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COUPLING EFFECT OF DIGITAL TECHNOLOGY AND TWO-WAY OPEN INNOVATION NETWORK: EMPIRICAL STUDY ON CHINESE ENTERPRISES

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ABSTRACT

The integration of open innovation networks and digital technology is a critical research frontier. Based on 532 survey samples from Chinese enterprises, this study constructs three coupling effects: (1) internal coupling between inward innovation network and outward innovation networks, (2) internal coupling between digital technology types and digital technology applications, and (3) external coupling between two-way open innovation networks and digital technology using a coupling coordination model. The results indicate that (1) both two-way open innovation networks and their internal coupling positively related to ambidextrous innovation, (2) digital technology variety, applications, and their coupling significantly enhance ambidextrous innovation, and (3) external coupling between innovation networks and the digital technology systems exerts a positive influence. The findings suggest that policymakers and managers should foster the integrated development of open innovation networks and digital technology to achieve synergistic innovation outcomes.

Keywords: *digital technology, inward open innovation, outward open innovation, coupling effect, innovation capability*

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INTRODUCTION

This study focuses on digital innovation management in emerging economies. With shortening innovation cycles and rising research and development (R&D) costs, firms increasingly adopt open innovation to access external resources (Gassmann & Enkel, 2004), which involves both inbound and outbound knowledge flows. However, many Chinese enterprises struggle to integrate external collaboration with internal capabilities, facing challenges such as high partner search costs, intellectual property risks, and low synergy from digital investments. In the digital economy, digital technologies are reshaping production methods, organisational forms, business models and innovation theories, expanding the connotation of innovation, and becoming key to sustaining competitive advantage. This underscores the urgent need to address the "digital island" phenomenon, where technological investments often decouple from innovation networks and to explore how to effectively couple these systems for synergistic gains. This research gap remains under-explored in existing studies.

Extending from physics to innovation management (Liang et al., 2025), coupling reflects how systems form mutually reinforcing relationships. In the digital economy, the pervasive adoption of technologies (e.g., big data, artificial intelligence) makes their systemic integration with open innovation networks a critical imperative (Kohli & Melville, 2019).

This study proposed a conceptual framework examining the direct effects of networks and digital technology on innovation, their internal couplings, and their combined external coupling effect. This study makes three novel contributions: (1) modelling the open innovation-digital technology coupling via a coordination degree model, (2) examining the two-way synergy between inbound and outbound networks, and (3) dimensionalising digitalisation into variety versus application to unpack its micro-foundations.

LITERATURE REVIEW

This section first reviews the theoretical foundations of open innovation and digital technology, then summarises relevant empirical evidence, and finally proposes the conceptual framework and research hypotheses based on the theory and evidence.

Two-way Open Innovation Networks and Ambidextrous Innovation Capability

The positive impact of inbound open innovation on firm innovation is well-established in the literature, with cognitive processes and creativity being critical micro-foundations for transforming external knowledge into business innovation (Putsom, 2025). Grounded in the resource-based and knowledge-based views, scholars have argued that accessing external knowledge pools were crucial for sustaining competitive advantage (Khan et al., 2022). Specifically, external knowledge inflowed complement internal R&D, provided novel insights, and reduced innovation uncertainty. This study conceptualised open innovation networks through the lens of innovation resource flow, comprised of two dimensions, namely inbound and outbound networks. Inbound networks were involved collaborating with external partners to absorb and utilised external knowledge. Outbound networks were entailed externalising internal resources through licensing, spin-offs, or joint commercialisation (Wang, 2024). Together, they formed a two-way structure that were embedded firms in multi-directional learning processes. Radical innovation capability refers to a firm's ability to achieve discontinuous change-developing next-generation products, exploring new technologies, or entering new markets to secure long-term advantage (Li et al., 2025; Zhao & Liu, 2024). Incremental innovation capability reflects continuous improvements in quality, cost, or flexibility, supporting short-term operational efficiency (Li et al., 2025; Zhang et al., 2018).

Inbound open innovation network and ambidextrous innovation capability

Inbound open innovation enables firms to internalise external resources (Li et al., 2024) through networks that integrate, absorb, and utilise external innovation resources. It influences ambidextrous innovation via three mechanisms: (1) inbound networks enhance ambidextrous innovation by facilitating both exploratory and exploitative learning, (2) enabling the absorption of novel and existing knowledge for radical, and (3) incremental gains respectively (Benner & Tushman, 2003; Zhang et al., 2025). Thus, we hypothesise:

H1a: Inbound networks positively relate to radical innovation, as external inflows provide novel insights for breakthroughs.

H1b: Inbound networks also enhance incremental innovation by facilitating explicit knowledge absorption for continuous improvement.

Outbound open innovation network and ambidextrous innovation capability

Outbound open innovation enables firms to externalise internal resources through collaborative networks (Li et al., 2024), supporting activities such as technology licensing and commercialisation. Outbound networks contribute by generating returns for R&D reinvestment, enabling market expansion, and fostering internal competition which collectively stimulate both breakthrough and incremental improvements (Ren & Gao, 2020; Wang, 2024). These pathways collectively strengthen radical and incremental innovation capabilities. Thus, we hypothesise:

H2a: Outbound open innovation networks positively relate to radical innovation capability, as externalising technologies generates revenue for reinvestment and signals market leadership.

H2b: Outbound open innovation networks positively relate to incremental innovation capability by creating internal competition and efficiency pressures that refine existing processes.

The Coupling Between Two-way Open Innovation Networks and Ambidextrous Innovation

Gassmann and Enkel (2004) identified three open innovation modes: (1) outside-in, (2) inside-out, and (3) coupled, based on a study of 124 firms. Firms often integrate inbound and outbound activities to build competitive advantage (Cassiman & Valentini, 2016), as these forms are synergistic rather than mutually exclusive. Inbound innovation enriches a firm's knowledge base, enabling outbound activities, while outbound innovation supports inbound processes through three mechanisms: (1) generating revenue and reducing redundancy to fund knowledge absorption (Ren & Gao, 2020), (2) expanding market scope to improve trend identification and guide targeted search, and (3) enhancing reputation and trust to facilitate access to core and tacit knowledge for radical innovation. The coupling of inbound and outbound networks further produces synergistic effects, strengthening technological capabilities in application, operations, problem solving (Ren & Gao, 2020), and integrating new and existing knowledge (Lopes & de Carvalho, 2018) to enhance ambidextrous innovation. While the complementarity between inbound and outbound flows has been questioned in some contexts (Cassiman & Valentini, 2016), which this study argues that their deliberate coupling within a network can create synergistic gains. Thus, we propose:

H3a: The coupling of inbound and outbound open innovation networks positively enhances radical innovation capability because of the synergistic knowledge loop between acquiring and commercialising ideas fuels breakthrough concepts.

