

The Impact of Digital Innovation Network Embedding on Firm Innovation Resilience: Perspective on Knowledge-based Dynamic Capability

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Research Article

Keywords: digital innovation network structural embedding, digital innovation network relational embedding, innovation resilience, knowledge-based dynamic capability

Posted Date: June 30th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9785027/v1>

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Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at Discover Sustainability on September 10th, 2026. See the published version at <https://doi.org/10.1007/s43621-026-04652-1>.

Abstract

The volatile, uncertain, complex, and ambiguous (VUCA) era has brought unprecedented impacts on the innovation development of enterprises. Amidst the transformative opportunities presented by digital technological advancements, whether firms can enhance their innovation resilience by embedding themselves within emerging digital innovation network has raised much attention and discussion. Therefore, this study constructs the theoretical analysis framework of “network embedding - dynamic-based knowledge capability - innovation resilience” to explore the relationship between digital innovation network and firm innovation resilience, and to analyze how the knowledge-based dynamic capability plays the role of pathway. Utilizing firms’ cooperative digital invention patents application data to construct digital innovation network and drawing on the panel data of A-listed firms over the period of 2012–2023, this study empirically investigates how embedding in digital innovation network affects firm innovation resilience. The key findings are as follows: (1) Both digital innovation network structural and relational embedding have significant positive effect on firm innovation resilience; (2) Knowledge-based dynamic capability which comprises of knowledge acquisition, integration, and reconfiguration plays a mechanism role in the relationship between digital innovation network embedding and innovation resilience; (3) Embedding in digital innovation network has a more pronounced effect in firms which executives with digital background, which are classified into non-high-tech industries, and which are insensitive to uncertainty. This study provides empirical evidence and practical insights for fostering innovation resilience in the context of digitization and openness, thereby enhancing the security and controllability of Chinese industrial and supply chains.

1. Introduction

Against the backdrop of multiple overlapping and resonating uncertainties, including escalating global trade frictions, intensifying geopolitical conflicts, public health crises, and technological disruptions, the security and stability of China's industry chains and supply chains have suffered severe shocks, posing formidable challenges to enterprises’ innovation and development [1]. In this context, some firms, due to shortages of innovation resources and insufficient innovation capabilities, have fallen into innovation stagnation [2], or even exited the “stage of innovation” entirely. In contrast, firms with innovation resilience which is characterized by their capability to maintain innovation stability, achieve rapid innovation recovery, and realize innovation upgrading in uncertain environments can instead stimulate their innovation potential, enhance innovation efficacy, successfully navigate crises and finally realize a long term development through gaining the competitive advantages [3–5]. It is evident that in the volatile, uncertainty, complex, and ambiguous (VUCA) era, enhancing firm innovation resilience is not only crucial for the survival and innovative development of firms themselves but also constitutes a vital task in safeguarding the autonomy and controllability of China's industry chains and supply chains.

Most prior research on the influencing factors of innovation resilience focus on internal resources within firms[3, 4] as well as organizational and learning capabilities [6]. However, amid the deep integration of digitization and open innovation, the traditional innovation model which works in isolation has become increasingly inadequate in adapting to the growing complexity of the innovation environment. It is being replaced by interconnected innovation models that operate across organizations and geographical boundaries within digital ecosystems [7]. As a form of interconnected innovation network catalyzed by the deep penetration of digital technologies such as artificial intelligence and big data, digital innovation network has characteristics such as diversified entities, data-based resources, and knowledge migration [8–10], breaking the “rigid constraints” of structure and the problem of homogeneous innovation resources inherent in traditional innovation network. It reshapes the collaborative innovation models for embedded firms, presenting a critical opportunity for enhancing firm innovation resilience. Therefore, it is essential to study the impact of digital innovation network embedding on innovation resilience. However, although some study have explored the impact of network embedding on the innovation resilience of enterprises from the perspective of open innovation [1, 11], overall, they have overlooked the reshaping effect of digital technology on open innovation organizations [12]. Moreover, the existing research on the innovation effect of digital innovation network embedding mostly focus on the influence of digital innovation network embedding on the performance of routine innovation from a static perspective [13–15]. The relationship between the emerging innovative network form of digital innovation network and innovation resilience has not been fully explored. In essence, innovation is a dynamic process of knowledge creation and recombination [16]. This determines that innovation resilience is highly dependent on the continuity and iterative upgrading capability of knowledge production. In the digital era, the massive volume of knowledge resources have become digitized and is growing explosively, while technology iteration cycles are continuously accelerating. This undoubtedly imposes higher demands on enterprises' capabilities in acquiring, utilizing, and creating knowledge during the innovation process. The “digital connections” among nodes in digital innovation network not only significantly reduce the cost of knowledge acquisition for enterprises but also facilitate the efficient aggregation and utilization of digital technologies for knowledge production [13], providing the resource foundation and core capability support for achieving sustainable innovation in uncertain environment. However, although there have been numerous study that have explored the significant role of capabilities such as knowledge acquisition and knowledge application in the transformation of innovation network resources into firm innovation performance [17], how

enterprises can achieve the dynamic transformation of digitized knowledge resources within the network into innovation resilience through embedding in the digital innovation network remains a mystery.

In light of the above background, the following questions arise: (1) How does embedding in digital innovation network influence firm innovation resilience? (2) How can the fragmented and static knowledge resources from digital innovation network be transformed into dynamic innovation resilience? (3) Does the digital innovation network embedding have differential effects on the innovation resilience of firms with different characteristics? To answer these questions, this study constructs a "network embedding - knowledge-based dynamic capability - innovation resilience" theoretical framework based on the network analysis method, and uses the data of cooperative digital invention patent applications of Chinese A-shared listed firms during the period of 2012–2023 to construct the digital innovation network, based on which calculate the level of structural and relational embedding of firms using the network packages of Python, and later on empirically explore the intrinsic relationship and underlying mechanism between digital innovation network embedding and firm innovation resilience. Meanwhile, a heterogeneity analysis is used to explore the contextual factors contributing to the different effect of digital innovation network embedding on the firm innovation resilience.

2. Literature Review

This study covers two mature fields: network embedding theory and innovation resilience. It also involves an emerging field: digital innovation network. Therefore, this review section aims to provide definitions for digital innovation network and innovation resilience by systematically reviewing and summarizing the research conducted by existing scholars. It also intends to further explore the research gaps in the fields of innovation resilience and digital innovation network to explore new research perspectives.

2.1. Digital Innovation Network

Digital innovation is defined as the process and outcome through which enterprises or organizations utilize combinations of digital technologies, such as information, computing, communication, and connectivity, to create new products or services and to transform innovation processes, business models, or commercial models [8, 18, 19]. The concept of innovation network was first proposed by Freeman(1991). Its essence lies in the complex resource allocation mechanism between enterprises and external organizations, with its core function being to facilitate the sharing and flow of innovation resources, such as knowledge and technology, through collaboration among network partners [20]. Against the backdrop of digitization, inter-organizational innovation forms have evolved into open digital innovation network [12, 21]. Such network can be defined as a new form of distributed network in which heterogeneous actors such as enterprises, digital service providers, and universities establish extensive connections, with the aim of sharing digital resources and stimulating digital innovation vitality [13, 22]. Its essence is to utilize digital technologies to search for, transfer, integrate and create knowledge resources within the networks[9]. Regarding the characteristics of digital innovation network, existing research primarily focuses on the following aspects: (1) Underlying architecture. It is based on general digital technologies and supports the cross-temporal and cross-organizational flow of distributed resources [7]. (2) Network structure. The network structure is more loosen and interconnected, facilitating the rapid formation and disbandment of distributed entities [9, 23]. (3) Network actors. The self-generative nature of digital innovation continuously incorporates heterogeneous innovation actors into the network, thereby continually expanding the boundaries of network innovation activities [15]. (4) Network resource. Resources exist in the form of data, which are non-competitive, editable and replicable, and exhibit strong network externality [8, 24]. Based on the existing research, this paper defines the connotation of the digital innovation network as a new form of innovation network in which heterogeneous innovation actors, such as enterprises and universities, establish extensive connections to acquire knowledge resources, and further supported by digital technologies, transfer innovation-related knowledge to collaboratively create new products and new models.

Grannovetter's (1985) network embedding theory posits that a firm's economic behavior is not isolated but is embedded within its social network. The theory divides network embedding into two dimensions: structural embedding and relational embedding [25], which provides a foundation for academic research to analyze how characteristics of innovation network, such as position and relationships, affect the innovation performance of network nodes[26, 27]. Starting from the logical framework of "network embedding - resources/capabilities - innovation performance", the current research focus on the impact of digital innovation network embedding on the innovation performance of enterprises. From the resource-based view, scholars regard external resources as crucial support for innovation activities and argue that both the structural and relationship embedding in digital innovation network helps firms efficiently aggregate the external digital technologies and knowledge, consequently boosting innovation performance [10, 14]. From a capability perspective, scholars emphasize the importance of dynamic knowledge management, noting that digital innovation network structure embedding assists firms in reshaping knowledge production and allocation processes to achieve breakthroughs in core technologies [15]; meanwhile, concentrating on the digitized characteristics of resources within digital innovation network, both structural and relational embedding primarily enhance open

innovation performance by improving a firm's digital sensing and digital collaboration capabilities [28]; furthermore, big data capability serves as the high-level dynamic capability mechanism for converting network data resources into innovation performance [10].

