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The Impact of Technology Acquisition on Innovation: Moderating Effects of Environmental Dynamism and Strategic Orientation in High-Tech Enterprises

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ABSTRACT

This study examines how internal research and development (R&D) and external technology acquisition affect innovation performance in high-tech enterprises, emphasizing the mediating role of organizational learning ability and the moderating roles of environmental dynamism and technology strategy orientation. Utilizing structural equation modeling on data collected from 509 high-tech companies in China, the analysis reveals that both internal and external technology acquisition significantly enhance learning ability, which in turn positively influences innovation performance. Learning ability partially mediates the effects of both acquisition modes on innovation outcomes. While technology strategy orientation significantly amplifies the positive relationship between learning ability and innovation results, whereas environmental dynamism shows no moderating effect. These results suggest that a firm's strategic focus on technological advancement reinforces the benefits of organizational learning, whereas dynamic environmental conditions do not significantly alter this relationship. The study contributes to theory by integrating the organizational learning, contingency, and synergy effects perspectives to explain innovation pathways. Practically, the findings urge high-tech enterprises to adopt context-specific technology acquisition strategies and to cultivate strong internal learning mechanisms aligned with clear technology strategies to achieve superior innovation performance.

Keywords: technology acquisition, innovation performance, technology strategy orientation, environmental dynamism

INTRODUCTION

The developmental paths and strategic orientations of various emerging economies in the realm of science and technology have exhibited considerable diversity. Nonetheless, a common overarching trend is the emphasis on innovation as a key driver of economic growth. This has entailed heightened investments in scientific and technological R&D and efforts to strengthen human capital, with the objectives of elevating the level of technological innovation, reducing the disparity with advanced economies, and bolstering international competitiveness. China, traditionally regarded as the global hub for industrial manufacturing, has been a major exporter of low-cost consumer goods such as footwear, apparel, and plastic products. However, in recent years, China has strategically shifted its focus toward high-tech industries, exemplified by initiatives such as the "Made in China 2025" plan. This policy framework seeks to accelerate advancements in ten key high-tech sectors, including aerospace, telecommunications, and biomedical engineering (Ministry of Industry and Information Technology, 2015). As reported by the National Bureau of Statistics of China (2024), high-tech manufacturing is projected to account for 15.7% of the value-added output of large-scale industrial enterprises by 2023, underscoring its status as one of the fastest-expanding areas within the Chinese economy.

Despite these advancements, emerging economies like China continue to grapple with challenges related to technological accumulation and lag behind developed markets in certain domains. However, they have demonstrated remarkable progress in high-tech sectors such as information technology. Over the four decades

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following China's reform and opening-up, the forces of globalization have driven the maturation and increased competitiveness of its market. Nevertheless, a significant gap persists between China's technology-intensive industries and those of developed nations, primarily attributable to deficiencies in technological innovation. As noted by Du, Zhu, and Li (2023), the intensification of global competition necessitates that enterprises integrate both internal and external technological resources to expedite product development cycles. While Chinese high-tech enterprises have increasingly emphasized the quantitative aspects of innovation, there remains a relative neglect of innovation quality. Often, these enterprises prioritize directing human and financial resources toward R&D activities, while paying insufficient attention to the integration and optimization of R&D resources and systemic efficiencies. This oversight impedes the effective synthesis of internal R&D capabilities and external technological resources, thereby compromising both innovation quality and enterprise performance. Consequently, whether at the national level, where innovation-driven strategies are promoted, or at the enterprise level, where independent innovation is emphasized, it is imperative to investigate the determinants of innovation quality and capability within high-tech enterprises.

This research investigates how technology acquisition interacts with organizational learning capabilities to impact innovation performance within high-tech firms. Through a survey of 509 high-tech firms, the research elucidates on the pathways through which technology acquisition contributes to innovation outcomes. The managerial implications derived from these findings are multifaceted. First, high-tech enterprises should choose differentiated technology acquisition modes in the light of their own enterprise characteristics and different scenarios. Second, high-tech enterprises should utilize a variety of technology acquisition modes to enhance their independent innovation capability. Third, strong internal capabilities of high-tech enterprises can help technology acquisition to deliver higher innovation value. Finally, it is necessary to combine their own development situation to formulate a technology strategy in line with the development of enterprises.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Organizational Learning View

Under the wave of digitization, the drastic changes in the environment have made enterprises increasingly aware of the importance of learning. Enterprises see learning as an effective way to overcome path dependency and develop their adaptive capacity. It has been widely accepted by scholars to consider how to cope with the dynamic environment through organizational learning (Ruel et al., 2021; Volberda et al., 2021). Organizational learning is characterized by two fundamental aspects: firstly, its dynamic nature—learning involves ongoing adaptation and the continuous evolution of behavioral patterns; and secondly, its purposeful orientation—learning serves as a strategic response to environmental complexity, aimed at enhancing an organization's core competitiveness. Building on this perspective, the current study posits that organizational learning plays a vital role in strengthening innovation capabilities in high-tech firms, which is mainly reflected in the optimization of the way of information processing and the way of information acquisition, so that the organization can make improvements based on past experiences, correct errors or prevent possible risks in a timely manner.

Contingency View

Contingency Theory was initially employed to examine the effectiveness of organizational leadership. This theory posits that leadership effectiveness is not solely determined by the traits of individual leaders but is influenced by three critical variables: the leader, the followers, and environmental factors (Otley, 2016). Contingency Theory further elucidates the dynamism of the environment and the orientation of technological strategies, emphasizing the importance for enterprises to adapt promptly to changes and to develop the most fitting solutions or management models. This study utilizes the theory of power change as a guiding framework, viewing high-tech enterprises as open systems. It interprets the incremental technological acquisition within these enterprises because of the interaction among relevant factors responding to internal and external environmental changes.

