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Abstract

As a successful example of the combination of science and technology and economy, SMEs are an important force to improve China's independent innovation ability, and play an important role in promoting national economic growth and social harmony and stability. As for SMEs based on science and technology, due to the lack of resources and limited innovation ability, it is difficult for enterprises to achieve sustainable innovation development by themselves, and they must establish extensive contacts with external social networks to help enterprises obtain scarce learning resources required for innovation activities. Therefore, compared with large science and technology enterprises, small and medium-sized science and technology enterprises have stronger demand for the linkage relationship between learning and knowledge and the innovation ability of employees, which can significantly affect the improvement of enterprise innovation performance. The innovation of SMEs in science and technology requires efficient use and allocation of interorganizational learning, and the experience and lessons acquired and management methods are internalized into the organization through the knowledge management process, combined with the innovation ability of knowledge employees, so as to continuously improve the creativity of the organization. This is exactly the personality of SMEs in science and technology. Based on the personality characteristics of technology-based SMEs, this study focuses on the relationship between inter-organizational learning, knowledge management process and innovation performance. By strengthening the positive influencing factors of innovation performance of technology-based SMEs, the integration and development of internal resources of enterprises can be realized, while innovation output can be achieved and competitive advantages can be maintained.

Keywords: Inter-organizational Learning, Knowledge Management Processes, Innovation Capability, Knowledge Workers, Innovation Performance

Introduction

With the development of society, in an organizational network where stakeholders participate together, users express differentiated demands, and organizations change their information communication structure to achieve goal synergy, information sharing, and mutual trust between organizations, breaking the power mechanism of classical resource dependence theory and forming a cooperative mechanism based on resource and benefit (Qi et al., 2020).

Inter-organizational learning and knowledge management are the soul of management innovation in technology-based small and medium-sized enterprises. The premise for the selective abandonment of the old traditional management model and related management methods is to introduce a large number of external knowledge resources to create new management models and corresponding management methods in accordance with the requirements of the modern enterprise system for "management innovation." The contact and development strategies adopted by technology-based small and medium-sized enterprises are also based on this theoretical viewpoint, that the value created by the internal resources of technology-based small and medium-sized enterprises may be less than the learning value brought by external resources (Chen et al., 2020).

The academic community generally describes the core content of knowledge management from two dimensions. On the one hand, it emphasizes that knowledge management can help create, store, share, and use the organization's explicitly recorded knowledge capacity (Wang, 2023); on the other hand, it emphasizes sharing knowledge through interpersonal communication. The strategic level uses social network dialogue to achieve the purpose of sharing knowledge through contact and assistance between people (Zhao & Gao, 2019). Practice has proved that the purpose of knowledge management is to take knowledge as the most important resource, to obtain, control, and use it as much as possible, to improve enterprise competitiveness, and to benefit enterprise development (Su et al., 2020).

The study's target area is Kunming City in Yunnan Province, China, which has a number of technology-based small and medium-sized businesses. The study's findings indicate that these three characteristics affect small and medium-sized businesses' capacity for innovation to a high or low degree, and they even interact with one another to affect the research subjects' capacity for innovation as a whole. The impact mechanisms of these three components must therefore be maximized based on the enterprise's innovation performance.

This study aims to address four main research questions: (1) What is the role of the knowledge management process in the chain-mediated effect of Inter-organizational learning and innovation performance of technology-based small and medium-sized enterprises? (2)What is the essence of the knowledge management process?Research Objectives: (1) To analyse the chain-mediated effect of the knowledge management process on the Inter-organizational learning and innovation performance of technology-based small and medium-sized enterprises. (2) To explore the essence of the knowledge management process and conduct in-depth analysis of the operational processes of knowledge creation, sharing, and utilization in the knowledge management process.

Research Theoretical Model

Based on the logical deduction of the mechanism of action between the variables of Interorganizational learning, knowledge management process, innovation capabilities of knowledge workers, and innovation performance, and the 6 hypotheses proposed above, this study sorts out the logical hypotheses and constructs a conceptual model of the relationships between variables, as shown in Figure 1.