2.2. Innovation Resilience

The concept of resilience, originating from physics, has since been extended to management and economics. Oeij et al. (2016) first introduces resilience into the domain of innovation, preliminarily defining innovation resilience as a restorative capacity capable against innovation-related shocks [29]. Subsequent research have largely conceptualized it from a capability perspective. For example, Lv et al. (2019) defines innovation resilience as an organization's capability to cope with innovation uncertainty by integrating the stability and flexibility of innovation system [30]; Fey and Kock(2022) defines innovation resilience as the capability that enterprises can get the innovation activities back on track when facing the critical incidents [31]; Zhang et al. (2025) defines innovation resilience as a capability that firms can withstand the shock, recovery from the disruption, and finally achieve a higher level of resilience through absorptive and adaptive capability [6]. Given that innovation fundamentally involves the creation and recombination of knowledge [16], some scholars argue that the key to interpreting innovation resilience should lie in understanding how firms accumulate knowledge resources and transform capabilities in uncertain environments, and define innovation resilience as a reinforcing mechanism that enables firms to maintain innovation continuity, accumulate knowledge resources, and transform them into new capabilities within uncertain environments [1, 3]. In light of this, this paper defines innovation resilience as: when faced with uncertain environments, firms possess the ability to continuously absorb and leverage knowledge and other innovation resources, thereby maintaining uninterrupted innovation stability, swiftly recovering innovative momentum, and ultimately achieving innovation upgrading.

Regarding the influencing factors of firm innovation resilience, existing research address both internal and external dimensions. Internally, existing study have explored the effects of R&D [3], innovation failure experience [6], leader behaviour [29], the risk preference of managers [32] and digital technology adoption [33]on innovation resilience. Notably, the "incremental" characteristics of digital transformation caused by long cycles, high investment, and slow returns generate a dual effect of both "enabling" and "debilitating" innovation resilience [10, 34]. externally, factors such as intellectual property protection[5], transportation infrastructure construction [35], high-level openness [2], and Industry-university-research cooperation [36], are important pathways for enhancing innovation resilience. And from a network embedding perspective, embedding in cooperative R&D network [11] and knowledge network [1] can bring firms more external innovation resources, thereby enhancing the innovation resilience. Nevertheless, some scholars note that excessive embedding in traditional innovation network can subject firms to an "embedding paradox" arising from structural "rigidity constraints" and a "curse" of low-liquidity resource from traditional innovation network, which are detrimental to innovation sustainability and upgrading [13].

2.3. Research Gap

Although existing research in the fields of digital innovation network and innovation resilience are extensive, the following gaps may persist: (1) Study on the antecedents of firm innovation resilience predominantly focus on the firm's own digitization level or traditional innovation network, while the study incorporate the digital innovation network - a novel network form that efficiently integrates the superior digital technologies and innovation resources of various organizations - into the consideration of influencing factors of innovation resilience remains scarce. (2) Existing research have primarily examined the relationship between digital innovation network embedding and various innovation performance outcomes from a static perspective, while the intrinsic link between such embedding and innovation resilience - a key concept reflects how the innovation process of a firm adapts to the environmental uncertainty - still remains unclarified. (3) Current study seldom focus on the essential dependence of innovation resilience on the accumulation and utilization of knowledge resources, and rarely integrate knowledge-based dynamic capabilities and innovation resilience into a unified research framework. This theoretical gap becomes even more pronounced in the digital contexts: within digital innovation network, knowledge resources exhibit characteristics such as digitization and high fluidity. Yet, research on how firms can transform these resources into innovation resilience after embedding in this network remains limited.

The marginal contributions of this study are threefold: (1) By focusing on the networked organizational model of digital innovation, and drawing on network embedding theory, this study integrates digital innovation network embedding and firm innovation resilience into a unified research framework. It examines the structural and relational embedding to dissects the intrinsic relationship and differentiated pathways through which different embedding modes influence innovation resilience, thereby deepening research on the determinants of innovation resilience and the innovation effects of digital innovation network. (2) Grounded in dynamic capability theory and positioning "knowledge-driven" processes as the core theoretical anchor of innovation resilience, this study constructs a "network embedding-knowledge-based dynamic capability - innovation resilience" theoretical analysis framework, unveiling the "black box" of how knowledge dynamic capability serve as a conduit for converting the static and fragmented knowledge resource in the digital innovation network into the innovation resilience, extending the applicability of dynamic capability theory to innovation network in the digital context. (3) This study empirically validates the impact of digital innovation network embedding on firm innovation resilience as well as the feasibility of the

"network embedding - knowledge-based dynamic capability - innovation resilience", while further exploring the differentiated effects of the digital innovation network embedding on the firm innovation resilience of various contextual factors. At the macro level, it informs the formulation of national digital innovation strategies. At the micro level, it assists guidance for firms seeking to build core capabilities within digital innovation network, thereby enhancing their innovation resilience.

3. Theory and Research Hypothesis

3.1. Digital Innovation Network Embedding and Firm Innovation Resilience

Classical network embedding theory divides network embedding into two dimensions: structural embedding and relational embedding. Structural embedding emphasizes the influence of network positional characteristics, such as centrality, on the behavior of actors. Actors with a high level of structural embedding often occupy core positions in the network, granting them greater advantages in accessing resources [17]. Relational embedding focuses on the impact of factors such as the frequency of interaction and the degree of trust between network actors on their behavior. Actors with strong relational embedding are more likely to obtain direct resource support from their partners [25]. The essence of a firm's embedding in innovation network lies in establishing cooperative relationships with heterogeneous actors, acquiring knowledge and other innovation resources through interaction, further leveraging these to build innovation-related capabilities, and ultimately influencing innovation outcomes [37]. Characteristics such as actor diversity, digitized carriers, loosening of structure and digitized resources interact with the positional and relational advantages gained from network embedding. This interaction not only enhances the efficiency with which firms acquire innovation resources from the network but also significantly influences the collaboration patterns and interaction quality among network nodes [26, 38, 39]. Consequently, it provides systematic support for firms to maintain innovation stability, to achieve rapid innovation recovery, and to realize innovation upgrading, thereby enhancing their innovation resilience.

3.2. Digital Innovation Network Structural Embedding and Firm Innovation Resilience

First, structural embedding in digital innovation network enhances agility in responding to innovation risks. On the one hand, dense digital connections enable firms to access large-scale data resources transferred in the form of bits from markets and consumers in real time [10, 24], and to utilize leverage digital technologies to capture future market trends [13]. This fosters a forward-thinking mindset that is oriented towards market gaps and to proactively assess potential innovation risks, thereby preventing disruptions at the source. On the other hand, enterprises can swiftly access complementary knowledge and technological resources through generalized API interfaces within the network and collaborate digitally with partners to develop contingency plans to address various innovation risks [40], thereby ensuring the continuity of innovation activities. Secondly, the digital innovation network structure embedding breaks through the "rigid constraints" of resources. Digital innovation network reduce the time cost for firms to search for external resources. When faced with the innovation risk, enterprises can quickly identify and match with network actors possessing the required resources on digital platforms, forming virtual innovation organizations in a short period to integrate standardized, modular digital innovation resources [41]. This flexible innovation collaboration model overcomes the constraints imposed by rigid traditional organizational hierarchies and poor mobility of technological resources [9], facilitating the rapid restart of enterprise innovation processes. Finally, structural embedding in digital innovation network enhances the flexibility of a firm's innovation pathways. In digital innovation network, each node possesses equal autonomy in innovation and engages in "pooling collective wisdom" on digital platforms [42]. This enables centrally positioned firms to secure a locational advantage in accessing information, knowledge, and digital resources within the network [1], thereby maintaining the continuous updating of their knowledge bases. Based on above literature, this study proposes:

Hypothesis1

The digital innovation network structural embedding can enhance the firm innovation resilience

3.3. Digital Innovation Network Relational Embedding and Firm Innovation Resilience

First, relational embedding in digital innovation network enables risk-sharing mechanisms. The data "traceability" of actors' behaviors significantly mitigates opportunistic conduct stemming from information asymmetry [43], establishing a deep foundation of trust that allows firms to "lock in" core knowledge resources from network partners [22], helping firms dynamically adjust the innovation layout to prevent innovation disruptions. Second, relational embedding in digital innovation network facilitates tacit knowledge sharing. Digital connectivity within the networks reduces interaction costs between nodes which strengthens firms' control over strong ties [10], thereby

enabling actors to share implicit knowledge such as R&D processes and failure experiences [44]. After further integration, a "structured" risk response mechanism and resource scheduling rules can be formed, shortening the innovation recovery cycle. Third, relational embedding in digital innovation network fosters deep knowledge co-creation. In digital innovation network, the co-evolution of factors such as technical prototype, digital business mindsets and cultural visions reinforces strong ties oriented toward value co-creation [13, 15]. The sharing among partners involves a large amount of key market data information of various stakeholders such as product users, giving rise to diverse innovation demands oriented and reorganize digital resources towards value creation [10, 42, 45, 46], supporting leaps in firms' innovation capabilities. Based on the above analysis, this study proposes:

Hypothesis2

The digital innovation network relational embedding can enhance the firm innovation resilience.

