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EFFECTS OF KNOWLEDGE INTEGRATION CAPABILITY, COLLABORATIVE R&D NETWORKS, AND REDUNDANT RESOURCES ON HIGH-TECH ENTERPRISE PERFORMANCE, IN CHINA

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Abstract

Driven by the global scientific and technological revolution and industrial change, innovation has become the main driving force for development, and China regards it as an important support for its national strategy. As the key to enhancing China's global competitiveness, high-tech enterprises need to be closely aligned with national strategic needs. This study examines the effects of Knowledge Integration Capability, Collaborative R&D Network and Redundant Resources on Chinese High-Tech Enterprise Performance. Based on the dual innovation theory, the study finds that Knowledge Integration Capability affects Enterprise Performance through direct and indirect paths, with Collaborative R&D Network and Redundant Resources acting as mediating variables. The study is based on 260 valid questionnaire data from high-tech enterprises in Guangdong Province and analyzed by SmartPLS 3.0 software. The results show that Knowledge Integration Capability has a significant positive effect on Redundant Resources, Collaborative R&D Network and Enterprise Performance, and Redundant Resources and Collaborative R&D Network play an important mediating role in the effect of Knowledge Integration Capability on Enterprise Performance. This study provides new theoretical support for high-tech Enterprise Performance enhancement through resource integration in a dynamic environment.

Keywords: Knowledge Integration Capability, Collaborative R&D Networks, Redundant Resources, High-Tech Enterprise Performance.

1. INTRODUCTION

Against the backdrop of the global scientific and technological revolution and industrial change, innovation has become the main driving force for development. In the face of the epidemic and the uncertainty of economic recovery, enterprises must strengthen independent innovation, master key technologies and improve the quality of science and technology innovation in order to promote high-quality development. High-tech enterprises play an important role in industrial restructuring and economic transformation, and need to focus on key technologies around national strategic needs in order to enhance global competitiveness.

Knowledge is a core element of innovation and a source of core resources and competitive advantages for enterprises. For high-tech enterprises, knowledge integration is crucial, which determines the quality of technological innovation and Enterprise Performance. High-tech enterprises promote patent innovation through knowledge integration and utilize the dual innovation theory to find a balance between existing and new knowledge to cope with competitive pressure.

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Knowledge integration promotes technological invention and performance improvement by recombining existing knowledge elements. High-tech firms need to efficiently utilize internal Redundant Resources and external Collaborative R&D Networks to accelerate the innovation process. This paper explores the relationship between Knowledge Integration, Dual Innovation, Open Innovation and Enterprise Performance, analyzes the roles of Redundant Resources and Collaborative R&D Network, and empirically examines the impact of Knowledge Integration Capability on the performance of high-tech enterprises.

2. LITERATURE REVIEW

2.1 Dual Innovation Theory

Dual innovation theory originated in the 1970s by Duncan, R. B. (1976) to address how firms can simultaneously manage conflicts and synergies between existing and new businesses, and March, J. G. (1991) further proposed two types of innovation, "exploration" and "utilization". "two types of innovation, which represent driving fundamental change through experimentation and discovery of new knowledge, and improving efficiency by refining existing knowledge, respectively.

With deeper research, scholars have found that these two types of innovation may either compete for resources or be mutually reinforcing through knowledge integration (Benner, M. J. et al., 2002). Dual innovation theory requires enterprises to find a balance between utilizing existing knowledge and exploring new knowledge, and through rational innovation strategies and effective knowledge integration, enterprises can achieve short-term financial performance and long-term competitive advantage (He, Z. L. et al., 2004).

According to this theory, firms need to balance exploratory and exploitative innovation to achieve sustainable competitive advantage. Knowledge Integration Capability is key in this process because it supports firms to effectively allocate internal resources and explore external innovation collaborations to ultimately achieve dual innovation goals. Through this theory, we can reveal how Knowledge Integration Capability directly and indirectly affects High-Tech Enterprise Performance through Redundant Resources and Collaborative R&D Network.