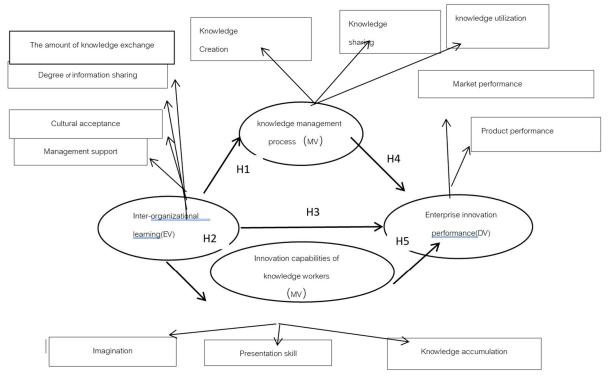


Figure 1 Relationship model between variables

Figure 1 Relationship model between variables

Based on this, this study proposes the following hypothesis:

H1: Inter-organizational learning has a positive impact on the knowledge management process.

H2: Inter-organizational learning has a positive impact on the innovation capability of knowledge workers.

H3: Inter-organizational learning has a positive impact on the innovation performance of technology-based small and medium-sized enterprises.

H4: The knowledge management process has a positive impact on the innovation performance of technology-based small and medium-sized enterprises.

H5: The innovation capability of knowledge workers has a positive impact on the innovation performance of technology-based small and medium-sized enterprises.

Research Methodology

The study was based on the quantitative explanatory design. The population in this study refers to the current technology-oriented small and medium-sized enterprises (SMEs) in Kunming, Yunnan Province, China. According to data published by the Kunming municipal government, there are approximately 1778 technology-oriented SMEs (Kunming Municipal Government Announcement, 2023). Each enterprise selects 3 to 4 individuals for a questionnaire survey, and those chosen are generally the boss, manager, or supervisor, resulting in a population sample size of between 4364 and 7152 people.

To ensure that the sample of technology-oriented SMEs in Kunming, Yunnan Province, China is representative, a random sampling method is employed among technology-oriented enterprises in Kunming. The total sample of this study is distributed among 1778 companies in 5 districts of Kunming. They are relatively concentrated in 5 administrative districts, and multi-stage sampling can be used by region. However, these 1778 companies have 4364 to 7152 executives, and it is impossible to study all of them. Therefore, sampling is carried out according to the region where the company is located. In addition, the multivariate method of structural equation modeling (SEM) should have a threshold to determine 20 times the observed variable of the sample volume for defining the sample procedure (Lindeman et al., 1980). These studies have 12 observed variables, so the sample volume is at least (20 x12) = 240 samples.

Looking at the existing research literature, it is widely accepted that the recovery rate of survey questionnaires should at least reach 60%. Practical experience over the years has shown that a recovery rate of over 60% is quite ideal and can guarantee the credibility and representativeness of the results. Statistical theory suggests that when the survey sample reaches 60% of the total sample, the sample error is within the 95% confidence interval. The academic community and professional research organizations generally believe that a response rate of 60% is an important reference standard for evaluating the quality of questionnaire results. Some countries and organizations' related standard plan all mention that the excellent questionnaire response rate should not be less than 60%. By comparing questionnaire results with different response rates, it is confirmed that a response rate of more than 60% can bring significantly more accurate results. In summary, the 60% standard for the general questionnaire response rate mainly comes from the summary of many practical experiences, theoretical basis, and the consensus of academic and professional institutions (Dillman et al., 2014). Finally, considering the response rate and quality problems of some questionnaires, an appropriate increase of 40% in the initial sample size of 240, the final sample size is 336.

Data analysis

Descriptive statistics of the sample

A total of 366 valid questionnaires were collected in this sampling survey. From the perspective of enterprise size, there are 183 valid samples for small enterprises (50-100 people) and 153 valid samples for medium-sized enterprises (100-500 people). Then, SPSS27.0 and AMOS26.0 were used to analyze the collected questionnaire data and construct a Structural Equation Model (SEM) to validate 5 hypotheses.