3.4. Digital Innovation Network Embedding, Knowledge-based Dynamic Capacity and Firm Innovation Resilience

The knowledge-based view posits that knowledge resources are the core elements for firms to innovate and build competitive advantages [47]. Building on Teece's(2007) dynamic capabilities theory [48], scholars have further proposed the concept of knowledge-based dynamic capability, which refers to the higher-order dynamic capability through which firms integrate, reconfigure, and create knowledge to adapt to dynamic environments and establish suitable competitive advantages [42, 49]. Based on the existing research, this paper divides knowledge-based dynamic capability into three dimensions: knowledge acquisition capability, knowledge integration capability, and knowledge reconfiguration capability. Knowledge acquisition capability refers to a firm's ability to rapidly search for, screen, and absorb critical knowledge [14]; Knowledge integration capability denotes the ability to transform fragmented and heterogeneous knowledge into systematic knowledge and incorporate it into the existing knowledge system [9, 22]. Knowledge reconfiguration capability refers to the ability to break down existing knowledge frameworks, reorganize knowledge systems, and create new knowledge [50, 51]. On the one hand, innovation resilience differs fundamentally from traditional organizational resilience. It represents a dynamic process through which firms continuously innovate by absorbing, utilizing, and creating new knowledge [52]. On the other hand, knowledge resources stored in data form within digital innovation network exhibit a fragmented distribution pattern, which cannot generate value directly [53]. Only through systematic knowledge processing can they be transformed into internal organizational capabilities that support innovation resilience. Furthermore, a firm's innovation capabilities, such as knowledge management, can be enhanced through continuous interaction with network nodes [17, 40]. Based on this, this paper posits that digital innovation network embedding influences firm innovation resilience by enhancing knowledge acquisition capability, knowledge integration capability, and knowledge reconfiguration capability, which manifests specifically as preventing innovation disruption, enabling rapid innovation recovery, and achieving innovation upgrading in an uncertain external environment.

3.5. Structural Embedding in Digital Innovation Network, Knowledge-based Dynamic Capacity and Innovation Resilience

First, structural embedding in digital innovation network drives firms to transcend knowledge acquisition boundaries. The underlying digital technologies within the network eliminate the time lag in knowledge transmission and reduce the cost of knowledge search [38, 54], creating favorable conditions for cross-domain knowledge transfer and sharing among actors [42]. Moreover, during the process of enterprises participating in the development of digital innovation prototypes, the diffusion and iterative update of digital resources, the self-growth of digital innovation enables enterprises to continuously incorporate cross-disciplinary heterogeneous knowledge resources [8], providing sustainable support for innovation. Second, structural embedding in digital innovation network enhances the efficiency of knowledge resource integration. Within digital innovation network, innovation actors establish common symbolic languages based on generalized digital technologies [9], which breaks down the cognitive barriers that firms face when integrating heterogeneous knowledge resources across boundaries. Furthermore, the external competitive pressure arising from extensive connections with diverse network actors drives firms to proactively extract critical knowledge from vast amounts of fragmented data [15] and integrate it with internal knowledge resources to build their unique competitive advantages [55]. The enhancement of this capability to integrate large-scale heterogeneous knowledge enables firms to quickly identify relationships between internal and external knowledge elements. When facing innovation interruption, they can efficiently combine old and new knowledge modules to accurately formulate action guidelines and develop resource allocation plans. Finally, structural embedding in digital innovation network activates the potential for knowledge reconfiguration. Distributed digital innovation network decentralize the control over the allocation of knowledge resources [38]. Firms occupying positions of advantage can selectively focus on the power center's knowledge domains in the network, thereby precisely grasping the trends in core technology iteration in the market and designing knowledge reconfiguration strategies accordingly. Furthermore, as a carrier that aggregates the superior digital technologies of various organizations, the network further improves the efficiency with which firms

decompose knowledge modules and reconstruct knowledge chains [56]. Leveraging knowledge reconfiguration capabilities based on the breadth of digital connections, firms can construct multi-layered, high-density, and highly interconnected internal knowledge network from which firms can continuously explore innovation opportunities and disrupt existing technological trajectories to achieve innovation upgrading[40]. Based on this, the study proposes:

Hypothesis3

The digital innovation network structural embedding can enhance firm innovation resilience by improving the knowledge-based dynamic capability composed of knowledge acquisition capability, knowledge integration capability, and knowledge reconfiguration capability.

3.6. Relational Embedding in Digital Innovation Network, Knowledge-based Dynamic Capacity and Firm Innovation Resilience

First, relational embedding in digital innovation network drives firms to acquire high-value contextual knowledge. Supported by a high degree of trust, firms and their partners share critical contextual data, such as user information and product concepts, and jointly analyze and extract key insights [15]. This not only reduces the cost of knowledge filtering from vast amounts of data but also enhances the firm's efficiency in absorbing and converting high-value knowledge resources. The accumulation of in-depth knowledge resources helps firms build core knowledge reserves oriented toward stakeholders, enabling enterprises predict and grasp market innovation trends and create value pathways that align with market demands [42], finally avoiding innovation disruptions caused by changes in the market environment. Second, relational embedding in digital innovation network optimizes the firm's knowledge integration model. Technologies such as blockchain within digital innovation network digitize firms' behavioral trajectories amplifies trust between strongly connected actors, increasing the degree and transfer efficiency of tacit knowledge sharing, such as technical experience and management models [57]. Leveraging general-purpose digital technologies such as knowledge graphs and digital twins, enterprises can achieve partial structural storage of tacit knowledge. This enables the boundaries between explicit and tacit knowledge to be transcended, allowing for their deep integration. The enhancement of the capability to integrate explicit and tacit knowledge refines the enterprise's knowledge framework, where modular explicit knowledge and contextualized tacit knowledge complement each other [9], thereby improving the speed and effectiveness of adjusting and restarting innovation processes. Third, relational embedding in digital innovation network accelerates the firm's knowledge reconfiguration. Under highly trusted relationships, nodes engage in joint development of core innovation projects such as core technologies and business models with the aim of value co-creation [13]. Through frequent digital connections, the collaborative evolution of innovation models is driven, the technical paradigms are revised and adjusted [43], and finally similar innovation organizational norms and cultural beliefs are formed, which helps enterprises quickly validate the results of knowledge reconfiguration and share the trial-and-error costs in the creation of new knowledge. The enhanced knowledge reconfiguration capability, grounded in deep collaboration, enables firms to grasp the underlying logic of knowledge reconfiguration and overcome traditional innovation mindset barriers in digital innovation knowledge creation in digital scenario, thereby achieving sustainable innovation upgrading. Based on this, the study proposes:

Hypothesis 4

The digital Relational embedding can enhance firm innovation resilience by improving the knowledge-based dynamic capability composed of knowledge acquisition capability, knowledge integration capability, and knowledge reconfiguration capability.

Figure 1. Theoretical Model

4. Research Design

4. Research Design

4.1. Data Sources

The patent data used in this study are sourced from the National Intellectual Property Administration and the CNRDS database. Data for the control variables are obtained from the CSMAR database. To ensure the rigor of the empirical analysis, the following procedures are applied to the sample data: (1) Excluding data from ST and ST* companies. (2) Removing firm-year observations with severe data missing. After this processing, the final sample comprises 22740 observations from 1895 enterprises spanning the period 2012–2023. All data processing and subsequent empirical analyses are conducted using Stata 18.0 software.

4.2. Variable Definition

4.2.1. Explained Variable

Innovation Resilience (*IR*): Existing approaches to measuring firm innovation resilience primarily include the indicator system method and the sensitivity indicator method. The indicator system method involves considerable subjectivity in the selection of indicators, whereas the sensitivity indicator method can more objectively reflect the sensitivity of a firm's innovation activities to exogenous shocks. Consequently, most scholars employ key indicators reflecting the sensitivity of innovation calculated based on the data reflecting the level of innovation output or input to measure innovation resilience [1, 5, 6]. Considering data availability and completeness, and given that the number of patent application situation is closely tied to the innovation environment a firm operates in within a given year, this study, building upon Martin's (2018) approach [58], uses patent application volume as the key variable to calculate the level of firm innovation resilience. The specific measurement formula is as follows.

$IR_{i,t} = (\Delta P_i - \Delta E) / \Delta E \quad (1)$
$\Delta P_i = P_{i,t} - P_{i,t-1} \quad (2)$
$\Delta E = ((P_{ind,t} - P_{ind,t-1}) / P_{ind,t-1}) P_{i,t-1} \quad (3)$

Here, *E* represents the predicted change in the number of patents for firm in year *t*, calculated based on the change in patent application within the firm's industry, *P_i* denotes the actual change in the number of patent applications for the firm in year *t*. *P_{ind, t}* and *P_{ind, t-1}* refer to the total number of patent applications in the firm's industry in years *t* and *t-1*, *P_{i, t}* and *P_{i, t-1}* indicate the firm's own patent applications in years *t* and *t-1*. *IR_{it}* represents the firm's relative innovation resilience in year *t*. A higher value of this indicator suggests that the firm exhibits greater innovation resilience compared to its industry peers when facing homogeneous environmental shocks such as resource shortages or sudden changes in market demand. To mitigate the influence of extreme values, the calculated results are transformed by adding 100 and then taking the logarithm.

4.2.2. Core Explanatory Variables

(1) Digital Innovation Network: Cooperative patent data can more clearly reveal the positional and relational characteristics of firms within innovation network and has been widely used in innovation network research [1, 7, 15]. Following the approach of the existing research, this study constructs the digital innovation network using data of cooperative digital invention patent application from Chinese A-shared listed companies between 2012 and 2023 [14]. Specifically, to identify the digital innovation patents, this study referred to the "Classification of Core Digital Economy Industries and International Patent Classification (2023)" to determine the IPC classification codes of the digital innovation patents as the basis for screening digital innovation patents, and only retain the patents involving more than two applicants. Furthermore, considering that the cooperative innovation relationship has not been terminated in the same year, based on whether there was a cooperative relationship among the various patent application entities within a 5-year window period, the joint invention patent application data will be converted into an undirected "0–1" matrix, which was then used to construct the digital innovation network of firms between 2012 and 2023.

