriptive statistics of relevant variables.

Variable	N	Mean	p50	SD	Min	Max
Ns	6141.000	0.144	0.060	0.328	0.020	5.006
Nr	6141.000	1.813	1.386	1.251	0.693	9.028
Eip	5543.000	2.735	2.565	1.347	0.693	9.031
Ka	5706.000	1.747	1.792	1.720	0.000	9.971
Dig	5171.000	0.609	0.000	0.878	0.000	4.745
Es	5987.000	22.473	22.261	1.645	17.917	28.636
Ea	6056.000	18.084	18.000	6.236	1.000	63.000
Eop	6051.000	0.091	0.085	0.198	−5.634	2.435
Rd	6141.000	4.338	5.425	3.000	0.000	10.653
En	6141.000	1.680	2.000	0.535	1.000	3.000

Table 3. Pearson correlation analysis.

	Eip	Ns	Nr	Ka	Dig	Es	Ea	Eop	Rd	En
Eip	1									
Ns	0.276 ***	1								
Nr	0.475 ***	0.538 ***	1							
Ka	0.440 ***	0.433 ***	0.714 ***	1						
Dig	0.119 ***	−0.047 ***	0.113 ***	0.027 *	1					
Es	0.420 ***	0.304 ***	0.326 ***	0.268 ***	−0.084 ***	1				
Ea	0.050 ***	−0.052 ***	0.084 ***	0.006	0.061 ***	0.210 ***	1			
Eop	−0.023 *	0.006	−0.016	0.005	0.008	−0.059 ***	−0.029 **	1		
Rd	0.213 ***	−0.076 ***	0.183 ***	0.075 ***	0.245 ***	0.333 ***	0.328 ***	−0.048 ***	1	
En	−0.119 ***	−0.141 ***	−0.075 ***	−0.085 ***	0.115 ***	−0.393 ***	−0.040 ***	0.053 ***	−0.025 *	1

t-statistics in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Main Effects Test

Table 4 shows the results of the main effects tests of digital technology innovation network embedding and the innovation performance of the listed firms. Columns (1) and (5) show the regression results of relational embedding, structural embedding, and firm innovation performance of digital technology innovation networks without adding control variables; columns (2) and (6) show the regression results of adding control variables to columns (1) and (5); columns (3) and (7) show the regression results of adding control time dummy variables to columns (2) and (6); columns (4) and (8) show the regression results of adding a dummy variable controlling for the industry of the firm to columns (3) and (7). From column (4), it can be seen that when controlling for other variables, the coefficient of the relational embedding of the digital technology innovation network of enterprises and innovation performance is 0.213 ***, which is significant at the level of $p < 0.01$ ($p < 0.01$), indicating that there is a positive relationship between the relational embedding of the digital technology innovation network of listed enterprises and innovation performance, such that hypothesis H1a is verified. From column (8), when other variables are controlled, the coefficient of structural embedding of the digital technology innovation network of enterprises and innovation performance is 0.219 ***, which is significant at the level of $p < 0.01$, indicating that there is a positive relationship between the structural embedding of the digital technology innovation network of listed enterprises and innovation performance, such that hypothesis H1b is verified.

4.3. Mediating Effect Test

Table 4 shows the results of testing the mediating effect of corporate technological knowledge acquisition. This study used the hierarchical regression method to test the significance of the mediating effect of enterprise knowledge acquisition. The method consists of three main steps: In the first step, the relationship between the independent and dependent variables is tested. Columns (1) and (4) in Table 4 test the relationship between the relational embedding and the structural embedding of the independent variable digital technology innovation network and the innovation performance of the dependent variable, respectively. We found a significant positive relationship between the relational embedding, structural embedding, and innovation performance of the digital technology innovation network of listed firms, indicating that embedding the digital technology innovation network enhances firms' innovation performance. In the second step, the relationship between independent variables and mediating variables was examined. Columns (2) and (5) in Table 4 test the relationship between the independent variable relational embedding, structural embedding, and the mediating variable knowledge acquisition, respectively. We found a significant positive relationship between relational embedding, structural embedding, and knowledge acquisition of the digital technology innovation networks. In the third step, the relationship between the independent variables, mediating variables, and dependent variables was tested. According to columns (3) and (6) in Table 5, we found that the results were still significant. This indicates that knowledge acquisition mediates between digital technology innovation network embedding and firm innovation performance, such that hypothesis H2a and H2b of this study are verified.

