Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 9, No. 4, August, 2025

A Study of the Effects of Knowledge Management on Enterprise Innovation Performance

Juanjuan Qu [1], Hira Batool [1*], Kalim Ullah [2]

[1] School of Accountancy and Finance, Walailak University, Tha Sala, Nakhon Si Thammarat, 80160, Thailand.

[2] Department of Management, Xidian University, Shanxi, Xian 710071, China.

Abstract

This study aims to explore how knowledge management capability and enterprise innovation behavior jointly affect the innovation performance of manufacturing SMEs. Based on the background of the knowledge economy, we selected manufacturing SMEs with knowledge as their core competitiveness as the research object and constructed and optimized the theoretical model of "Knowledge Management Capability-Innovation Behavior-Innovation Performance". Based on the research data from 400 manufacturing SMEs in China, the study adopts the empirical analysis method and examines the relationship between the variables through structural equation modeling. The results show that knowledge management capability has a significant positive impact on firms' innovation performance, while firms' innovation behavior mediates the relationship between knowledge management capability and innovation performance. The findings of this study not only validate the key role of knowledge management in enhancing the innovation capability of enterprises but also reveal the path mechanism for enterprises to realize knowledge transformation and innovation results by stimulating innovative behaviors. Compared with previous studies, this study systematically optimizes the construction of theoretical models and the analysis of mediating effects, enriches the research content in the field of knowledge management and innovation performance, and provides new theoretical support and empirical evidence for the knowledge management practice and innovation strategy formulation of manufacturing SMEs.

Keywords:

Knowledge Management;
Innovative Behavior;
Enterprise Innovation Performance;
SEMs.

Article History:

Received:	31	March	2025
Revised:	09	July	2025
Accepted:	13	July	2025
Published:	01	August	2025

1- Introduction

In the present knowledge-driven economic environment, inter-enterprise competition increasingly relies on the acquisition, integration, and application of knowledge [1]. Especially in the context of manufacturing SMEs facing the double pressure of digital transformation and high-quality development, how to effectively carry out knowledge management (KM) to improve innovation performance has become an important issue that needs to be solved urgently [2]. Although studies have pointed out that knowledge management has a positive effect on enterprise innovation [3], there is still a lack of in-depth discussion on how knowledge management affects innovation performance through specific innovative behaviors.

Current literature mainly explores the direct impact of KM on enterprise innovation from the dimensions of knowledge acquisition [4], sharing [5], and application [6], or from the perspective of organizational learning [7],

* **CONTACT**: hira.ba@wu.ac.th; drbatoolhira@gmail.com

DOI: http://dx.doi.org/10.28991/ESJ-2025-09-04-030

absorptive capacity [8], and other mechanisms, but pays less attention to the mediating role of innovative behaviors, especially exploratory innovation and exploitative innovation, in which KM plays an important role. However, less attention has been paid to the mediating role of innovative behavior, especially exploratory innovation and exploitative innovation. In addition, most of the research focuses on large-scale or high-tech enterprises [9], and there is a relative lack of systematic research on how manufacturing SMEs can apply knowledge management to drive innovation in the context of limited resources and high organizational flexibility. Therefore, there is an urgent need to further refine the theoretical paths and conduct empirical studies that take into account the organizational characteristics of SMEs.

In order to fill the research gap mentioned above, this paper takes manufacturing SMEs as the research object, and explores how knowledge management affects enterprise innovation performance through two different types of innovative behaviors, namely, exploratory innovation and exploitative innovation. Based on the knowledge base view and dual innovation theory, the mediation model of "knowledge management → exploratory/exploitative innovation → innovation performance" is constructed, aiming at revealing the internal mechanism of knowledge management affecting innovation performance, and providing theoretical support and practical paths for SMEs to enhance their innovation capability.