2.2 Knowledge Integration Capability

Knowledge Integration Capability refers to the ability to utilize existing or newly acquired knowledge to create new applications and was first introduced by Henderson, R. et al. (1990). Subsequent studies have extended it from technological activities to the strategic level of the firm, arguing that knowledge integration contributes to enhancing entrepreneurial performance, fostering innovation, and leading to new opportunities for revenue and competitive advantage (Salunke, S. et al., 2019).

The deployment of internal resources in firms is seen as the utilization of Redundant Resources, while external innovation cooperation is achieved through Collaborative R&D Networks (Belderbos, R. et al.,2018;Chen, J.,2021;Islam, S. M. T. et al.,2021), which is an important knowledge acquisition strategy (Gkypali, A. et al.,2018).

The Seybold Report
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Based on this, this study proposes the following hypotheses:

H1: Knowledge Integration Capability has a positive effect on Redundant Resources

H2: Knowledge Integration Capability has a positive effect on Enterprise Performance

H3: Knowledge Integration Capability has a positive impact on Collaborative R&D Networks

2.3 Collaborative R&D Network

Collaborative R&D Network refers to the collaborative R&D between an enterprise across organizational boundaries and its external partners in order to acquire more external knowledge and resources and enhance innovation capability and organizational Performance. It originated from the concept of collaboration proposed by Haken (1971) based on systems theory. Later, its concept was extended to the study of enterprises, and scholars believe that Collaborative R&D Network is an important strategy for enterprise knowledge acquisition, which aims at exploring new ways to transcend knowledge boundaries (Gkypali, A. et al.,2018), and can provide enterprises, especially high-tech enterprises, with the opportunity to explore in an outward-looking mode, so that they can access and utilize external knowledge and market information to achieve synergies and Enterprise Performance enhancement (Heil, S. et al.,2018). Based on this, this study proposes the following hypotheses:

H4: Collaborative R&D Network has a positive effect on Enterprise Performance

2.4 Redundant Resources

Redundant resources refer to actual or potential idle resources within a company that can be used to respond to environmental changes. The concept of "redundancy" was first introduced by Simon and March in their 1959 book 《Organizations》. CYERT, R. M. et al. (1963) defined redundant resources as the difference between the company's existing resource stock and actual resource demand, noting that these resources have a buffering effect, helping the company adapt to internal pressures and external changes. Scholars suggest that organizational redundant resources provide essential support, enhancing the efficiency of strategic adjustments to environmental changes, and thus improving performance (Islam, S. M. T. et al., 2021; Xu, J. et al., 2023). Based on this, the study proposes the following hypothesis:

H5: Redundant resources have a positive impact on company performance.

2.5 Enterprise Performance

Enterprise Performance refers to the operating condition of an enterprise, which is expressed as its current relative financial efficiency. In her study of listed high-tech firms in the Chinese manufacturing industry, Chen, J. (2021) found that Redundant Resources play a mediating role between Knowledge Integration Capability and Enterprise Performance (Wang, Y.,2022;Zhang, X.,2022). On the other hand, Gkypali (2018) argued that Collaborative R&D Network is an important strategy for firms' knowledge acquisition, Collaborative R&D Network contributes to firms' innovation performance (Kobarg, S. et al.,2019), and Collaborative R&D Network is a mediator of the relationship between Knowledge Integration

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Capability and Enterprise Performance (Yang, Z. et al.,2020). Based on this, the following hypotheses are proposed in this study:

H6: Redundant Resources mediate the effect of Knowledge Integration Capability on Enterprise Performance

H7: Collaborative R&D Network has a mediating role in the effect of Knowledge Integration Capability on Enterprise Performance