Table 4. Main effects test results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Eip	**Eip**	**Eip**	**Eip**	**Eip**	**Eip**	**Eip**	**Eip**
Nr	0.508 *** (40.13)	0.211 *** (11.21)	0.215 *** (11.56)	0.213 *** (11.89)				
Ns					1.219 *** (21.35)	0.184 *** (3.08)	0.153 *** (2.59)	0.219 *** (3.74)
Ka		0.175 *** (13.05)	0.153 *** (11.44)	0.147 *** (11.41)		0.267 *** (25.06)	0.251 *** (23.95)	0.239 *** (23.67)
Dig		0.140 *** (7.26)	0.133 *** (6.94)	0.155 *** (7.58)		0.168 *** (8.68)	0.155 *** (7.98)	0.174 *** (8.43)
Es		0.270 *** (20.58)	0.224 *** (16.88)	0.313 *** (22.13)		0.286 *** (20.99)	0.239 *** (17.33)	0.325 *** (22.26)
Ea		−0.014 *** (−4.94)	−0.005 * (−1.92)	−0.011 *** (−3.97)		−0.012 *** (−4.30)	−0.005 * (−1.65)	−0.010 *** (−3.70)
Eop		0.024 (0.29)	0.102 (1.25)	0.141 * (1.77)		−0.000 (−0.00)	0.076 (0.91)	0.112 (1.39)
Rd		0.035 *** (5.25)	0.184 *** (15.08)	0.123 *** (9.72)		0.043 *** (6.26)	0.197 *** (15.86)	0.136 *** (10.59)
En		−0.003 (−0.10)	0.003 (0.11)	−0.076 ** (−2.45)		0.012 (0.38)	0.016 (0.49)	−0.066 ** (−2.08)
_cons	1.804 *** (64.07)	−4.031 *** (−13.17)	−2.895 *** (−8.70)	−4.993 *** (−12.16)	2.566 *** (134.23)	−4.288 *** (−13.57)	−3.248 *** (−9.57)	−5.346 *** (−12.81)
N	5543	4717	4717	4717	5543	4717	4717	4717
Year	NO	NO	YES	YES	NO	NO	YES	YES
Industry	NO	NO	NO	YES	NO	NO	NO	YES
R^2	0.225	0.336	0.371	0.422	0.076	0.320	0.354	0.406
adj. R^2	0.225	0.335	0.369	0.418	0.076	0.319	0.352	0.402

t-statistics in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Results of the mediating effect test.

	(1)	(2)	(3)	(4)	(5)	(6)
	Eip	**Ka**	**Eip**	**Eip**	**Ka**	**Eip**
Nr	0.384 *** (31.56)	0.965 *** (72.54)	0.254 *** (15.22)			
Ns				0.818 *** (14.41)	2.031 *** (29.81)	0.253 *** (4.37)
Es	0.340 *** (27.11)	0.0476 *** (3.50)	0.334 *** (26.93)	0.388 *** (28.67)	0.167 *** (9.43)	0.352 *** (27.41)
Ea	−0.018 *** (−7.01)	−0.007 ** (−2.45)	−0.017 *** (−6.76)	−0.018 *** (−6.42)	−0.005 (−1.50)	−0.016 *** (−6.31)
Eop	0.154 ** (2.06)	0.229 *** (2.77)	0.122 * (1.66)	0.132 * (1.65)	0.151 (1.41)	0.089 (1.18)
Rd	0.035 *** (4.21)	−0.004 (−0.46)	0.035 *** (4.30)	0.055 *** (6.28)	0.048 *** (4.13)	0.043 *** (5.12)
En	−0.055 * (−1.83)	−0.048 (−1.46)	−0.048 (−1.64)	−0.019 (−0.61)	0.049 (1.15)	−0.028 (−0.93)
Ka			0.134 *** (11.16)			0.245 *** (25.76)
_cons	−5.579 *** (−15.06)	−0.0194 (−0.05)	−5.592 *** (−15.26)	−6.707 *** (−16.99)	−2.942 *** (−5.62)	−6.102 *** (−16.34)
N	5470	5589	5470	5470	5589	5470
Year	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
R^2	0.390	0.540	0.403	0.304	0.228	0.380
adj. R^2	0.386	0.538	0.400	0.300	0.224	0.376

t-statistics in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4. Moderating Effect Test