The purpose of this study is to explore the impact mechanism of knowledge management on enterprise innovation performance and further analyze the mediating role played by innovation behavior in the process. To achieve the research objectives, the article is structured as follows. The introduction of this study introduces the research background, research gap, research content, and methodology. The theoretical background and hypotheses combine the relevant research results about knowledge management, innovative behavior, and innovation performance, clarifying the theoretical foundation, constructing the research model, and putting forward the research hypotheses. The research method, introducing the sample and explaining how each variable is measured. Data analysis and results, based on the questionnaire data, using empirical methods to validate the model and analyze how knowledge management affects enterprise innovation performance through innovative behavior. Lastly, the discussion and conclusion chapter summarizes the results of the study, presenting managerial insights and pointing out the shortcomings of the study and the future research direction.

2- Theoretical Background and Hypotheses

2-1- Knowledge Management and Exploratory & Exploitative Innovation

The resource-based view recognizes that knowledge is an important source of innovation and that enterprise innovation requires effective management of knowledge [10]. KM (knowledge management) provides an effective knowledge infrastructure for an organization, which collects, organizes, stores, and shares knowledge inside and outside the organization in a systematic way [11], which not only helps employees acquire the knowledge they need but also facilitates the flow of knowledge between different departments and hierarchical levels [12]. Through effective knowledge management, enterprises are better able to capture and utilize explicit and tacit knowledge, which is often the source of innovation [13]; at the same time, enterprises are able to stimulate the creativity and innovative thinking of their employees, thus facilitating breakthroughs in product development, process improvement, and market development [14].

KM emphasizes knowledge sharing and collaboration, which is particularly important for innovative behavior [15]. In a corporate culture that encourages knowledge sharing, employees are more willing to share their experiences and insights, which helps team members inspire each other to solve problems together [16]. Through cross-functional collaboration, enterprises can break down knowledge silos and realize the integrated use of knowledge to generate new ideas and solutions [17]. Knowledge management (KM) promotes knowledge acquisition, knowledge transformation, and knowledge exploitation through a systematic approach to enhance the innovation capability of enterprises in a comprehensive manner [18], and the interaction between KM and innovation behavior is reflected in the following three aspects.

First, knowledge acquisition is the starting point of KM, which involves the collection of explicit and tacit knowledge from internal and external environments [19]. This acquisition process involves not only extracting explicit knowledge from the literature, databases, and market research but also acquiring tacit knowledge through interaction, observation, and experience accumulation [20]. The effectiveness of knowledge acquisition depends on whether the organization has established a good knowledge-sharing culture and incentives [21].

Second, knowledge transformation is the process of organizing and integrating acquired knowledge [22], transforming tacit knowledge into explicit knowledge through the modes of socialization, externalization, combination, and internalization [23]. The encouragement of innovative behaviors by enterprises promotes mutual learning and exchange among employees, facilitating the process of making tacit knowledge explicit [24]. In addition, knowledge transformation requires technical and managerial support such as knowledge management systems and leadership involvement [21].

Finally, knowledge exploitation is the application of transformed knowledge to real business scenarios to solve problems and drive innovation [25, 26]. The key to knowledge exploitation is ensuring that knowledge is properly understood and applied to support decision-making, process improvement, and new product development [27]. Knowledge exploitation is not only dependent on individual competencies but also requires the support of organizational structures and processes [28]. The success of KM lies in its ability to efficiently transform and utilize acquired knowledge to continuously enhance the competitive advantage of the organization [29, 30].

In summary, KM helps enterprises remain innovative and competitive by allowing them to acquire, transform, and exploit knowledge [31]. On the basis of the above theoretical analyses, this paper proposes the following hypotheses:

Hypothesis 1a (H1a): Knowledge acquisition positively influences exploratory innovation.

Hypothesis 2a (H2a): Knowledge acquisition positively influences exploitative innovation.

Hypothesis 1b (H1b): Knowledge transformation positively influences exploratory innovation.

Hypothesis 2b (H2b): Knowledge transformation positively influences exploitative innovation.

Hypothesis 1c (H1c): Knowledge exploitation positively influences exploratory innovation.

Hypothesis 2c (H2c): Knowledge exploitation positively influences exploitative innovation.

