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Enterprise Informatics Capabilities and Innovation Management Effectiveness in Chinese Technology-Based Firms: The Roles of Innovation Process Quality and Digital Transformation

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Abstract. This study examines how enterprise informatics capabilities influence innovation management effectiveness in Chinese technology-based firms. Drawing on the resource-based view and organizational learning theory, it investigates whether knowledge management capability, organizational learning culture, and technology resource investment improve innovation management effectiveness directly and indirectly through innovation process quality, and whether digital transformation strengthens the effect of innovation process quality on innovation management effectiveness. Data were collected from 312 managers and innovation professionals in certified Chinese technology-based firms. Confirmatory factor analysis, structural equation modeling, bootstrap mediation tests, and interaction analysis were used to test the hypotheses. The results show that knowledge management capability, organizational learning culture, and technology resource investment each have significant positive effects on innovation management effectiveness. Innovation process quality partially mediates these relationships, indicating that firms translate knowledge resources, learning-oriented culture, and technology investment into stronger innovation outcomes partly by improving the discipline and quality of their innovation processes. Digital transformation also positively moderates the relationship between innovation process quality and innovation management effectiveness, suggesting that digitally enabled firms obtain greater value from well-managed innovation processes. The study contributes to research on enterprise informatics and innovation management by identifying process quality as a core conversion mechanism and digital transformation as an important contextual amplifier. The findings suggest that firms should align knowledge systems, learning culture, technology investment, and digital infrastructure as an integrated innovation management system.

Keywords: Enterprise informatics; Innovation management effectiveness; Knowledge management capability; Innovation process quality; Digital transformation; Chinese technology-based firms.

1. Introduction

In an era characterized by accelerating technological change and intensifying global competition, the capacity to manage innovation effectively has become one of the most consequential capabilities a technology-based firm can develop (Tsakalerou et al., 2025; Daronco et al., 2023). This capacity is deeply embedded in the informatics infrastructure of the modern enterprise: innovation today is fundamentally an information-intensive activity, relying on knowledge acquisition and sharing, digital platforms for cross-functional coordination, and data-driven decision systems that connect strategic intent with operational execution. Innovation management effectiveness (IME), broadly understood as a firm's systematic ability to plan, execute, and exploit innovation activities in ways that generate desired competitive outcomes, thus sits at the intersection of enterprise informatics, knowledge management, and digital transformation (Chung et al., 2022; Shamim et al., 2025). Yet despite the widely acknowledged importance of IME, organizational research has produced only a fragmented understanding of the resource conditions and process mechanisms that enable high levels of IME, particularly in technology-intensive industries where innovation cycles are short and failure costs are high.

Prior literature has identified numerous antecedents of innovation performance, ranging from leadership behavior and organizational culture to technological investments and knowledge-related capabilities (Harsono et al., 2025; Sofiyabadi et al., 2022; Bhatti et al., 2025). Among these, three resource-based antecedents have repeatedly demonstrated empirical relevance: the firm's ability to manage and leverage knowledge (Knowledge Management Capability, KMC), the extent to which the organizational culture promotes continuous learning and knowledge exchange (Organizational Learning Culture, OLC), and the level of financial and human resource investment directed toward technology acquisition and development (Technology Resource Investment, TRI). These three constructs correspond closely to the foundational tenets of the Resource-Based View (RBV), which attributes sustained competitive advantage to the possession and deployment of valuable, rare, and inimitable organizational resources (Barney, 1991; Teece et al., 1997). Importantly, each of these antecedents reflects a core dimension of enterprise informatics capability: KMC concerns the organizational systems for capturing and sharing knowledge, OLC addresses the cultural conditions for organizational learning and information exchange, and TRI represents the tangible investment in the technological infrastructure that underpins information-driven innovation.

However, a critical question that existing research has insufficiently addressed is how these resource antecedents are translated into effective innovation management outcomes. The innovation management literature increasingly recognizes that resource availability alone is insufficient to produce superior outcomes; rather, the quality of the innovation process itself, encompassing the rigor of project selection, the discipline of stage-gate reviews, and the efficiency of iterative improvement cycles, serves as the proximate driver of IME (Dzenopoljac et al., 2025; Qiao et al., 2025). We conceptualize this process-level construct as Innovation Process Quality (IPQ), and argue that it mediates the relationships from KMC, OLC, and TRI to IME. In doing so, we adopt an innovation systems perspective in which resources, processes, and outcomes form an integrated value chain within the enterprise informatics architecture.

Furthermore, the contemporary context of digital transformation introduces an important boundary condition. As firms invest in digital technologies and platforms, their capacity to leverage high-quality innovation processes is substantially enhanced through data-driven decision support, agile project management tools, and digital collaboration infrastructures (Vial, 2019; Lu et al., 2023; Cheng et al., 2026). We therefore propose that Digital Transformation Level (DTL) positively moderates the effect of IPQ on IME, amplifying the performance returns to process quality investments. This moderation hypothesis directly addresses how digital transformation reshapes the functioning of enterprise innovation systems, a question of central relevance to the informatics and service science community.

This study makes three primary contributions to the literature. First, it integrates resource-based and organizational learning perspectives into a single, theory-grounded model that explains both the direct and process-mediated paths from enterprise informatics capabilities to IME, thereby contributing to the knowledge management and sharing literature by demonstrating how knowledge-related resources operate through process mechanisms. Second, by positioning IPQ as the key mediating mechanism, the study advances a process-theoretic account of how firms translate resources into innovation outcomes within their innovation systems, extending prior work that has focused predominantly on output-level mediation constructs. Third, by incorporating DTL as a moderating variable, the study contributes to the emerging digital transformation literature by offering a nuanced view of digital technology as a productivity amplifier within innovation service systems rather than a standalone driver of innovation.

The remainder of the article is structured as follows. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 describes the research methodology, including sample characteristics and measurement instruments. Section 4 presents the empirical results. Section 5 discusses the findings, followed by the conclusion in Section 6.

