THE RELATIONSHIP BETWEEN KNOWLEDGE MANAGEMENT CAPABILITY AND INNOVATION PERFORMANCE OF SMALL AND MEDIUM-SIZED ENTERPRISES

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ABSTRACT

This study explores the impact of Knowledge Management Capability (KMC) on the innovation performance of small and medium-sized enterprises (SMEs) in Hunan Province, China. Given the pivotal role SMEs play in China's economic development, particularly in the diverse industrial landscape of Hunan, this research investigates how key dimensions of KMC—namely, knowledge production, knowledge conversion, and knowledge application capabilities—influence innovation performance. Using a quantitative survey methodology, the study employed structured questionnaires to collect data. The results reveal a significant positive relationship between the dimensions of KMC and innovation performance, suggesting that enhancing knowledge management practices significantly boosts the innovation output of SMEs. These findings offer valuable insights for shaping regional economic strategies and underscore the importance of KMC in driving sustainable growth and competitiveness among SMEs.

Keywords: Knowledge Production Capability, Knowledge Conversion Capability, Knowledge Application Capability, Innovation Performance

1. INTRODUCTION

Small and Medium-sized Enterprises (SMEs) play a crucial role in driving a nation’s economic development, acting as engines of growth and serving as significant contributors to job creation and innovation (Wang, 2014; Yang et al., 2016). SMEs are often more adaptable and flexible compared to larger corporations, making them critical players in fostering innovation within various industries. Given their agility and ability to quickly respond to market demands, SMEs are well-positioned to experiment with new products, services, and business models, which enables them to thrive in a competitive environment (Xie & Wang, 2017). In the current global economy, where technological advancements and market shifts occur at an unprecedented rate, the ability to innovate is not just an advantage—it is a necessity for SMEs (Gong et al., 2018). Innovation enables SMEs to differentiate themselves from competitors, meet the evolving needs of their customers, and improve operational efficiency (Zhao & Li, 2019). For instance, adopting innovative technologies can enhance product development processes, leading to the creation of higher-quality goods or services that resonate more effectively with market demands (Cheng & Hu, 2020). Additionally, SMEs that prioritize innovation are often better equipped to exploit new opportunities, reduce operational costs, and address the challenges posed by globalization and digital transformation (Chen et al., 2020). Moreover, the significance of innovation extends beyond individual firm success. It plays a pivotal role in boosting regional and national economies by enhancing productivity and stimulating new industries (Liu & Zhang, 2019). According to a study by Zhao and Li (2019), SMEs that engage in consistent innovation contribute significantly to the creation of new job opportunities, particularly in sectors characterized by rapid technological change. Consequently, innovation within SMEs not only ensures their sustainability but also positively impacts broader economic growth and development (Cheng & Hu, 2020).In summary, innovation is indispensable for SMEs seeking long-term success and competitiveness. By embedding innovation into their core strategies, SMEs can achieve greater market penetration, enhance customer satisfaction, and sustain their growth trajectory in an increasingly dynamic business environment (Chen et al., 2020; Liu & Zhang, 2019).

The innovation capacity of SMEs is shaped by both external market conditions and internal factors, with Knowledge Management Capability (KMC) being a critical element. KMC refers to an organization's ability to create, acquire, store, share, and apply knowledge effectively (Gu et al., 2017). For SMEs, leveraging KMC offers a strategic advantage, allowing them to stay competitive and enhance innovation (Tseng & Goo, 2005). KMC enhances innovation by facilitating knowledge creation, acquisition, storage, sharing, and application (Nonaka & Takeuchi, 1995). These processes help SMEs to adapt to market changes, optimize resources, and implement innovative solutions (Zack, 1999). For instance, knowledge creation enables SMEs to generate new ideas, while knowledge sharing promotes collaboration across units, leading to better problem-solving (Yang, 2007). Moreover, knowledge application allows SMEs to implement innovative solutions in products and processes, directly boosting innovation performance (Darroch, 2005).