2-2- Knowledge Management and Enterprise Innovation Performance

The knowledge base view further states that the processes of knowledge creation, integration, and application within an organization are decisive in driving innovation performance [32]. Knowledge management (KM) provides a structured infrastructure for collecting, organizing, storing, and sharing knowledge within and beyond organizations [11]. This facilitates knowledge flow across departments and hierarchies, enabling employees to access necessary information and fostering collaboration [12]. By capturing and leveraging both explicit and tacit knowledge—key drivers of innovation—KM stimulates creativity, leading to breakthroughs in product development, process optimization, and market expansion [13, 14].

KM emphasizes knowledge sharing and collaboration, which are essential for fostering innovation [32]. A culture of knowledge sharing enhances problem solving and teamwork [16], whereas cross-functional collaboration dismantles knowledge silos, promoting the transformation of diverse knowledge sources to generate novel ideas [33, 34].

KM enhances innovation through three key processes: knowledge acquisition, transformation, and exploitation [18]. Knowledge acquisition involves collecting explicit and tacit knowledge from internal and external sources, such as databases, market research, and experiential learning, with its effectiveness relying on a strong knowledge-sharing culture and incentives [19, 21]. Knowledge transformation refers to organizing and converting tacit knowledge into explicit knowledge through socialization, internalization, combination, and internalization, a process that is strengthened by KM systems and leadership support [21-23]. Finally, knowledge exploitation ensures that transformed knowledge is effectively applied in business contexts to support decision-making, process improvement, and innovation, which requires both individual competencies and organizational support [25, 28].

Hypothesis 3a (H3a): Knowledge acquisition positively affects enterprise innovation performance.

Hypothesis 3b (H3b): Knowledge transformation positively affects enterprise innovation performance.

Hypothesis 3c (H3c): Knowledge exploitation positively affects enterprise innovation performance.

2-3- Exploratory & Exploitative Innovation and Enterprise Innovation Performance

Behavioral innovation theory emphasizes that innovation is not only a change in concepts, but must be transformed into practical results through concrete actions [35]. Only when creativity is implemented into the actual behavior of the organization can the value of innovation be truly manifested [36]. Exploratory innovation (EI) involves groundbreaking attempts at technology, products, or markets, often with high risks and uncertainty [37, 38]. While it can provide significant market advantages, it requires effective risk management and resource allocation [39, 40]. It has been noted that breakthrough innovations can disrupt markets and create new growth opportunities [41]. Zahra & George (2002) [42] suggested that absorptive capacity helps enterprises manage the risks of EI and enhances innovation performance.

A dual innovation strategy, which combines exploratory and exploitative innovation, is key to improving overall innovation [43, 44]. Enterprises must optimize their organizational design to achieve this balance [45]. Absorptive capacity theory, which emphasizes the ability to recognize, absorb, and convert new knowledge into innovation, plays a crucial role in enterprise innovation [46].

On the basis of the above analyses, the following hypotheses were formulated for this study:

Hypothesis 4 (H4): Exploratory innovation has a positive effect on enterprise innovation performance.

Hypothesis 5 (H5): Exploitative innovation has a positive effect on enterprise innovation performance.

2-4- The Mediating Effects of Innovative Behavior

Exploratory innovation (EI) involves the development of new technologies, products, or services, often experimenting in uncharted territory [27]. It focuses on long-term technological breakthroughs and market opportunities and drives enterprises to create and apply knowledge in new areas [38, 47]. Exploratory innovation requires enterprises to invest significant resources and time in acquiring and integrating new knowledge and exploring unknown market needs or technology trends [37]. Effective knowledge management systems can support exploratory innovation by facilitating the acquisition, storage, and sharing of knowledge to enhance an enterprise's ability to innovate [21]. Jansen et al. (2005) [48] showed that an enterprise's knowledge management capabilities significantly affect its implementation of exploratory innovation. Knowledge management systems can help enterprises identify and integrate external knowledge resources and facilitate the generation and application of new knowledge, thus contributing to the success of exploratory innovation [32, 48].