Category	Classify		Frequency	Percentag e (%)
Establishment time of	Less than 3 years		80	23.81%
	4-6 years		87	25.89%
enterprise	7-10 years		100	29.76%
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Table 1 Basic information statistics

	More than 10 years	69	20.54%
Network of automotion	State-owned and state-holding enterprise	79	23.51%
Nature of enterprise	Private enterprise	108	32.14%
ownership	Three kinds of investment enterprise	149	44.35%
	Electronic information	56	16.67%
Inductory of the	Biomedical	75	22.32%
Industry of the	Software development	79	23.51%
enterprise	High-tech service industry	89	26.49%
	Information transmission industry	37	11.01%
Enterprise scale	Small enterprise (50-100 people)	183	54.46%
	medium-sized enterprise (100- 500 people)	153	45.54%

Reliability and validity test Reliability analysis

Reliability analysis is mainly used to test the reliability and stability of scale data. In order to ensure that each dimension and items under the scale are less affected by errors, Cronbach's α is finally used to test all measurement items, so as to evaluate the internal consistency of the scale. Reliability analysis results are shown in Table 4.2. Cronbach's α value of all items in the overall model is 0.936. The value of corrected item total correlation (CITI) is greater than 0.4, indicating that untitled items need to be deleted. The Cronbach's α value after each item is deleted is smaller than the Cronbach's α value of the overall dimension of the variable or the scale. Cronbach's α values of all dimensions and scales were higher than 0.8, indicating high reliability of the questionnaire data.

Latent Variable	Observational Variable	Measurement Item	CITC	Item deleted Cronbach's	Cronbach's α
				α	
		IL1	0.652	0.740	
Turken	The amount of	IL2	0.575	0.765	
Inter-	knowledge	IL3	0.604	0.755	0.800
organizational	exchange	IL4	0.431	0.807	
Learning		IL5	0.660	0.739	
		IL6	0.652	0.771	0.819

Table 2 Results of formal survey reliability test

		IL7	0.580	0.793	
	Degree of	IL8	0.609	0.784	
	information	IL9	0.603	0.786	
	sharing	IL10	0.612	0.783	
		IL11	0.666	0.815	
	NA (IL12	0.657	0.818	
	Management	IL13	0.649	0.820	0.849
	support	IL14	0.634	0.824	
		IL15	0.684	0.811	
		IL16	0.795	0.880	
	C 1 1	IL17	0.759	0.887	
	Cultural	IL18	0.738	0.892	0.907
	acceptance	IL19	0.768	0.886	
		IL20	0.768	0.886	
		KM1	0.724	0.850	
	77 1 1	KM2	0.665	0.864	
	Knowledge Creation	KM3	0.694	0.857	0.879
	Creation	KM4	0.695	0.857	
		KM5	0.781	0.837	
	Knowledge	KM6	0.723	0.830	
Knowledge		KM7	0.732	0.828	
Management		KM8	0.619	0.855	0.867
Process	Sharing	KM9	0.671	0.843	
		KM10	0.700	0.836	
		KM11	0.690	0.838	
		KM12	0.680	0.840	
	Knowledge	KM13	0.586	0.862	0.866
	Utilization	KM14	0.684	0.839	
		KM15	0.805	0.808	
		IC1	0.751	0.869	
		IC2	0.734	0.873	
. .	Imagination	IC3	0.753	0.868	0.894
Innovation	-	IC4	0.702	0.879	
Capabilities		IC5	0.760	0.867	
of		IC6	0.729	0.825	
Knowledge		IC7	0.703	0.832	
workers	Presentation	IC8	0.644	0.846	0.865
	Skill	IC9	0.656	0.843	
		IC10	0.694	0.834	

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		IC11	0.674	0.785			
	Vnowladge	IC12	0.579	0.812			
	Knowledge Accumulation	IC13	0.583	0.812	0.832		
	Accumulation	IC14	0.606	0.805			
		IC15	0.714	0.774			
		EI1	0.736	0.869			
	Market Performance	EI2	0.791	0.856			
		EI3	0.714	0.874	0.892		
F ()		EI4	0.660	0.885			
Enterprise		EI5	0.780	0.859			
Innovation Performance		EI6	0.744	0.867			
renormance	Due las t	EI7	0.729	0.871			
	Product	EI8	0.699	0.877	0.892		
	Performance	EI9	0.745	0.867			
		EI10	0.766	0.862			
The Cronbach'	aire	0.936					

Validity analysis

The confirmatory factor analysis is carried out on each model when it reaches the optimum. As shown in Table 3, the standardized factor loads of all items ranged from 0.48 to.084, and were tested for significance. The component reliability (CR) is greater than 0.8. The mean variance-explanatory value (AVE) of each dimension is greater than 0.5, which is in line with the standards of (Black et al., 2010; Sharma et al., 1996), that is, the standardized factor load is greater than 0.5, the component reliability (CR) is greater than 0.7, and the mean variance-explanatory value (AVE) is greater than 0.5. Therefore, the convergence validity of each dimension of Inter-organizational Learning is confirmed.