While extensive research has been conducted on the relationship between knowledge management and organizational performance, there remains a lack of comprehensive studies that focus specifically on Knowledge Management Capability (KMC) and its direct impact on innovation performance within SMEs, particularly in the context of emerging markets like Hunan Province, China (Li & Zhang, 2019). Many existing studies emphasize large corporations, often overlooking the unique challenges and opportunities faced by SMEs in implementing effective knowledge management practices (Wang et al., 2018). Furthermore, there is limited research on the mediating role of Organizational Intelligence (OI) in this relationship. The ability of OI to bridge the gap between KMC and innovation performance has not been adequately explored, leaving a gap in understanding how SMEs can leverage their knowledge management processes to drive smarter decision-making and more adaptive innovation strategies (Chen & Xu, 2020).

This study examines how the various dimensions of KMC impact the innovation performance of SMEs with a specific emphasis on the mediating role of Organizational Intelligence. By examining SMEs in Hunan Province, this research contributes to the field by providing insights into how knowledge management can be optimized in resource-constrained environments, offering practical recommendations for improving innovation outcomes through enhanced knowledge management and intelligence systems.

2. LITERATURE REVIEW

The literature reviews the existing literature on knowledge management capability, organizational intelligence, and innovation performance, with a focus on understanding how these concepts are interrelated and influence the innovation outcomes of small and medium-sized enterprises in Hunan Province, China. The study is anchored on the premise that KMC significantly impacts innovation performance, either directly or indirectly through organizational intelligence, a key mediator in this relationship.

2.1 Knowledge Management Capabilities

Knowledge management capability refers to the processes and practices by which organizations create, acquire, store, share, and apply knowledge to enhance performance. Effective knowledge management is essential for organizations aiming to sustain a competitive advantage, especially in dynamic and innovation-driven markets like SMEs (Chuang & Lin, 2013). The literature identifies three core dimensions of KMC, each playing a distinct role in the innovation process.

Knowledge production capability refers to an organization’s ability to generate new knowledge by acquiring and integrating knowledge from external and internal sources. Studies have consistently found a direct relationship between knowledge production and innovation performance. Firms with high knowledge production capabilities can more effectively generate innovative ideas, leading to improved innovation outcomes in terms of product, process, and management innovations (Oliveira, 2019; Daghfous & Belhassen, 2018). Additionally, knowledge production is crucial in enhancing organizational intelligence (OI), as it fosters a culture of learning and adaptability, which enhances decision-making and responsiveness.

The ability to transform tacit knowledge into explicit knowledge and vice versa is critical for innovation. Nonaka and Takeuchi’s SECI model (1995)—which highlights socialization, externalization, combination, and internalization—forms the foundation for understanding knowledge conversion in organizations. By effectively converting knowledge, firms can create a continuous cycle of innovation that supports both incremental and radical innovations (Choi & Lee, 2003). Research suggests that knowledge conversion has a direct impact on innovation performance, as it enables organizations to transfer valuable insights across departments and functions, improving overall innovation efficiency(Damanpour, 1991).

Knowledge application capability focuses on how organizations utilize their knowledge to improve processes, decision-making, and product development. Firms that can apply their knowledge effectively are better able to translate their intellectual resources into tangible outcomes, such as new products or improved operational efficiency (Weisberg, 2006). Knowledge application capability is particularly important in SMEs, where agility and adaptability can significantly influence success in fast-paced markets (Sarin & McDermott, 2003). This capability has been found to have a direct and significant effect on innovation performance, as it enables firms to maintain a competitive edge by continuously enhancing their products and services.

2.2 Organizational Intelligence

Organizational Intelligence refers to an organization's capacity to make smart decisions, adapt to changes, and leverage its intellectual resources effectively. OI has become increasingly important in the modern business environment, where firms must navigate complex and rapidly changing market conditions (Albrecht, 2002). The literature suggests that OI plays a crucial role in mediating the relationship between KMC and innovation performance. Firms that possess high levels of OI are better equipped to apply their knowledge management capabilities to foster innovation, as they can make more informed decisions, react more swiftly to market changes, and align their innovation strategies with external demands.