Table 6 shows the test results for the moderating effect of digital transformation on firms conducting digital technology innovation. Column (1) shows the effect of the interaction term (Nr*Dig) between the relational embedding of the digital technology innovation network of listed firms and digital transformation on firms' innovation performance. A significant positive effect was found, with a regression coefficient of 0.0574 ***. Therefore, digital transformation positively moderates the relationship between relational embedding and innovation performance of the digital technology innovation networks and hypothesis H3a holds. Column (2) shows the effect of the interaction term (Ns*Dig) between the structural embedding of a digital technology innovation network and digital transformation of the listed firms on the firms' innovation performance. It was found that it also had a significant positive effect, with a regression coefficient of 0.566 ***. Therefore, digital transformation positively moderates the relationship between the structural embedding of digital technology innovation networks and innovation performance, i.e., hypothesis H3b holds.

Table 6. Results of the test for moderating effects.

	(2)	(3)
	Eip	**Eip**
Nr	0.313 *** (21.17)	
Ns		0.536 *** (8.35)
Es	0.323 *** (22.56)	0.360 *** (23.40)
Ea	−0.012 *** (−4.22)	−0.011 *** (−3.75)
Eop	0.171 ** (2.12)	0.118 (1.38)
Rd	0.121 *** (9.46)	0.162 *** (11.99)
En	−0.075 ** (−2.37)	−0.046 (−1.38)
Nr*Dig	0.057 *** (7.20)	
Ns*Dig		0.566 *** (8.34)
_cons	−5.053 *** (−12.14)	−5.910 *** (−13.40)
N	4717	4717
Year	YES	YES
Industry	YES	YES
R^2	0.406	0.334
adj. R^2	0.402	0.330

t-statistics in parentheses: ** $p < 0.05$, *** $p < 0.01$.

4.5. Robustness Tests

To further test the robustness of the findings, this study used both changing the calculation of independent variables and lagged independent variable regression for robustness testing since this study started with a 3-year rolling time window. In order to test the robustness of the results, a 5-year rolling time window was used, which split the digital technology innovation network of the listed companies into eight periods (2010–2014, 2011–2015, 2012–2016, . . . , 2017–2021) from 2010–2021, and regression analysis was performed again. We found that the effects of relational and structural embedding of the digital technology innovation networks of the listed firms on innovation performance were still significant and robust after changing the rolling period of the independent variable (Table 7).

Table 7. Regression analysis for a rolling period of 5 years for network embedding.

	(1)	(2)
	Eip	**Eip**
Nr	0.341 *** (27.66)	
Ns		0.856 *** (12.44)
Es	0.312 *** (22.07)	0.366 *** (24.33)
Ea	−0.019 *** (−7.06)	−0.018 *** (−6.18)
Eop	0.206 *** (2.69)	0.153 * (1.88)
Rd	0.044 *** (5.13)	0.062 *** (6.83)
En	−0.063 ** (−1.97)	−0.032 (−0.94)
_cons	−4.979 *** (−12.78)	−5.946 *** (−14.33)
N	4774	4774
Year	YES	YES
Industry	YES	YES
R^2	0.367	0.288
adj. R^2	0.364	0.284

t-statistics in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, this study used lagged independent variable regression for the analysis, which could ensure the robustness of the results to some extent. In Table 8, the digital technology innovation network embedding is lagged for three different periods. Then, the impact of the lagged network embedding on innovation performance was examined. It was found that the regression results were still significant and robust for both the relational and structural embedding of the digital technology innovation networks. Comparing the coefficients of the regressions of network embedding in different lag years, it was found that the impact of relational and structural embedding on firms' innovation performance showed a decreasing trend as the lag time increased.