Synergy Effects Theory

From a sociological standpoint, synergy is defined as the interdependence and collaborative interactions among diverse attributes or units within a social group. It involves the cooperative dynamics and mutual engagement

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among actors—such as investors, employees, and other stakeholders—in economic activities, enabling reciprocal support, shared gains, and collective advancement (Yuk & Garrett, 2023). Within the internal framework of an enterprise, synergy manifests between technological upgrading and corporate strategy; specifically, a well-defined corporate strategy amplifies an organization's ability to acquire technology and allocates essential resources to drive technological progress. Externally, a synergistic relationship exists between the economic system and its environment, wherein a supportive and dynamic environment facilitates performance enhancement, while an adverse external environment constrains it. Various studies have explored the concept of synergy, including research on corporate culture synergy (Radicic & Balavac, 2018), corporate mergers and acquisitions (Pang et al., 2020), strategic alliances (Zhao & Gu, 2018), and technological innovation (Alzamora-Ruiz et al., 2021). This research builds upon synergy effects theory to explore how technology acquisition can synergistically enhance innovation performance in high-tech enterprises.

Hypothesis Development

Technology acquisition refers to the process of obtaining technological knowledge resulting from the creation of new products and processes. In this study, technology acquisition is categorized into two dimensions: internal R&D activities and external acquisition of technology. As a key factor influencing an organization's learning capacity, technology acquisition encompasses the acquisition, dissemination and application of new knowledge that is much needed. Learning ability is a necessary capability for high technology enterprises. This includes the ability to integrate and refine knowledge within R&D teams, leveraging their learning potential to foster innovation and generate novel insights (Abubakar et al., 2019). Based on this foundation, this research formulates the following hypothesis:

H1: Internal technology R&D positively influences learning ability.

H2: External technology acquisition positively influences learning ability.

Organizational learning capability has been widely acknowledged by scholars as a crucial contributor to various enterprise functions, including marketing effectiveness, innovation output, financial performance, productivity, and customer satisfaction. Basten and Haamann (2018) showed that organizational learning ability can increase the efficiency of technological innovation and improve the performance of enterprises. Similarly, Zhang and Zhu (2019) observed a direct positive effect of organizational learning ability on the performance of innovative enterprises. Empirical research further supports the view that the generation of new knowledge significantly contributes to business success and studies such as Naqshbandi and Tabche (2018) suggest that promoting organizational learning enhances knowledge capabilities and strengthens innovative performance. Based on these insights, the following hypothesis is proposed:

H3: Learning ability positively influences innovation performance.

For enterprises, R&D organizations can provide some complementary technological resources for themselves, playing a pivotal role in sustaining operations and fostering innovation in high-tech enterprises (McKelvie et al., 2018). A well-structured and efficient R&D system equips these enterprises to better navigate the complexities of innovation activities (Schot & Steinmueller, 2018). If the internal R&D reaches the corresponding scale, it can reduce the R&D cost and further enhance the technological content (Wang & Zhao, 2018), thereby enhancing innovation quality and performance. Hence, this research proposes the following hypotheses:

H4: Internal technology R&D positively influences innovation performance.

Through the acquisition of external technologies, high-tech enterprises can progressively develop capabilities and technologies that are complementary to their own. This acquisition process not only enhances internal innovation capacity but also elevates the overall quality of innovative output. Xu (2019) use the inter-provincial panel data of high-tech industries from 2012-2018, and find in their empirical analysis that both external technology acquisition, foreign technology acquisition and domestic technology acquisition had a positive influence on innovation outcomes. Supporting this, Wang (2020) affirmed that external technology acquisition plays a foundational role in innovation, directly contributing to improved innovation performance. Based on this, the next hypothesis is proposed:

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H5: External technology acquisition positively influences innovation performance.

Previous researches suggest that environmental dynamism serves as a key moderating factor in the innovation process. For instance, Mikalef et al. (2019) found that under conditions of environmental uncertainty, the relationship between exploratory innovation and strategic flexibility is strengthened. Likewise, Peng et al. (2019) identified innovativeness—an essential component of entrepreneurial orientation—as being enhanced under dynamic environmental conditions, thereby improving innovation outcomes. Moreover, Wang and Huang (2019) noted that environmental dynamism amplifies the positive effect of organizational unlearning on radical innovation. In light of this evidence, the following hypothesis is proposed:

H6: Environmental dynamism moderates the relationship between learning ability and innovation performance.

Technology oriented enterprises alocate their resources to the development and acquisition of advanced processes, products, and services. Previous research has consistently demonstrated a positive link between technology orientation and enterprise performance, and scholars have long recognized the important role of technology orientation in innovation (Park, Anderson, & Seo, 2021). Technology-oriented enterprises that combine customer value innovation with technological innovation have more opportunities to enjoy sustainable profits and performance (He et al., 2020). Empirical studies also indicate that the impact of technology orientation on innovation performance becomes even more significant under conditions of technological and market turbulence (Adams et al., 2019). Therefore, the final hypothesis is as follows:

H7: Technology strategy orientation moderates the relationship between learning ability and innovation performance.