2.6 Research Theoretical Framework

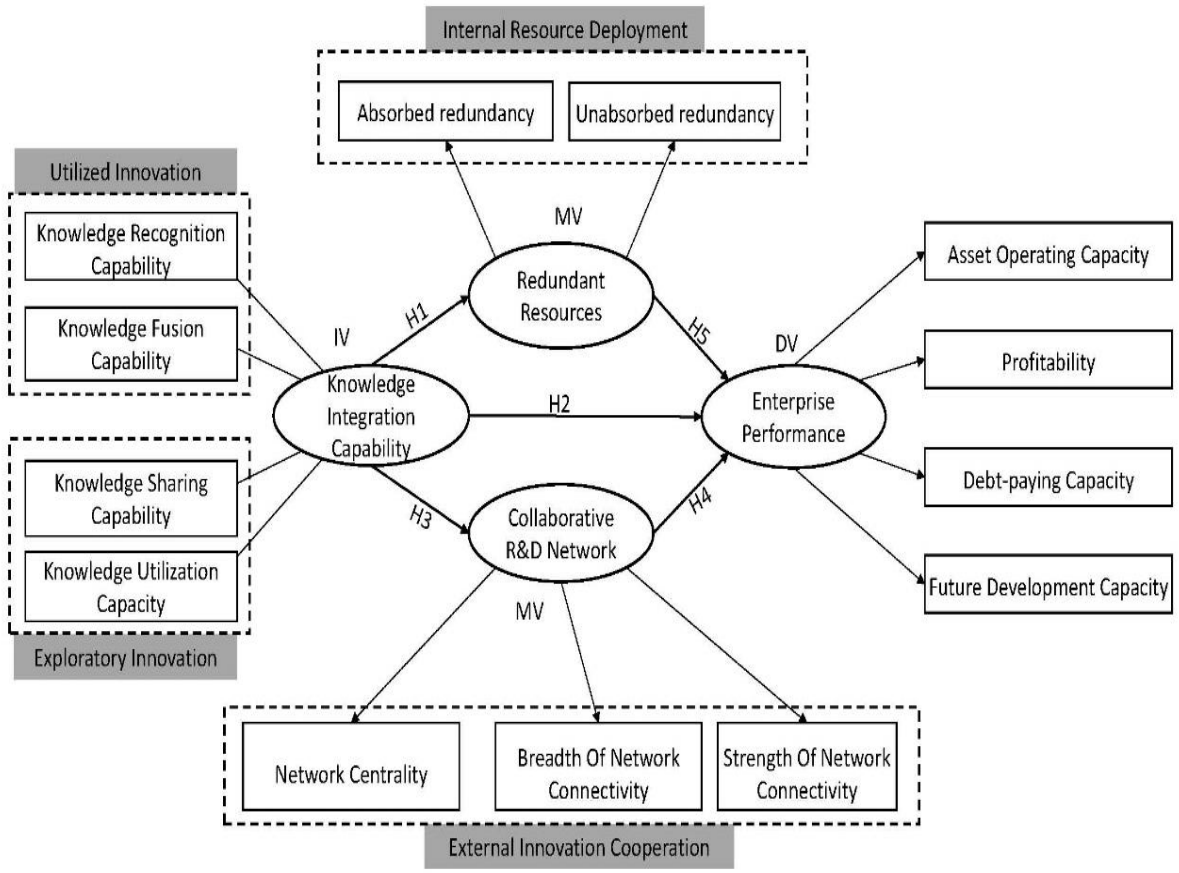

Figure 1: Research Theoretical Framework

3. METHODOLOGY

3.1 Data Collection and Sampling

According to the Guangdong Science and Technology Innovation Dynamic Data, the number of high-tech enterprises in China is growing rapidly, and Guangdong Province ranks first in the country with 76,000 high-tech enterprises. These enterprises are categorized into six groups:

The Seybold Report
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pharmaceutical manufacturing, aviation and spacecraft and equipment, electronics and communication equipment, computers and office equipment, medical instruments and apparatus, and information chemicals manufacturing. They are mainly concentrated in Guangzhou, Shenzhen, Zhuhai, Shantou, Foshan and Shaoguan. In view of the prominence of Guangdong Province in the field of high-tech enterprises, Guangdong Province was chosen as the research site for this study.