Table 8. Regression analysis of digital technology innovation network embedding after lagging for phase 1, phase 2, and phase 3.

	(1)	(2)	(3)	(4)	(5)	(6)
	Eip	**Eip**	**Eip**	**Eip**	**Eip**	**Eip**
L.Nr	0.333 *** (22.74)					

Table 8. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)
	Eip	**Eip**	**Eip**	**Eip**	**Eip**	**Eip**
L2.Nr		0.284 *** (16.33)				
L3.Nr			0.229 *** (11.17)			
L.Ns				0.644 *** (10.65)		
L2.Ns					0.517 *** (8.05)	
L3.Ns						0.376 *** (5.41)
Es	0.400 *** (26.15)	0.429 *** (23.56)	0.472 *** (21.73)	0.438 *** (26.92)	0.454 *** (23.64)	0.490 *** (21.47)
Ea	−0.020 *** (−6.33)	−0.019 *** (−4.92)	−0.018 *** (−3.93)	−0.019 *** (−5.70)	−0.017 *** (−4.26)	−0.016 *** (−3.31)
Eop	0.238 *** (2.68)	0.277 *** (2.72)	0.305 ** (2.50)	0.197 ** (2.12)	0.253 ** (2.40)	0.277 ** (2.22)
Rd	0.035 *** (3.41)	0.047 *** (3.70)	0.061 *** (3.88)	0.055 *** (5.08)	0.067 *** (5.07)	0.077 *** (4.79)
En	−0.064 * (−1.76)	−0.086 ** (−1.99)	−0.096 * (−1.87)	−0.030 (−0.78)	−0.062 (−1.39)	−0.077 (−1.48)
_cons	−6.681 *** (−14.65)	−7.087 *** (−11.91)	−8.445 *** (−10.95)	−7.457 *** (−15.51)	−7.754 *** (−12.56)	−8.895 *** (−11.18)
N	3977	2879	2037	3977	2879	2037
Year	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
R^2	0.386	0.379	0.386	0.325	0.336	0.357
adj. R^2	0.381	0.373	0.378	0.320	0.329	0.349

t-statistics in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Discussion and Conclusions

In the context of "Digital China" construction and digital transformation in China, research on how digital technology innovation network embedding affects firms' innovation performance remains to be explored. From the perspective of digital technology innovation, this study extends innovation network research to the digital technology innovation network context based on the "structure–behavior–performance" research paradigm to analyze the relationship between digital technology innovation network embedding and the innovation performance of enterprises in order to open the black box of the role of digital technology innovation network embedding in firms' innovation performance. This study is an empirical study of Chinese A-share listed firms engaged in digital technology innovation from 2010–2021. The study's findings are as follows:

(1) The relational and structural embedding of digital technology innovation networks positively affects firms' innovation performance. The stronger the digital technology innovation network embedding of enterprises, the higher the innovation performance of enterprises. This suggests that, on the one hand, firms with strong relationships have more frequent and deeper communication with partners in the digital innovation process and have similar value bases, thus facilitating firms' access to more social capital [32]. Such strong relationships further help firms acquire tacit knowledge by helping them to build trust and supervisory relationships that facilitate sharing and communication [10,11]. This

is because the trust mechanism represents significant capital that strengthens the emotional base and enables the smooth flow of tacit knowledge [41], thus promoting the innovation performance of firms. On the other hand, with the increasing demand for various aspects of digital technology R&D, it is more difficult for firms to develop independently. Firms with higher centrality have more partners and can maintain cooperative relationships with many members, which can help them access various relational technological knowledge resources and obtain complementary knowledge and skills [6,46]. In addition, firms with highly central locations have more vital coordination and control over technical knowledge resources, which makes firms in the same industry more dependent on them [38]. This dependency empowers enterprises, giving them more network power, making it easier to access and control relevant technological resources in the network. Therefore, enterprises should focus on building external cooperative networks in the process of digital technology innovation, actively establish an excellent corporate image, strengthen communication and cooperation with network members, and establish a mutually beneficial cooperative belief to improve their innovation performance.