H3b: The coupling of inbound and outbound open innovation networks positively enhances incremental innovation capability, as the balanced resource flow between networks optimises continuous improvement cycles.

Digital Technology, Coupling Effects, and Ambidextrous Innovation

Drawing on Liu et al. (2020), this study divides digitalisation into two core elements: (1) digital technology variety and (2) application. Digital technology variety captures the breadth of a firm's adopted technologies, measure across seven categories, namely big data, artificial intelligence (AI), mobile communications, cloud computing, the Internet of Things (IoT), social platforms, and platform ecosystems. Digital technology application reflects the extent to which these technologies are deployed across innovation and managerial processes, integrating them into operations and business models. As Chen et al. (2020) observe, digital technologies evolve from enabling innovation through efficiency gains to empowering it through widespread application and business model renewal—a progression consistent with the two-dimensional framework adopted here.

Types of digital technology and ambidextrous innovation capability

Digital technologies are recognised as key drivers that reshape innovation processes and networks (Kohli & Melville, 2019; Wang et al., 2025). As general-purpose technologies (GPTs), digital technologies enhance innovation through multiple pathways. Big data facilitates knowledge acquisition, creation, and integration enabling firms to extract insights from complex data environments (Mikalef et al., 2019). It supports incremental innovation by addressing knowledge gaps in product upgrades and aids radical innovation by identifying market trends (Lin & Kunnathur, 2019), and distilling frontier knowledge (Ferraris et al., 2019). AI enhances both radical innovation (e.g., through market forecasting) and incremental innovation (e.g., via market trend prediction), by optimising processes through data structuring and multi-party collaboration. The IoT enhances innovation through sensing and intelligent capabilities-autonomously acquiring information and enabling analysis-to optimise existing processes (incremental innovation), and introduce novel offerings (radical innovation). Virtual reality (VR) supports incremental innovation through simulation-based optimisation and customisation, improving design refinement, and user interaction (Chen et al., 2020). Therefore, we hypothesise:

H4a: Digital technology variety positively relates to radical innovation capability, since a broader digital toolkit enables novel combinations of technologies for disruptive solutions.

H4b: Digital technology variety positively relates to incremental innovation capability, because of the access to diverse technologies allows for finer optimisation of existing products and processes.

Digital technology application and ambidextrous innovation capability

Digital technologies are transforming organisational functions through integration with operational networks (Xie et al., 2021). In human resource management, they enable data-driven talent development, biometric performance monitoring, and platform-mediated employment relations. Supply chain management benefits from real-time production monitoring and risk mitigation (Chen et al., 2020; Gong et al., 2021), while marketing becomes more precise through personalised engagement (Xie et al., 2024). Product management improves via data-informed design and dynamic pricing (Chen et al., 2020). Digital applications in R&D, user and innovation management strengthen in both innovation types. R&D tools enhance external collaboration and reduce costs (Liu et al., 2020); user management employs data-driven forecasting for targeted offerings. Innovation management operates through four mechanisms: (1) cost reduction via data-driven monitoring (Chen et al., 2020), (2) accelerated R&D through AI and IoT, (3) enhanced analytical capacity, and (4) expanded innovation boundaries via digital platforms (Yu et al., 2017). Thus, we hypothesise:

- H5a: Digital technology application positively relates to radical innovation capability, as deep integration of digital tools into R&D accelerates experimentation and prototyping.
- H5b: Digital technology application positively relates to incremental innovation capability, by automating and streamlining operational processes to enhance quality and reduce costs.

As Zhang and Long (2022) note, understanding digital technology's role requires examining both variety and application. Thus, we propose:

- H6a: The coupling of digital technology variety and application enhances radical innovation capability, as the alignment between having diverse tools and deeply applying them creates a powerful infrastructure for exploration.
- H6b: The coupling of digital technology variety and application enhances incremental innovation capability because its application amplifies the value derived from a broad technology portfolio for exploitation.

The Synergy between Two-way Open Innovation Networks and Digital Technology

The coupling effect arises from synergistic interactions between systems that amplify their original attributes. In innovation settings, two-way open innovation networks and digital technology interact as interdependent systems, operating through three mechanisms. From a knowledge acquisition view, digital technology development relies on internal R&D and external sourcing-processes mediated through open innovation networks. A firm's network management shapes external engagement and knowledge absorption, while digital technologies provide the infrastructure to manage networks and apply knowledge, especially tacit forms. In knowledge dissemination, coupling improves access to complementary resources and tacit knowledge diffusion. Digital tools lower context-specific application costs, accelerating knowledge transfer and technological upgrading. From an ecosystem perspective, digitally enabled firms inject new resources into innovation networks, stimulating collaboration among governments, universities, financial entities, and talent. This collective engagement strengthens innovation outcomes through agglomeration effects. Thus, we hypothesise:

H7a: The coupling between two-way open innovation networks and digital technology positively influences radical innovation capability, through mechanisms like digital-augmented knowledge absorption and network-expanding platforms.

H7b: The coupling enhances incremental innovation capability, via digitally enhanced feedback loops and efficiency gains across the coupled system.

The external coupling between the holistic innovation network (X) and digital technology system (T) (H7) represents a macro-level synergy. To unpack this black box and understand the micro-mechanisms, we further examine the pairwise coupling between each network dimension and each technology dimension. Inbound and outbound networks involve distinct knowledge processes (absorption vs. externalisation), while digital technology variety and application serve different functions (resource pool vs. process enabler). Their specific pairings create four unique synergies. First, inbound open innovation network and digital technology variety: a broad external knowledge search (inbound) is greatly amplified by access to diverse digital tools (variety) for data processing and analysis (Mikalef et al., 2019), fuelling radical idea generation. Second, inbound open innovation network and digital technology application: deep application of digital tools in operations (e.g., AI in R&D) enhances the efficiency and depth of absorbing and integrating the external knowledge acquired through the inbound network (Chen et al., 2020), benefiting incremental refinement. Third, outbound open innovation network and digital technology variety: externalising innovations (outbound) via licensing or spin-offs requires diverse digital platforms (e.g., social platforms, IoT ecosystems) to reach and connect with a wider range of potential partners, expanding market scope (Wang, 2024). Finally, outbound open innovation network and digital technology application: applying digital technologies deeply in business processes (e.g., blockchain in supply chain) can secure and streamline the commercialisation of internal technologies, protecting intellectual property while improving operational efficiency for incremental gains (Gong et al., 2021). Therefore, we further propose:

H8a: Pairwise coupling between inbound/outbound networks and digital technology variety/application fosters radical innovation capability, as each specific pairing (e.g., inbound network with technology variety) addresses unique facets of exploratory innovation.