OI itself directly influences a firm’s ability to innovate by fostering a culture of informed decision-making and active adaptation to market conditions. Firms with high OI are more likely to engage in innovative activities because they can anticipate future trends, assess risks, and make decisions that align with long-term strategic goals (Alavi & Leidner, 2001). OI mediates the relationship between KMC and innovation performance by ensuring that the knowledge produced, converted, and applied is aligned with the organization’s strategic objectives. As firms enhance their knowledge management capabilities, OI helps in translating these capabilities into actionable innovations that improve performance. This mediating role is essential for SMEs, as it allows them to bridge the gap between knowledge and innovation outcomes (Subramaniam & Youndt, 2005).

2.3 Innovation Performance

Innovation performance refers to an organization’s success in developing and implementing new ideas, products, or processes that result in competitive advantages. In the context of SMEs, innovation performance is a critical determinant of long-term survival and growth, as these firms often operate in highly competitive and resource-constrained environments (Rosenbusch et al., 2011). In terms of measuring innovation performance, numerous previous literature by scholars has been conducted from the following three dimensions. Innovation speed, The pace at which new innovations are developed and introduced to the market. Faster innovation speeds are crucial for SMEs in rapidly evolving markets, where being first to market can provide significant advantages (Yusuf & Udin, 2019). Innovation quality means the extent to which innovations meet customer needs, improve product or process performance, and offer unique value propositions. High-quality innovations contribute to customer satisfaction, market differentiation, and long-term success (Jiménez-Jiménez & Sanz-Valle, 2011). Innovation quantity refers to the number of new products, services, or processes introduced during a certain period of time. A higher innovation quantity reflects an organization’s active pursuit of opportunities and willingness to take risks in new ventures (Du et al., 2014).

2.4 Relationship between KMC, OI, and Innovation Performance

Empirical studies consistently demonstrate the significant impact of KMC on innovation performance (Scarborough, 2003; Borghini, 2005). Enterprises with robust knowledge management capabilities are better equipped to reduce redundancy, enhance responsiveness to market changes, and foster creativity—key factors in achieving superior innovation outcomes.

This study builds on this literature by examining not only the direct effects of KMC on innovation performance but also the mediating role of organizational intelligence in this relationship.

The three dimensions of KMC—knowledge production, conversion, and application—are all found to have direct, positive effects on innovation performance . Organizations with stronger capabilities in these areas are more likely to excel in innovation speed, quality, and quantity (Nonaka & Takeuchi, 1995). The study also posits that OI mediates the relationship between KMC and innovation performance. Firms with high OI can more effectively harness their KMC to drive innovation, ensuring that their knowledge management efforts lead to actionable and market-relevant innovations (Subramaniam & Youndt, 2005). Based on the literature review, the study proposes the following hypotheses.

H1: Knowledge production capability has a direct and significant effect on innovation performance.

H2: Knowledge conversion capability has a direct and significant effect on innovation performance.

H3: Knowledge application capability has a direct and significant effect on innovation performance.

H4: Knowledge production capability has a direct and significant effect on organizational intelligence.

H5: Knowledge conversion capability has a direct and significant effect on organizational intelligence.

H6: Knowledge application capability has a direct and significant effect on organizational intelligence.

H7: Organizational intelligence has a direct and significant effect on innovation performance.

H8: Organizational intelligence plays a mediating role in the impact of KMC on innovation performance.

3. Research Methodology

To test the research model, a structured survey was conducted among SMEs in Hunan Province, China. A five-point Likert scale ranging from "1" (totally disagree) to "5" (totally agree)" was used to collect data on various constructs. The measurement scales for the variables were adapted from previous studies.