2. Literature Review and Hypothesis Development

This chapter reviews the theoretical and empirical foundations of the proposed research model. The review is organized around four logical moves. First, we survey what is already established regarding the relationships among knowledge management, organizational learning, technology investment, and innovation outcomes. Second, we identify critical gaps in existing research, particularly the lack of process-level mediating mechanisms and contextual boundary conditions. Third, we develop the theoretical rationale for Innovation Process Quality (IPQ) as the mediating mechanism through which organizational resources translate into innovation management effectiveness. Fourth, we introduce Digital Transformation Level (DTL) as the boundary condition that shapes the performance returns to process quality. Before proceeding, we clarify three frequently conflated concepts, innovation performance, innovation capability, and innovation management effectiveness, to establish the precise theoretical scope of this study.

Distinguishing Innovation Performance, Innovation Capability, and Innovation Management Effectiveness. Innovation performance refers to the measurable outputs and outcomes of a firm's innovation activities, typically operationalized through indicators such as patent counts, new product introduction rates, or the revenue share attributable to new products (Harsono et al., 2025; Bhatti et al., 2025). Innovation capability denotes a firm's latent potential to generate, develop, and implement innovations, encompassing absorptive capacity, technological competence, and the organizational routines that support creative problem-solving (Le & Le, 2023; Do et al., 2025). Innovation management effectiveness (IME), the focal dependent variable in this study, is a broader construct that captures the degree to which a firm's innovation management system, its planning, resource allocation, process governance, and portfolio management practices, successfully achieves intended innovation objectives (Chung et al., 2022; Daronco et al., 2023; Shamim et al., 2025). While innovation performance measures what a firm has achieved and innovation capability measures what a firm could achieve, IME evaluates how well the firm manages the innovation process as a whole, encompassing both efficiency and strategic alignment. This distinction is important because two firms with equivalent innovation capabilities may differ substantially in IME if their management systems differ in process discipline, resource coordination, and strategic coherence.

2.1 Conceptualizing Innovation Management Effectiveness

Innovation management effectiveness (IME) is a multidimensional construct that captures the degree to which a firm's innovation management system successfully achieves its intended innovation objectives (Chung et al., 2022). Unlike narrower measures of innovation output such as patent counts or new product introduction rates, IME encompasses both process efficiency, whether innovation activities are managed in a timely and resource-effective manner, and outcome quality, including the competitive and strategic value generated by innovation investments (Daronco et al., 2023; Tsakalerou et al., 2025).

Shamim et al. (2025) further distinguish between operational and strategic dimensions of innovation management capability, noting that firms must develop rapid and adaptive innovation management routines to respond to crisis-induced market disruptions. Consistent with this perspective, we conceptualize IME as a composite construct that spans five dimensions: achievement of innovation project objectives, improvements in products or services, efficiency of innovation resource utilization, portfolio balance between incremental and radical innovations, and overall perceived effectiveness of the innovation management system. This multidimensional conceptualization is consistent with recent empirical work (Chung et al., 2022; Daronco et al., 2023) and provides a rich outcome construct against which the effects of upstream antecedents can be assessed.

2.2 Knowledge Management Capability and Innovation Management Effectiveness

Knowledge Management Capability (KMC) refers to a firm's capacity to systematically acquire, organize, transfer, and apply knowledge assets in support of its strategic objectives (Nonaka & Takeuchi, 1995; Sofiyabadi et al., 2022). Grounded in the RBV, KMC constitutes a tacit, socially complex organizational capability that is difficult for competitors to imitate, thereby providing a durable source of competitive differentiation (Barney, 1991).

Empirical research has consistently demonstrated that KMC exerts a positive effect on innovation outcomes. Sofiyabadi et al. (2022) found that knowledge management practices, including strategic knowledge management, knowledge-driven employment, and IT-enabled knowledge sharing, significantly improve innovation performance in financial services firms. Harsono et al. (2025) showed that knowledge management enhances both innovation capability and innovation performance in state-owned enterprises. Bhatti et al. (2025) extended this finding to knowledge-intensive business services, demonstrating that knowledge acquisition drives innovation performance through absorptive capacity. Chen and Liu (2024) linked knowledge creation mechanisms to innovation performance in the context of top management team diversity. Dzenopoljac et al. (2025) highlighted the role of knowledge sharing quality, showing that high-quality knowledge exchange substantially elevates innovation outcomes. Al Rawashdeh et al. (2025) demonstrated that integrating business intelligence with knowledge management significantly enhances innovation capability in SME contexts, with the effect being amplified under stronger IT infrastructure maturity and higher digital literacy.

Drawing on these converging findings, we propose:

H1: Knowledge Management Capability (KMC) has a significant positive effect on Innovation Management Effectiveness (IME).

2.3 Organizational Learning Culture and Innovation Management Effectiveness

Organizational Learning Culture (OLC) denotes the shared values, norms, and behavioral dispositions within a firm that promote continuous learning, open knowledge exchange, experimentation, and reflection (Lek et al., 2022). OLC represents a culturally embedded dynamic capability that enables firms to continuously renew their knowledge bases and adapt to environmental change (Teece et al., 1997).

The relationship between OLC and innovation is well established. Ferreira et al. (2025) demonstrated that human-related organizational factors, including learning orientation and knowledge-sharing culture, are significant predictors of both innovation and organizational performance, with effects mediated through capability development. Raji et al. (2026) showed that learning capability drives innovation performance in market-oriented creative industry firms. Le and Le (2023) found that knowledge management capability, embedded in organizational learning culture, enables both exploitative and exploratory innovation, moderated by competitive intensity. Zhao et al. (2025) demonstrated that organizational culture dimensions, including learning encouragement and openness, indirectly shape innovation performance through their effects on employee behavior. Al-Kharabsheh (2026) corroborated these findings in the banking sector, showing that organizational learning culture significantly enhances human capital sustainability through employee empowerment.

Based on this evidence, we hypothesize:

H2: Organizational Learning Culture (OLC) has a significant positive effect on Innovation Management Effectiveness (IME).