Table 3 Convergence validity analysis of Inter-organizational Learning									
Items	Path	Dimensions	Estimate	S.E.	C.R.	P- value	Std	CR	AVE
X11	<	IL	0.702	0.102	6.866	***	0.60		
X12	<	IL	1.014	0.129	7.856	***	0.79	0.805	0.512
X13	<	IL	1.101	0.141	7.788	***	0.805	0.803	
X14	<	IL	1.000				0.65		
IL5	<	X11	1.000				0.76	0.808	0.513
IL4	<	X11	0.643	0.080	8.034	***	0.48	0.000	0.313

Table 3 Convergence validity analysis of Inter-organizational Learning

IL3	<	X11	0.987	0.085	11.658	***	0.70		
IL2	<	X11	0.882	0.078	11.254	***	0.65		
IL1	<	X11	1.043	0.083	12.535	***	0.75		
IL10	<	X12	1.000				0.70		
IL9	<	X12	1.044	0.098	10.701	***	0.69		
IL8	<	X12	1.006	0.091	11.087	***	0.67	0.818	0.504
IL7	<	X12	0.863	0.083	10.398	***	0.65		
IL6	<	X12	1.046	0.091	11.505	***	0.73		
IL15	<	X13	1.000				0.75		
IL14	<	X13	0.983	0.081	12.066	***	0.70		
IL13	<	X13	0.980	0.078	12.601	***	0.71	0.848	0.528
IL12	<	X13	0.986	0.075	13.206	***	0.75		
IL11	<	X13	0.985	0.078	12.633	***	0.72		
IL20	<	X14	1.000				0.81		
IL19	<	X14	1.074	0.063	16.935	***	0.82		
IL18	<	X14	0.981	0.061	16.034	***	0.79	0.906	0.660
IL17	<	X14	1.012	0.060	16.741	***	0.80		
IL16	<	X14	1.074	0.061	17.531	***	0.84		

The confirmatory factor analysis is carried out on each model when it reaches the optimum. As shown in Table 4, the standardized factor loads of all items ranged from 0.62 to 0.89, and passed the significance test. The component reliability (CR) is greater than 0.8. The mean variance-explanatory value (AVE) of each dimension is greater than 0.5, which is in line with the standards of (Black et al., 2010; Sharma et al., 1996), that is, the standardized factor load is greater than 0.5, the component reliability (CR) is greater than 0.7, and the mean variance-explanatory value (AVE) is greater than 0.5. Therefore, the convergence validity of each dimension of Knowledge Management Process can be verified.

Table 4 Convergence	e validity analysis	s of Knowledge	Management Process
			8

Items	Path	Dimensions	Estimate	S.E.	C.R.	P- value	Std	CR	AVE
M11	<	KM	1.071	0.127	8.406	***	0.82		
M12	<	KM	0.764	0.095	8.063	***	0.67	0.792	0.561
M13	<	KM	1				0.75		
KM5	<	M11	1				0.84	0.000	0.595
KM4	<	M11	0.899	0.058	15.464	***	0.75	0.880	

KM3	<	M11	0.915	0.060	15.332	***	0.75		
KM2	<	M11	0.865	0.059	14.648	***	0.72		
KM1	<	M11	0.976	0.060	16.280	***	0.79		
KM10	<	M12	1				0.78		
KM9	<	M12	0.984	0.075	13.057	***	0.72		
KM8	<	M12	0.897	0.072	12.409	***	0.68	0.867	0.568
KM7	<	M12	1.120	0.077	14.633	***	0.80		
KM6	<	M12	1.058	0.072	14.646	***	0.78		
KM15	<	M13	1				0.89		
KM14	<	M13	0.808	0.052	15.570	***	0.74		
KM13	<	M13	0.630	0.052	12.156	***	0.62	0.869	0.573
KM12	<	M13	0.821	0.051	16.173	***	0.74		
KM11	<	M13	0.883	0.052	17.028	***	0.77		

The confirmatory factor analysis is carried out on each model when it reaches the optimum. As shown in Table 5, the standardized factor loads of all items ranged from 0.65 to 0.83 and passed the significance test. The component reliability (CR) is greater than 0.8. The mean variance-explanatory value (AVE) of each dimension is greater than 0.5, which is in line with the standards of (Black et al., 2010; Sharma et al., 1996), that is, the standardized factor load is greater than 0.5, the component reliability (CR) is greater than 0.7, and the mean variance-explanatory value (AVE) is greater than 0.5. Therefore, the convergence validity of Innovation Capabilities of Knowledge workers in each dimension is confirmed.