Knowledge production capability was measured using items developed by Fong and Choi (2009), focusing on the organization’s ability to generate and acquire new knowledge. Knowledge conversion capability, based on the SECI model (Nonaka & Takeuchi, 1995) and adapted by Choi and Lee (2003), assessed how well the organization can transform knowledge between explicit and tacit forms. Knowledge application capability, also adapted from Fong and Choi (2009), measured the effectiveness of utilizing knowledge for process improvement and decision-making.

For innovation performance, innovation speed was measured with five items, following Chen and Hambrick (1995) and Liao et al. (2010), evaluating the firm's ability to generate ideas and launch new products quickly. Innovation quality was assessed with scales developed by Haner (2002), Lahiri (2010), and Lee and Choi (2003), measuring creativity and novelty. Innovation quantity was measured using scales adapted from Keeble and Wilkinson (1999) and Du et al. (2014), focusing on the number of new products, services, and processes introduced.

A sample of CEOs, senior managers, and experts from different industries participated in the study. Data analysis was conducted using SPSS and AMOS, employing Structural Equation Modeling (SEM) to analyze the relationships between knowledge management capabilities, organizational intelligence, and innovation performance.

4. Results and Finding

The analysis was conducted using SPSS and Smart-pls, with the primary objective of testing the proposed hypotheses and examining the relationships between knowledge management capabilities, organizational intelligence, and innovation performance.This article analyzes data collected from small and medium-sized enterprises in Hunan Province, China, and the research results and findings are as follows.

4.1 Descriptive Statistics

The survey questionnaire design of this study is to examine the relationship between knowledge management capability and corporate innovation performance. The questionnaire is prepared based on the research purpose, referring to relevant literature data and previous scales. This study first conducted a descriptive statistical analysis on the personal characteristics of the survey subjects (gender, age, education level, company position, time of establishment, and nature of the company), as shown in Table 1.

Table 1 Description of sample feature distribution

Variable	Category	Percentage
Gender	male	53.3%
	female	46.7%
Age	≦25	18.9%
	26 ~ 35	29.1%
	36 ~ 45	23.5%
	46 ~ 55	19.3%
	≧56	9.2%
Education	High school and below	7.7%
	Junior college	33.7%
	Undergraduate	45.3%
	Master and above	13.3%
Levels	Middle and senior managers	43.2%

	Line managers	33.0%
	General staff	23.8%
Years of establishment	More than 10 years	21.7%
	5 ~ 10 years	33.0%
	2~ 4 years	38.0%
	1 year and less	7.3%
Nature of enterprise	State-owned enterprise	31.9%
	Private enterprise	49.8%
	Other	18.3%

As shown in the table above, the number of male respondents in this survey is higher than that of female respondents, accounting for 53.3% and 46.7% respectively; The majority of respondents were aged between 26 and 35, accounting for 29.1%, followed by those aged between 36 and 45, accounting for 23.5%. Among the respondents, the number of undergraduates is the highest, accounting for 45.3%, while the proportion of Junior college proportion 33.7%. The number of respondents whose company position is middle and senior managers is the highest, accounting for 43.2%; The number of line managers is relatively high, accounting for 33.0%; Many respondents come from companies that have been established for 2-4 years, accounting for 38.0%. The proportion of respondents whose business nature is private enterprise is the highest, accounting for 49.8%, while the proportion of state-owned enterprise is 31.9%.

4.2 Reliability and Validity

As indicated in Table 2 and Table 3, the Cronbach's Alpha values for all first-order and second-order dimensions range from 0.800 to 0.896, surpassing the threshold of 0.7, which suggests good reliability for each dimension (DeVellis, 2016). The factor loadings for each item within these dimensions vary between 0.803 and 0.922, exceeding the recommended minimum of 0.7, further supporting the reliability of the measurements (Hair et al., 2019). Moreover, the Composite Reliability (CR) values for the dimensions range from 0.883 to 0.933, which is well above the acceptable threshold of 0.7 (Hair et al., 2017). The Average Variance Extracted (AVE) values, ranging from 0.653 to 0.833, also surpass the benchmark of 0.5, indicating strong convergent validity for each dimension (Hair et al., 2017). These results confirm that the constructs used in this study exhibit robust reliability and validity.