(2) Digital Innovation Network embedding: Degree centrality, measured as the number of network entities with which a firm has collaborative relationships, most directly reflects the firm's positional centrality within the network. Referring to the Muller et al.(2019) [59], this paper uses degree centrality to represent a firm's structural embedding in the digital innovation network (*Em1*). Tie strength reflects the depth of collaboration between network actors. Drawing on research by Zheng and Yang (2015) [60], relational embedding in the digital innovation network (*Em2*) is measured using the geometric mean of the frequency of joint digital innovation patent applications involving the firm. To mitigate the influence of extreme values, both indicators are transformed by adding 1 and then taking the logarithm.

4.2.3. Mechanism Variables

(1) Knowledge Acquisition Capability (*KDC1*): Following the approach of Wang et al. (2020) [61], this study measures a firm's knowledge acquisition capability using the backward citation method, specifically by taking the logarithm of the number of times a firm cites patents granted to other enterprises after adding 1. A higher value of this indicator indicates stronger knowledge acquisition capability.

(2) Knowledge Integration Capability (*KDC2*): In order to measure an enterprise's ability to integrate across multiple knowledge domains, referring to the method of Carnabuci and Operti (2013) [62], this paper take the logarithm of the number of the combinations of the first four IPC codes in the patents of the firms for the current year after adding 1 as the measurement indicator for the knowledge integration ability. A higher value indicates that the firm's stronger integration capability for heterogeneous knowledge from different domains.

(3) Knowledge Reconfiguration Capability (*KDC3*): adopting the method of Byun et al. (2021) [63], this study employs a dynamic tracking approach to measure a firm's knowledge renewal level. Using a five-year rolling time window, a knowledge pool of IPC subclass codes involved in the firm's patents from year *t*-5 to *t*-1 is constructed after adding 1. The logarithm of the number of newly involved IPC subclass codes in year *t* serves as the proxy indicator for knowledge reconfiguration capability. A higher value indicates a stronger ability to achieve breakthrough knowledge creation based on the existing knowledge system, which presents greater knowledge reconfiguration capability.

4.2.4. Control Variables

Building on the existing research [5, 15], we included the following variables as control Variables: *Age, Soe, Cash, Lev, Roa, Value, Fixed, Sep, Indep, Inno*. To further control for unobservable factors at the year, industry, and regional levels, this study incorporates year fixed effects, industry fixed effects, and region fixed effects in the empirical analysis. The detailed definitions and measurements of these variables are presented in the Table 1.

Table 1
Variable definition

Variable Type	Variable Name	Variable Symbol	Variable Definition
Explained Variable	Innovation Resilience	IR	The sensitivity indicator calculated based on the number of patent applications
Explanatory Variable	Structural Embedding	Em1	Degree centrality
	Relational Embedding	Em2	Take the geometric mean of the frequency of all cooperative digital innovation patent applications, and then take the logarithm after adding 1
Mechanism Variables	Knowledge acquisition ability	KDC1	the backward citation of the patents after adding 1
	knowledge integration ability	KDC2	take the logarithm of the number of the combinations of the first four IPC codes after adding 1
	Knowledge Reconfiguration Capability	KDC3	Take the logarithm of the sum of the top four IPCs that have been newly added within a five-year time frame after adding 1
Control Variables	Firm Size	Size	Take the logarithm of the sum of the years since the establishment after adding 1
	Nature of Property Right	Soe	State-owned firms are assigned a value of 1, while non-state-owned firms are assigned a value of 0
	Cash Flow	Cash	The ratio of the net operating cash flow to total assets
	Asset-Liability Ration	Lev	The ratio of total liabilities to total assets
	Return on Total Assets	Roa	The ratio of net profit to total assets
	Book-to-Market	Value	The ratio of market price to book value
	Fixed Asset Ratio	Fixed	The ratio of fixed assets to total assets
	Rate of Separation of Ownership and Management	Sep	The difference between the proportion of control rights and the proportion of ownership held by the actual controller
	Proportion of Independent Directors	Indep	The proportion of independent directors
	Innovation Capability	Inno	Take the logarithm of the sum of patents applied for by firm after adding 1.

4.2.5. Descriptive Statistics

The descriptive statistics for the variables in Table 2 indicate that the level of innovation resilience has a minimum value of -2.846 and a maximum value of 9.201. While there is some variation, the mean value is 4.719, suggesting that the innovation resilience of Chinese listed firms is generally at a moderate level. The structural embedding in the digital innovation network ranges from 0 to 4.745, with a mean of 0.195, while relational embedding ranges from 0 to 3.864, with a mean of 0.142. These figures indicate that many firms have not yet embedded themselves into digital innovation network.

Table 2
Description Statistics Results

	Var	Obs	Mean	Max	Min	Std
Explained Variable	IR	22740	4.719	9.201	-2.846	0.513
Explanatory Variable	Em1	22740	0.195	4.745	0	0.540
	Em2	22740	0.142	3.846	0	0.405
Mechanism Variables	KDC1	22740	3.244	11.601	0	2.592
	KDC2	22740	1.057	7.246	0	1.217
	KDC3	22740	0.635	4.489	0	0.843
Control Variables	Size	22740	20.632	27.320	7.594	1.781
	Age	22740	2.935	4.043	0	0.502
	Soe	22740	0.432	1	0	0.495
	Cash	22740	0.048	0.876	-0.744	0.070
	Lev	22740	0.444	1.592	0.008	0.205
	Roa	22740	0.047	0.831	-1.224	0.070
	Value	22740	0.654	1.636	0	0.276
	Fixed	22740	0.208	0.954	9.00e-06	0.165
	Sep	22740	0.461	0.581	-0.530	0.075
	Indep	22740	0.376	0.8	0	0.058
	Inno	22740	3.027	9.638	0	1.906

4.3. Model Construction

To investigate the effect of the digital innovation embedding on innovation resilience, we establish the following model:

$$IR_{i,t} = \alpha_0 + \alpha_1 Em1_{i,t} + \alpha_2 Controls + \alpha_3 Year + \alpha_4 Ind + \alpha_5 City + \epsilon_{i,t}$$

5

$$IR_{i,t} = \alpha_0 + \alpha_1 Em2_{i,t} + \alpha_2 Controls + \alpha_3 Year + \alpha_4 Ind + \alpha_5 City + \epsilon_{i,t}$$

6

In this model the Variable IR represents the innovation resilience of the i-th firm in year t. The explanatory variable *Em1* and *Em2* represent the level of digital innovation network structure embedding and relationship embedding of the i-th firm in year t. Controls represents the series of control variables mentioned in the research. *Year*, *Ind* and *City* represents year, industry and city fixed effects. And ϵ represents the random error term of the model.

5. Empirical Results and Analysis

5.1.1. Correlation Analysis

Table 3 presents the Pearson correlation coefficients matrix of the key variables. The correlation coefficients between digital innovation structural embedding and relational embedding with innovation resilience are 0.194 and 0.173 respectively, both significant at the 1% level, which suggests that digital innovation embedding has the potential to improve the innovation resilience of the enterprises. The correlation coefficients among the variables included in the same model are predominantly below 0.2, effectively ruling out potential issues of multicollinearity.

Table 3
Pearson correlation coefficients of key variables

IR	IR	Em1	Em2	Size	Age	Soe	Cash	Lev
	1							
Em1	0.194***	1						
Em2	0.173***	0.900***	1					
Size	0.207***	0.239***	0.205***	1				
Age	-0.030***	0.039***	0.032***	0.112***	1			
Soe	0.074***	0.056***	0.049***	0.271***	0.149***	1		
Cash	0.038***	0.027***	0.014**	0.202***	0.003	-0.012*	1	
Lev	0.105***	0.080***	0.079***	0.364***	0.143***	0.253***	-0.146***	1
Roa	0.056***	0.009	0.003	0.089***	-0.052***	-0.003	0.383***	-0.218***
Value	0.055***	0.094***	0.074***	0.428***	0.330***	0.238***	-0.092***	0.395***
Fixed	-0.016***	0.018***	0.015**	0.551***	-0.021***	0.133***	0.240***	-0.020***
Sep	0.009	-0.000	-0.008	0.072***	0.016	-0.043***	0.050***	0.039***
Indep	0.046***	0.035***	0.028***	0.001	-0.009	-0.028***	-0.012*	0.003
Inno	0.249***	0.391***	0.367***	0.389***	0.046***	-0.009	0.079***	0.090***
	Roa	Value	Fixed	Sep	Indep	Inno		
Roa	1							
Value	-0.134***	1						
Fixed	0.041***	0.091***	1					
Sep	0.063***	0.031***	0.070***	1				
Indep	-0.028***	-0.017***	-0.043***	-0.071***	1			
Inno	0.043***	0.088***	0.008	0.032***	0.041***	1		
Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.								

5.1.2. Baseline Results

Table 4 presents the baseline regression results derived from Model (1). Columns (1) and (4) show the results without control variables and without controlling for fixed effects. Columns (2) and (5) report the results without control variables but with fixed effects included. Columns (3) and (6) display the results with both control variables and year, industry, and region fixed effects controlled for. As can be seen, all results indicate that structural embedding (*Em1*) and relational embedding (*Em2*) in the digital innovation network significantly enhance the firm's innovation resilience (*IR*) at the 1% level. Therefore, hypotheses H1 and H2 are supported.