Items	Path	Dimensions	Estimate	S.E.	C.R.	P- value	Std	CR	AVE
M21	<	IC	1.149	0.129	8.927	***	0.83		
M22	<	IC	0.976	0.113	8.608	***	0.75	0.827	0.615
M23	<	IC	1				0.77		
IC5	<	M21	1				0.81		
IC4	<	M21	0.906	0.061	14.952	***	0.75		0.628
IC3	<	M21	1.023	0.062	16.492	***	0.81	0.894	
IC2	<	M21	0.962	0.061	15.796	***	0.78		
IC1	<	M21	1.017	0.061	16.638	***	0.81		
IC10	<	M22	1				0.76		
IC9	<	M22	0.918	0.071	13.013	***	0.72	0.864	0 560
IC8	<	M22	0.94	0.074	12.625	***	0.71		0.560
IC7	<	M22	1	0.072	13.855	***	0.76		

Table 5 Convergence validity analysis of Innovation Capabilities of Knowledge workers

IC6	<	M22	1.11	0.078	14.249	***	0.79		
IC15	<	M23	1				0.80		
IC14	<	M23	0.81	0.067	12.126	***	0.67		
IC13	<	M23	0.84	0.071	11.818	***	0.66	0.835	0.505
IC12	<	M23	0.785	0.066	11.814	***	0.65		
IC11	<	M23	0.989	0.07	14.055	***	0.76		

The confirmatory factor analysis is carried out on each model when it reaches the optimum. As shown in Table 6, the standardized factor loads of all items ranged from 0.70 to 0.84 and passed the significance test. The component reliability (CR) is greater than 0.8. The mean variance-explanatory value (AVE) of each dimension is greater than 0.6, which is in line with the standards of (Black et al., 2010; Sharma et al., 1996), that is, the standardized factor load is greater than 0.5, the component reliability (CR) is greater than 0.7, and the mean variance-explanatory value (AVE) is greater than 0.5. Therefore, the convergence validity of each dimension of Enterprise Innovation Performance is confirmed.

Items	Path	Dimensions	Estimate	S.E.	C.R.	P- value	Std	CR	AVE
EI5	<	Y11	1				0.84		
EI4	<	Y11	0.783	0.056	14.006	***	0.70		
EI3	<	Y11	0.86	0.054	15.852	***	0.77	0.893	0.627
EI2	<	Y11	1.016	0.054	18.954	***	0.86		
EI1	<	Y11	0.924	0.056	16.376	***	0.78		
EI10	<	Y12	1				0.81		
EI9	<	Y12	0.965	0.062	15.636	***	0.80		
EI8	<	Y12	0.897	0.06	14.988	***	0.75	0.892	0.625
EI7	<	Y12	0.965	0.061	15.891	***	0.78		
EI6	<	Y12	1.029	0.064	15.971	***	0.81		

Table 6 Convergence validity analysis of Enterprise Innovation Performance

After checking the fit of the model, the structural equation model is used to test the relationship between the study variables. AMOS output results show that the standardized factor load of each observed variable is almost greater than 0.7, which is in line with the ideal standard. All parameter estimates reach significant levels, and the measured residuals for each variable are small and positive. Figure 2 shows the structural equation model.