Exploratory innovation usually drives enterprise innovation performance through the introduction of new technologies and business models [49]. Katila & Ahuja (2002) [50] reported that exploratory innovation helps enterprises gain a competitive advantage in the long run and enhances innovation performance. By continuously exploring and developing new areas, enterprises are able to identify new market opportunities and technological applications, thereby significantly improving their overall innovativeness and market competitiveness [50, 51]. Zahra & George (2002) [42] suggested that an enterprise's absorptive capacity, i.e., its ability to acquire, assimilate, and utilize new knowledge, is important for the exploration of new knowledge. They also suggest that an enterprise's absorptive capacity, i.e., its ability to acquire, assimilate, and utilize new knowledge, has a significant effect on exploratory innovation and innovation performance. Effective knowledge management can improve an enterprise's absorptive capacity, which in turn can contribute to the success of exploratory innovation and innovation performance [42, 52].

Exploitative innovation focuses on optimization within the framework of existing knowledge and technology, with an emphasis on efficiency and operational improvements [53]. It involves the modification of existing products, services, or business processes with the goal of increasing operational efficiency and reducing costs [27, 38]. Exploitative innovation typically has shorter implementation cycles and faster market returns [54]. Knowledge management (KM) also plays an important role in exploitative innovation by optimizing the use and sharing of existing knowledge to enhance an enterprise's ability to improve existing technologies and processes [32]. Benner & Tushman (2003) [55] showed that effective KM can improve innovation performance by improving the performance of existing products and processes and contributing to the success of leveraged innovation. Exploitative innovation has a significant effect on enterprises' short- and long-term innovation performance by improving the efficiency of existing products and processes [56]. Lavie (2006) [57] reported that exploitative innovation helps enterprises achieve higher market share and better financial performance in established markets. By continuously improving and optimizing existing operations, enterprises are able to increase their market competitiveness and profitability [57, 58]. Kotabe & Helsen (2022) [59] argued that knowledge management enhances the effectiveness of exploitational innovation by facilitating the efficient application of knowledge and process optimization, which in turn enhances an enterprise's overall innovation performance.

On the basis of the analysis of the above study, the following hypotheses are proposed:

Hypothesis 6 (H6): Exploratory innovation mediates the relationship between knowledge management (knowledge acquisition, knowledge transformation, and knowledge exploitation) and enterprise innovation performance.

Hypothesis 7 (H7): Exploitative innovation mediates the relationship between knowledge management (knowledge acquisition, knowledge transformation, and knowledge exploitation) and enterprise innovation performance.

In summary, in this study, the impact of knowledge management on enterprise innovation performance is the topic, and the theoretical research framework is constructed based on the Resource-Based View (RBV) and the Knowledge-Based View (KBV). The Resource-Based View (RBV) emphasizes that an organization's resources, particularly its irreducible knowledge assets, are key to achieving sustained competitive advantage. The knowledge base view further states that the processes of knowledge creation, integration, and application within the organization are decisive in driving innovation performance [60].

On this basis, this study introduces innovation behavior as a mediating variable and combines it with Behavioral Innovation Theory (BIT), which argues that KM practices do not directly translate into innovation performance but indirectly enhance enterprises' innovation outcomes by stimulating innovative behaviors (e.g., exploratory behaviors, exploitative behaviors, etc.) in the organization [61]. Therefore, this study proposes that the three dimensions of knowledge acquisition, knowledge transformation, and knowledge exploitation positively influence innovative behavior, which further influences the performance of enterprise innovation. So, the theoretical research model on the relationships among knowledge management, innovative behavior, and enterprise innovation performance is as shown in Figure 1.