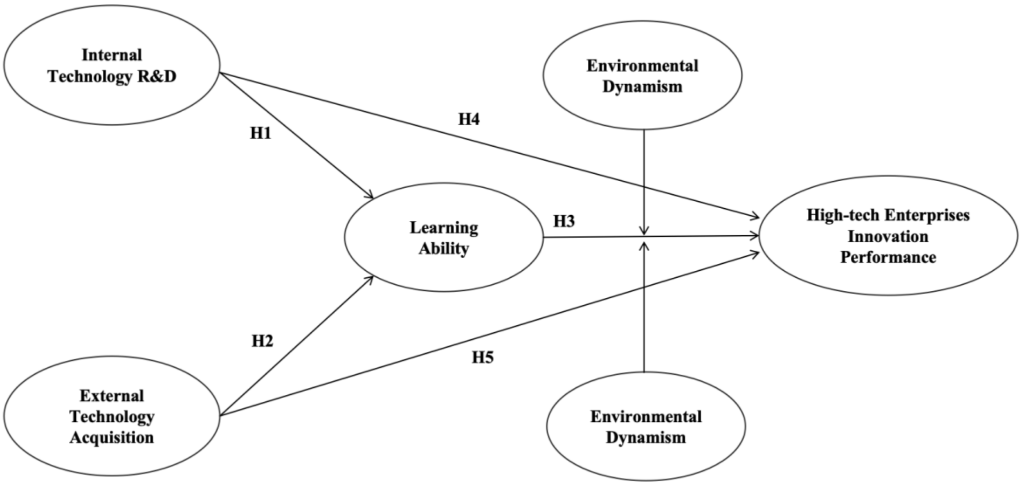

Figure 1. Research Model

METHODOLOGY

Measurement Scales

This study used a well-established scale from the previous literature to measure the potential structure. Each variable was measured by Likert five scale. First, the technology acquisition is based on the measurement model of Knudsen and Mortensen (2011), Cai and Yan (2013), Zhang, Huang and Liu (2014), and Liu, Ding and Zhao (2016). Secondly, for the measurement of learning ability, this study set up five items adapting the scale proposed by Feng (2020) and combined with the current research situation. Third, Environmental dynamism was evaluated using four items modified from Zhang, Guo and Zhang (2021). Fourth, technology strategy orientation was measured across four dimensions: strategic objectives, development funding, developer capabilities, and R&D levels of new

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products (He et al., 2020). Finally, innovation performance was operationalized using a five-dimensional scale informed by Zhu and Huang (2011), Cai, Liu, Deng and Cao (2014).

Sampling and Data Collection

This research focuses on innovation performance of high-tech enterprises, a subject closely linked to strategic decision-making at the executive level. Consequently, the survey primarily targeted top corporate leaders, including CEOs and technology-focused executives such as CTOs. In late June 2024, 1,773 potential respondents were contacted through 1,491 online and 282 postal surveys, with a five-week data collection period. Initial responses were gathered within the first three weeks, followed by telephone reminders to non-respondents. A second online survey was distributed to non-respondents after four weeks. The final data set comprised 574 responses, including 509 complete and 65 incomplete surveys.

RESULTS

Descriptive Statistics

The demographic analysis of 509 surveyed high-tech enterprises reveals several key characteristics. As presented in Table 1, respondents predominantly held the position of deputy general manager (32.5%). The majority of enterprises reported operational durations between 5 to 10 years (32.8%) and were geographically concentrated in Jiangsu Province (38.3%). In terms of workforce size, 51.5% of enterprises employed 100-300 staff members, with state-owned enterprises constituting the majority (51.9%). Regarding industrial classification, the new energy and materials sector represented the largest proportion, comprising 202 enterprises (39.7%) of the total.

Table 1 *Description of the Distribution of Sample Features*

Demographics	Scale	Frequency	Percent
Position	CTO	80	15.7
	General Manager	39	7.7
	Technical Director	119	23.4
	Vice General Manager	165	32.5
Firm age	Less than 3 years	91	17.9
	3-5 years	90	17.7
	5-10 years	167	32.8
	10-15 years	117	23.0
	More than 15 years	44	8.6
Region	Anhui	49	9.6
	Beijing	2	0.4
	Fujian	76	14.9
	Guangdong	7	1.4
	Hainan	3	0.6
	Hebei	13	2.6
	Henan	4	0.8
	Hubei	24	4.7
	Hunan	5	1.0
	Jiangsu	195	38.3
	Jiangxi	4	0.8
	Jilin	1	0.2
	Liaoning	62	12.2
	Neimenggu	2	0.4
	Shandong	5	1.0
	Shanghai	1	0.2
	Shanxi	11	2.2
	Sichuan	1	0.2
	Zhejiang	44	8.6
Firm size	Less than 10 employees	14	2.8
	10-100 employees	102	20.0
	100-300 employees	262	51.5
	300-1000 employees	105	20.6

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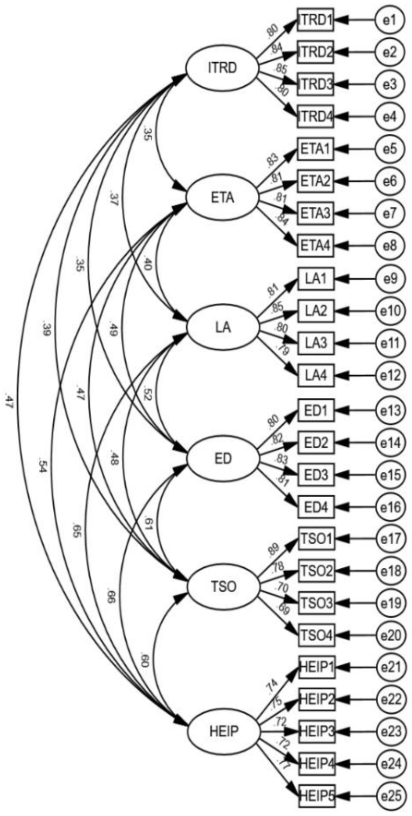
	Greater than 1000 employees	26	5.1
Nature of high-tech enterprises	State-owned	264	51.9
	Private	198	38.9
	Foreign-invested enterprises	47	9.2
Industry Sectors	New energy and new materials	202	39.7
	Aerospace	15	2.9
	Bio pharmaceuticals	114	22.4
	Information and communications	110	21.6
	Medical instrumentation and instrumentation	68	13.4