Table 2 Results of Reliability and Validity Analysis of First-order Variables

Item	Factor loading	T	P	Cronbach 's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
EA1 <- A1-EA	0.895	82.457	0.000	0.893	0.901	0.933	0.823
EA2 <- A1-EA	0.922	127.927	0.000				
EA3 <- A1-EA	0.904	107.668	0.000				
IA1 <- A2-IA	0.908	107.858	0.000	0.851	0.853	0.910	0.771

IA2 <- A2-IA	0.871	67.571	0.000				
IA3 <- A2-IA	0.853	63.953	0.000				
KC1 <- A3-KC	0.836	56.578	0.000	0.894	0.895	0.922	0.703
KC2 <- A3-KC	0.848	65.304	0.000				
KC3 <- A3-KC	0.834	51.172	0.000				
KC4 <- A3-KC	0.833	55.244	0.000				
KC5 <- A3-KC	0.840	60.192	0.000				
IT1 <- B1-IT	0.891	85.598	0.000	0.845	0.853	0.906	0.763
IT2 <- B1-IT	0.858	56.042	0.000				
IT3 <- B1-IT	0.870	65.855	0.000				
ET1 <- B2-ET	0.855	56.549	0.000	0.832	0.833	0.899	0.748
ET2 <- B2-ET	0.875	75.768	0.000				
ET3 <- B2-ET	0.865	65.860	0.000				
SC1 <- B3-SC	0.879	71.536	0.000	0.849	0.853	0.908	0.767
SC2 <- B3-SC	0.869	65.857	0.000				
SC3 <- B3-SC	0.880	73.376	0.000				
CB1 <- B4-CB	0.865	69.425	0.000	0.850	0.853	0.909	0.769
CB2 <- B4-CB	0.885	93.263	0.000				
CB3 <- B4-CB	0.881	75.509	0.000				
MK1 <- C1-MK	0.862	73.894	0.000	0.896	0.897	0.923	0.707
MK2 <- C1-MK	0.817	49.985	0.000				
MK3 <- C1-MK	0.832	66.492	0.000				
MK4 <- C1-MK	0.844	64.644	0.000				
MK5 <- C1-MK	0.848	67.116	0.000				
UK1 <- C2-UK	0.872	73.806	0.000	0.828	0.831	0.897	0.744
UK2 <- C2-UK	0.868	69.344	0.000				
UK3 <- C2-UK	0.848	53.966	0.000				
PK1 <- C3-PK	0.856	61.679	0.000	0.823	0.824	0.894	0.738
PK2 <- C3-PK	0.862	70.523	0.000				
PK3 <- C3-PK	0.859	62.332	0.000				
SD1 <- D1-SD	0.850	68.114	0.000	0.868	0.868	0.910	0.717
SD2 <- D1-SD	0.855	66.264	0.000				
SD3 <- D1-SD	0.850	63.097	0.000				
SD4 <- D1-SD	0.831	61.579	0.000				
AA1 <- D2-AA	0.902	111.992	0.000	0.858	0.860	0.914	0.779
AA2 <- D2-AA	0.879	87.178	0.000				
AA3 <- D2-AA	0.867	72.001	0.000				
IS1 <- E1-IS	0.865	81.155	0.000	0.885	0.886	0.916	0.684
IS2 <- E1-IS	0.817	52.751	0.000				
IS3 <- E1-IS	0.831	57.767	0.000				
IS4 <- E1-IS	0.804	49.928	0.000				
IS5 <- E1-IS	0.819	49.372	0.000				