(2) Knowledge acquisition mediates the role of network embedding in digital technology innovation and innovation performance. This finding is consistent with the view that "network embedding helps firms to acquire information, knowledge, and other resources," as mentioned in existing studies [68]. In the knowledge economy, firms need to acquire a large amount of knowledge to meet the demand for innovation to achieve sustainable development [16]. The knowledge absorbed in digital technology innovation networks can improve the thickness and breadth of enterprises' knowledge, reduce R&D costs, increase the frequency of product updates, and thus enhance the innovation performance of enterprises [46]. Enterprises can acquire knowledge of different natures, including tacit and explicit knowledge, through embedding digital technology innovation networks [15]. Knowledge acquisition plays a mediating role in determining whether the digital technology innovation network is embedded relationally or structurally. The frequency, efficiency, scope, and depth of communication between firms with strong relationships are high. The acquired technical knowledge is of high quality and can facilitate innovative behaviors, products, and technologies after processing [69]. At the same time, good relationships between companies symbolize high sincerity and trust, making the knowledge acquired authentic and reliable [41]. Therefore, firms embedded in digital technology innovation networks can all improve their innovation performance through the mediating role of knowledge acquisition.

(3) Digital transformation positively moderates the relationship between digital technology innovation network embedding and innovation performance. This suggests that digital transformation enhances the degree of a firm's embedding in the digital technology innovation network, enhancing its innovation performance. The rapid development and diffusion of digital technology have become essential drivers of corporate innovation, and digital transformation is considered an essential means to achieve digital technology innovation [5]. With the continuous progress of the Internet and information technology, the demand for digital technology in enterprises is also increasing. In the digital era, the digital transformation of enterprises involves not only keeping up with trends but also being invincible in engagement with the market competition. Digital transformation, as a strategic change, involves changes in several aspects of business organization, management, and technology [70]. Digital transformation can improve operational efficiency, reduce costs, improve customer satisfaction, and enhance a company's competitiveness [56,57]. Digital transformation provides enterprises with a broader range of digital technology application scenarios, enhances their innovation capabilities, and makes it easier for them to integrate into digital technology innovation networks and access the knowledge resources and innovation opportunities therein [50]. At the same time, digital transformation can also strengthen enterprises' internal collaboration and information-sharing capabilities, thus avoiding the problems of duplication of work and information silos and improving the overall operational efficiency of enterprises [52]. It allows closer collaboration between

various enterprise departments and achieves efficient business processes. Overall, digital transformation positively contributes to enterprises' embedding and innovation performance in digital technology innovation networks, providing an essential strategic reference for enterprises to achieve sustainable development in the digital era.

6. Limitations of the Study and Future Research Perspectives

There are still some shortcomings to this study, which require improvement and extension. First, this study explored the influence of relational and structural embedding on innovation performance in digital technology innovation network embedding. However, with the rapid development of network relationship research, the dimensions and indicators of network embedding have been gradually enriched by such factors as social embedding and geographical embedding. In future research, multi-dimensional indicators of network embedding will be introduced on the existing basis, improving the quality of relationships and the scale and density of the network to continuously enrich the research on network embedding and innovation performance in digital technology innovation. Second, compared with the existing way of collecting data by conducting questionnaires, this study was more objective given that data were collected based on commercial databases and annual reports disclosed by enterprises. However, since the selected sample consisted of listed enterprises, the construction of a digital technology innovation network ought to be extended to listed enterprises, non-listed enterprises, and small and medium-sized enterprises. Due to a relative lack of resources, these enterprises often need to be embedded in the digital technology innovation network to draw on external resources and knowledge in order to promote their innovation results. Whether the findings of this study can be applied to such non-listed enterprises is one of the questions for future research. Third, this study revealed the weighting factors of the economic consequences of embedding digital technology innovation networks only from the digital transformation perspective. Moreover, other important factors, such as dynamic capabilities in practice, may affect the relationship between digital technology innovation network embedding and firm innovation performance. Therefore, future research can explore the weighting of factors related to firms' digital technology innovation network embedding that affect their innovation performance from multiple perspectives.

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