Table 4
Results of basic regression

VAR	(1)	(2)	(3)	(4)	(5)	(6)
	IR	IR	IR	IR	IR	IR
Em1	0.184*** (0.020)		0.091*** (0.016)		0.091*** (0.015)	
Em2		0.219*** (0.026)		0.103*** (0.021)		0.100*** (0.020)
Size			0.057*** (0.006)	0.059*** (0.006)	0.070*** (0.006)	0.072*** (0.006)
Age			-0.063*** (0.010)	-0.063*** (0.010)	-0.012 (0.009)	-0.012 (0.009)
Soe			0.046*** (0.011)	0.033*** (0.012)	0.028** (0.011)	0.029** (0.012)
Cash			0.040 (0.053)	0.044 (0.054)	0.093* (0.052)	0.096* (0.052)
Lev			0.074*** (0.023)	0.068*** (0.023)	-0.009 (0.025)	-0.013 (0.026)
Roa			0.248*** (0.0523)	0.244*** (0.052)	0.184*** (0.050)	0.181*** (0.050)
Value			-0.066** (0.020)	-0.064*** (0.020)	-0.067** (0.023)	-0.067** (0.023)
Fixed			-0.418*** (0.050)	-0.427** (0.050)	-0.380*** (0.046)	-0.391*** (0.047)
Sep			0.019 (0.060)	0.022 (0.060)	0.108* (0.061)	0.113* (0.062)
Indep			0.293*** (0.110)	0.300** (0.113)	0.330** (0.099)	0.337** (0.102)
Inno			0.036*** (0.004)	0.037*** (0.004)	0.032*** (0.005)	0.033*** (0.005)
Con	4.684*** (0.005)	4.688*** (0.005)	3.546*** (0.121)	3.512*** (0.124)	3.018*** (0.126)	3.135*** (0.130)
Year/Ind/City	NO	NO	NO	NO	YES	YES
Observes	22,740	22,740	22,740	22,740	22,735	22,735
R2	0.038	0.030	0.105	0.103	0.176	0.174

*Note: Values in parentheses are robust standard errors clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The following table is the same.*

5.2. Robustness Check

5.2.1. Replacing the Core Explained Variable

This study uses the number of patents granted to firms within the same industry to remeasure firm innovation resilience. The regression results in columns (1)-(2) of Table 5 indicate that after replacing the core dependent variable, the findings remain statistically significant.

5.2.2. Replacing the Core Explanatory variables

The measure for structural embedding in the digital innovation network is replaced with the firm's betweenness centrality (*Em3*), and the measure for relational embedding is replaced with the arithmetic mean of the firm's joint digital innovation applications with its partners (*Em4*). The regression results in columns (3)-(4) of Table 5 remain significant.

5.2.3. Excluding the Influence of Other Innovation Networks

Firm innovation resilience might also be affected by other non-digital innovation network in which the firm participates. This study calculates the firm's level of structural embedding (*UmEm1*) and relational embedding (*UmEm2*) in non-digital innovation network and includes them as control variables in the regression. As shown in columns (5)-(6) of Table 5, after controlling for the influence of non-digital innovation network embedding, the enhancing effect of digital innovation network embedding on innovation resilience remains significant. Furthermore, the regression coefficients for digital innovation network embedding are notably larger than those for non-digital innovation network embedding.

5.2.4. Incorporating Lagged Explanatory Variables.

Considering the potential time lag in the innovation effects of digital innovation network embedding, the explanatory variables are lagged by one period in the regression. The results in columns (1)-(2) of Table 6 remain significant.

5.2.5. Including High-dimensional Fixed Effects

To account for time-varying unobservable factors at the industry and regional levels, high-dimensional fixed effects for industry-year and region-year interactions are further added. The regression results in columns (3)-(4) of Table 6 remain significant.

5.2.6. Adjusting the Level of Clustered Robust Standard Errors

Considering the sensitivity of the empirical test results to the clustering levels, this study further adjusts the clustering standard errors to the industry and city levels. The columns (5)-(6) represent the regression results after adjusting the clustering standard errors to the industry level, and columns (7)-(8) show the regression results after adjusting the clustering standard errors to the city level. The results indicate that the conclusion remains significant.

Table 5
Results of robustness test

VAR	(1)	(2)	(3)	(4)	(5)	(6)
	IR2	IR2	IR	IR	IR	IR
Em1	0.065*** (0.012)				0.087*** (0.016)	
Em2		0.058*** (0.014)				0.109*** (0.020)
Em3			0.225** (0.071)			
Em4				0.103*** (0.018)		
UnEm1					0.004 (0.007)	
UnEm2						-0.010 (0.008)
Con	4.16*** (0.063)	4.115*** (0.069)	3.062*** (0.136)	3.162*** (0.129)	3.183*** (0.143)	3.133*** (0.131)
Controls	YES	YES	YES	YES	YES	YES
Year/Ind/City	YES	YES	YES	YES	YES	YES
Observes	22,735	22,735	22,735	22,735	22,735	22,735
R2	0.083	0.080	0.170	0.176	0.176	0.174

Table 6
Results of robustness test

VAR	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IR	IR	IR	IR	IR	IR	IR	IR
Em1			0.094*** (0.017)		0.091*** (0.013)		0.091*** (0.013)	
Em2				0.102*** (0.021)		0.100*** (0.016)		0.100*** (0.018)
L.Em1	0.094*** (0.016)							
L.Em2		0.109*** (0.020)						
Con	3.113*** (0.135)	3.074*** (0.138)	3.137*** (0.138)	3.091*** (0.143)	3.179*** (0.332)	3.135*** (0.339)	3.179*** (0.230)	3.135*** (0.231)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year/Ind/City	YES	YES	YES	YES	YES	YES	YES	YES
Year-Ind/Year-City	NO	NO	YES	YES	NO	NO	NO	NO
Observes	20,840	20,840	22,218	22,218	22,735	22,735	22,735	22,735
R2	0.181	0.180	0.297	0.295	0.176	0.174	0.176	0.174

5.3. Endogeneity test

To address potential endogeneity concerns arising from reverse causality, omitted variables, and sample selection bias, this study employs the following methods to mitigate their impact:

5.3.1. Instrumental Variable Method

The instrumental variable (IV) method can help mitigate issues of omitted variables and reverse causality. First, following the Lewbel method, a Lewbel-type instrument is constructed by taking the cubic term of the difference between a firm's digital innovation network embedding and the average embedding of its city and industry (excluding the firm itself), which serves as the first instrumental variable (IV1). Second, drawing on the approach of Nunn(2014) [64], the product of the 1998 cable length and the firm's digital innovation network embedding lagged by two periods is used as the second instrumental variable (IV2). The regression results in column (1)-(2) and (3)-(4) in Table 7 indicate that in the first stage, the coefficients of IV1 and IV2 on the explanatory variables are both statistically significant. Both instrumental variables pass the under-identification test, and the Kleibergen-Paap rk LM statistics exceed the critical value of 16.38 at the 10% significance level, satisfying the weak instrument test and confirming the validity of the chosen instruments. Moreover, the second-stage regression results shown in column (3)-(4) and (7)-(8) in Table7 indicate that the coefficients for structural embedding and relational embedding in the digital innovation network remain significantly positive. This demonstrates that the core conclusions of this study remain robust after addressing potential endogeneity concerns using the instrumental variable method.

5.4. PSM-DID

The PSM-DID method can alleviate the endogeneity problem caused by selection bias. Firms that have been embedded in the digital innovation network at least once are classified as the treatment group. Using the control variables from the benchmark regression as characteristic variables, a 1:1 nearest neighbor matching was performed, resulting in 3931 sample observations for the treatment group. After completing the sample matching, the treat variable was set to 1 for firms embedded in the digital innovation network. The post variable was set to 1 for the year of their first embedding into the network and all subsequent years. A Difference-in-Differences (DID) variable (treat*post) was constructed for regression analysis. The results in column (9) of Table 7 show that the DID regression coefficient is significantly positive. This indicates that the main conclusions of this research remain robust after addressing endogeneity issues using the PSM-DID method.

5.4.1. Heckman Two-Stage Method

The Heckman two-stage method can address potential sample selection bias issues. In the first stage, a dummy variable (*treat*) is constructed based on whether a firm engages in digital innovation network embedding. The Inverse Mills Ratio (*IMR*) is then estimated using a Probit model to examine whether firm characteristic variables influence the decision to embed into the digital innovation network. In the second stage, the *IMR* is included as a control variable in the benchmark regression equation to correct for selection bias. The regression results in column (10)-(11) of Table 7 show that after incorporating the *IMR*, the coefficients for both structural and relational embedding in the digital innovation network remain significantly positive. This indicates that the research conclusions of this paper remain robust after addressing endogeneity issues using the Heckman two-stage method.