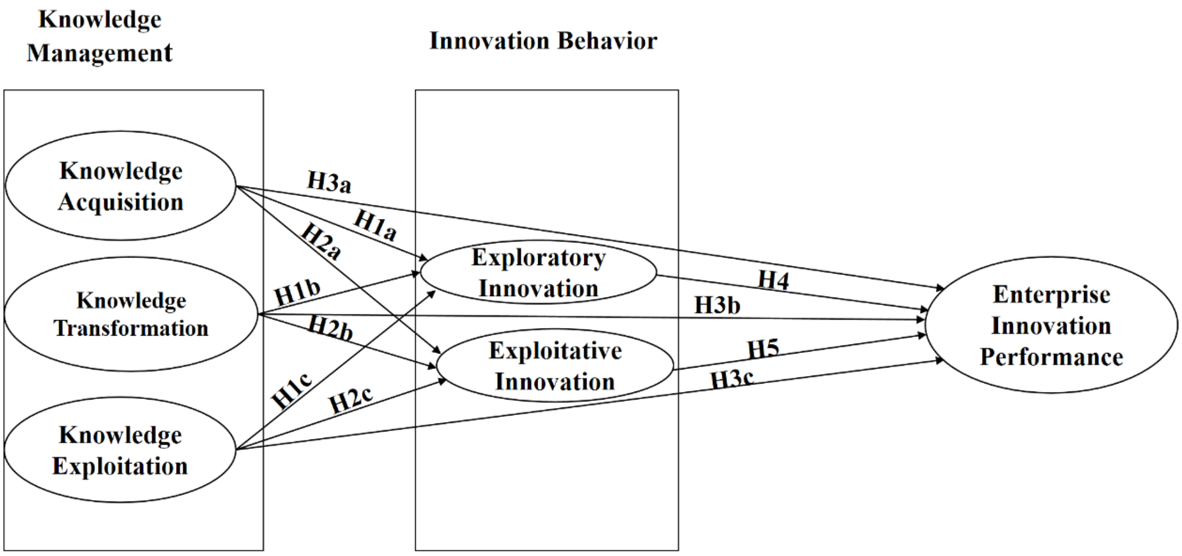

Figure 1. Research model

3- Method

This study fully considered the possible impact of enterprise characteristics on innovation performance and thus included enterprise size and enterprise age as control variables in the model for regression analysis in the empirical analysis. Among them, enterprise size is measured by the number of employees, and enterprise age is calculated based on the year of enterprise establishment. Considering the feasibility of data acquisition and the control of model complexity, we did not conduct a more refined stratified regression for manufacturing sub-industries in this paper. In subsequent studies, the sample size can be further expanded, and finer industry categorization can be introduced to deeply explore the impact of industry heterogeneity on innovation performance. At present, this study mainly focuses on the direct impact of each knowledge management element and has not yet explored in depth the interactive effects between different KMs. In subsequent research, the synergistic mechanism between knowledge acquisition and transformation, exploitation, and other elements can be further considered to enrich the model structure and enhance the explanatory power of the study.

3-1-Sample

In this study, the top managers of manufacturing companies were selected as the research objects, and the online survey was conducted in the Pearl River Delta region of China through simple random sampling. The data was collected through questionnaire from Chinese manufacturing enterprises workers in the innovation and technology sector. A total of 408 questionnaires were distributed in order to meet the calculated sample size of 400 by using $n = N / (1 + N \times e^2)$ formula. 400 valid questionnaires were obtained after excluding invalid questionnaires such as omissions and irregular responses. The statistics in Table 1 indicate that, in terms of the structure and education of the respondents, there are 157 senior managers with a undergraduate degree or above, accounting for 39.25%, and 18 with postgraduate degree or above, accounting for 4.5%; in terms of the number of years of business operation, there are 52 companies with 1 year or less, accounting for 13%, 114 companies with 1-3 years, accounting for 28.5%, 129 companies with 3-5 years accounting for 32.25%, 5-10 years 77, accounting for 18.9%; in terms of enterprise size, there are 100 joint ventures, accounting for 25.0%, single owner 82, accounting for 20.5%, 44 enterprises are listed companies, accounting for 11% of the total sample, and the number of limited companies is the largest, 174, accounting for 43.5%; in terms of enterprise size, there are 210 small enterprises, accounting for 52.5 %, and 190 medium enterprises, accounting for 47.5%.