Measurement Model

This study employed AMOS 26 for construct measurement and model fit assessment. The results of the Confirmatory Factor Analysis (CFA) indicated an acceptable fit between the model and the observed data, with $\chi^2/df = 1.308$ (<2.00), RMSEA = 0.025 (<0.05), and GFI = 0.950 (≥0.95) (Diamantopoulos & Siguaw, 2000). Additional indices exceeded recommended thresholds: CFI = 0.989 and TLI = 0.987 (>0.95) (Diamantopoulos et al., 2000; Schumacker & Lomax, 2004), while NFI = 0.956, IFI = 0.989, and RFI = 0.949 (>0.90). As shown in Figure 2, all first-order CFA regression coefficients were statistically significant at the $p < 0.001$ level.



$\chi^2 = 339.991$, df = 206, $\chi^2/df = 1.308$, RMSEA = 0.025, GFI = 0.950,

CFI = 0.989, TFI = 0.987, NFI = 0.989, IFI = 0.989, RFI = 0.949

Figure 1. The Confirmatory Factor Analysis

Testing the construct validity

Indicator reliability was assessed through factor loadings, which ranged from 0.689 to 0.888, each exceeding the 0.5 threshold (Costello & Osborne, 2005), confirming satisfactory measurement model adequacy. Construct reliability, evaluated through composite reliability (CR), with values between 0.8510 and 0.8932, surpassing the minimum

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recommended 0.70 benchmark (Chin, 1998; Fornell & Larcker, 1981; Nunnally & Bernstein, 1994). Convergent validity was confirmed through average variance extracted (AVE), which fell within the range of 0.546 to 0.677 across constructs. Detailed indicator loadings, CR, and AVE values are provided in Table 2.

Table 2

Factor loading, Composite Reliability and Average Variance Extracted

Constructs and Items	Loading
Internal Technology R&D(ITRD) (AVE=0.677, CR=0.893)	
1.Enterprise relies heavily on internal resources to provide the next generation of products and process technologies for its own use.	0.797
2.Enterprise spends more on purchasing product technology from other companies than it does on developing its own products and processes.	0.839
3.Enterprise's products and business processes are primarily based on self-developed and relevant technologies.	0.853
4.Enterprise regularly obtains most of its product and process technologies from externa partner firms or third-party providers.	0.800
External Technology Acquisition(ETA) (AVE=0.669, CR=0.890)	
1.Enterprise acquires most of its technology and patents mainly from external sources or partnerships.	0.827
2.Enterprise relies heavily on external companies for the provision of new technologies.	0.805
3.Enterprise is adept at using a business plan or vision to attract patents and technology.	0.805
4.Enterprise is adept at leveraging its reputation to attract patents and technology.	0.835
Learning Ability (LA)(AVE=0.659, CR=0.885)	
1.Enterprise considers employee learning capabilities as a core factor in organizational development.	0.806
2.Enterprise views training of employees as an investment rather than a cost.	0.848
3.Enterprise has a clear definition and description of its position and future development.	0.799
4.As an employee of the enterprise, you consider yourself responsible for the future development of the organization.	0.793
Environmental Dynamism(ED) (AVE=0.664, CR=0.888)	
1. The changing composition of customers in the industry in which enterprise belongs.	0.801
2. Changing customer preferences for products within the industry in which enterprise belongs.	0.820
3. The dominant technology of the industry in which enterprise belongs is changing rapidly.	0.826
4. It is difficult to determine the development of the dominant technology of the industry in which enterprise belongs after three years.	0.813
Technology Strategy Orientation (TSO)(AVE=0.591, CR=0.851)	
1. Enterprise has always sought to be a technological leader in its industry.	0.888
2. Enterprise invest very heavily in R&D	0.781
3. The overall quality of R&D personnel in enterprise is high.	0.700
4. Continuous development of new products by enterprise.	0.689

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High-tech Enterprises Innovation Performance (HEIP)(AVE=0.546, CR=0.857)	
1.Compared with high-tech enterprises in the same industry, your enterprises possess more proprietary technologies or have applied for more patents.	0.740
2. Your enterprise is often the first in the industry to introduce new products as compared to its peers.	0.746
3. Compared with the industry, your enterprise has first-class technology and process.	0.723
4. Your enterprise's product innovations and improvements have been well received by the market as compared to its peers.	0.719
5.Introducing more efficient management practices in your enterprise compared to its peers.	0.766

Discriminant validity was evaluated using the Fornell-Larcker criterion (Fornell & Larcker, 1981). As presented in Table 3, the square root of AVE for each construct was greater than its correlations with other constructs, thus supporting the presence of discriminant validity.

Table 3 *Result of Discriminant Validity Test*

Variables	ITRD	ETA	LA	ED	TSO	HEIP
ITRD	0.677					
ETA	0.349	0.669				
LA	0.369	0.398	0.659			
ED	0.346	0.494	0.525	0.664		
TSO	0.394	0.468	0.480	0.613	0.591	
HEIP	0.468	0.544	0.652	0.658	0.601	0.546
The Square root of AVE	0.823	0.818	0.812	0.815	0.769	0.739

Testing the Correlation Analysis

This study employed Pearson's bivariate correlation analysis to examine variable relationships. A two-tailed significance test was applied at level $p < 0.01$.