2.4 Technology Resource Investment and Innovation Management Effectiveness

Technology Resource Investment (TRI) captures the level of financial and human resource commitment that a firm directs toward acquiring advanced technologies, building R&D infrastructure, and developing technology-related competencies (Teece et al., 1997). From a dynamic capability's perspective, TRI enables firms to build absorptive capacity, the ability to identify, assimilate, and exploit external knowledge, which is a critical prerequisite for sustained innovation performance (Barney, 1991). Setiawan et al. (2026) empirically confirmed this logic, demonstrating that resource capabilities, including technological and digital resources, are significant drivers of business performance in B2C firms.

Raj et al. (2024) demonstrated that technology orientation significantly enhances organizational performance. Lu et al. (2025) showed that digital technology capability has a significant positive effect on enterprise innovation performance, with network adaptation and coordination partially mediating this relationship. Yin et al. (2024) confirmed that among high-tech Chinese semiconductor enterprises, science and technology personnel investment and management quality are primary drivers of innovation performance. Do et al. (2025) found that technological innovation capability positively influences organizational resilience and, indirectly, performance outcomes in SMEs. Sati (2024) showed that R&D expenditure intensity and digital skill investment are among the most important determinants of digital innovation performance across European economies.

We therefore propose:

H3: Technology Resource Investment (TRI) has a significant positive effect on Innovation Management Effectiveness (IME).

2.5 The Mediating Role of Innovation Process Quality

The preceding sections establish that KMC, OLC, and TRI are each positively associated with innovation outcomes, this constitutes the established knowledge base. However, a critical gap persists: existing studies overwhelmingly treat the resource-to-outcome relationship as a direct link, leaving the intervening process mechanisms underspecified. If resources alone were sufficient, firms with equivalent knowledge assets, learning cultures, and technology investments would achieve identical innovation outcomes, yet they do not. The missing explanatory link lies in the quality of the innovation process through which resources are converted into outcomes.

We conceptualize Innovation Process Quality (IPQ) as the extent to which a firm's innovation activities follow well-structured, rigorously managed, and continuously improving process frameworks, including disciplined idea screening, feasibility assessment, stage-gate control, and iterative refinement (Dzenopoljac et al., 2025). We argue that KMC, OLC, and TRI exert their effects on IME primarily by enhancing IPQ.

The logic linking KMC to IPQ is that knowledge management routines directly improve the information richness, cross-functional coordination, and learning cycles embedded in innovation processes (Harsono et al., 2025; Hu et al., 2024). Firms with strong KMC are better positioned to identify promising innovation opportunities, integrate diverse knowledge inputs into feasibility assessments, and rapidly incorporate feedback into iterative development cycles. Qiao et al. (2025) demonstrated that knowledge integration and absorption capabilities mediate the effect of generative AI adoption on innovation performance, implying that knowledge-process linkages are a central mechanism. Similarly, Chen and Liu (2024) showed that knowledge creation processes serve as the mediating pathway from managerial characteristics to innovation outcomes.

The relationship between OLC and IPQ operates through a complementary mechanism. Organizations with strong learning cultures institutionalize systematic reflection, encourage cross-project knowledge transfer, and create psychological safety conditions that allow teams to apply rigorous process discipline without fear of penalization for experimentation failures (Le & Le, 2023; Lek et al., 2022). Henao-Garcia (2026) demonstrated that management innovation, as a social integration mechanism, mediates the absorptive capacity‑innovation performance relationship, suggesting that culturally embedded process practices constitute the critical link between cultural antecedents and innovation outputs. Zou et al. (2025) extended this mediation logic by showing that organizational incentives serve as a prominent mediating pathway from policy perception to innovation performance, with innovation leadership moderating the effectiveness of this mechanism.

TRI, in turn, provides the technological infrastructure—including project management software, data analytics platforms, and digital prototyping tools—that enables firms to implement and execute high-quality innovation processes (Raj et al., 2024). Singh et al. (2022) showed that technological investment enhances absorptive capacity and innovation capability through a mediation chain, reinforcing the view that resource inputs improve performance through process-level mechanisms. Khanh and Do (2025) provide further evidence that digital transformation competency drives business performance through business innovation as a mediating mechanism.

Finally, IPQ directly elevates IME by increasing the reliability of innovation project execution, reducing waste and rework, accelerating time-to-market, and improving the commercial viability of innovation outputs (Shamim et al., 2025; Daronco et al., 2023). In summary, we propose that IPQ partially mediates the effects of KMC, OLC, and TRI on IME, as direct resource effects on IME co-exist with process-mediated pathways:

H4: KMC has a significant positive effect on IPQ.

H5: OLC has a significant positive effect on IPQ.

H6: TRI has a significant positive effect on IPQ.

H7: IPQ has a significant positive effect on IME.

H8a: IPQ partially mediates the positive effect of KMC on IME.

H8b: IPQ partially mediates the positive effect of OLC on IME.

H8c: IPQ partially mediates the positive effect of TRI on IME.

2.6 The Moderating Role of Digital Transformation Level

Establishing that IPQ mediates the resource‑IME relationship addresses the mechanistic gap but leaves a further question unanswered: under what conditions does process quality yield the greatest returns? This is the boundary condition question.

Digital Transformation Level (DTL) reflects the degree to which a firm has embedded digital technologies, including cloud computing, big data analytics, artificial intelligence, and digital platforms, into its core operational and strategic processes (Vial, 2019). We argue that DTL specifically moderates the effect of IPQ on IME. While a firm with high IPQ will consistently manage innovation processes with discipline and rigor, the extent to which such process quality translates into superior outcomes depends on the quality of the informational and technological support environment. Highly digitally transformed firms can leverage real-time data dashboards, AI-powered project risk monitoring, digital stage-gate tools, and automated workflow systems to ensure that high process quality is fully capitalized in terms of innovation outcomes (Lu et al., 2023; Chen et al., 2025). In contrast, firms operating in lower-DTL environments may possess rigorous innovation processes but lack the digital infrastructure to extract full performance value, for example, due to slower feedback loops, more manual decision-making, or limited analytical capacity to learn across innovation projects.