IQN1 <- E2-IQN	0.901	107.742	0.000	0.873	0.873	0.922	0.797
IQN2 <- E2-IQN	0.889	89.562	0.000				
IQN3 <- E2-IQN	0.888	90.878	0.000				
IQI1 <- E3-IQI	0.851	77.707	0.000	0.894	0.895	0.922	0.702
IQI2 <- E3-IQI	0.840	66.064	0.000				
IQI3 <- E3-IQI	0.844	72.348	0.000				
IQI4 <- E3-IQI	0.839	63.191	0.000				
IQI5 <- E3-IQI	0.816	53.625	0.000				

Table 3 Results of Reliability and Validity Analysis of Second-order Variables

Item	Factor loading	T	P	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
A1-EA <- A-KPC	0.861	62.071	0.000	0.841	0.844	0.904	0.758
A2-IA <- A-KPC	0.873	75.022	0.000				
A3-KC <- A-KPC	0.878	81.436	0.000				
B1-IT <- B-KCC	0.809	39.524	0.000	0.823	0.824	0.883	0.653
B2-ET <- B-KCC	0.803	47.578	0.000				
B3-SC <- B-KCC	0.811	49.824	0.000				
B4-CB <- B-KCC	0.809	45.445	0.000				
C1-MK <- C-KAC	0.860	67.419	0.000	0.807	0.809	0.886	0.721
C2-UK <- C-KAC	0.834	50.350	0.000				
C3-PK <- C-KAC	0.853	58.794	0.000				
D1-SD <- D-OI	0.919	126.320	0.000	0.800	0.802	0.909	0.833
D2-AA <- D-OI	0.907	108.182	0.000				
E1-IS <- E-EIP	0.878	83.776	0.000	0.845	0.845	0.907	0.764
E2-IQN <- E-EIP	0.880	78.744	0.000				
E3-IQI <- E-EIP	0.864	71.509	0.000				

To assess discriminant validity, the study first employed the AVE method. As seen in Table 4, the square roots of the AVE for each construct are higher than the correlations with other constructs, confirming discriminant validity (Fornell & Larcker, 1981). Additionally, the HTMT (Heterotrait-Monotrait) ratio was used, with all values falling below the threshold, further affirming the constructs' distinctiveness (Henseler, Ringle, & Sarstedt, 2015). Finally, the study assessed discriminant validity through cross-loading analysis, which revealed no cross-loadings. All items had higher loadings on their respective constructs than on others, reinforcing the presence of discriminant validity (Hair et al., 2010).

Table 4 Results of Discriminant Validity (Fornell-Larcker approach)

	A-KPC	B-KCC	C-KAC	D-OI	E-EIP
A-KPC	0.871				
B-KCC	0.454	0.808			
C-KAC	0.372	0.425	0.849		
D-OI	0.529	0.589	0.582	0.913	
E-EIP	0.541	0.579	0.552	0.661	0.874

4.3 The Evaluation of Structural Model

The structural model was evaluated using several key standards to ensure its robustness and validity, including assessments of model fit, predictive ability, collinearity diagnostics, and the significance and strength of path impacts.

As shown in Table 5, the R^2 value for D-OI (Organizational Intelligence) is 0.529, with an adjusted R^2 of 0.526, indicating that the model explains 52.9% of the variance in D-OI, reflecting strong explanatory power (Hair et al., 2019). Similarly, the R^2 value for E-EIP (Enterprise Innovation Performance) is 0.552, with an adjusted R^2 of 0.549, demonstrating that the model accounts for 55.2% of the variance in E-EIP, confirming the model's robustness. Additionally, the Q^2 values for D-OI and E-EIP are 0.435 and 0.416(Table 5), respectively, both exceeding the 0.35 threshold, suggesting that the model has strong predictive ability (Hair et al., 2019).

Table 5 The Results of R-squared (R^2) and Q-squared (Q^2)

Items	R-square	R-square adjusted	Q-square
D-OI	0.529	0.526	0.435
E-EIP	0.552	0.549	0.416

The Variance Inflation Factor (VIF) values were also examined to diagnose collinearity among predictor variables. As shown in Table 6, all VIF values are well below the threshold of 10, indicating no issues with multicollinearity in the model. Furthermore, the model fit was assessed using the Standardized Root Mean Square Residual (SRMR), with a value of 0.056, which is below the 0.08 threshold, indicating a good fit (Hu & Bentler, 1999).