Table 4 *Descriptive Statistics and Correlations Matrix*

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Mean	3.228	3.316	3.219	3.185	3.133	3.082
S.D.	0.978	0.933	0.851	0.909	0.829	0.802
(1)ITRD	1					
(2)ETA	0.313**	1				
(3)LA	0.327**	0.356**	1			
(4)ED	0.308**	0.439**	0;463**	1		
(5)TSO	0.350**	0.426**	0.420**	0.549**	1	
(6)HEIP	0.410**	0.476**	0.566**	0.575**	0.529**	1

Note: N=509 ** Correlation is significant at the 0.01 level (2-tailed).

Common Method Variance

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To evaluate common method bias (CMB), this research used Harman's one-way test and exploratory factor analysis (EFA). According to Podsakoff and Organ's (1986) criteria, CMB is considered insignificant if a single unrotated factor accounts for less than 50% of the total variance.

Table 5 *Total Variance Explained*

Component	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %
1	9.576	38.306	38.306	9.576	38.306	38.306
2	2.268	9.072	47.378	2.268	9.072	47.378
3	1.976	7.906	55.284	1.976	7.906	55.284
4	1.704	6.816	62.1	1.704	6.816	62.1
5	1.289	5.158	67.257	1.289	5.158	67.257
6	1.192	4.77	72.027	1.192	4.77	72.027
7	0.598	2.391	74.418			
8	0.537	2.149	76.567			
9	0.521	2.083	78.65			
10	0.475	1.899	80.548			
11	0.454	1.814	82.363			
12	0.423	1.69	84.053			
13	0.412	1.649	85.702			
14	0.387	1.548	87.25			
15	0.367	1.47	88.719			
16	0.353	1.413	90.133			
17	0.322	1.286	91.419			
18	0.318	1.273	92.692			
19	0.308	1.23	93.922			
20	0.296	1.185	95.107			
21	0.288	1.15	96.257			
22	0.26	1.039	97.296			
23	0.244	0.977	98.273			
24	0.232	0.929	99.203			
25	0.199	0.797	100			

Multicollinearity

Multicollinearity assessment was conducted to address potential parameter estimation issues (Hair et al., 2011). Variance inflation factors (VIFs) and tolerance values were calculated for each construct component, yielding VIFs ranging from 1.226 to 1.665 and tolerance values between 0.601 and 0.815. These metrics fall within the acceptable thresholds (VIF < 3.3, tolerance > 0.20), indicating that multicollinearity is not an issue. The detailed outcomes are presented in Table 6.

Table 1 *Variance Inflation Factor (VIF) and Tolerance Value*

Constructs	VIF	Tolerance
Internal technology R&D	1.226	0.815
External technology acquisition	1.373	0.728
Learning ability	1.404	0.712
Environmental dynamism	1.665	0.601
Technology strategy orientation	1.617	0.618

Note: Dependent variable: High-tech enterprises innovation performance.

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Structural Equation Modeling Analysis (SEM)

The outcomes of the five main hypothesis, as previously discussed, the proposed model show the structural relationships among all constructs. The result of model assessment and parameter estimation is presented in Figure 3 and Table 7.

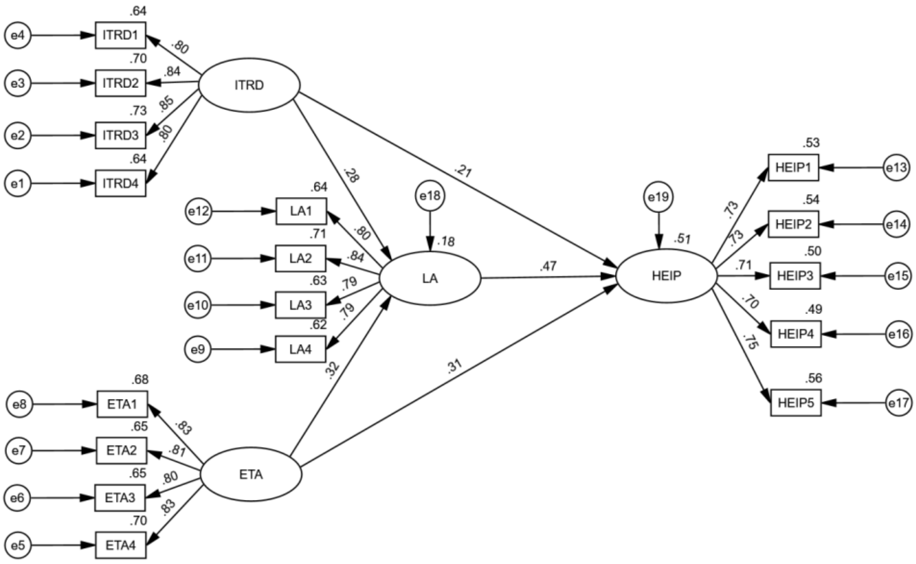

Figure 3. The Structure Model for Main Hypothesis Testing

Table 2 *Comparison of Goodness-of-Fit Index of Proposed Model and the Recommended Points*

Goodness-of-fit indices	The cutoff point	Proposed model
CMIN/DF(χ2/df)	≦ 2.00	1.403
RMSEA	< 0.05	0.028
CFI	> 0.95	0.990
TFI	> 0.95	0.989
NFI	≧0.90	0.968
IFI	≧0.90	0.991
RFI	≧0.90	0.961

As previously discussed, the proposed model Figure 3 shows the structural relationships among all main constructs. Whereas parameter estimation and the significance test are shown in Table 8.