Empirical support for DTL as a boundary condition comes from multiple sources. Cheng et al. (2026) showed that digital transformation enhances firm performance through knowledge-based value creation, with digital capability acting as a productivity multiplier. Liu et al. (2025) found that digital transformation significantly improves company performance in the Chinese Baijiu industry, with servitization partially mediating this relationship. Dahms et al. (2025) found that digitalization configures with organizational agility to produce superior innovation performance in foreign-owned subsidiaries, suggesting that DTL shapes the effectiveness of innovation-enabling capabilities. Tran et al. (2025) provided additional evidence that digital technology adoption strongly predicts firm competitiveness, with innovation capability partially mediating this relationship. Gao et al. (2023) demonstrated that manufacturing firm heterogeneity in digital transformation level modulates the relationship between innovation inputs and innovation performance outputs.

We therefore propose:

H9: Digital Transformation Level (DTL) positively moderates the effect of IPQ on IME, such that the positive relationship between IPQ and IME is stronger at higher levels of DTL.

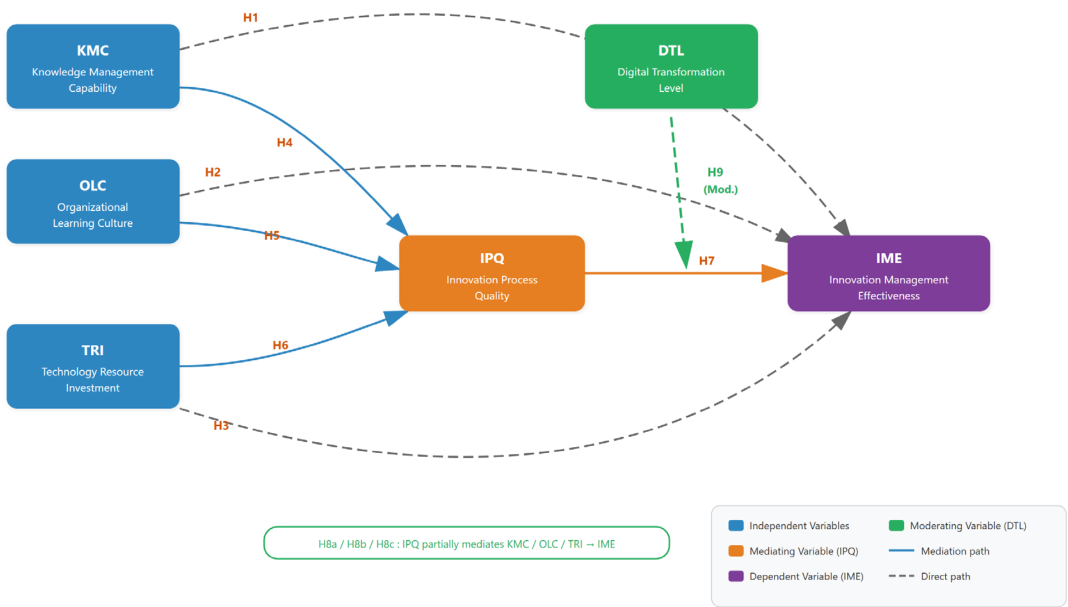

Fig.1: Conceptual Model of the Research Framework

3. Research Methodology

3.1 Sample and Data Collection

The study targeted managers and innovation professionals at Chinese technology-based firms, defined as firms classified under the Ministry of Science and Technology's high-technology enterprise certification criteria, spanning industries including software and IT services, electronics and hardware manufacturing, and biotechnology and pharmaceuticals. A random sampling approach was applied to a comprehensive directory of certified high-technology enterprises listed in the National High-Tech Enterprise Management Database.

Structured questionnaires were administered electronically between March and August 2023. To ensure respondent competence, only senior and middle managers directly involved in innovation management were invited to participate. Of 456 questionnaires distributed, 327 were returned, yielding a raw response rate of 71.7%. After removing 15 responses with more than 10% missing data and implausible straight-lining patterns, the final usable sample consisted of **N = 312 responses**, representing an effective response rate of 68.4%.

Table 1 presents the sample's demographic characteristics.

Table 1. Sample Demographic Characteristics (N = 312)

Characteristic	Category	n	%
Company Size	< 100 employees	78	25.0
	100–499 employees	134	42.9
	500–999 employees	61	19.6
	≥ 1,000 employees	39	12.5
Industry	Software & IT Services	112	35.9
	Electronics & Hardware	87	27.9
	Biotechnology & Pharma	54	17.3
	Other Technology	59	18.9
R&D Intensity	< 5% of annual revenue	89	28.5
	5–15% of annual revenue	158	50.6
	> 15% of annual revenue	65	20.8
Respondent Role	Senior Management	118	37.8
	R&D / Innovation Manager	139	44.6
	Technology / Product Manager	55	17.6

The sample profile indicates a predominance of medium-sized tech firms with moderate R&D intensity, consistent with the broader population of certified Chinese high-technology enterprises.

3.2 Measurement Instruments

All constructs were measured using reflective multi-item scales adapted from validated prior research. All items employed a five-point Likert scale anchored at 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). The complete item pool comprised 24 items across six constructs.