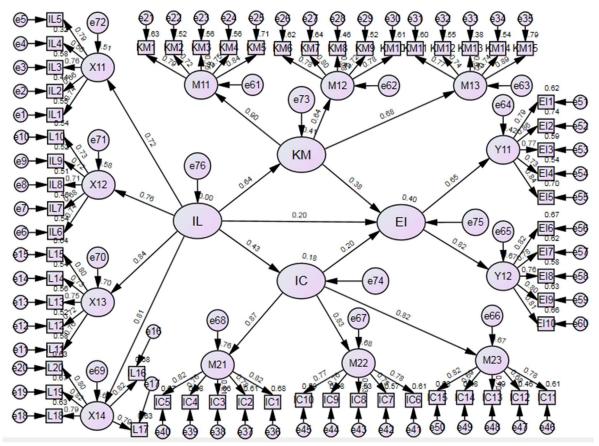


Figure 2 Overall results of structural equation model

Hypothesis testing

According to the theoretical conceptual model, the structural equation model constructed in this study contains four main variables, including the independent variable Inter-organizational Learning. Mediator variables Knowledge Management Process, Innovation Capabilities of Knowledge workers, dependent variables Enterprise Innovation Performance. Each of these four variables has two or more dimensions, Among them, Inter-organizational Learning includes The amount of knowledge exchange, Degree of information sharing and Management support and Cultural acceptance, Knowledge Management Process includes Knowledge Creation, Knowledge Sharing and Knowledge Utilization; Innovation Capabilities of Knowledge workers include Imagination, Presentation Skill and Knowledge Accumulation; Enterprise Innovation Performance includes Market Performance and Product Performance. In this study, AMOS software was used to draw a path map, the maximum likelihood method was used to test the fit degree of the research model, and the fitting index of the model and the estimated value of each path coefficient were calculated. The specific path coefficient of each hypothesis was shown in Figure 3-7.

The standardized path coefficient of Inter-organizational Learning (IL) on Knowledge Management Process (KM) is 0.638 (P<0.001), it can be seen that Inter-organizational Learning (IL) has a significant positive impact on Knowledge Management Process (KM), assuming H1 is established, as shown in FIG. 3.



Note: *** indicates a significant difference at the 0.001 level

Figure 3 Test results of hypothesis 1

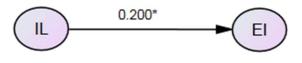
The standardized path coefficient of Inter-organizational Learning (IL) on Innovation Capabilities of Knowledge workers (IC) was 0.428 (P< 0.001), it can be seen that Inter-organizational Learning (IL) has a significant positive impact on Innovation Capabilities of Knowledge workers (IC), assuming H2 is established, as shown in FIG. 4.



Note: *** indicates a significant difference at the 0.001 level

Figure 4 Test results of hypothesis 2

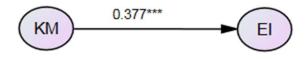
The standardized path coefficient of Inter-organizational Learning (IL) on Enterprise Innovation Performance (EI) is 0.200 (P<0.05), it can be seen that Inter-organizational Learning (IL) has a significant positive impact on Enterprise Innovation Performance (EI), assuming that H3 is established, as shown in Figure 5.



Note: * indicates a significant difference at the 0.05 level

Figure 5 Test results of hypothesis 3

The standardized path coefficient of Knowledge Management Process (KM) on Enterprise Innovation Performance (EI) is 0.377 (P< 0.001), it can be seen that Knowledge Management Process (KM) has a significant positive impact on Enterprise Innovation Performance (EI), assuming that H4 is established, as shown in Figure 6.



Note: * indicates a significant difference at the 0.01level

Figure 6 Test results of hypothesis 4

The standardized path coefficient of Innovation Capabilities of Knowledge workers (IC) for Enterprise Innovation Performance (EI) was 0.204 (P<0.001), it can be seen that Innovation Capabilities of Knowledge workers (IC) have a significant positive impact on Enterprise Innovation Performance (EI), assuming that H5 is established, as shown in Figure 7.



Note: * indicates a significant difference at the 0.01level

Figure 7 Test results of hypothesis 5

Detailed information on path coefficients and hypothesis testing of the four latent variables in this study is shown in Table 7.