Table 3 *Main effect: Parameter Estimation and the Significance Test*

Hypotheses	β	Std.	t-value	p-value	Outcome
ITRD -->	0.278	0.047	5.787	0.000	H1 accept
ETA --> LA	0.321	0.047	6.613	0.000	H2 accept
LA --> HEIP	0.472	0.043	9.123	0.000	H3 accept
ITRD -->	0.213	0.035	4.915	0.000	H4 accept
ETA -->	0.308	0.037	6.774	0.000	H5 accept

Note: 1. ITRD is internal technology R&D; ETA is external technology acquisition; LA is learning ability; HEIP is high-tech enterprises innovation performance.

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2. t-value is significant at *** p-value < 0.001.

Table 8 reports the indices used to test main hypotheses, including β coefficients, p-values, and t-values. The hypothesis predicts that internal technology R&D and external technology acquisition have positive direct effects on learning ability. The results in Table 8 support hypothesis H1 ($\beta = 0.28$, $p < 0.001$, $t = 5.79$) and H2 ($\beta = 0.32$, $p < 0.001$, $t = 6.61$). Table 8 also reveals that learning ability is positively directly associated with high-tech enterprises innovation performance ($\beta = 0.47$, $p < 0.001$, $t = 9.12$), providing support for H3. In addition, Table 4 also reveals that internal technology R&D and external technology acquisition positively directly affects high-tech enterprises innovation performance, thereby supporting H4($\beta = 0.21$, $p < 0.001$, $t = 4.92$) and H5($\beta = 0.31$, $p < 0.001$, $t = 6.78$). Using AMOS 26.0, the Bootstrap method was used to perform 5000 iterations. Table 9 presents the findings related to the mediation effect.

Table 4 *Mediating Effect Validation Using the Bootstrap Method*

Effect	Parameter	Estimate	Bootstrap 95% CI		Percentile 95% CI	
			Lower	Upper	Lower	Upper
Total effect	ITRD --> HEIP	0.345	0.254	0.433	0.254	0.433
	ETA --> HEIP	0.460	0.382	0.543	0.381	0.542
Indirect effect	ITRD --> LA --> HEIP	0.131	0.083	0.185	0.082	0.184
	ETA --> LA --> HEIP	0.152	0.106	0.207	0.104	0.204
Direct effect	ITRD --> HEIP	0.213	0.121	0.298	0.122	0.299
	ETA --> HEIP	0.308	0.225	0.394	0.225	0.394

Note: ITRD is internal technology R&D; ETA is external technology acquisition; LA is learning ability; HEIP is high-tech enterprises innovation performance.

As illustrated in Table 9, the total effect values are 0.345 and 0.460, which confirms the presence of a total effect. The observed indirect effect values are 0.131 and 0.152, demonstrating the presence of an indirect effect. Similarly, the direct effect values of 0.213 and 0.308 suggest that direct relationships remain significant. In conclusion, learning ability serves as a partial mediator between both internal technology R&D, external technology acquisition, and the innovation performance of high-tech enterprises.

Table 5 *Coefficients for the role of ED in moderating between LA and HEIP*

Variables	HEIP			
	Model 1	Model 2	Model 3	Model 4
Firm age	0.032	0.019	0.007	0.007
Firm size	0.066	0.069	0.069	0.070*
LA		0.478***	0.323***	0.326***
ED			0.351***	0.348***
LA*ED				0.039
R^2	0.007	0.327	0.451	0.452
ΔR^2	0.007	0.320	0.124	0.001
F	1.747	81.615***	103.338***	83.078***

Note: 1. LA is learning ability; ED is environmental dynamism, HEIP is high-tech enterprises innovation performance.

2. *** significance level at 0.001, ** significance level at 0.01, * significance level at 0.05

As shown in Table 10, environmental dynamism does not significantly moderate the relationship between learning ability and the innovation performance of high-tech enterprises (β = 0.039, p > 0.05). Consequently, Hypothesis 6 is not supported.

Table 6 *Coefficients for the role of TSO in moderating between LA and HEIP*

Variables	HEIP			
	Model 1	Model 2	Model 3	Model 4
Firm age	0.032	0.019	0.025	0.026
Firm size	0.066	0.069	0.078	0.077*
LA		0.478***	0.351***	0.353***
TSO			0.345***	0.346***
LA*TSO				0.100***
R^2	0.007	0.327	0.431	0.443
ΔR^2	0.007	0.320	0.105	0.011
F	1.747	81.615***	95.551***	79.854***

Note: 1. LA is learning ability; TSO is technology strategy orientation, HEIP is high-tech enterprises innovation performance.

2. *** significance level at 0.001, ** significance level at 0.01, * significance level at 0.05

In contrast, Table 11 reveals that learning ability and technology strategy orientation has a significant positive impact on the innovation performance of high-tech enterprises (β = 0.100, p < 0.01), thereby supporting Hypothesis 7.

Figure 4 can visualize the positive moderating role of technology strategy orientation in the effect of learning ability on high-tech enterprises innovation performance.