Table 6 Variance Inflation Factor (VIF) of Variable

Item	VIF
A1-EA	1.933
A2-IA	2.103
A3-KC	1.955
B1-IT	1.801
B2-ET	1.695
B3-SC	1.715
B4-CB	1.686

C1-MK	1.766
C2-UK	1.702
C3-PK	1.779
D1-SD	1.800
D2-AA	1.800
E1-IS	2.097
E2-IQN	2.155
E3-IQI	1.887
A-KPC -> D-OI	1.325
A-KPC -> E-EIP	1.458
B-KCC -> D-OI	1.393
B-KCC -> E-EIP	1.618
C-KAC -> D-OI	1.284
C-KAC -> E-EIP	1.545
D-OI -> E-EIP	2.122

The bootstrap method (with 5,000 resamples) was used to calculate path coefficients and corresponding T-values, ensuring accuracy. Table 7 presents the path coefficients along with their T-values and significance levels. The results demonstrate a significant relationship between knowledge production capability and innovation performance, with a T-value of 5.761 at the 1% significance level, supporting the research hypothesis. Similar results were observed for the other six hypotheses, all of which were supported by the model.

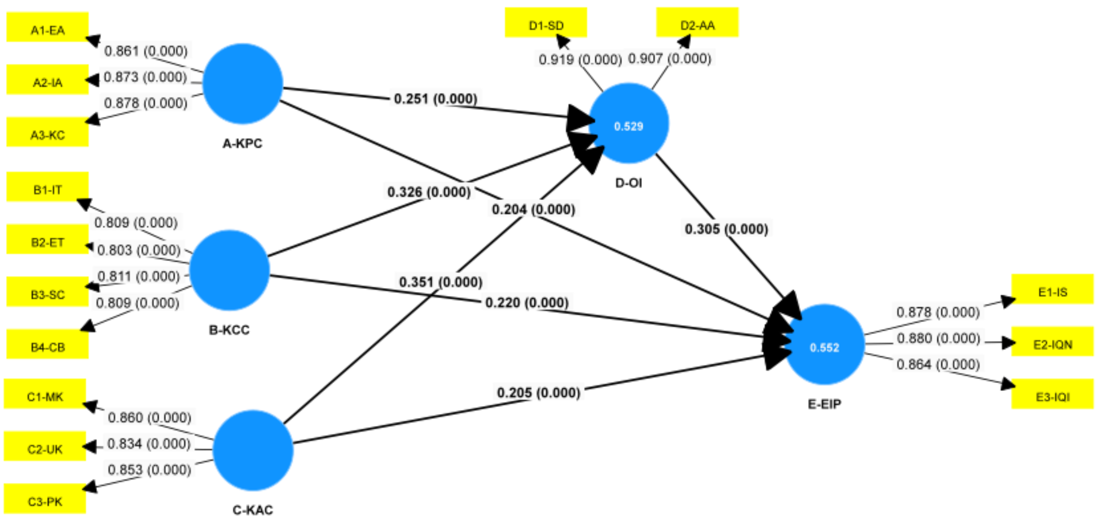

Figure 1 Path Coefficients of Structural Model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Hypothesis

A-KPC -> D-OI	0.251	0.251	0.038	6.666	0.000	accepted
A-KPC -> E-EIP	0.204	0.204	0.035	5.761	0.000	accepted
B-KCC -> D-OI	0.326	0.327	0.036	9.075	0.000	accepted
B-KCC -> E-EIP	0.220	0.219	0.040	5.515	0.000	accepted
C-KAC -> D-OI	0.351	0.349	0.038	9.248	0.000	accepted
C-KAC -> E-EIP	0.205	0.206	0.041	4.966	0.000	accepted
D-OI -> E-EIP	0.305	0.305	0.049	6.254	0.000	accepted

Table 7 The Results of Structural Model Path Hypothesis Testing

4.4 Mediation Analysis

This study analyzed the mediating effect of organizational intelligence on the relationship between the three dimensions of knowledge management capabilities —knowledge production capability, knowledge conversion capability, and knowledge application capability—and innovation performance using the Bootstrap mediation effect test.