Knowledge Management Capability (KMC, 4 items) was adapted from Nonaka and Takeuchi (1995) and Sofiyabadi et al. (2022). Sample items: *"Our firm effectively acquires knowledge from both internal and external sources"*; *"Our firm successfully applies accumulated knowledge to create new products or processes."*

Organizational Learning Culture (OLC, 4 items) was adapted from Lek et al. (2022) and Ferreira et al. (2025). Sample items: *"Our organization encourages employees to continuously learn and develop new skills"*; *"Our organization supports experimentation and tolerates mistakes as part of learning."*

Technology Resource Investment (TRI, 3 items) was adapted from Teece et al. (1997) and Raj et al. (2024). Sample items: *"Our firm invests substantially in acquiring advanced technologies relevant to our core business"*; *"Our firm proactively upgrades its technological infrastructure to maintain competitive advantages."*

Innovation Process Quality (IPQ, 4 items) was adapted from Dzenopoljac et al. (2025) and Qiao et al. (2025). Sample items: *"Our innovation projects follow well-defined and structured development processes"*; *"Our innovation processes facilitate rapid iteration and continuous improvement."*

Digital Transformation Level (DTL, 4 items) was adapted from Vial (2019) and Cheng et al. (2026). Sample items: *"Our firm has substantially digitized its core operational processes"*; *"Our firm's digital capabilities enable us to rapidly adapt to market changes."*

Innovation Management Effectiveness (IME, 5 items) was adapted from Chung et al. (2022) and Daronco et al. (2023). Sample items: *"Our firm consistently achieves its predetermined innovation project objectives"*; *"Overall, our firm's innovation management system is highly effective."*

3.3 Common Method Bias

Since data for all constructs were collected from a single source at a single point in time, common method bias (CMB) was assessed following Podsakoff et al. (2003). Harman's single-factor test was conducted by loading all items into an unrotated exploratory factor analysis. The largest single factor accounted for **24.6%** of the total variance, well below the 50% threshold commonly used to indicate problematic CMB. In addition, procedural remedies were applied during survey design, including temporal separation of predictor and outcome items, assurance of respondent anonymity, and reverse-coded items to reduce response-set tendencies. Collectively, these results suggest that CMB is unlikely to represent a serious confound in the present study.

4. Results

4.1 Descriptive Statistics and Correlation Analysis

Table 2 presents the means, standard deviations, and bivariate Pearson correlations for all study variables. All six constructs exhibit moderate-to-high inter-correlations, consistent with theoretical expectations, while the magnitudes of the correlations are modest enough to preclude multicollinearity concerns.

Table 2. Descriptive Statistics and Pearson Correlation Matrix

Variable	M	SD	1	2	3	4	5	6
1. KMC	3.64	0.71	—					
2. OLC	3.58	0.68	.487**	—				
3. TRI	3.47	0.74	.456**	.441**	—			
4. IPQ	3.52	0.69	.512**	.478**	.443**	—		
5. DTL	3.43	0.72	.401**	.375**	.491**	.428**	—	
6. IME	3.59	0.67	.531**	.513**	.473**	.545**	.431**	—

*Note. N = 312. KMC = Knowledge Management Capability; OLC = Organizational Learning Culture; TRI = Technology Resource Investment; IPQ = Innovation Process Quality; DTL = Digital Transformation Level; IME = Innovation Management Effectiveness. ** p < .01 (two-tailed).*

All correlations are significant at $p < .01$ and directionally consistent with the hypothesized model. The highest correlation is between IPQ and IME ($r = .545$), and the lowest is between OLC and DTL ($r = .375$), providing no evidence of severe multicollinearity.

4.2 Measurement Model: Reliability and Validity

Confirmatory factor analysis (CFA) was conducted using AMOS 24.0 to assess the psychometric properties of the measurement model. The six-factor model demonstrated acceptable fit: $\chi^2/df = 2.14$, CFI = 0.954, TLI = 0.947, RMSEA = 0.061 (90% CI [0.047, 0.074]), SRMR = 0.052—all indices meeting recommended thresholds (Hair et al., 2010).

Table 3 reports standardized factor loadings, Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) for all constructs.

Table 3. Reliability and Convergent Validity Results

Construct	Item	Std. Loading	α	CR	AVE
KMC	KMC1	0.732	0.873	0.891	0.621
	KMC2	0.768			
	KMC3	0.784			
	KMC4	0.819			
OLC	OLC1	0.721	0.861	0.879	0.607
	OLC2	0.755			
	OLC3	0.783			
	OLC4	0.798			
TRI	TRI1	0.753	0.844	0.869	0.625
	TRI2	0.789			
	TRI3	0.821			
IPQ	IPQ1	0.738	0.882	0.903	0.638
	IPQ2	0.772			
	IPQ3	0.801			
	IPQ4	0.826			
DTL	DTL1	0.714	0.856	0.878	0.594
	DTL2	0.748			
	DTL3	0.783			
	DTL4	0.812			
IME	IME1	0.721	0.891	0.912	0.674
	IME2	0.745			
	IME3	0.769			
	IME4	0.793			
	IME5	0.831			

Note. All standardized loadings significant at $p < .001$. α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted. Threshold criteria: α > 0.70, CR > 0.70, AVE > 0.50 (Hair et al., 2010).

All Cronbach's alpha coefficients exceed 0.84, all CR values exceed 0.86, and all AVE values exceed 0.59, satisfying the convergent validity criteria proposed by Hair et al. (2010). All factor loadings exceed 0.70, indicating strong item-level convergence.

Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. Table 4 presents the inter-construct correlations alongside the square roots of AVE on the diagonal.

Table 4. Discriminant Validity: Fornell-Larcker Criterion and HTMT Ratios

	KMC	OLC	TRI	IPQ	DTL	IME
KMC	**0.788**					
OLC	.487 (.792)	**0.779**				
TRI	.456 (.756)	.441 (.741)	**0.790**			
IPQ	.512 (.804)	.478 (.783)	.443 (.742)	**0.799**		
DTL	.401 (.682)	.375 (.647)	.491 (.790)	.428 (.703)	**0.771**	
IME	.531 (.822)	.513 (.802)	.473 (.768)	.545 (.830)	.431 (.709)	**0.821**

Note. Bold diagonal values = square root of AVE. Off-diagonal lower triangle = Pearson correlations. Off-diagonal values in parentheses = HTMT ratios. Discriminant validity is supported when diagonal values exceed all off-diagonal correlations in the corresponding row and column (Fornell-Larcker), and HTMT < 0.85 (Henseler et al., 2015). All criteria satisfied.

All diagonal values exceed the corresponding off-diagonal values, and all HTMT ratios fall below the 0.85 threshold, confirming discriminant validity for all construct pairs.