Table 1. Descriptive statistics of the questionnaire

	Ownership	Frequency	Percentage	Valid percent	Cumulative percentage
Education of respondents	Junior high school and below	12	3.0	3.0	3.0
	Undergraduate	157	39.25	39.25	42.25
	High school (vocational)	56	14	14	56.25
	Postgraduate and above	18	4.5	4.5	60.75
	Junior college	157	39.25	39.25	100.0
	Total	400	100.0	100.0	
Years of enterprise	More than 10 years	28	7	7	7
	Less than 1 year	52	13	13	20
	1-3 years	114	28.5	28.5	48.5
	3-5 years	129	32.25	32.25	80.75
	5-10 years	77	18.9	18.9	100.0
	Total	400	100.0	100.0	
Nature of enterprise	Sole proprietorship (not limited company)	82	20.5	20.5	20.5
	Joint ventures	100	25.0	25.0	45.5
	Listed company	44	11.0	11.0	56.5
	Limited company	174	43.5	43.5	100
	Total	400	100	100	
Scale of enterprise	M(51~1000)	190	47.5	47.5	47.5
	S(1~50)	210	52.5	52.5	100.0
	Total	400	100.0	100.0	

3-2-Measures

3-2-1- Knowledge Management

This study draws on a mature scale, and the measurement refers to Shenkar & Li (1999) [62], Jansen et al. (2005) [48], Szulanski (1996) [63], and Jaworski & Kohli (1993) [64], combined with the characteristics of Chinese industry and the management characteristics of science and technology enterprises, to reduce the impact of factors such as organizational culture differences in scale design. Three important variables, knowledge acquisition, knowledge transformation and knowledge exploitation, and their corresponding measurement items are designed. Each has 5 items, for a total of 15 items.

3-2-2- Exploitative Innovation and Exploratory Innovation

This topic draws on the research of Jansen et al. (2006) [65], Stettner & Lavie (2014) [66], and Wang et al. (2019) [67]. Specifically, 5 items are used to measure exploratory innovation and exploitative innovation.

3-2-3- Enterprise Innovation Performance

Considering that the object of this study is a science and manufacturing enterprise, we combined the research of Lopes & Farinha (2018) [68], Zhang et al. (2020) [69], Qian et al. (2010) [70], and Akaraphan (2024) [71] to measure enterprise innovation performance in terms of the following eight items.

4- Statistical Analysis and Results

4-1-Descriptive Statistics of the Scale

As shown in Table 2, the absolute value of the skewness for all the variables is less than 1, and the absolute value of the kurtosis is less than 2, indicating that the distribution of the data is close to normal [72]. The sample size of 400 is sufficient to support the analysis of structural equation modelling.

Table 2. Descriptive statistics of the variables

	N	Minimum	Maximum	Mean	SD	Skewness	Kurtosis
KA	400	1.20	7.00	4.419	1.39970	-0.170	-0.951
KT	400	1.40	7.00	4.375	1.45502	-0.105	-1.141
KE	400	1.40	7.00	4.218	1.40469	-0.016	-1.146
EI	400	1.20	7.00	4.336	1.45385	-0.005	-1.068
EXI	400	1.00	7.00	4.366	1.45403	-0.132	-1.128
EIP	400	1.50	7.00	4.324	1.46361	0.008	-1.321
Number of Valid Cases	***400***						

4-2- Common Method Bias

In this study, considering that all the data were filled in by the respondents themselves via questionnaires, in order to reduce the impact of this bias on the results of the study, this paper deals with this aspect of statistical testing. After the completion of data collection, the Harman one-way test was used to test the common method bias at the statistical level. A non-rotated exploratory factor analysis of all measurement items in the questionnaire showed that the maximum variance explained was 28.98%, which was below the cautionary value of 40%, indicating that there was no significant single-factor dominance, ruling out common method bias.

4-3- Reliability and Validity Test

As shown in Table 3, the Cronbach's alpha coefficients for each latent variable involved in this study (knowledge acquisition, knowledge transformation, knowledge exploitation, exploratory innovation, exploitation innovation, and enterprise innovation performance) are 0.895, 0.902, 0.891, 0.902, 0.903, and 0.939, respectively, all of which are greater than 0.7, indicating that the questionnaire scales have high internal consistency and good reliability. In addition, the combined reliability (CR) values (Table 4) in the structural equation modeling (SEM) analysis were greater than 0.7, which further verified the reliability of the measurement instrument and indicated that the measured variables could reflect the actual characteristics of the latent variables in a more stable manner.