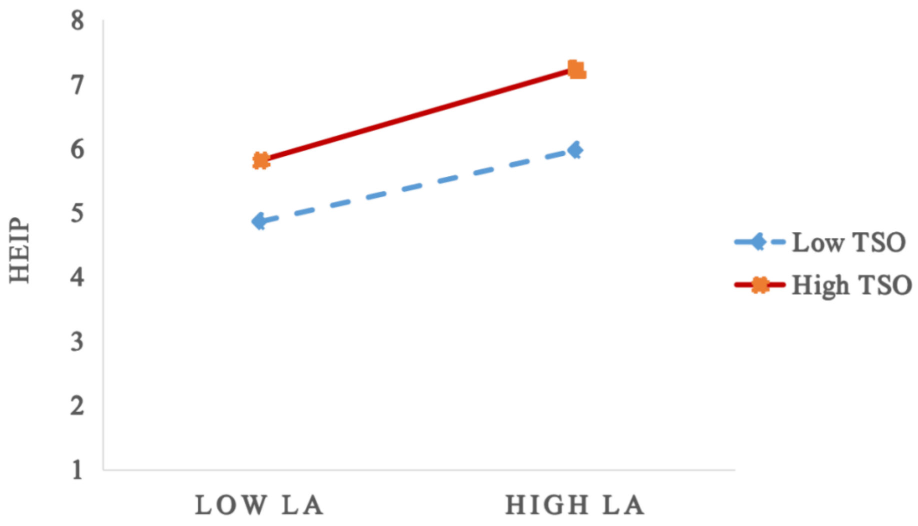

Figure 4. Moderating effects of technology strategy orientation

DISCUSSION

The results of this study offer empirical evidence for the positive influence of both internal technology R&D and external technology acquisition on organizational learning ability in high-tech enterprises (H1, H2). Specifically, internal R&D initiatives facilitate the development of behavioral patterns centered on knowledge sharing and

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collaborative exploration, fostering a deeper understanding of technological frameworks, experiences, and applications. An increase in R&D activities strengthens a firm's ability to acquire and assimilate new knowledge (Ukpabio et al., 2016). Concurrently, external technology acquisition allows enterprises to access advanced technological resources, prompting them to critically assess their internal capabilities, identify technological gaps, and internalize external knowledge for future innovation. This learning process, characterized by assimilation and adaptation, improves an enterprise's ability to leverage acquired technologies effectively. Consistent with prior research, learning ability was found to significantly and positively impact innovation performance (H3), reinforcing its role as a critical competency in knowledge-intensive environments. Organizational learning capability enables firms to process external and internal information more effectively, leading to enhanced innovation outcomes (Xu & Wu, 2018). Liu and Song (2023) similarly highlighted that learning capabilities contribute substantially to innovation performance by supporting knowledge creation, adaptation, and deployment within high-tech contexts.

The study also confirmed that both internal technology R&D and external technology acquisition exert direct positive effects on innovation performance (H4, H5). The impact of internal R&D aligns with the findings of Xu, Wang, and Liu (2021) and Wu et al. (2020), who emphasize that internally driven technological development supports the generation of proprietary knowledge, facilitates effective knowledge exchange among stakeholders, and underpins product and process upgrades. These efforts contribute to long-term innovation performance through cost efficiencies, knowledge accumulation, and strategic autonomy. Similarly, the observed positive link between external technology acquisition and innovation performance aligns with the findings of Papa et al. (2020) and Sahoo et al. (2023). External acquisition provides access to novel technologies, diverse markets, and talent pools, allowing enterprises to overcome internal limitations and stimulate innovative thinking. It also encourages companies to restructure their R&D activities and adapt to emerging industry trends, thereby enhancing innovation outputs.

Unexpectedly, environmental dynamism did not significantly moderate the relationship between learning ability and innovation performance (H6). This outcome indicates that the effect of learning ability on innovation outcomes is robust, regardless of the volatility of external market conditions. Although prior studies have acknowledged the potential influence of environmental factors on innovation (Peng et al., 2019), the current results align with those of Migdadi (2021) and Farzaneh et al. (2021), who found limited or non-significant moderating effects of environmental dynamism. This may indicate that internally cultivated capabilities such as learning ability remain pivotal in driving innovation, even in rapidly changing environments. In contrast, technology strategy orientation significantly moderated the relationship between learning ability and innovation performance (H7), reinforcing its strategic relevance. Enterprises with a strong technology orientation—characterized by substantial investment in R&D, high-quality technical personnel, and continuous product development—are better positioned to translate learning capabilities into tangible innovation outcomes (Adams et al., 2019; He et al., 2020). This interaction effect supports the argument that a well-defined and proactive technology strategy enhances the absorptive and integrative functions of organizational learning (Zhu & Zhu, 2018). Firms that strategically commit to technological leadership are more likely to establish structures and cultures conducive to knowledge transfer, exploratory learning, and innovation acceleration.

Furthermore, this study verified that learning ability plays a partial mediating role in the connection between technology acquisition and innovation performance. The findings indicate that both internal R&D and external technology acquisition influence innovation not only through direct pathways but also indirectly by strengthening organizational learning processes. This mediating role underscores the critical need of developing strong learning infrastructures and knowledge management systems to fully capitalize on technology acquisition efforts. The results empirically suppoert the theoretical proposition that learning serves as a key mechanism through which technology inputs are transformed into innovation outputs (Abubakar et al., 2019; Basten & Haamann, 2018). All in all, this study demonstrates that technology acquisition, when complemented by strong learning capabilities and guided by strategic technological orientation, leads to superior innovation performance in high-tech enterprises. These insights present meaningful implications for both academic research and managerial practice, particularly in the context of emerging economies striving to strengthen their innovation capabilities through effective technology management and organizational learning.

Implications for Theory

This study uncovers the innovation-oriented pathways through which technology acquisition influences the innovation performance of high-tech enterprises and conducts a comprehensive analysis of the synergistic effects of internal and external influencing factors. It elucidates the role-playing mechanism by which high-tech enterprises concurrently influence their own innovation performance through internal and external technology acquisition. This not only broadens the research scope on the relationship between technology acquisition and innovation performance in high-tech enterprises but also provides valuable theoretical advancements in the field of innovation studies. Simultaneously, the study analyzes the internal and external conditions under which high-tech enterprises opt for different technology acquisition modes. This can guide Chinese high-tech enterprises in making differentiated technology acquisition choices, optimizing their learning capabilities, and continuously enhancing their innovation performance.