To ensure the representativeness of the sample, this study used stratified sampling to extract 1,396 high-tech enterprises from different administrative regions of Guangdong Province and categorized them by industry. After excluding enterprises that have not carried out knowledge integration within three years, 900 remain.

According to the suggestion of Hair, J. J. F. et al. (2016), the distribution weight of the sample size is based on the order of the main business revenue of high-tech enterprises in the "Guangdong Province Science and Technology Innovation Dynamic Data", and combined with the ratio of the number of high-tech enterprises to the sampling size, 260 samples are finally determined for random sampling.

The data were collected by questionnaires, and the top management of high-tech enterprises filled in the electronic questionnaires by scanning the QR code. The basic information of the sample is shown in Table 1.

Table 1: Basic Information of respondents (n = 260)

Demographic Variables	Items	Frequency	Percentage	Cumulative Percent
Age of enterprise (years)	1—10	60	23.08	23.08
	11—20	69	26.54	49.62
	21—30	62	23.85	73.46
	＞30	69	26.54	100
Enterprise size (Number of persons)	1—10	58	22.31	22.31
	10—100	59	22.69	45
	100—300	48	18.46	63.46
	300—1000	52	20	83.46
	＞1000	43	16.54	100
Industry type	Electronics and communications equipment manufacturing	51	19.62	19.62
	Computer and office equipment manufacturing	41	15.77	35.38
	Medical Instrumentation and Instrumentation Manufacturing	39	15	50.38
	Pharmaceutical manufacturing	45	17.31	67.69
	Aeronautics, spacecraft and equipment manufacturing	41	15.77	83.46
	Manufacture of information chemicals	43	16.54	100
Nature of enterprise	Nationalized	91	35	35
	Private	85	32.69	67.69
	Joint venture	84	32.31	100

The Seybold Report
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3.2 Measurement

All variables in this study were second-order constructs, and the measurement scales were selected from well-established scales in existing studies and adapted to the context of this study, involving a total of 46 entries. All entries were measured using a five-point Likert scale, where 1 means strongly disagree and 5 means strongly agree.

3.3 Data Analysis Techniques

The study used SmartPLS 3.0 software to analyze the data. First, the measurement model was analyzed to confirm the structural validity and internal consistency of the measurement model and to ensure the reliability and validity of the measurement instruments used.

Subsequently, model fitting and path analysis were conducted using SmartPLS to assess the relationship between Knowledge Integration Capability, Collaborative R&D Network, Redundant Resources and Enterprise Performance and to test the significance of the paths. This data analysis technique provides insight into the mechanisms by which Knowledge Integration Capability influences Enterprise Performance.

4. RESULTS

4.1 Measurement Model

In this study, reliability and validity were analyzed, mainly including internal consistency (Cronbach's Alpha), construct reliability (Composite Reliability, CR), and average variance extracted (AVE). According to the results shown in Table 2, in terms of internal consistency, the Cronbach's Alpha values for all variables ranged from 0.703 to 0.778, which exceeded the accepted standard of 0.7, indicating that the measurement instrument had good consistency.

In terms of construct reliability, the CR values for all variables ranged from 0.839 to 0.869, which is well above the recommended standard of 0.7, indicating high construct reliability (Hair, J. J. F. et al., 2016). In terms of mean variance explained, the AVE values for all variables ranged from 0.591 to 0.769, which exceeded the generally accepted criterion of 0.5, indicating that the variables explained sufficient variance and had good convergent validity.

In this study, the discriminant validity of the measurement scales was assessed using the HTMT analysis method, which is more advantageous in SmartPLS than the Forell-Larcker criterion proposed by Fornell, C. et al. (1981). Henseler, J. et al. (2015) showed that the HTMT method was able to more accurately determine the discriminant validity.