To ensure the reliability and validity of the measurement instrument, convergent validity was assessed via validated factor analysis. According to scholars such as Ahire et al. (1996) [73], the test of convergent validity usually involves the calculation of several key model metrics, including model fit indices, such as the chi-square (χ^2), comparative fit index (CFI), index of value-added fit (IFI), and root mean square error (RMSEA), to assess the overall model fit. Standardized factor loadings reflect the extent to which the observed variables explain the latent variables and are usually required to be greater than 0.5 [74]. The average variance extracted (AVE) measures the proportion of variance explained by the latent variable. According to the recommendation of Fornell & Larcker (1981) [75], the AVE value should be greater than 0.5, indicating that the construct has good convergent validity. The meanings of the specific validity measures are shown in Table 5.

Table 3. Questionnaire reliability

Variable	Cronbach's a coefficient	Number of terms
KA	0.895	5
KT	0.902	5
KE	0.891	5
EI	0.902	5
EXI	0.903	5
EIP	0.939	8

Table 4. Verification parameters of the confirmatory factor model

			Estimate	S.E.	C.R.	P	Factor loading	CR.	AVE
Q15		KA	1				0.796		
Q14		KA	0.924	0.056	16.389	***	0.764		
Q13		KA	1.032	0.057	18.108	***	0.829	0.895	0.630
Q12		KA	0.945	0.056	16.922	***	0.784		
Q11		KA	0.997	0.058	17.157	***	0.793		
Q20		KT	1				0.806		
Q19		KT	0.977	0.055	17.713	***	0.798		
Q18		KT	1.017	0.056	18.013	***	0.809	0.902	0.647
Q17		KT	0.957	0.053	17.983	***	0.808		
Q16		KT	1.005	0.056	17.827	***	0.802		
Q25		KE	1				0.795		
Q24		KE	0.885	0.056	15.753	***	0.742		
Q23		KE	0.999	0.059	16.956	***	0.788	0.891	0.621
Q22		KE	1.004	0.058	17.291	***	0.801		
Q21		KE	1.024	0.058	17.601	***	0.813		
Q30		EI	1				0.802		
Q29	←	EI	1.003	0.056	18.020	***	0.813		
Q28		EI	0.958	0.056	17.171	***	0.783	0.902	0.649
Q27		EI	0.998	0.056	17.948	***	0.810		
Q26		EI	1.032	0.057	18.156	***	0.818		
Q35		EXI	1				0.764		
Q34		EXI	1.074	0.064	16.796	***	0.807		
Q33		EXI	1.185	0.067	17.788	***	0.849	0.903	0.653
Q32		EXI	1.102	0.065	16.943	***	0.813		
Q31		EXI	1.103	0.066	16.737	***	0.804		
Q43		EIP	1				0.808		
Q42		EIP	0.976	0.051	19.170	***	0.820		
Q41		EIP	0.936	0.051	18.493	***	0.799		
Q40		EIP	0.982	0.052	18.862	***	0.810	0.939	0.656
Q39		EIP	0.992	0.052	19.088	***	0.817		
Q38		EIP	0.983	0.052	18.890	***	0.811		
Q37		EIP	0.996	0.053	18.854	***	0.810		
Q36		EIP	0.986	0.053	18.718	***	0.806		