H8b: Pairwise coupling fosters incremental innovation capability, because of the complementary fit between specific network and technology dimensions drives exploitative efficiency.

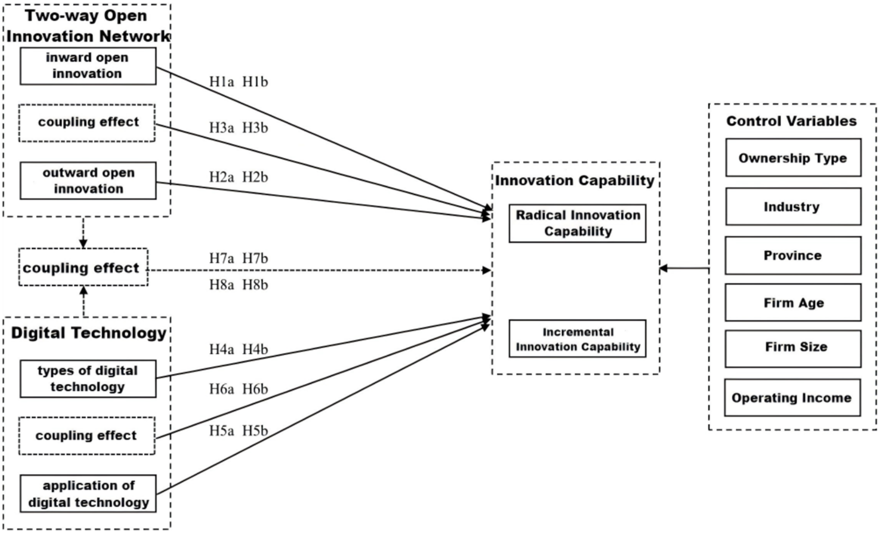

Figure 1. The study's framework

METHODOLOGY

Data Sources and Sample

A national survey on two-way open innovation in Chinese enterprises was conducted from August to October 2022, targeting mid- and senior-level managers. The questionnaire measured key constructs, including inbound/outbound networks, radical/incremental innovation capabilities, and digital technology types/applications. This design supports a comprehensive analysis of open innovation activities, collaboration patterns, digital technology development, and innovation capacity. After screening, 532 valid questionnaires were retained from 622 initial responses.

To ensure broad coverage, the sampling frame aimed to include firms of various sizes (micro, small, medium, and large based on employee count and revenue) and from diverse industries (including manufacturing, services, and high-tech sectors). The survey was distributed through a professional online survey platform and industry association networks, employing a stratified convenience sampling method. The sample is geographically and industrially diverse but not random, thus representing actively innovating firms more than the broader population. Future studies with truly random sampling are encouraged to enhance generalisability.

Table 1
Descriptive characteristics of the sample

Attribute	Category	Number of samples	Percentage
Ownership type	State-owned enterprises	198	37.22
	Private enterprises	187	35.15
	Wholly foreign-owned enterprises	89	16.73
	Sino-foreign joint ventures	35	6.58
	Others	23	4.32
Industry	Manufacturing	135	25.38
	Wholesale and retail	32	6.02
	Services	45	8.46
	Information technology	90	16.92
	Finance and real estate	136	25.56
	Education, scientific research, and technical services	19	3.57
	Culture, sports, and entertainment	16	3.01
	Others	59	11.09
Firm age	Less than 2 years	14	2.63
	2–5 years	48	9.02
	6–10 years	73	13.72
	11–15 years	73	13.72
	More than 15 years	324	60.90
Firm size (number of employees)	≤ 50	55	10.34
	51–200	66	12.41
	201–500	107	20.11
	501–2,000	137	25.75
	> 2,000	167	31.39

(*continued*)

Table 1 (*continued*)

Attribute	Category	Number of samples	Percentage
Average annual revenue (past two years, in RMB)	< 1 million	12	2.26
	1–10 million	39	7.33
	10–50 million	46	8.65
	50–100 million	49	9.21
	100 million – 1 billion	100	18.80
	1–5 billion	102	19.17
	5–10 billion	64	12.03
	> 10 billion	120	22.56

Variable Measurement

All constructs were measured using five-point Likert scales (1 = "strongly disagree" to 5 = "strongly agree"). Measurement items were primarily adapted from established scales, with contextual refinements or new items developed where necessary to fit the research focus. The specific sources and rationale for each variable are summarised in Table 2 and elaborated below. As summarised in Table 2, radical and incremental innovation capabilities—the dependent variables—were each assessed using six items. The scales were adapted from the work of Zhang et al. (2018) on exploitative and exploratory innovation, supplemented with new items to fit the context of capability (e.g., ability to develop next-generation products). Open innovation networks were distinguished as inbound and outbound types, with five items measuring each based on innovation resource flows. The item design primarily drew on the conceptualisation of Gassmann and Enkel (2004) and the operationalisation in studies like Ren and Gao (2020). Digital technology was categorised into variety and application, with seven items developed for each dimension based on existing scales and contextual adaptation. Scales for digital technology variety were adapted from established taxonomies (Kohli & Melville, 2019; Liu et al., 2020), while the application items were developed based on the discussion of digital integration in organisational functions by Chen et al. (2020) and Xie et al. (2021). Control variables included ownership type, industry, province, firm age, firm size, and annual revenue following Yang and Zhao (2020). Firm age was categorised into five tiers, firm size by employee numbers, and annual revenue into eight brackets to capture structural and operational heterogeneity.

Common Method Bias, Reliability and Validity Tests

Given the single-source, cross-sectional design, common method bias was assessed via Harman's single-factor test. The first factor accounted for 18.223% of total variance-well below the 40% threshold-indicating no substantial bias. Scale reliability and validity were examined using exploratory and confirmatory factor analyses. All constructs demonstrated good psychometric properties (KMO > 0.9, Cronbach's α > 0.8, CR > 0.8, AVE > 0.5, factor loadings > 0.6). Discriminant validity was established, as the square root of each construct's average variance extracted (AVE) exceeded its correlations with other variables. Overall, the measures demonstrate strong psychometric properties.