According to the results shown in Table 3, for each research construct, the heterologous trait-homologous trait (HTMT) ratio was used to assess discriminant validity. In general, HTMT values above 0.9 may lead to potential problems in terms of discriminant validity. However, in the present study, none of the values exceeded 0.9, which suggests that there is sufficient discriminant validity between the constructs. In conclusion, the results of the reliability and validity analyses in this study indicate that the measurement instrument used has high reliability and validity and accurately reflects the concepts under study.

The Seybold Report
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Table 2: Reliability and Validity Analysis

First-ordered Construct	Factor loading	Cronbach Alpha	CR	AVE
Knowledge Recognition Capability	0.771	0.770	0.853	0.591
Knowledge Fusion Capability	0.747			
Knowledge Sharing Capability	0.792			
Knowledge Utilization Capacity	0.765			
Absorbed redundancy	0.85	0.703	0.869	0.769
Unabsorbed redundancy	0.903			
Network Centrality	0.807	0.714	0.839	0.635
Breadth Of Network Connectivity	0.822			
Strength Of Network Connectivity	0.76			
Asset Operating Capacity	0.804	0.778	0.857	0.599
Profitability	0.766			
Debt-paying Capacity	0.768			
Future Development Capacity	0.757			

Table 3: Discriminant Validity (HTMT Analysis)

	Knowledge Integration Capability	Redundant Resources	Collaborative R&D Network	Enterprise Performance
Knowledge Integration Capability				
Redundant Resources	0.5			
Collaborative R&D Network	0.544	0.527		
Enterprise Performance	0.636	0.594	0.581	

4.2 Common Method Biases Test

In survey research, a phenomenon known as “common method bias” often occurs, which may arise when the same or similar methods are used, thus affecting the accuracy and credibility of the results. In order to assess the impact of this bias on the results of the study, the Harman's one-way test was used in this study. This method detects common method bias by loading all measured variables onto a common factor and checking whether that single factor explains most of the variability in the data. The results showed that the variability explained by the single factor was 26.547%, which is much lower than the critical value of 40%, indicating that the data in this study do not suffer from a serious problem of common method bias. Therefore, the data of this study can be considered to have high validity and provide a reliable basis for subsequent analysis.

4.3 Direct Path Analysis

In this study, a structural equation model as shown in Figure 1 was constructed using SmartPLS 3.0 and the path coefficients were examined. The results are shown in Table 4. Knowledge Integration Capability has a significant positive effect on Redundant Resources (path coefficient =0.345,t-statistic value =5.89,p-value = 0.000), which supports Hypothesis 1; Knowledge Integration Capability has a significant positive effect on Enterprise Performance (path coefficient =0.323,t- statistic value = 4.949,p-value = 0.000) path coefficient is 0.323 ($t=4.949$, $p<0.05$), supporting Hypothesis 2; Knowledge Integration Capability has a

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significant positive effect on Collaborative R&D Network (path coefficient = 0.402,t-statistic value = 6.128,p-value = 0.000), supporting Hypothesis 3; Collaborative R&D Network has a significant positive effect on Enterprise Performance (path coefficient =0.223,t-statistic value =3.522,p-value = 0.000), supporting Hypothesis 4; Redundant Resources has a significant positive effect on Enterprise Performance (path coefficient = 0.230,t-statistic value = 4.096,p-value = 0.000), supporting hypothesis 5.

The R-squared values of all the variables in this study were distributed between 0.545 and 0.911, while the adjusted R-squared values ranged from 0.543 to 0.911. The higher values of the latent variables such as authority and avoidance of similarity indicate a better fit, while the variables such as consumer motivation to innovate and behavioral intention are weak in explaining the model. Overall, the model effectively explains the relationship between the variables. According to the criteria of Haile et al. (2017), we can determine the degree of influence of exogenous structures on specific endogenous structures by looking at the f-squared value. In this study, Knowledge Integration Capability has a large effect on Redundant Resources (0.162), a moderate effect on Enterprise Performance (0.123), and a large effect on Collaborative R&D Network (0.200). Collaborative R&D Network has a moderate effect on Enterprise Performance (0.055). Redundant Resources has a moderate effect on Enterprise Performance (0.077).