This research employs learning ability as a bridge between technology acquisition and high-tech enterprises. By focusing on the "innovation process", it explores the mediating role of learning ability in the relationship between technology acquisition and innovation outcomes, thereby contributing to empirical advancements in mediation analysis. This study incorporates environmental dynamism and technology strategy orientation as moderating variables, expanding the situational boundaries of innovation performance research. While existing literature often focuses on knowledge distribution or industry modularity, this research comprehensively analyzes the synergistic and moderating effects of factors influencing innovation performance. It identifies internal and external boundary factors affecting innovation performance, confirming that internal strategic factors moderate the innovation dynamics in high-tech enterprises. This enables firms to adjust their network configurations based on internal technological strategies, thereby achieving better innovation performance.

Implications for Practice

High-tech enterprises should choose differentiated technology acquisition modes in the light of their own enterprise characteristics and different scenarios. The effect triggered by technology acquisition is very complicated and uncertain. High-tech enterprises can utilize their existing advantages, construct a combination of multiple modes according to the characteristics of the external environment and the layout of technology strategy, integrate advantageous resources, suit the needs of their own development, and improve their innovation ability through technology acquisition. This research has confirmed that the effect of internal and external technology acquisition on the innovation performance of high-tech enterprises is different depending on factors such as the policy environments, risk-bearing ability, managers' technology preference, R&D cost acceptance, technology complexity and technology market maturity. Therefore, considering that high-tech enterprises involve multiple industries and positions, and sometimes an enterprise may be involved in technological challenges in multiple fields, and that the technological development routes and existing resources of different enterprises are also different, high-tech enterprises should nowadays review the situation, re-examine and evaluate their own internal and external technological environments and influencing factors, and choose a technology acquisition mode that align with their distinct characteristics and development, thereby enhancing their innovation performance.

On the other hand, high-tech enterprises should utilize a variety of technology acquisition modes to enhance their independent innovation capability. Enterprises should adhere to internal technology research and development, using their own R&D effort as a catalyst to accelerate innovation performance. Especially for Chinese high-tech enterprises and high-tech state-owned enterprises, faced with the late start of domestic industry technology and foreign political technology blockade, enterprises must focus on organizing a large amount of manpower and capital to carry out technology research and development work up and down the organization. While adhering to the internal technology research and development, it is also necessary to carry out external technology acquisition to realize the all-round development of technology level. In the era of accelerating globalization, there are certain links between different economic individuals, and it is impractical to blindly rely on independent research and development to achieve innovative performance. On the one hand, at this stage, Chinese high-tech enterprises or R&D institutions have not yet realized their own technology leadership in all aspects, through the introduction of technology can make up for the relevant technology gaps, while realizing the learning and mastery of advanced technology; on the other hand, for some relatively simple technology but more R&D investment in the technology, through the acquisition of external technology is often able to realize the cost savings for the enterprise. At present, most high-tech enterprises in China have not yet encountered the threshold where external technology acquisition negatively impacts their innovation capabilities. Therefore, high-tech enterprises can try to communicate and cooperate with more types of partners in more geographic regions and industries according to their own specific conditions, to find suitable technologies to introduce. Development strategy is like a rudder, mastering the development of an enterprise's direction. High-tech enterprises should formulate a correct technology strategy grounded in an evaluation of internal and external resources and situation. The so-called correct technology strategy refers to the technology strategy aligns with the enterprise's unique development needs—can clearly define its growth trajectory, so that high-tech enterprises can maximize cost savings to focus internal and external resources on advancing core technologies, ultimately paving a path of innovation and development of their own.

CONCLUSION

This study empirically examined the impact of technology acquisition through both internal R&D and external technology acquisition on the innovation performance of high-tech enterprises, with a focus on the mediating role of learning ability and the moderating effects of environmental dynamism and technology strategy orientation. The results confirm that both internal and external technology acquisition significantly enhance an enterprise's learning ability, which in turn positively influences innovation performance. Learning ability was found to partially mediate the relationship between technology acquisition and innovation outcomes, indicating that the process of internalizing and applying acquired knowledge plays a crucial role in translating technological investments into innovation success. This study further revealed that internal technology R&D ($\beta = 0.213$) and external technology acquisition ($\beta = 0.308$) exert significant direct effects on innovation performance, underscoring the complementary value of combining internally generated knowledge with externally sourced technologies. However, environmental dynamism did not significantly moderate the relationship between learning ability and innovation performance, suggesting that the effect of learning remains stable regardless of environmental volatility. In contrast, technology strategy orientation demonstrated a significant positive moderating effect ($\beta = 0.100$), indicating that firms with a stronger strategic commitment to technological leadership are better positioned to convert learning capabilities into innovation outcomes.

These findings offer important theoretical implications by integrating organizational learning theory, contingency theory, and synergy effects theory to explain how internal and external mechanisms interact to drive innovation. Practically, the study recommends that high-tech enterprises adopt a flexible and context-sensitive approach to technology acquisition, emphasizing the cultivation of learning capabilities and alignment with clear technological strategies. This dual approach enables firms to better absorb, adapt, and innovate in response to both internal goals and external market demands. While the study provides robust empirical evidence, it is not without limitations. The sample is limited to high-tech enterprises in China, which may constrain the generalizability of the findings across other national or industrial contexts. Additionally, the cross-sectional design restricts insights into the long-term dynamics of technology acquisition and innovation development. Future research should consider longitudinal studies and comparative international datasets to further explore these relationships across different economic and institutional environments.

Conflict of Interest

The authors declare no conflict of interest.

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