Research Methods for Coupling Effects

This section outlines the calculation of coupling effects. First, we construct the composite variables used in the model. Ambidextrous open X: This is a second-order construct representing the overall level of a firm's two-way open innovation activity. It is derived from its two dimensions: (1) inbound open innovation network (X1) – the mean score of the five measurement items for inbound networks, and (2) outbound open innovation network (X2) – the mean score of the five measurement items for outbound networks (from Table 2). The digital technology system (T) is a second-order construct representing the firm's overall digitalisation. It is derived from its two dimensions: (1) digital technology variety (T1) – the mean score of the seven measurement items for technology variety; (2) digital technology application (T2) – the mean score of the seven measurement items for technology application (from Table 2). The coupling effects depicted in Figure 1 are not directly measured by survey items listed in Table 2. Instead, they are calculated using the coupling coordination degree model based on the normalised values of these first-order composite variables. The following subsections detail this calculation process.

Data normalisation

Variables related to the ambidextrous open innovation network and digital technology were normalised using min–max normalisation. The procedure differs for positive and negative indicators, as specified in Equations (1) and (2).

$$\text{Positive indicator: } U_{ij} = \frac{X_{ij} - \min X_{ij}}{\max X_{ij} - \min X_{ij}} \tag{1}$$

$$\text{Negative indicator: } U_{ij} = \frac{\max X_{ij} - X_{ij}}{\max X_{ij} - \min X_{ij}} \tag{2}$$

Table 2
Results of factor analysis for each variable

Variable	Factor	Measurement Items	Factor loading	Cronbach's α	Variance (%)	CR	AVE (√AVE)	KMO	Bartlett's Test (Sig.)
Two-way open innovation network	Inbound innovation network	Scans external environment for technologies and knowledge	0.822	0.901	38.714	0.896	0.636 (0.797)	0.909	3,412.88 (0.000)
		Seeks external knowledge sources	0.854						
		Uses external knowledge to supplement internal R&D	0.857						
		Embeds external knowledge into internal R&D	0.773						
		Searches for external technologies and patents	0.664						
	Outbound innovation network	Seeks commercialisation pathways	0.628	0.861	70.462	0.851	0.537 (0.733)		
		Believes that external commercialisation enhances performance	0.709						
		Transfers incomplete R&D projects externally	0.838						
		Participates in external technology commercialisation	0.620						
		Sells intellectual property	0.838						

(*continued*)

Table 2 (*continued*)

Variable	Factor	Measurement Items	Factor loading	Cronbach's α	Variance (%)	CR	AVE (√AVE)	KMO	Bartlett's Test (Sig.)
Digital technology	Technology variety	Big data technologies	0.775	0.918	35.095	0.908	0.585 (0.765)	0.935	6,051.22 (0.000)
		Intelligent technologies	0.757						
		Mobile technologies	0.805						
		Cloud computing technologies	0.823						
		IoT technologies	0.719						
		Social interaction technologies	0.754						
		VR technologies	0.715						
	Technology application	Human resource management	0.742	0.933	69.655	0.917	0.615 (0.784)		
		Supply chain management	0.732						
		Marketing management	0.830						
		Product management	0.831						
		R&D management	0.649						
		User management	0.844						
		Innovation management	0.842						

(*continued*)

Table 2 (*continued*)

Variable	Factor	Measurement Items	Factor loading	Cronbach's α	Variance (%)	CR	AVE (√AVE)	KMO	Bartlett's Test (Sig.)
Ambidextrous innovation	Radical innovation	Develops next-generation products/services	0.789	0.926	38.939	0.924	0.668 (0.817)	0.917	5,678.74 (0.000)
		Explores new technological domains	0.807						
		Enters new markets	0.846						
		Reaches new customers	0.856						
		Experiments with new distribution channels	0.809						
		Experiments with new business strategies	0.796						
	Incremental innovation	Improves product/service quality	0.871	0.942	75.653	0.937	0.713 (0.844)		
		Reduces product/service costs	0.805						
		Enhances production/service flexibility	0.859						
		Improves product designs/technologies	0.846						
		Improves service levels	0.825						
		Applies accumulated experience	0.858						

Note: Principal component analysis was employed; values in the table represent factor loadings after Varimax rotation; KMO = Kaiser-Meyer-Olkin test; CR = composite reliability

Indicator weights

X1 and X2 open innovation networks-forming a coupled innovation network and between T1 and T2 of digital technology. The weights of X1, X2, T1, and T2 are determined based on factor analysis results, calculated as each factor's rotated variance explained proportion relative to the cumulative variance explained.

We analysed two types of external coupling: (1) between the overall open X and the T, and (2) between each network dimension (X1, X2) and each digital technology dimension (T1, T2). The weights for the composite systems (X and T) were derived from exploratory factor analysis. This equal-weighting approach is common in prior research examining system coordination (e.g., Wang et al., 2021; Liang et al., 2025).

Coupling correlation degree

The concept of coupling, derived from capacitive coupling in physics, provides the basis for the coupling correlation and coordination degree models—analytical tools extended from the capacitive coupling coefficient model to examine inter-system relationships. Coupling correlation degree quantifies the strength of interaction between two elements or systems (Liang et al., 2025), as expressed in Equation (3):

$$C = \left[\frac{\prod_{i=1}^{n} U_i}{\left(\frac{1}{n} \sum_{i=1}^{n} U_i \right)} \right]^{\frac{1}{n}} \tag{3}$$

Here, C represents the coupling correlation degree, U denotes system values, and n is the number of systems. The value of C lies in [0, 1], where values closer to 1 indicate "benign resonance" between systems, while values near 0 reflect "systemic disorder" (Liang et al., 2025). For two-system analysis, Equation (3) simplifies to Equation (4):

$$C = \frac{\sqrt[2]{U_1 + U_2}}{U_1 + U_2} \tag{4}$$

Coupling coordination degree

While the coupling correlation degree (C) measures interaction strength, it has known limitations in capturing synergistic development. Therefore, we employ the coupling coordination degree (D) (Liang et al., 2025; Wang et al., 2021), calculated as Equation (5):

$$D = \sqrt{C \cdot R} \tag{5}$$

$$R = aU_1 + bU_2 \tag{6}$$

In Equation (5), DD represents the coupling coordination degree, CC the coupling degree, and RR the comprehensive evaluation index of the two systems. In Equation (6), RR is calculated from the values UU of the respective systems, with aa and bb as undetermined coefficients reflecting their respective contributions. These coefficients satisfy $a + b = 1$, and are generally set as $a = b = 0.5$, indicating that both systems are considered equally important in the analysis (Wang et al., 2021). Based on the value of DD, the coupling coordination degree can be categorised into three broad stages and eight specific grades, as detailed in Table 3 (Liu et al., 2022).