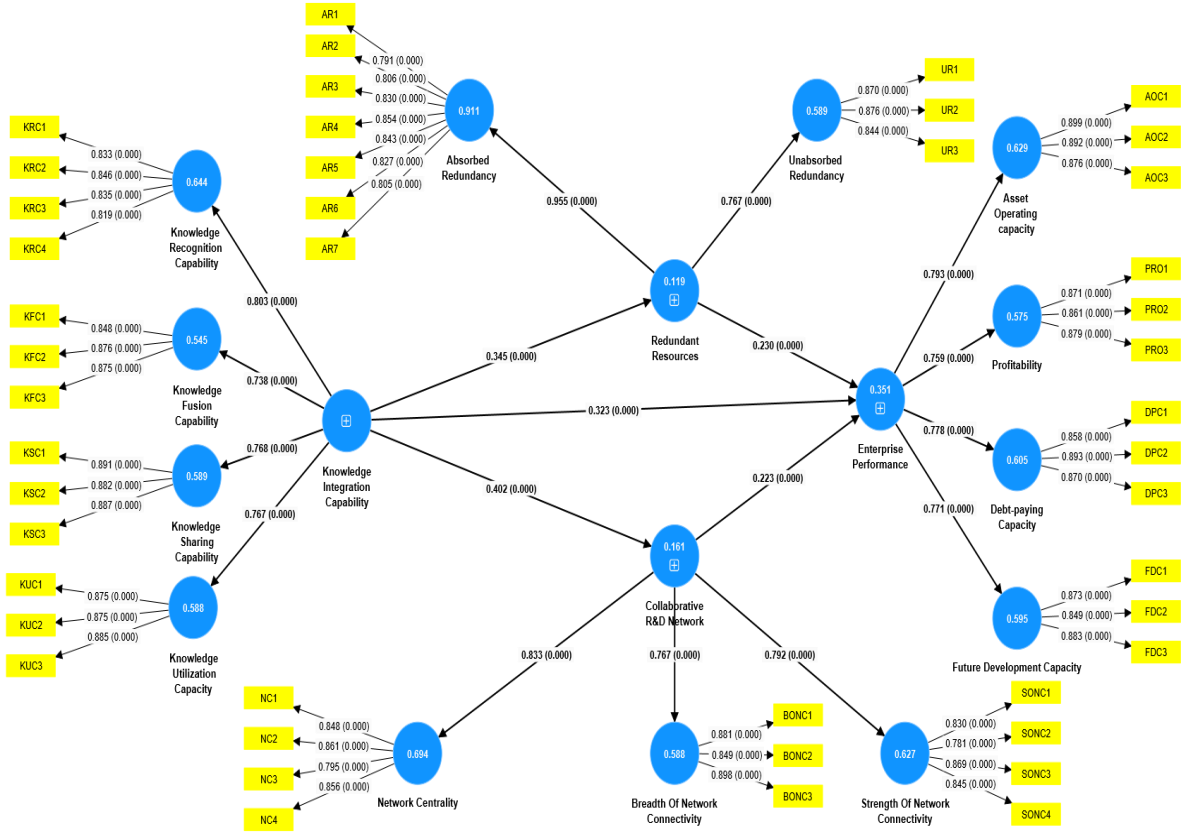

Figure 2: Structural Equation Model in SmartPLS 3.0

The Seybold Report
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Table 4: Path Coefficient Test of Structural Equation Model

No.	Path	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P-value	f^2
H1	Knowledge Integration Capability -> Redundant Resources	0.345	0.059	5.89	0.000	0.162
H2	Knowledge Integration Capability -> Enterprise Performance	0.323	0.065	4.949	0.000	0.123
H3	Knowledge Integration Capability -> Collaborative R&D Network	0.402	0.066	6.128	0.000	0.200
H4	Collaborative R&D Network -> Enterprise Performance	0.223	0.063	3.522	0.000	0.055
H5	Redundant Resources -> Enterprise Performance	0.230	0.056	4.096	0.000	0.077