Path	1		Estimate	S.E.	C.R.	P-value	Std Regressior Weights	Resul t
KM	< -	IL	0.500	0.069	7.247	***	0.638	TRUE
IC	< -	IL	0.440	0.075	5.899	***	0.428	TRUE
EI	< -	KM	0.457	0.137	3.344	***	0.377	TRUE
EI	< -	IC	0.188	0.069	2.728	**	0.204	TRUE
EI	< -	IL	0.190	0.097	1.962	*	0.200	TRUE
X1 1	< -	IL	0.717	0.077	9.293	***	0.715	TRUE
X1 2	< -	IL	0.832	0.087	9.546	***	0.759	TRUE
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Table 7 The path coefficient between latent variables and the result of hypothesis testing

X1	<	IL	0.939	0.090	10.42	***	0.835	TRUE
3	-				1			
X1	<	IL	1.000				0.806	TRUE
4	-							
M1	<	KM	1.427	0.165	8.667	***	0.898	TRUE
1	-							
M1	<	KM	0.959	0.121	7.921	***	0.642	TRUE
2	-			-				
M1	<	KM	1.000				0.684	TRUE
3	-							
M2	<	IC	1.146	0.107	10.75	***	0.875	TRUE
1	-	10	11110	0.107	0		0.072	IRCL
M2	<	IC	1.085	0.106	10.23	***	0.827	TRUE
2	-	ie	1.005	0.100	8		0.027	IROL
M2	<	IC	1.000				0.819	TRUE
3	-	IC .	1.000				0.017	IKUL
Y1	<	EI	0.826	0.129	6.403	***	0.647	TRUE
1	-	LI	0.820	0.129	0.405		0.047	IKUE
Y1	<	EI	1.000				0.817	TRUE
2	-	EI	1.000				0.01/	IKUE
$N_{ata} * * * (D > 0.001) * * (D > 0.005) * (D > 0.01)$								

Note: ***(P<0.001), **(P<0.005), *(P<0.01),

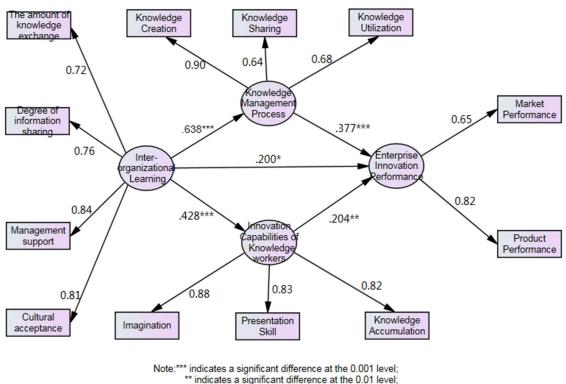
Hypothesis test result

According to the results analyzed in the previous section, this study summarized the test results of the research hypotheses. Out of the five research hypotheses proposed in this study, five hypotheses were supported, as shown in Table 4.8, and the results of conceptual model path analysis were shown in Figure 8.

Table 8 Hypothesis test result

Hypothesi s	Hypothetical content	Result
H1	Inter-organizational learning has a positive impact on the knowledge management process.	Supported
H2	Inter-organizational learning has a positive impact on the innovation capability of knowledge workers.	Supported
Н3	Inter-organizational learning has a positive impact on the innovation performance of technology-based small and medium-sized enterprises.	Supported
H4	The knowledge management process has a positive impact on the innovation performance of technology-based small and medium-sized enterprises.	Supported

The innovation capability of knowledge workers has apositive impact on the innovation performance of technology- Supportedbased small and medium-sized enterprises.



* indicates a significant difference at the 0.05 level.

Figure 8 Conceptual model path analysis results

Conclusion

This paper takes enterprise innovation performance as the core of the research, puts forward a conceptual model, and shows that inter-organizational learning and knowledge management are becoming more and more important to the innovation of technology-based SMEs. The empirical test draws the following conclusions:

First, inter-organizational learning positively affects the innovation performance of SMEs. Inter-organization learning improves innovation performance through various kinds of information exchange and knowledge exchange, and enterprises can obtain complementary resources by utilizing the innovation process of external partners. Second, inter-organizational learning positively affects the knowledge management process. Because of the mediation effect mechanism in the knowledge management process, the inter-organization learning on the knowledge management process is actually the test of the chain mediation effect. Third, the process of knowledge management positively affects the innovation performance of small and medium-sized technology-based enterprises. Because of the intermediary effect mechanism within the knowledge management process, the influence of the knowledge management process on the innovation performance is a chain. Fourth, the innovation ability of knowledge-based employees

positively regulates the relationship between knowledge utilization and innovation performance of technology-based SMEs. When the innovation ability of knowledge-based employees is stronger, the knowledge utilization degree of the organization will be higher, and small and medium-sized technology-based enterprises The better the innovation performance will be.

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