RESULTS

Descriptive Statistics and Correlation Analysis

Descriptive statistics and correlation analyses were conducted for all variables, as summarised in Table 4. All Pearson correlation coefficients among the independent variables remained below 0.8. Further, variance inflation factor (VIF) tests showed all independent variables had VIF values < 10, indicating no serious multicollinearity.

Tests of Main and Internal Coupling Effects

To test the main and internal coupling effects, we employed hierarchical multiple regression analysis (ordinary least squares, OLS). Table 5 shows that both inbound and outbound networks have significant positive effects on radical innovation (supporting H1a and H2a). Their interaction (coupling) effect is even stronger ($\beta = 3.661$, $p < 0.01$), confirming H3a.

Similarly, T1 ($\beta = 0.223$, $p < 0.01$) and T2 ($\beta = 0.108$, $p < 0.05$) positively influence radical innovation, validating H4a and H5a, with their interaction (technology variety and application, representing their internal coupling) also being significant ($\beta = 1.259$, $p < 0.01$, H6a supported). This underscores the importance of deep technology application over mere possession for breakthrough innovation. Model 8 (Table 5) includes all four main independent variables simultaneously: The X1, X2, T1, and T2. In this model, inbound and outbound networks along with technology variety remain significant, further supporting H1a, H2a, and H4a. Model 9 extends Model 8 by adding the two internal coupling terms (the coupling between [X1X2] and the coupling [T1T2]). In Model 9, both coupling

Table 3

Evaluation criteria for coupling coordination degree

Coupling level	Dysfunctional zone			Adaptive zone		Coupled zone		
Coupling grade	Severe dysfunction	Moderate dysfunction	Mild dysfunction	Near dysfunction	Primary coordination	Intermediate coordination	Good coordination	High-quality coordination
Coupling degree	[0–0.1]	(0.1–0.3]	(0.3–0.4]	(0.4–0.5]	(0.5–0.6]	(0.6–0.7]	(0.7–0.9]	(0.9–1]

Table 4

Means, standard deviations, and correlation coefficients of variables

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11
Ownership type	2.056	1.091	(1.12)										
Industry	3.895	2.247	−0.287***	(1.18)									
Firm age	4.212	1.141	−0.023	−0.151***	(1.58)								
Firm size	3.555	1.322	0.002	0.058	0.518***	(2.07)							
Revenue	5.534	1.971	−0.025	−0.038	0.486***	0.661***	(1.96)						
Digital tech types	3.495	1.004	0.062	0.032	0.088**	0.270***	0.255***	(1.92)					
Digital tech application	3.386	1.025	0.074*	0.078	0.054	0.247***	0.277***	0.673***	(2.29)				
Inbound OIN	3.459	0.960	0.077*	−0.013	0.185***	0.190***	0.187***	0.485***	0.574***	(2.24)			
Outbound OIN	2.879	1.026	0.044	0.055	0.105**	0.160***	0.166***	0.405***	0.490***	0.671***	(1.89)		
Radical innovation capability	3.366	1.040	0.059	−0.138***	0.140***	0.196***	0.223***	0.504***	0.503***	0.660***	0.674***	—	
Incremental innovation capability	3.530	1.005	0.148***	0.048	0.198***	0.269***	0.221***	0.547***	0.557***	0.739***	0.474***	0.560***	—

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; standard errors of the regression coefficients are reported in parentheses; OIN - open innovation network

Table 5

Test results of main effects and internal coupling effects (dependent variable: radical innovation capability)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ownership type	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Province	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Firm age	−0.014 (0.050)	−0.057* (0.03)	−0.025 (0.035)	−0.066** (0.030)	−0.056* (0.033)	−0.055* (0.032)	−0.051 (0.031)	−0.057* (0.032)	−0.062** (0.029)
Firm size	0.099** (0.048)	0.032 (0.032)	0.039 (0.033)	0.019 (0.030)	0.033 (0.031)	0.047 (0.032)	0.029 (0.032)	0.033 (0.031)	0.017 (0.031)
Revenue	0.072** (0.034)	0.037 (0.025)	0.019 (0.022)	0.045** (0.020)	0.029 (0.020)	0.031 (0.022)	0.023 (0.020)	0.029 (0.021)	0.040** (0.019)
T1		0.235*** (0.052)	0.257*** (0.047)	0.211*** (0.046)	0.223*** (0.041)			0.226*** (0.046)	
T2		0.045 (0.055)	0.078 (0.051)	0.006 (0.047)		0.108** (0.045)		−0.007 (0.050)	
T1×T2							1.259*** (0.242)		1.147*** (0.245)
X1		0.544*** (0.044)			0.287*** (0.050)	0.322*** (0.048)	0.267*** (0.049)	0.289*** (0.048)	
X2			0.537*** (0.041)		0.420*** (0.050)	0.425*** (0.053)	0.415*** (0.051)	0.421*** (0.051)	

(*continued*)

Table 5 (*continued*)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
X1×X2				3.661*** (0.208)					3.585*** (0.209)
Constant	2.888*** (0.257)	0.647*** (0.204)	0.853*** (0.195)	0.164 (0.193)	0.596*** (0.191)	0.804*** (0.186)	0.557*** (0.192)	0.598*** (0.190)	0.149 (0.203)
R^2	0.173	0.524	0.584	0.637	0.612	0.589	0.610	0.612	0.633
Adj-R^2	0.157	0.508	0.570	0.625	0.599	0.575	0.598	0.599	0.622
Observations	532	532	532	532	532	532	532	532	532

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; standard errors of the regression coefficients are reported in parentheses effects show significant positive coefficients, reinforcing H3a and H6a. These findings collectively underscore that internal synergy—both within the innovation network system and within the digital technology system—is a critical driver of radical innovation capability.

As shown in Table 6, Models 11–13 demonstrate that X1 (β = 0.608, p < 0.01), X2 (β = 0.169, p < 0.01), and their coupling (β = 2.318, p < 0.01) each significantly enhance incremental innovation, supporting H1b–H3b. Models 14–16 further confirm positive effects of T1 (β = 0.229, p < 0.01), T2 (β = 0.160, p < 0.01), and their interaction (β = 1.492, p < 0.01), validating H4b–H6b. Model 17, incorporating all variables, maintains significant effects for X1 and T1, further confirming H1b and H4b. Finally, Model 18 shows that coupling innovation networks with digital technology yields significantly positive coefficients, reinforcing H3b and H6b.