4.4 Mediation Effect in the Research Model

The results of the mediated effects analysis in this study are shown in Table 5. In H6, the indirect effect of Knowledge Integration Capability on Redundant Resources is 0.089, with a bias-corrected 95% confidence interval (CI) of [0.034,0.157] and a p-value of 0.005. This suggests that Redundant Resources play a significant mediating role between Knowledge Integration Capability and Enterprise Performance.

In H7, the profile effect of Knowledge Integration Capability on Collaborative R&D Network is 0.079, with a bias-corrected 95% Confidence Interval (CI) of [0.035,0.126] and a p-value of 0.001. This suggests that Collaborative R&D Network plays a significant mediating role between Knowledge Integration Capability and Enterprise Performance.

Table 5: Mediation Effect

No.	Path	Original sample (O)	Bias-corrected 95%CI		P-value
			2.50%	97.50%	
H6	Knowledge Integration Capability -> Redundant Resources -> Enterprise Performance	0.089	0.034	0.157	0.005
H7	Knowledge Integration Capability -> Collaborative R&D Network -> Enterprise Performance	0.079	0.035	0.126	0.001

4.5 Hypotheses Test

A total of seven hypotheses were proposed in this study, all of which were supported by the experimental results.

The Seybold Report
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Table 6: Hypotheses Test Results

No.	Hypothesis	Results
H1	Knowledge Integration Capability Positively Impacts Redundant Resources	Supported
H2	Knowledge Integration Capability Has a Positive Impact on Enterprise Performance	Supported
H3	Knowledge Integration Capability Positively Affects Collaborative R&D Networks	Supported
H4	Collaborative R&D Networks Have a Positive Impact on Enterprise Performance	Supported
H5	Redundant Resources Have a Positive Impact on Enterprise Performance	Supported
H6	Redundant Resources Mediate the Effect of Knowledge Integration Capability on Enterprise Performance	Supported
H7	Collaborative R&D Networks Mediate the Effect of Knowledge Integration Capability on Enterprise Performance	Supported

5. CONCLUSIONS

This study investigates the impact of Knowledge Integration Capability on Enterprise Performance of High-Tech Enterprises, and constructs an integrative theoretical framework covering Knowledge Integration, Redundant Resources, Collaborative R&D Network and Enterprise Performance based on Dual Innovation Theory.

The study not only clarifies the impact of Knowledge Integration Capability on Enterprise Performance of High-Tech Enterprises, but also provides important theoretical support for the innovative development of enterprises. The main conclusions are as follows:

First, the study shows that Knowledge Integration Capability has a significant positive impact on Redundant Resources, Enterprise Performance and Collaborative R&D Network. Through effective knowledge integration, Enterprise Performance can be enhanced both by improving internal resource reserves and by enhancing cooperation with external organizations.

Second, Redundant Resources and Collaborative R&D Network play an important mediating role between Knowledge Integration Capability and Enterprise Performance. Knowledge Integration Capability not only directly enhances Enterprise Performance, but also further strengthens the competitiveness and innovation capability of the firm through these two mediating factors.

Overall, Knowledge Integration Capability is proved to be a key factor in enhancing the competitiveness of high-tech enterprises. By accumulating and effectively utilizing Redundant Resources as well as strengthening Collaborative R&D Networks, firms are able to achieve sustained innovation and growth in complex market environments.

The Seybold Report
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This study provides theoretical and practical support for high-tech Enterprise Performance enhancement in innovation-driven development strategies. Given that knowledge integration is the embodiment of innovation activities at the knowledge level, future research may consider introducing mediating variables at other levels to more comprehensively understand the factors affecting Enterprise Performance.

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