Table 7
Results of endogeneity treatment test

VAR	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Em1	Em2	IR	IR	Em1	Em2	IR	IR	IR	IR	IR
IV1-Em1	0.135* ** (0.015)									0.0296** (0.0104)	
IV1-Em2		0.185* ** (0.021)									0.036** (0.014)
IV2-Em1					0.964* ** (0.027)						
IV2-Em2						0.871* ** (0.031)					
Em1			0.144* ** (0.026)				0.105* ** (0.022)				
Em2				0.113* * (0.035)				0.128*** (0.024)			
DID									0.126* ** (0.035)		
IMR										3.135* ** (0.172)	
Con	—	—	—	—	—	—	—	—	2.456* ** (0.289)	-2.106* ** (0.336)	-2.151* ** (0.334)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year/Ind/City	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observes	22,735	22,735	22,735	22,735	18,946	18,946	18,946	18,946	3,931	22,735	22,735
R2	0.492	0.498	—	—	0.496	0.492	—	—	0.230	0.279	0.279
Centred R2	—	—	0.075	0.076	—	—	0.082	0.081			
K-P rk W- Wald Test	—	—	85.620	75.379	—	—	1271.004	770.515			
K-P rk LM	—	—	0.000	0.000	—	—	0.000	0.000			

6. Further Analysis

6.1. Mechanism Analysis

Based on the mechanisms of knowledge-based dynamic capability proposed above, this paper constructs the following mechanism variable test model:

Mechanism_{i,t} = \beta_0 + \beta_1 Em1_{i,t} + \beta_2 Controls + \beta_3 Year + \beta_4 Ind + \beta_5 City + \epsilon_{i,t}

7

IR_{i,t} = \beta_0 + \beta_1 Mechanism_{i,t} + \beta_2 Controls + \beta_3 Year + \beta_4 Ind + \beta_5 City + \epsilon_{i,t}

8

Here, Mechanism_{i,t} represents the mediating variables for the three dimensions of knowledge dynamic capability. All other variables and fixed effects remain consistent with those in the baseline model.

As shown in columns (1)-(3) of Table 8, both structural embedding and relational embedding in the digital innovation network can enhance the firm's knowledge acquisition capability, knowledge integration capability, and knowledge reconfiguration capability, respectively. The results in column (4) indicate that knowledge acquisition capability, knowledge integration capability, and knowledge reconfiguration capability all significantly improve firm innovation resilience. Thus, hypotheses H3 and H4 of this study are supported.

Table 8
Results of mechanism analysis

VAR	KDC1		KDC2		KDC3		IR		
	(1)		(2)		(3)		(4)		
Em1	0.490*** (0.044)		0.713*** (0.029)		0.413*** (0.018)				
Em2		0.571*** (0.058)		0.836*** (0.044)		0.491*** (0.028)			
KDC1							0.033*** (0.004)		
KDC2							0.037*** (0.007)		
KDC3								0.042*** (0.009)	
Con	-0.441 (0.519)	-0.652 (0.517)	-0.524** (0.251)	-0.827*** (0.267)	0.060 (0.158)	-0.110 (0.162)	3.086*** (0.134)	3.105*** (0.133)	3.071*** (0.135)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year/Ind/City	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observes	22,735	22,735	22,735	22,735	22,735	22,735	22,735	22,735	22,735
R2	0.703	0.702	0.487	0.473	0.440	0.432	0.178	0.174	0.172

6.2. Heterogeneity test

The impact effect of digital innovation network embedding on the innovation resilience of enterprises is not determined by a single factor, but is the result of the joint action of internal conditions of the enterprise and the external environment. Considering that the digital background of enterprise executives, the industry environment, and the enterprise's perception level of the external environment will have an impact on the digital strategic thinking, technical resources, and cooperative innovation decisions of the enterprise, this paper explores the boundary conditions of the impact of digital innovation network embedding on the innovation resilience of firms from three levels: the

digital background of enterprise executives, the type of the industry in which the enterprise is located, and the enterprise's perception level of uncertainty.

6.2.1. Heterogeneity of Digital Knowledge among Senior Executives

Firms with executives possessing a digital background typically demonstrate digital strategic thinking. After embedding into digital innovation network, they are able to more accurately identify high-value digital resources and complementary digital partners. Furthermore, they actively integrate the positional and relational advantages gained from the digital network with internal contextual factors such as digital culture and vision, thereby forming an agile and difficult-to-imitate innovation ecosystem. Therefore, this paper hypothesizes that the enhancing effect of digital innovation network embedding on innovation resilience is stronger for firms with executives possessing a digital background. This study constructs a dummy variable for executives' digital background using information on the academic majors of listed company executives. Specifically, if an executive's major involves digital-related disciplines, they are considered to have a digital background. Based on whether at least one executive in the firm possesses a digital background, the sample firms are divided into a high-level executive digital knowledge group and a low-level executive digital knowledge group. The regression results in columns (1)-(4) of Table 9 indicate that the coefficient for the effect of digital innovation network embedding on innovation resilience is larger for firms with high-level executive digital knowledge. Thus, the above hypothesis is supported.

Table 9
Results of mechanism analysis heterogeneity test

Var	high-level executive digital knowledge	low-level executive digital knowledge	high-level executive digital knowledge	low-level executive digital knowledge	high-tech	non-high-tech	high-tech	non-high-tech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IR	IR	IR	IR	IR	IR	IR	IR	
Em1	0.180*** (0.044)	0.086*** (0.016)			0.076*** (0.020)	0.110*** (0.024)		
Em2			0.244*** (0.070)	0.094*** (0.020)			0.078*** (0.023)	0.138*** (0.037)
Con	3.384*** (0.520)	3.142*** (0.130)	3.339*** (0.480)	3.099*** (0.135)	2.841*** (0.182)	3.316*** (0.174)	2.792*** (0.223)	3.275*** (0.179)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year/Ind/City	YES	YES	YES	YES	YES	YES	YES	YES
Observes	1,669	21,049	1,600	21,049	10,954	11,767	10,954	11,767
R2	0.236	0.181	0.232	0.199	0.182	0.199	0.181	0.197

6.2.2. Heterogeneity in the high-tech industry

High-tech enterprises inherently possess greater technological and knowledge resource advantages within the digital context, whereas non-high-tech firms are more likely to confront innovation challenges rooted in their traditional business domains. Embedding into digital innovation network can assist the latter in acquiring extensive knowledge related to areas such as industrial internet and digital supply chains, thereby enabling them to establish an innovation system paradigm that bridges the digital-non-digital divide. This helps reduce innovation risks and enhance market adaptability. Therefore, this paper hypothesizes that non-high-tech firms will experience a greater improvement in innovation resilience after embedding into digital innovation network compared to high-tech firms. Based on the industry classification codes, enterprises were divided into high-tech industry and non-high-tech industry groups. The regression results in columns (5)-(8) of Table 9 show that the enhancing effect of digital innovation network embedding on innovation resilience is more pronounced for non-high-tech firms, confirming the aforementioned hypothesis.

6.2.3. Heterogeneity of Uncertain Perception Levels

Firms with a higher perception of external environmental uncertainty typically exhibit stronger motivation to proactively seek external resources and build a risk "buffer zone" compared to those with lower uncertainty perception. Consequently, after embedding into digital innovation network, they are more likely to actively leverage collaborative relationships to acquire complementary knowledge resources and

form innovation risk contingency alliances, thereby enhancing the environmental adaptability of their innovation systems. Therefore, this paper hypothesizes that the innovation resilience-enhancing effect of embedding into digital innovation network is stronger for firms with high uncertainty perception than for those with low uncertainty perception. Following the approach of existing study [65], if terms such as "external environment" and "uncertainty" appear in a firm's annual report text, the firm is considered to perceive uncertainty in the external environment. The frequency of such terms in the textual information of listed firms' annual reports is calculated using Python as a proxy indicator for the level of uncertainty perception. Firms are then divided into high-uncertainty-perception and low-uncertainty-perception groups based on the median value of this indicator. The regression results in columns (1)-(4) of Table 10 show that the innovation resilience-enhancing effect of digital innovation network embedding is more pronounced for firms with high uncertainty perception, supporting the above hypothesis.

Table 10
Results of mechanism analysis heterogeneity test

VAR	High Uncertain Perception	Low Uncertain Perception	High Uncertain Perception	Low Uncertain Perception
	(1)	(2)	(3)	(4)
IR	IR	IR	IR	
Em1	0.086*** (0.017)	0.080*** (0.022)	0.094*** (0.022)	
Em2				0.094*** (0.026)
Con	2.796*** (0.176)	3.634*** (0.121)	2.725*** (0.181)	3.621*** (0.122)
Controls	YES	YES	YES	YES
Year/Ind/City	YES	YES	YES	YES
Observes	11,397	11,326	11,397	11,326
R2	0.229	0.124	0.227	0.124

7. Conclusions, Implications, and Prospects

7.1. Conclusions

In the theoretical part, based on the theory of network embedding and dynamic capability, this builds a theoretical mechanism framework of "network embedding - knowledge-based dynamic capability - innovation resilience", exploring the intrinsic relationship between digital innovation network embedding and innovation resilience. In the empirical part, this study constructs a digital innovation network using cooperative digital invention patent applications data and validates the direct impact and mechanism of digital innovation network embedding on firm innovation resilience based on the panel data of listed companies from 2012 to 2023. The results indicate that the structural embedding and relational embedding of the digital innovation network can enhance the innovation resilience of firms, and the results remain valid after a series of robustness and endogeneity tests; the mechanism test results reveal that the knowledge-based dynamic capability, composed of three sub-dimensions of knowledge acquisition capability, knowledge integration capability, and knowledge reconstruction capability, plays a mechanism role in both; the heterogeneity analysis test results show that firms with higher digital knowledge levels of senior management, non-high-tech firms, and firms with a higher uncertainty perception level have a higher enhancement effect on innovation resilience by embedding in the digital innovation network.

7.2. Implications

First, fostering a collaborative and symbiotic digital innovation network ecosystem to enhance the level of firm embedding within digital innovation network is of great significance. At the macro level, governments should take the lead in jointly constructing digital innovation network with firms, research institutions, universities, etc., and build digital innovation infrastructure such as digital open-source platforms and technology middle platforms to lower the entry barriers for enterprises to embed into digital innovation network. Furthermore, it is crucial to accelerate the formulation of laws and regulations concerning data circulation and transactions, providing a solid institutional guarantee for enterprise embedding. At the micro level, enterprises should actively cultivate diversified digital innovation partnerships to

compensate for their own shortcomings in digital capabilities, thereby laying a foundation of broad innovation resources for enhancing their innovation resilience. Simultaneously, they should diligently maintain core collaborative relationships to secure a supply of high-value innovation resources and enable deep innovation collaboration, which supports the improvement of innovation resilience.