4.3 Structural Model: Direct Path Coefficients

The structural model was estimated using maximum likelihood estimation in AMOS 24.0. The model fit indices for the structural model were: $\chi^2/df = 2.14$, CFI = 0.954, TLI = 0.947, RMSEA = 0.061, SRMR = 0.052, indicating adequate model fit (Hair et al., 2010). The structural model explained 41.2% of the variance in IPQ ($R^2 = 0.412$) and 48.7% of the variance in IME ($R^2 = 0.487$).

Table 5 presents the standardized path coefficients, standard errors, t-values, p-values, and 95% confidence intervals for all structural paths.

Table 5. Structural Model Path Coefficients

Hypothesis	Path	Std. β	SE	t-value	p-value	95% CI	Result
H1	KMC → IME	0.187	0.051	3.67	< .001	[0.087, 0.287]	Supported
H2	OLC → IME	0.214	0.048	4.46	< .001	[0.120, 0.308]	Supported
H3	TRI → IME	0.163	0.055	2.96	.003	[0.055, 0.271]	Supported
H4	KMC → IPQ	0.241	0.053	4.55	< .001	[0.137, 0.345]	Supported
H5	OLC → IPQ	0.229	0.050	4.58	< .001	[0.131, 0.327]	Supported
H6	TRI → IPQ	0.198	0.057	3.47	.001	[0.086, 0.310]	Supported
H7	IPQ → IME	0.312	0.046	6.78	< .001	[0.222, 0.402]	Supported

Note. Standardized coefficients reported. SE = standard error. All hypotheses supported at p < .01. The structural model also includes firm size and R&D intensity as control variables (coefficients not shown for brevity).

All seven direct-path hypotheses are supported. OLC exhibits the strongest direct effect on IME (β = 0.214), followed by KMC (β = 0.187) and TRI (β = 0.163). Among the paths to IPQ, KMC (β = 0.241) and OLC (β = 0.229) are the strongest predictors, with TRI contributing significantly but at a lower magnitude (β = 0.198). IPQ itself exerts the strongest single effect on IME in the model (β = 0.312), reinforcing its importance as a process-level driver of innovation outcomes.

4.4 Mediation Analysis: Testing H8a–H8c

To test the partial mediation hypotheses (H8a, H8b, H8c), we employed bias-corrected bootstrap confidence intervals based on 5,000 resamples, following Preacher and Hayes (2008). Both the direct effects (H1–H3) and the indirect effects through IPQ were estimated simultaneously within the structural model. Table 6 presents the results.

Table 6. Mediation Analysis Results (Bootstrap Indirect Effects, 5,000 Replications)

Indirect Path	Hypothesis	Indirect β	Boot SE	95% Boot CI	Mediation Type
KMC → IPQ → IME	H8a	0.075	0.019	[0.041, 0.118]	Partial ✓
OLC → IPQ → IME	H8b	0.071	0.018	[0.039, 0.112]	Partial ✓
TRI → IPQ → IME	H8c	0.062	0.020	[0.028, 0.105]	Partial ✓

Note. Indirect effects are standardized. Bootstrap CIs are bias-corrected and accelerated (BCa). Partial mediation is confirmed when both the indirect effect CI excludes zero and the direct effect remains significant (Preacher & Hayes, 2008).

All three bootstrap confidence intervals exclude zero, confirming statistically significant indirect effects for H8a, H8b, and H8c. The KMC→IPQ→IME indirect path is the largest (β = 0.075), followed by OLC (β = 0.071) and TRI (β = 0.062). Because the direct paths from KMC, OLC, and TRI to IME (H1–H3) also remain significant after controlling for IPQ, the mediation is classified as partial, consistent with our theoretical expectation that organizational resources influence innovation management through both direct and process-mediated pathways. The proportion of total effect mediated through IPQ ranges from 22.7% (TRI) to 28.6% (KMC), indicating that while the process mechanism is substantively important, substantial direct effects persist.

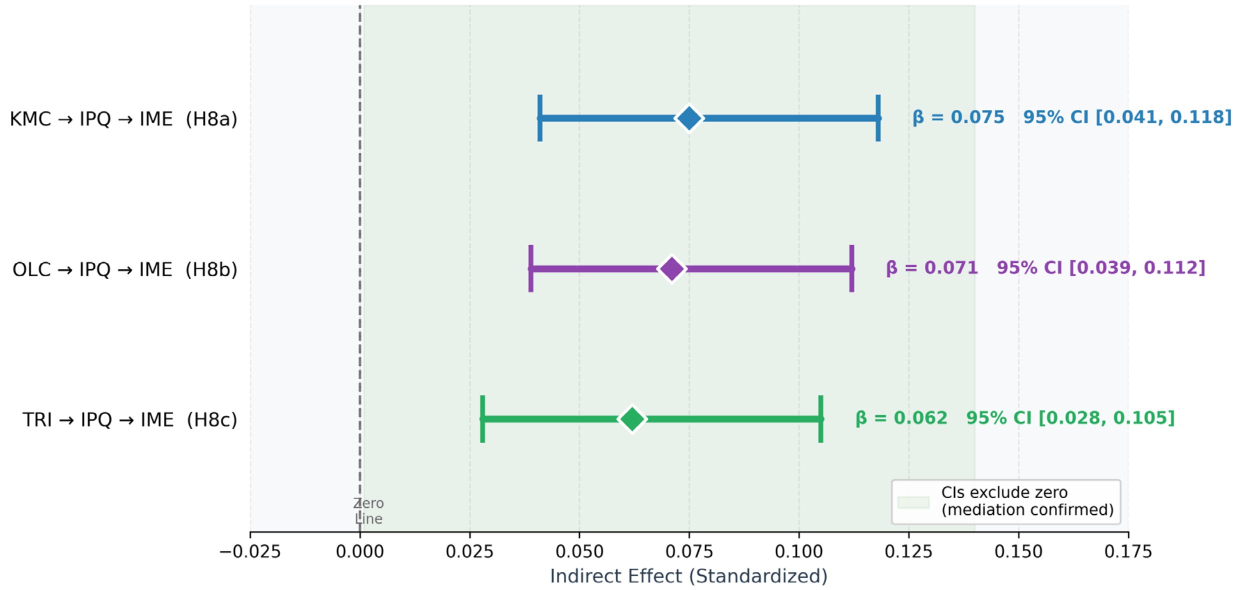

Fig.2: Forest Plot of Bootstrap Indirect Effects for Mediation Hypotheses (H8a–H8c)

4.5 Moderation Analysis: Testing H9

To test H9—that DTL positively moderates the effect of IPQ on IME—we followed the hierarchical regression approach recommended by Aiken and West (1991), with all continuous variables mean-centered prior to computing the interaction term. Table 7 reports the regression results predicting IME.