External Coupling Effects

As shown in Table 7, the coupling between two-way open innovation networks and digital technology exhibits significant positive coefficients in Models 19 and 24 (β = 2.433, β = 2.377, p < 0.01), supporting H7a and H7b. This confirms open innovation networks and digital technology function as mutually reinforcing systems. Models 20 and 25 further confirm the positive effects of coupling between X1 and T1 (β = 3.786, β = 4.017, p < 0.01). Additionally, significant results are observed for couplings between: X1 and T2 (Models 21/26, β = 3.714/3.906), X2 and T1 (Models 22/27, β = 4.306/3.094), and X2 and T2 (Models 23/28, β = 4.231/3.019). All coefficients are statistically significant (p < 0.01), collectively validating H8a and H8b. The significance of all four pairwise couplings reveals that the macro-level synergy is rooted in multiple, complementary micro-mechanisms between specific network and technology functions.

Robustness Checks

To verify the robustness of our findings, we adopt an alternative measure of innovation capability grounded in an input–process–output perspective (Yang et al., 2021), complementing the original classification based on innovation magnitude and knowledge base (Zhang et al., 2018). The alternative variable comprises four items: (1) sufficient R&D funding, (2) adequate R&D personnel, (3) well-established R&D system, and (4) high innovation performance. All items exhibited strong psychometric properties (factor loadings > 0.7, KMO > 0.8, Cronbach's α > 0.8, CR > 0.8, AVE > 0.5, and Bartlett's test p < 0.000), confirming reliability and validity. Due to space constraints, only the main and internal coupling effects are reported in Table 8.

Table 6

Test results of main effects and internal coupling effects (dependent variable: incremental innovation capability)

Variable	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Ownership type	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Province	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Firm age	0.095** (0.039)	0.046* (0.026)	0.118*** (0.031)	0.078*** (0.028)	0.039 (0.026)	0.047* (0.028)	0.048* (0.026)	0.046* (0.026)	0.073*** (0.026)
Firm size	0.115** (0.046)	0.047 (0.033)	0.061 (0.040)	0.046 (0.036)	0.047 (0.032)	0.060* (0.033)	0.040 (0.033)	0.047 (0.032)	0.036 (0.036)
Revenue	0.020 (0.029)	−0.015 (0.019)	−0.035 (0.025)	−0.019 (0.022)	−0.009 (0.019)	−0.011 (0.019)	−0.017 (0.019)	−0.013 (0.019)	−0.020 (0.021)
T1		0.203*** (0.029)	0.276*** (0.019)	0.227*** (0.025)	0.229*** (0.022)			0.205*** (0.019)	
T2		0.043 (0.042)	0.252*** (0.049)	0.139*** (0.048)		0.160*** (0.037)		0.056 (0.041)	
T1×T2						1.492*** (0.230)		1.898*** (0.243)	
X1		0.608*** (0.039)			0.687*** (0.043)	0.698*** (0.043)	0.650*** (0.044)	0.669*** (0.044)	
X2			0.169*** (0.043)		−0.095** (0.041)	−0.097** (0.041)	−0.105*** (0.040)	−0.101** (0.040)	

(*continued*)

Table 6 (*continued*)

Variable	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
X1×X2				2.318***					2.281***
				(0.242)					(0.246)
Constant	2.448***	0.117	0.720***	0.136	0.145	0.316	0.051	0.129	0.065
	(0.238)	(0.192)	(0.208)	(0.195)	(0.190)	(0.197)	(0.193)	(0.193)	(0.184)
R^2	0.216	0.623	0.469	0.553	0.627	0.608	0.635	0.628	0.560
Adj-R^2	0.195	0.610	0.451	0.538	0.615	0.595	0.623	0.615	0.546
Observations	532	532	532	532	532	532	532	532	532

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; standard errors of the regression coefficients are reported in parentheses

Table 7

External coupling effects test results

Variable	Radical innovation capability					Incremental innovation capability				
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
Ownership type	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Province	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Firm age	−0.057*	−0.051	−0.017	−0.045	−0.019	0.045*	0.056**	0.092***	0.073**	0.092***
	(0.031)	(0.034)	(0.035)	(0.032)	(0.032)	(0.043)	(0.022)	(0.027)	(0.029)	(0.030)
Firm size	0.028	0.021	0.026	0.020	0.020	0.043	0.032	0.038	0.058	0.059
	(0.031)	(0.033)	(0.034)	(0.030)	(0.033)	(0.032)	(0.033)	(0.035)	(0.038)	(0.039)

(*continued*)

Table 7 *(continued)*

Variable	Radical innovation capability					Incremental innovation capability				
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
Revenue	0.029 (0.020)	0.040 (0.024)	0.034 (0.025)	0.035* (0.020)	0.026 (0.020)	−0.012 (0.019)	−0.015 (0.021)	−0.020 (0.021)	−0.007 (0.024)	−0.013 (0.023)
T1	0.117** (0.053)					0.099 (0.060)				
T2	−0.079 (0.050)					−0.014 (0.047)				
X1	0.170*** (0.055)					0.552*** (0.054)				
X2	0.320*** (0.059)					−0.199*** (0.051)				
XT	2.433*** (0.650)					2.377*** (0.696)				
X1T1		3.786*** (0.222)					4.017*** (0.197)			
X1T2			3.714*** (0.220)					3.906*** (0.203)		
X2T1				4.306*** (0.188)					3.094*** (0.249)	
X2T2					4.231*** (0.176)					3.019*** (0.245)

(continued)

Table 7 (*continued*)

Variable	Radical innovation capability					Incremental innovation capability				
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
Constant	0.082 (0.241)	0.636*** (0.222)	0.652*** (0.229)	0.586*** (0.200)	0.668*** (0.179)	−0.375* (0.226)	−0.059 (0.167)	0.097 (0.194)	0.794*** (0.187)	0.864*** (0.195)
R^2	0.623	0.499	0.488	0.619	0.611	0.639	0.600	0.581	0.459	0.451
Adj-R^2	0.609	0.434	0.473	0.608	0.599	0.626	0.589	0.569	0.443	0.435
Observations	532	532	532	532	532	532	532	532	532	532

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; values in parentheses are standard errors of the regression coefficients; OIN = open innovation network

Models 30–32 confirm the positive effects of X1 ($\beta = 0.363$, $p < 0.01$) and X2 ($\beta = 0.187$, $p < 0.01$), as well as their coupling ($\beta = 1.509$, $p < 0.01$), supporting H1–H3. Models 33–35 further validate the positive influence of T1 ($\beta = 0.247$, $p < 0.01$), T2 ($\beta = 0.422$, $p < 0.01$), and their interaction ($\beta = 1.981$, $p < 0.01$), confirming H4–H6. In Model 36, which incorporates all main variables, all coefficients except X2 remain significant, reinforcing H1, H4, and H5. Model 37 shows that both coupling terms remain positively significant, supporting H3 and H6.