Second, firms should fully recognize the importance of knowledge-based dynamic capabilities and leverage digital innovation network to improve the efficiency of transforming knowledge resources into innovation resilience. Regarding knowledge acquisition capability, they should utilize cross-boundary knowledge interfaces within digital innovation network to obtain heterogeneous knowledge and strengthen the establishment of contextual knowledge-sharing mechanisms. In terms of knowledge integration capability, they ought to fully employ digital collaboration tools to facilitate broad and deep knowledge sharing, and use digital technologies like visualization to deepen the connections within their knowledge systems, thereby optimizing their knowledge integration models. For knowledge reconfiguration capability, they should actively collaborate with other network actors to establish digital laboratories, creating an efficient "knowledge - technology - market" conversion chain to break path dependence in innovation.

Finally, implement targeted strategies for building digital innovation network. For enterprises with a digital background, support their transformation into "digital leaders", and encourage them to assist enterprises without a digital background in cultivating digital innovation thinking. For non-high-tech enterprises in traditional manufacturing, agriculture, and other sectors, it is necessary to accelerate the development of digital toolkits that are easy to integrate and lightweight, provide scenario-based solutions, enhance the compatibility between digital network resources and industry innovation content, and cultivate leading enterprises within digital innovation industry. For enterprises with high perceived uncertainty, establishing innovation risk compensation funds can incentivize them to proactively engage in digital innovation network for innovation risk management and pursue forward-looking innovation layouts.

7.3. Research Shortcomings and Prospects

This paper also has certain limitations and we hope to conduct further research in the future: (1) Measurement of innovation resilience. This paper uses an indirect measurement method based on the result perspective, using indicators reflecting the sensitivity of firms' innovation to the external environment to measure innovation resilience. In the future, we can start from the perspective of capability or process to construct an innovation resilience measurement system consisting of multiple dimensions of indicators. (2) Division of the network embedding dimension. This paper mainly conducts theoretical analysis and empirical research based on the centrality of the enterprise digital innovation network and the strength of cooperative relationships. In the future, we can discuss the impact of intermediary centrality, structural holes, trust level, and mutual benefit level on firm innovation resilience from these network position characteristics, and also further incorporate other types of network embedding such as geographical embedding and cognitive embedding into the research framework.

Declarations

Ethical approval and consent to participate

Not applicable.

Consent to publish

Not applicable.

Competing interests

The authors declare no competing interests.

Author Contribution

Hu Yue and Yiqi Luo wrote the main manuscript text and finished the empirical part. Yiqi Luo Prepared all the figures in the text. Hu Yue Yiqi Luo and Jing Zhou participated in the methodology construction and reviewed the manuscript.

Acknowledgements

This study was supported by the National Social Science Fund of China (23&ZD090), The Guangdong Social Science Foundation Project (GD23XYJ23).

Data Availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

References

1. Luo TY, Qu JJ, Cheng S. Knowledge Network embedding and Innovation Resilience. *IEEE Trans Engineering Manage.* 2024;71:11454–62. <https://doi.org/10.1109/TEM.2024.3422106>.
2. Zhang LL, Zhang XQ, Yao YC, Sun PP, Liu ZP. High-level opening-up and enterprise innovation resilience: Evidence from a quasi-natural experiment of China's belt and road initiative. *China Economic Review.* 2025;93:102485.
3. Wziatek-Kubiak A, Peczkowski M. Strengthening the innovation resilience of Polish manufacturing firms in unstable environments. *J Knowl Econ.* 2021;12(2):716–39.
4. Lengnick-Hall CA, Beck TE, Lengnick-Hall ML. Developing a capacity for organizational resilience through strategic human resource management. *Hum. Resources Management.* Volume 21. Rev; 2011. pp. 243–55.
5. Hu K, Wang J. Intellectual property litigation, financing constraints, and firms' innovation resilience. *Finance Res Lett.* 2025;87:109085.
6. Zhang Y, Zhou WT, Ma LN. Innovation failure experience, digital inclusive finance and enterprise innovation resilience: Evidence from China. *J Eng Technol Manage.* 2025;76:101879.
7. An TL, Wei JL, Jiang K. (2023). Complex Networks-Based Interconnected Innovation in Chinese Enterprises. *Social Sci China*, (10), 24–43.
8. Yoo Y, Boland RJ, Lyytinen K, Majchrzak A. Organizing for innovation in the digitized world. *Organ Sci.* 2012;23:1398–408.
9. Macarthy S, O'Raghallaigh P, Kelleher C, Adam F. A socio-cognitive perspective of knowledge integration in digital innovation networks. *J Strategic Inform Syst.* 2025;34(1):101871.
10. Peng YY, Jia LX. Impacts of Digital Transformation on Enterprise Innovation Resilience: A Study from China. *South African J Bussinss Manage.* 2024;55(1):1–11.
11. Zheng L, Luo G, Peng D. The impact of multi-dimensional social capital in collaborative R&D networks on firm innovation resilience: The moderation of knowledge network cohesion. *J Intellect Capital.* 2025;26(6):1257–80.
12. Liu HH, Wang P, Li ZJ. Is There Any Difference in the Impact of Digital Transformation on the Quantity and Efficiency of Enterprise Technological Innovation? Taking China's Agricultural Listed Companies as an Example. *Sustainability.* 2021;13(23):12972.
13. Yu CP, Li ZF, Lin CP, Liao YY. The Impact of Digital Innovation Network Embeddedness on New Product Development Performance of Manufacturing Enterprises. *Frontiers Bus Res in China.* 2025;19(1):79–121.
14. Ge CW, Lv WD, Wang JL. The Impact of Digital Technology Innovation Network Embedding on Firms Innovation Performance: The Role of Knowledge Acquisition and Digital Transformation. *Sustainability.* 2023;15(8):6938.
15. Yang ZN, Yuan ZJ. (2025). Digital Innovation Network Embedding and Key Core Technology Breakthroughs. *China Industrial Econ*, (5), 156–73.
16. Nonaka I. A dynamic theory of organizational knowledge creation. *Organ Sci.* 1994;5(1):14–37.
17. Tan J, Zhang HJ, Wang L. Network Closure or Structural Hole? The Conditioning Effects of Network-Level Social Capital on Innovation Performance. *Entrepreneurship Theory Pract.* 2015;39(5):1189–212.
18. Huesig S, Endres H. Exploring the Digital Innovation Process: The Role of Functionality for the Adoption of Innovation Management Software by Innovation Managers. *Euroupean J Innov Managnt.* 2019;22(2):302–14.
19. Hodapp D, Hanelt A. Interoperability in the era of digital innovation: An information systems research agenda. *J Inform Technol.* 2022;37(5):407–27.
20. Freeman C. Networks of Innovators: A Synthesis of Research Issues. *Res Policy.* 1991;20(5):499–514.
21. Bailey DE, Faraj S, Hinds PJ, Leonardi PM, Vonkrogh G. We Are All Theorists of Technology Now: A Relational Perspective on Emerging Technology and Organizing. *Organ Sci.* 2022;33(1):1–18.
22. Liu J. Trust trigger and knowledge elicitor: the role of epistemic objects in coordinating the fragmentation and heterogeneity of knowledge in digital innovation networks. *Knowl Process Manage.* 2019;26(4):332–45.
23. Lu RY, Zhou Y, Ding YW, Zhou DM, Feng, Xu. Enterprise Innovation Network: Tracing, Evolution and Research Prospect. *Manage World.* 2021;37(1):217–33.
24. Baiyere A, Grover V, Lyytinen KJ, Woerner S, Gupta A. Digital x—Charting a Path for Digital-Themed Research. *Inform Syst Res.* 2023;34(1):463–86.