Table 7. Moderation Analysis: Interaction Effect of IPQ × DTL on IME

Predictor	β	SE	t-value	p-value
Control Variables				
Firm Size	0.051	0.034	1.50	.134
R&D Intensity	0.073	0.039	1.87	.062
Main Effects				
IPQ	0.312	0.046	6.78	< .001
DTL	0.089	0.043	2.07	.039
Interaction Effect				
IPQ × DTL	0.143	0.038	3.76	< .001
R^2	**0.487**			
ΔR^2 (interaction term)	**0.031**			
F for ΔR^2	**14.14**			**< .001**

Note. Standardized coefficients reported. N = 312. All continuous predictors mean-centered prior to computing the interaction term. R^2 = total explained variance; ΔR^2 = incremental R^2 contributed by the interaction term.

The interaction term IPQ × DTL is significant (β = 0.143, p < .001), and its addition to the model explains an additional 3.1% of variance in IME (ΔR^2 = 0.031, ΔF = 14.14, p < .001), supporting H9. Simple slope analysis reveals that at high DTL (+1 SD above mean), the slope of IPQ on IME is β = 0.455 (t = 8.34, p < .001), while at low DTL (−1 SD below mean), the slope is β = 0.169 (t = 2.73, p = .007). As illustrated in Figure 3, the positive effect of IPQ on IME is substantially steeper for firms operating at high DTL, confirming that digital transformation amplifies the performance returns to innovation process quality. This interaction pattern is consistent with a synergistic moderating effect, wherein the combination of high process quality and high digital transformation is disproportionately beneficial for innovation management effectiveness.

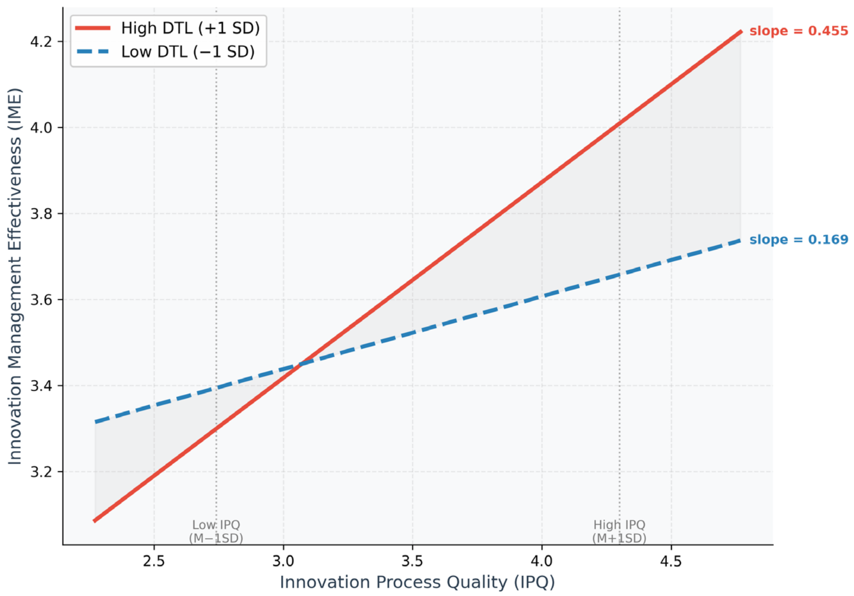

Fig.3: Moderating Effect of Digital Transformation Level on the IPQ–IME Relationship

5. Discussion

5.1 Theoretical Implications

This study makes several contributions to the theoretical understanding of innovation management effectiveness in technology-based firms.

First, the study advances a unified, process-theoretic model of IME antecedents. Prior research has examined the effects of KMC, OLC, and TRI on innovation outcomes largely in isolation, or with mediators focused on innovation capability or absorptive capacity (Harsono et al., 2025; Singh et al., 2022). By positioning IPQ as the key mediating mechanism, the present model identifies the *how* of resource-to-outcome conversion with greater process specificity. The finding that IPQ partially mediates the effects of all three antecedents is consistent with the innovation process perspective (Qiao et al., 2025; Dzenopoljac et al., 2025), and extends prior work by demonstrating the generalizability of this mediation mechanism across three distinct types of resource antecedents simultaneously.

Second, the study enriches the RBV by demonstrating that the resource–performance relationship is contingent on digital infrastructure. While the RBV has long recognized that competitive advantage derives from resource bundles rather than individual resources, the conditions that moderate the resource–performance conversion process have received comparatively less theoretical attention. Our finding that DTL moderates the IPQ–IME path suggests that the value of process-quality investments is not uniform across firms; rather, digital transformation capabilities function as a performance amplifier that enables firms to translate process discipline into superior innovation outcomes more effectively (Cheng et al., 2026; Lu et al., 2023). This extends Vial's (2019) conceptualization of digital transformation as a value-creating process by identifying a specific intra-organizational performance mechanism.

Third, the study contributes to the emerging literature on innovation management in the Chinese technology sector. The significant effects of all three antecedents confirm that the theoretical relationships documented in Western contexts are generalizable to Chinese technology-based firms operating under distinct institutional and competitive conditions (Yin et al., 2024; Gao et al., 2023). The moderating role of DTL is particularly noteworthy in the Chinese context, given the rapid pace of enterprise digitalization driven by national policy initiatives such as "Made in China 2025" and

"Digital China," which have made digital transformation an especially salient strategic imperative for Chinese technology firms (Cheng et al., 2026; Dahms et al., 2025).