Table 8 The Results of Analysis Bootstrap Mediation Effect Test

Items	Effect	Original sample	Sample mean	S.D.	T	P	2.50 %	97.50 %	Proportion
A-KPC -> D-OI -> E-EIP	Direct Effect	0.204	0.204	0.035	5.761	0.000	0.134	0.273	72.9%
	Indirect Effect	0.076	0.077	0.017	4.430	0.000	0.046	0.113	27.1%
	Total Effect	0.280	0.280	0.034	8.332	0.000	0.214	0.346	
B-KCC -> D-OI -> E-EIP	Direct Effect	0.220	0.219	0.040	5.515	0.000	0.140	0.297	69.0%
	Indirect Effect	0.099	0.100	0.020	4.987	0.000	0.064	0.141	31.0%
	Total Effect	0.319	0.319	0.036	8.930	0.000	0.249	0.388	
C-KAC -> D-OI -> E-EIP	Direct Effect	0.205	0.206	0.041	4.966	0.000	0.124	0.286	65.7%
	Indirect Effect	0.107	0.106	0.019	5.486	0.000	0.073	0.149	34.3%
	Total Effect	0.312	0.313	0.037	8.429	0.000	0.240	0.383	

As shown in Table 8, the results from the Bootstrap analysis confirm that organizational intelligence significantly mediates the relationship between each dimension of knowledge management capability and innovation performance. This suggests that organizational intelligence plays a crucial role in translating knowledge management capabilities into enhanced innovation performance, supporting the hypothesized mediating effect. The mediating role of OI strengthens the overall influence of KPC, KCC, and KAC on EIP, indicating that enterprises with strong organizational intelligence are more likely to leverage their knowledge management capabilities for improved innovation outcomes.

5. Conclusion and Discussion

This study reveals that the three dimensions of Knowledge Management (KM) capability—knowledge production capability (KPC), knowledge conversion capability (KCC), and knowledge application capability (KAC)—positively influence the innovation performance of small and medium-sized enterprises (SMEs) in Hunan Province. The empirical results demonstrate significant positive effects for each dimension, confirming their crucial role in driving innovation. These findings align with prior research that underscores the importance of KM capabilities in expanding the breadth and depth of knowledge resources, which in turn fosters innovation (Li Mingxing et al., 2011; Zhu Hongbo, 2015; Weisberg, 2006). For instance, Nonaka and Takeuchi (1995) highlight that effective KM practices enhance knowledge creation and utilization, while Li Mingxing et al. (2011), Sarin and McDermott (2003), and Xu Haining (2007) emphasize the impact of KM on innovation by improving knowledge storage and application.

The study provides valuable insights into how different KM capabilities contribute to innovation performance in SMEs. Specifically, it illustrates how effective knowledge production, conversion, and application can significantly enhance innovation outcomes. For SME managers and owners, these findings offer practical recommendations to optimize KM initiatives. By focusing on strengthening these KM dimensions, SMEs can improve their innovation capabilities, achieve better financial performance, and streamline operational processes. This, in turn, reinforces the connection between KM practices and overall business performance.

However, the study faces certain limitations. The sample is drawn exclusively from Hunan Province, which may limit the generalizability of the findings to other regions or countries. Future research should include firms from diverse regions and countries to offer a more global perspective. Additionally, the use of subjective performance measures may affect the robustness of the results. Future studies should incorporate objective performance metrics and examine companies over longer periods to account for the evolution of KM programs and their implementation lifecycle.

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