25. Granovetter M. Economic Action and Social Structure: The Problem of embedding. *Am J Sociol.* 1985;91(3):481–510.
26. Yang XM, Qu S, Kong LK. The Impact of Cooperation Network Evolution on Communication Technology Innovation: A Network Interaction Perspective. *Systems.* 2025;13(2):126.
27. Yin S, Zhao YD. Digital green value co-creation behavior, digital green network embedding and digital green innovation performance: Moderating effects of digital green network fragmentation. *Humanit Soccial Sciennces Commun.* 2024;11(1):228.
28. Wang YT, Yi JB. Embedding Enterprise Networks, Digital Capabilities, and Open Innovation of Digital Economic Industrial Park. *Technol Econ.* 2023;42,(10):10, 81–93.
29. Oeij RP, Dhondt S, Gaspersz J. Mindful infrastructure as an enabler of innovation resilience behaviour in innovation teams. *Team Perform Manage.* 2016;22(78):334–53.
30. Lv WD, Tian D, Wei Y, Xi RX. Innovation resilience: a new approach for managing uncertainties concerned with sustainable innovation. *Sustainability.* 2018;10(1):3641.
31. Fey S, Kock A. Meeting challenges with resilience-how innovation projects deal with adversity. *Int J Project Manage.* 2022;40(8):941–50.
32. Sajko M, Boone C, Buly T. CEO greed, corporate social responsibility, and organizational resilience to systemic shocks. *J Manage.* 2021;47(4):957–92.
33. Guo M, Wang JB, Liu H, Zhai H. Analyzing the role of digital technology to enhance firms' green innovation resilience: A moderated mediation model. *Int J Prod Econ.* 2025;288:109720.
34. Lu ZY, Xu K. Research on Dual Effects of Digital Transformation on Enterprise Innovation Resilience. *Chin Journal Management.* 2024;21(07):1046–55.
35. Li EJ, An ZW. Does Transportation Infrastructure Construction Enhance Enterprise Innovation Resilience in China? *Sustainability.* 2024;16(7):2931.
36. Xia HX, Liu MW, Wang PC, Tan XK. (2024). Strategies to enhance the corporate innovation resilience in digital era: A cross-organizational collaboration perspective. *Heliyon*, 10(20), e39132.
37. Tsai W. Knowledge Transfer in Intraorganizational Networks: Effects of Network Position and Absorptive Capacity on Business Unit Innovation and Performance. *Acad Manag J.* 2001;44:996–1004.
38. Wang P. Connecting the parts with the whole: Toward an information ecology theory of digital innovation ecosystems. *MIS Q.* 2021;45:397–422.
39. Li LX, Zhu WW, Wei L, Yang SL. How can digital collaboration capability boost service innovation? Evidence from the information technology industry. *Technol Forecast Soical Change.* 2022;182:121830.
40. Lyytinen K, Yoo Y, Boland RJ. Digital product innovation within four classes of innovation networks. *Inform Syst J.* 2016;26(1):47–75.
41. Vuchkovski D, Zalaznik M, Mitrega M, Pfajfar G. A Look at the Future of Work: The Digital Transformation of Teams from Conventional to Virtual. *J Bus Res.* 2023;163:113912.
42. Pershina R, Soppe B, Thune TM. Bridging analog and digital expertise: Cross-domain collaboration and boundary-spanning tools in the creation of digital innovation. *Res Policy.* 2019;48(9):103819.
43. Hadjielias E, Dada O, Cruz AD, Zekas S, Christofi M, Sakka G. How do digital innovation teams function? Understanding the team cognition-process nexus within the context of digital transformation. *J Busines Res.* 2021;122:373–86.
44. Faraj S, Vonkrough G, Monteiro E, Lakhani KR. Online Community as Space for Knowledge Flows. *Inform Syst Res.* 2016;27(4):668–84.
45. Li LX, Zhu WW, Wei L, Yang SL. How can digital collaboration capability boost service innovation? Evidence from the information technology industry. *Technol Forecast Socical Change.* 2022;182:121830.
46. Kellogg KC, Orlikowski WJ, Yates J. Life in the trading zone: Structuring coordination across boundaries in post bureaucratic organizations. *Organ Sci.* 2006;17(1):22–44.
47. Grant RM. Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. *Organ Sci.* 1996;7(4):375–87.
48. Teece DJ. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strateg Manag J.* 2007;28(13):1319–50.
49. Nieves J, Haller S. Building dynamic capabilities through knowledge resources. *Tour Manag.* 2014;40:224–32.
50. Zheng SL, Zhang W, Wu XB, Du J. Knowledge-based dynamic capabilities and innovation in networked environments. *J Knowl Manage.* 2011;15(6):035–1051.

51. Verona G, Ravasi D. Unbundling dynamic capabilities: an exploratory study of continuous product innovation. *Indusretal Corp Chang*. 2003;12(3):577–606.
52. Burnard K, Bhamra R. Organisational resilience: development of a conceptual framework for organisational responses. *Int J Prod Res*. 2011;49(18):5581–99.
53. Shamim S, Zeng J, Choksy US, Sharq SM. (2020). Connecting big data management capabilities with employee ambidexterity in Chinese multinational enterprises through the mediation of big data value creation at the employee level. *International Business Review*, 29(6), 101604. 1-101604.12.
54. Nambisan S, Wright M, Feldman M. The Digital Transformation of Innovation and Entrepreneurship Progress Challenges and Key Themes. *Res Policy*. 2019;48(8):67–72.
55. Chesbrough HW. Open Innovation: The New Imperative for Creating and Profiting from Technology. Harvard Business; 2003.
56. Hund A, Wagner HT, Beimborn D, Weitzel T. Digital innovation: Review and novel perspective. *Journal Strategic Inform Systems*. 2021;30(4):101695.
57. Forman C, Van Zeebroeck N. Digital Technology Adoption and Knowledge Flows within Firms Can the Internet Overcome Geographic and Technological Distance? *Res Policy*. 2019;48:103697.
58. Martin R. Regional economic resilience, hysteresis and recessionary shocks. *J Econ Geogr*. 2012;12(1):1–32.
59. Muller E, Peres R. The effect of social networks structure on innovation performance: a review and directions for research. *Int J Res Markeing*. 2019;36(1):3–19.
60. Zheng YF, Yang HB. Does familiarity foster innovation? The impact of alliance partner repeatedness on breakthrough innovations. *J Manage Stud*. 2015;52(2):213–30.
61. Wang CH, Chin T, Lin JH. Openness and firm innovation performance: The moderating effect of ambidextrous knowledge search strategy. *J Knowl Manage*. 2020;24(2):301–23.
62. Carnabuci G, Operti E. Where do firms' recombinant capabilities come from? Intraor-ganizational networks, knowledge, and firms' ability to innovate through technological recombination. *Strateg Manag J*. 2013;34(13):1591–613.
63. Byun SK, Oh JM, Xia H. Incremental vs. Breakthrough Innovation: The Role of Technology Spillovers. *Managemen Sci*. 2021;67(3):1779–802.
64. Nunn N, Qian N. US Food Aid and Civil Conflict. *Am Econ Rev*. 2014;104(6):1630–66.
65. Zhang SS, Gu C. (2024). Enterprise Digital Transformation and Supply Chain Resilience. *China J Econ*, (8), 137–58.

Figures

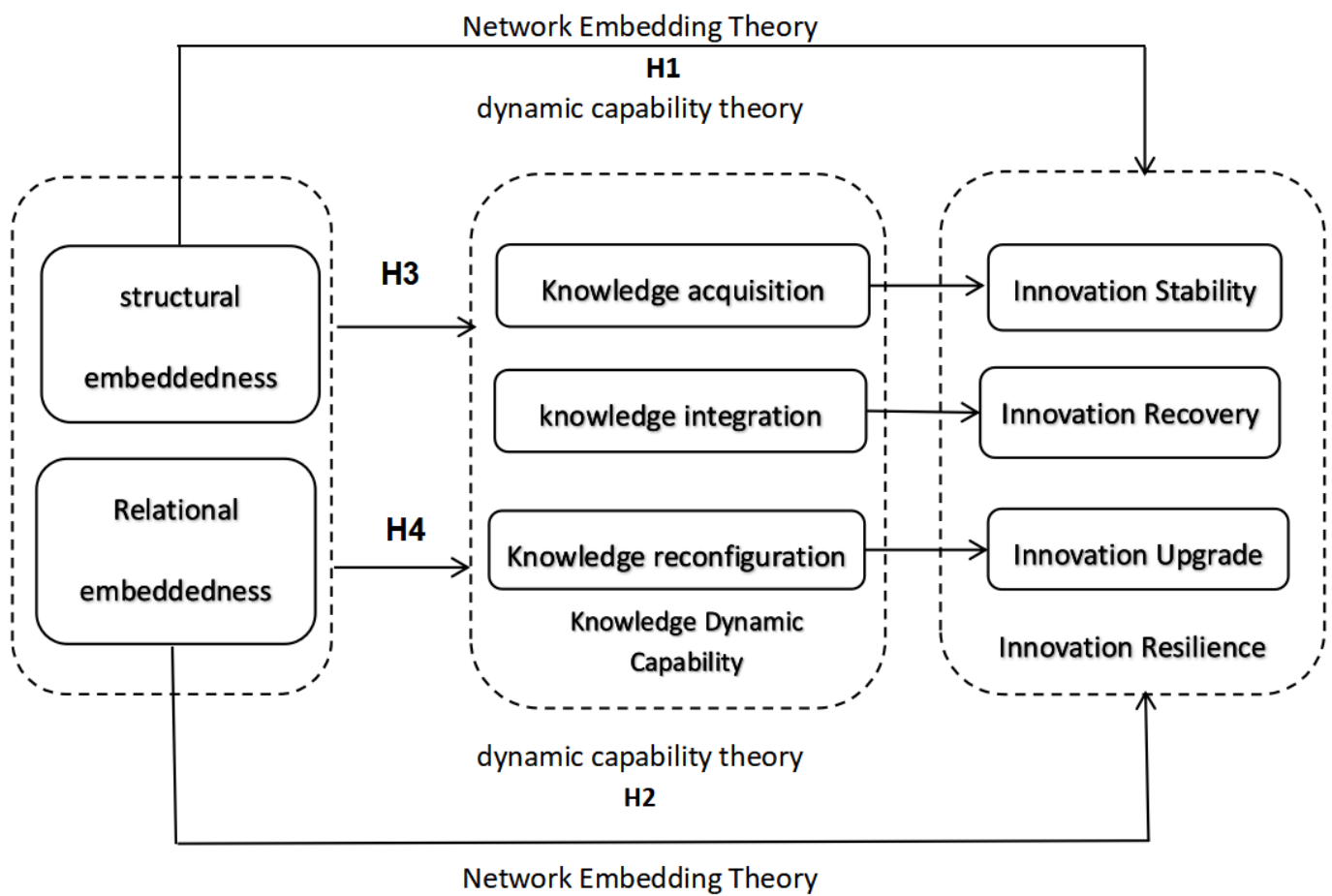


Figure 1

Theoretical Model