Fourth, the partial mediation finding carries important theoretical implications. The co-existence of significant direct and indirect paths from KMC, OLC, and TRI to IME suggests that organizational resources influence innovation management effectiveness through multiple mechanisms—not only through their effects on process quality but also through direct signaling, cultural legitimization, and resource slack effects that cannot be fully channeled through IPQ. This nuance distinguishes the present model from full-mediation frameworks and calls for continued theoretical development of the complex, multi-path relationships between organizational resources and innovation outcomes (Bhatti et al., 2025; Le & Le, 2023).

5.2 Practical Implications

The findings of this study offer several actionable insights for managers of technology-based firms.

Invest in knowledge management systems as a dual-purpose lever. The significant effects of KMC on both IPQ ($\beta = 0.241$) and IME ($\beta = 0.187$) indicate that knowledge management investment is not merely a process-improvement initiative but simultaneously enhances end-state innovation outcomes. Managers should therefore prioritize the development of systematic knowledge acquisition and transfer routines, such as communities of practice, cross-project learning forums, and knowledge repository systems, recognizing that these investments will yield returns through both direct and process-mediated channels (Sofiyabadi et al., 2022; Chen & Liu, 2024).

Cultivate organizational learning culture as a strategic asset. OLC exerts the strongest direct effect on IME among the three antecedents ($\beta = 0.214$), highlighting the importance of building a learning-oriented organizational climate for innovation effectiveness. Managers can foster OLC through deliberate HR practices, including innovation time allocations, post-project retrospectives, tolerance of productive failure, and open communication channels between R&D and marketing functions—consistent with the findings of Lek et al. (2022) and Raji et al. (2026). The indirect effect of OLC through IPQ ($\beta = 0.071$) further indicates that learning culture improvements will organically elevate innovation process discipline over time.

Align technology resource investments with innovation process maturity. The significant effect of TRI on both IPQ and IME underscores the importance of resource commitment as a foundation for effective innovation management. However, the moderation findings suggest that TRI will be most productively deployed when accompanied by advances in digital transformation. Managers should therefore treat TRI and DTL as complementary investments: improvements in technology resources must be paired with the digital infrastructure necessary to effectively manage those resources in innovation processes (Raj et al., 2024; Sati, 2024).

Prioritize digital transformation as a process-effectiveness multiplier. The moderating role of DTL is among the most actionable findings of this study. Firms with high DTL are able to extract significantly greater IME benefits from a given level of IPQ (simple slope = 0.455) compared to firms with low DTL (simple slope = 0.169). This finding suggests that digital transformation investments should not be evaluated purely on their direct performance impact, but rather as multiplicative investments that enhance the productivity of existing innovation management practices. Specific digital capabilities that firms should develop include real-time innovation project dashboards, AI-assisted feasibility assessment tools, digital stage-gate management systems, and cross-functional collaboration platforms (Lu et al., 2023; Chen et al., 2025).

5.3 Limitations and Future Research Directions

Despite its contributions, this study has several limitations that should be acknowledged.

First, the cross-sectional research design precludes causal inferences. While SEM with bootstrap estimation provides stronger inferential support than simple regression, the single time-point data collection means that temporal ordering among constructs cannot be definitively established. Future research should employ longitudinal designs or natural experiment approaches to better capture the dynamic and evolving relationships among KMC, OLC, TRI, IPQ, and IME (Gerdoci et al., 2023).

Second, the use of self-reported survey data introduces potential social desirability and recall biases. Although procedural and statistical CMB checks were conducted, future studies should consider multi-source designs, for example, collecting process quality measures from innovation project documentation and IME outcomes from objective financial or patent records, to provide more objective construct operationalizations (Podsakoff et al., 2003; Liu et al., 2024).

Third, the sample is limited to Chinese technology-based firms. While the Chinese context provides a valuable and policy-relevant empirical setting, the generalizability of the findings to firms in other national and institutional contexts remains to be established. Comparative cross-national studies would be valuable in determining whether the relative importance of KMC, OLC, TRI, and DTL varies across different institutional environments (Adusei et al., 2025; Henao-García, 2026).

Fourth, the measurement of DTL and IPQ as perceptual constructs may not fully capture objective digital transformation and process maturity. Future research could supplement perceptual measures with archival indicators of digital investment (e.g., IT capital expenditure as a percentage of revenue) and process quality (e.g., innovation project on-time delivery rates) to improve construct validity. Cheng et al. (2026) and Sati (2024) suggest that composite measures drawing on both managerial perceptions and objective indicators may provide more robust estimates of construct effects.

Fifth, the study does not account for potential nonlinear effects or threshold relationships. It is plausible that the marginal returns to KMC, OLC, and TRI are diminishing at high levels of these constructs, or that there exists a minimum threshold of DTL below which the process-quality–effectiveness link is fundamentally weak. Future research employing response surface analysis or threshold regression models could provide a more nuanced understanding of these boundary conditions (Dahms et al., 2025).

6. Conclusion

This study examined how enterprise informatics capabilities and digital transformation shape innovation management effectiveness in Chinese technology-based firms. The findings show that knowledge management capability, organizational learning culture, and technology resource investment each improve innovation management effectiveness both directly and indirectly through innovation process quality. Innovation process quality therefore serves as a central mechanism through which organizational knowledge, learning routines, and technology resources are translated into more effective innovation outcomes. The results also show that digital transformation strengthens the effect of innovation process quality on innovation management effectiveness, indicating that firms with stronger digital infrastructures gain greater performance returns from disciplined and well-managed innovation processes.

These findings contribute to research on enterprise informatics, knowledge management, and digital transformation by showing that digitalization is most valuable when combined with strong internal process quality rather than treated as a standalone solution. For managers, the implication is clear: knowledge systems, learning culture, technology investment, process governance, and digital tools should be developed as a complementary portfolio rather than as isolated initiatives. Because the study is cross-sectional, relies on self-reported data, and focuses on Chinese technology-based firms, future research should adopt longitudinal and multi-source designs and examine whether the model holds in logistics, platform, and service-system contexts.

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