These results align with our primary analyses, underscoring the robustness of the findings.

Further Analysis

Table 9 shows that most internal and external coupling coordination scores fall between 0.7 and 0.9, indicating overall well-coordinated states. Internally, T1T2 coupling shows higher coordination quality than X1X2 coupling. Externally, the coupling between the overall innovation network and the digital technology system performs strongest, while the X2T2 shows the weakest coordination, highlighting a key area for improvement.

Open innovation network (OIN) and Digital Tech (XT) coupling performs strongest, with 310 samples in good coordination and 476 in the coupling zone. Among external couplings, X1T1 shows the most effective coordination (308 in good coordination, 468 in coupling zone). In contrast, X2T2 coupling performs weakest (219 in good coordination, 384 in coupling zone), revealing limited integration between outbound networks and digital technology application among surveyed Chinese firms and highlighting the need for improved alignment in this area.

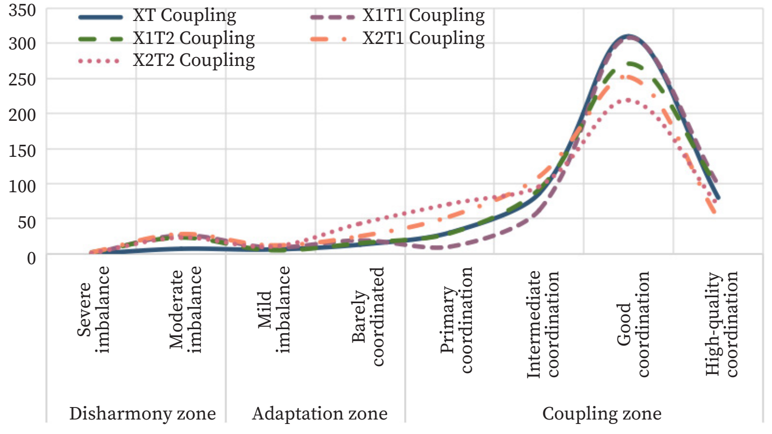

Figure 2. Distribution of internal coupling coordination

Table 8

Main effects and internal coupling effects test result (with innovation capability as dependent variable)

Variable	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)
Ownership type	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Industry	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Province	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Firm age	−0.091* (0.049)	−0.088** (0.034)	−0.052 (0.032)	−0.072** (0.033)	−0.133*** (0.038)	−0.088** (0.034)	−0.118*** (0.035)	−0.088*** (0.033)	−0.103*** (0.034)
Firm size	0.135*** (0.044)	0.075** (0.033)	0.082** (0.035)	0.073** (0.034)	0.072** (0.034)	0.080** (0.033)	0.058* (0.034)	0.075** (0.033)	0.054 (0.035)
Revenue	0.134*** (0.031)	0.076 (0.025)	0.064** (0.025)	0.074*** (0.026)	0.101*** (0.026)	0.075*** (0.026)	0.086*** (0.025)	0.075*** (0.025)	0.088*** (0.026)
T1		0.088* (0.048)	0.122** (0.049)	0.099** (0.047)	0.247*** (0.041)			0.087* (0.048)	
T2		0.385*** (0.055)	0.476*** (0.055)	0.432*** (0.056)		0.422*** (0.045)		0.378*** (0.056)	
T1×T2					1.981*** (0.261)		2.300*** (0.265)		
X1		0.363*** (0.048)			0.457*** (0.061)	0.344*** (0.060)	0.385*** (0.064)	0.331*** (0.059)	
X2			0.187*** (0.035)		0.088* (0.048)	0.054 (0.042)	0.071 (0.045)	0.053 (0.042)	
X1×X2 Coupling				1.509*** (0.211)				1.802*** (0.227)	

(*continued*)

Table 8 (*continued*)

Variable	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)	(37)
Constant	2.446***	0.237	0.523**	0.209	0.338	0.310	0.138	0.231	0.123
	(0.245)	(0.212)	(0.204)	(0.214)	(0.225)	(0.211)	(0.220)	(0.212)	(0.231)
R^2	0.320	0.611	0.583	0.598	0.569	0.610	0.594	0.612	0.570
Adj-R^2	0.302	0.598	0.569	0.584	0.554	0.597	0.581	0.599	0.557
Observations	532	532	532	532	532	532	532	532	532

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively; standard errors are in parentheses

Table 9

Distribution of coupling coordination degree between two-way open innovation network and digital technology

Coupling type	Severe imbalance [0–0.1]	Moderate imbalance (0.1–0.3]	Mild imbalance (0.3–0.4]	Verge of imbalance (0.4–0.5]	Primary coordination (0.5–0.6]	Intermediate coordination (0.6–0.7]	Good coordination (0.7–0.9]	High-quality coordination (0.9–1]	Total
X1X2	8	13	20	19	60	108	246	58	532
T1T2	3	24	6	12	42	65	269	111	532
XT	0	7	6	13	30	86	310	80	532
X1T1	0	26	9	19	10	62	308	98	532
X1T2	2	23	5	15	29	92	271	95	532
X2T1	2	28	12	25	53	110	252	50	532
X2T2	1	23	10	43	71	96	219	69	532

Note: The numbers in the table represent the sample counts within different intervals.

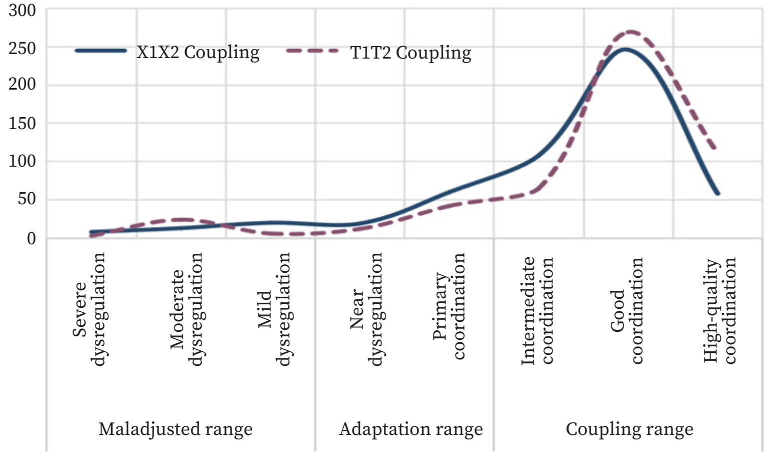

Figure 3. Distribution of external coupling coordination

DISCUSSION

This study empirically validates the positive effects of two-way open innovation networks, digital technology, and their internal and external couplings on ambidextrous innovation capability (Zhang et al., 2018). The findings confirm that synergistic interactions rather than isolated factors are key drivers of innovation performance in Chinese enterprises.

Inbound and Outbound Innovation Networks and Ambidextrous Innovation

Our findings confirm that both inbound and outbound innovation networks independently contribute to ambidextrous innovation (H1a, H1b, H2a, H2b, supported). The strong effect of inbound networks on radical innovation (β = 0.544) highlights the capability of Chinese enterprises to leverage external knowledge for breakthroughs—a vital mechanism in emerging economies with constrained internal R&D. Conversely, the weaker effect of outbound networks on incremental innovation (β = 0.169) suggests a developmental lag, where technology externalisation in Chinese firms is currently geared more toward market expansion than internal process refinement (Wang, 2024), a finding that underscores the time needed to build commercialisation capabilities. Notably, manufacturing enterprises account for over 60% of the sample, and this weak effect is highly consistent with the immature technical commercialisation channels and insufficient attention to internal process optimisation in China's manufacturing sector, which is a typical characteristic of emerging economy enterprises in the transition period of innovation development.

The Synergistic Power of Coupling: Internal Network Coupling

This coupling matters through two mechanisms. First, inbound innovation enriches the firm's knowledge base, providing the raw material for outbound activities, while outbound innovation generates revenue and market intelligence that fuels further inbound search (Ren & Gao, 2020). Second, as Lopes and de Carvalho (2018) argue, the integration of new (inbound) and existing (outbound) knowledge facilitates both exploratory and exploitative learning. Our empirical evidence supports this theoretical assertion, and the far stronger synergistic effect of network coupling (β = 3.661) than the independent effects of single inbound or outbound networks further verify the value of the "knowledge absorption-externalisation" closed loop, which is particularly adaptive to Chinese enterprises with scattered innovation resources that rely on coupling to achieve effective resource integration. For managers, this implies that treating inbound and outbound activities as separate functions is suboptimal; they should be orchestrated as an integrated system.

Digital Technology: Variety, Application, and Their Coupling

Consistent with prior research (Kohli & Melville, 2019; Mikalef et al., 2019), our findings confirm that both digital technology variety and application positively influence ambidextrous innovation (H4a–H5b supported). However, the significant effect of their coupling (H6a, H6b, supported) provides a more nuanced insight: the value of possessing diverse digital tools (variety) is contingent upon their deep integration into organisational processes (application). The stronger effect of technology coupling on incremental innovation (β = 1.492, $p < 0.01$) compared to radical innovation (β = 1.259, $p < 0.01$) suggests that Chinese enterprises may currently be using digital technologies more for process optimisation than for breakthrough discovery. This pattern echoes the "digital enablement" rather than the "digital empowerment" stage described by Chen et al. (2020). In our sample, nearly 70% are micro, small, and medium-sized enterprises (MSMEs), whose digital technologies are mostly concentrated in basic operational applications such as supply chain digitalisation, with insufficient capacity for integrating digital tools in breakthrough technological R&D; large enterprises, despite possessing diverse digital technologies, still face the constraint of inadequate application depth, which jointly leads to the stronger effect of digital coupling on incremental innovation.

External Coupling: The Innovation Network-Digital Technology Synergy

These finding bridges two previously separate streams of literature—open innovation and digital innovation—and provides empirical evidence for their synergistic potential. This synergy operates through knowledge acquisition, dissemination, and ecosystem mechanisms (Gong et al., 2021; Xie et al., 2024), with the coupling of inbound networks and technology variety showing the strongest effect and outbound networks with technology application the weakest—identifying a critical capability gap for Chinese enterprises. The significant effects of all four pairwise couplings (H8a, H8b supported) further unpack this macro-level synergy. Notably, the coupling of X1T1 exerts the strongest effect on both innovation types, as digital technologies such as big data and AI drastically reduce the costs of external knowledge search and screening, which is highly in line with the "external knowledge-dependent" innovation characteristics of Chinese enterprises with limited internal R&D resources. In contrast, the relatively weaker effect of X2T2 reveals a core capability gap: Chinese firms' digital technology applications are mostly focused on internal operations rather than extended to the entire process of technological commercialisation, and the imperfect digital protection system for intellectual property further restricts the synergy of this coupling. This finding offers a targeted direction for managerial intervention.

Practical Implications

For policymakers, four strategies emerge. First, invest in digital-integrated open innovation platforms focused on technological commercialisation (e.g., AI-driven partner matchmaking for technology licensing and spin-offs) to lower search and transaction costs and make up for the synergy shortfall of X2T2 coupling. Second, move from technology adoption to deep and extended integration—embed AI and IoT into core innovation processes and extend digital technology applications from internal operations to the whole process of outbound technological commercialisation (e.g., real-time sensor data for prototyping and digital traceability for technology licensing). Third, facilitate governance frameworks for data sharing and IP protection to enable tacit knowledge flow. Fourth, cultivate hybrid talent ecosystems at the intersection of digital technology and innovation management. For managers, implications are equally concrete. First, orchestrate dual networks as an integrated system—balance knowledge acquisition and externalisation through dedicated roles. Second, move from technology adoption to deep integration—embed AI and IoT into core innovation processes (e.g., real-time sensor data for prototyping). Third, leverage digital tools for network intelligence—use analytics to map, analyse, and manage the innovation network itself. Fourth, cultivate coupling capabilities at the leadership level by breaking down silos between R&D and business development.

CONCLUSION

Drawing on a coupling coordination perspective, this study demonstrates that the synergy between two-way open innovation networks and digital technology—through both internal and external couplings—significantly enhances ambidextrous innovation capability in Chinese enterprises. Several limitations warrant consideration. First, the cross-sectional design limits causal inference. Second, the single-source survey data may introduce common method bias. Third, the sample may over-represent actively innovating firms. Fourth, this study does not further distinguish the heterogeneous impacts of firm size and industry types on coupling effects, which provides a clear direction for subsequent research to refine the boundary conditions of coupling synergy in open innovation. Future research should address these limitations through longitudinal designs, objective performance measures, validation in diverse institutional contexts, and investigation of boundary conditions and potential dark sides of coupled innovation. Qualitative case studies would also be valuable to uncover implementation mechanisms.

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