Table 5. Criteria for validity measurement indicators

Statistical indicator	Value range	Evaluation criteria
Chi-square freedom ratio (χ2/df)	> 0	$> 1, < 3,$ *the closer to* 1 *the better*
Root mean square error of approximation (RMSEA)	> 0	$< 0.08,$ *the closer to* 0 *the better*
Standardized Root Mean Square Residual (SRMR)	> 0	$< 0.05,$ *the closer to* 0 *the better*
Goodness-of-fit Index (GFI)	$0 - 1$	$> 0.8,$ *the closer to* 1 *the better*
Comparative fit index (CFI)	$0 - 1$	$> 0.8,$ *the closer to* 1 *the better*
Normed fit index	$0 - 1$	$> 0.8,$ *the closer to* 1 *the better*
Tucker–Lewis index (TLI)	$0 - 1$	$> 0.8,$ *the closer to* 1 *the better*
Average Variance Extracted (AVE)	$0 - 1$	$0.50 \leq AVE < 0.90$

As shown in Table 6, all the fit indices of the structural equation model (SEM) constructed in this study met the good fit criteria. Among them, the chi-square degrees of freedom ratio (χ^2/df) is 1.132, which is lower than the commonly recommended criterion of less than 3, indicating that the model is well fitted. Looking further at the other fit indices, the goodness-of-fit index (GFI) was 0.921, and the adjusted goodness-of-fit index (AGFI) was 0.908, both of which are greater than 0.9, indicating that the model better explains the structure of the data. In addition, the RMSEA (root mean square error approximation) value is 0.018, which is much lower than the threshold of 0.08, indicating that the model has less error and a better fit. Moreover, the NFI (fan fit index) was 0.930, the Tucker–Lewis index (TLI) was 0.990, and the comparative fit index (CFI) was 0.991, all of which are greater than the recommended criterion of 0.8, further confirming the excellent fit of the model.

Table 6. Confirmatory factor model test fit indices for questionnaire scales

Test statistic	Reference standard	Value	Model Fit
χ^2		688.484	
df		608	
χ^2/df	1-3	1.132	Yes
GFI	≥ 0.9	0.921	Yes
AGFI	≥ 0.9	0.908	Yes
RMSEA	≤ 0.08	0.018	Yes
NFI	≥ 0.9	0.930	Yes
TLI	≥ 0.9	0.990	Yes
CFI	≥ 0.9	0.991	Yes

In this study, the factor model was estimated via AMOS software and SEM by using Smart PLS, as shown in Table 6. The standardized coefficients of the 33 observed variables are listed in the table, and all standardized coefficients are greater than 0.5, indicating that the relationships between these observed variables and their corresponding latent variables are strong and meet the requirements of a good measurement model. The construct reliability (CR) of each latent variable is much greater than 0.7, and the average variance extracted (AVE) is greater than 0.5, which meets a high standard and verifies the reliability and convergent validity of the model.

4-4- Correlation Analysis and Discriminant Validity

On the basis of the results of the correlation analysis in Table 7, we find that there are significant positive correlations between knowledge acquisition and several important variables. The correlation coefficients between knowledge acquisition and knowledge transformation, knowledge exploitation, exploratory innovation, exploitative innovation, enterprise innovation performance, and organizational courage are 0.293, 0.233, 0.248, 0.230, 0.284, and 0.308, respectively. In addition, all of these correlation coefficients are statistically significant at the 0.01 level of significance, which suggests that the relationships between these variables are highly reliable. The table shows that the AVE open root value of each dimension is greater than its correlation coefficient with the other dimensions, indicating that the scale has good discriminant validity.

Table 7. Correlation analysis and discriminant validity

	EIP	EXI	EI	KE	KT	KA
EIP	0.810					
EXI	0.332***	0.808				
EI	0.342***	0.247***	0.806			
KE	0.399***	0.270***	0.406***	0.788		
KT	0.311***	0.279***	0.270***	0.236***	0.804	
KA	0.284***	0.230***	0.248***	0.233***	0.293***	0.794
AVE	0.656	0.653	0.649	0.621	0.647	0.630

Diagonal: square root of the average variance extracted (AVE); Off-diagonal elements: correlations between constructs; * Significant at p< 0.05; ** significant at p < 0.01; *** significant at p< 0.001.

4-5- Hypothesis Testing

After testing the reliability and validity of the constructs, we analyzed the structural model. First, due to the need to avoid multicollinearity between the antecedent variables of each endogenous construct, we checked for the presence of problems related to covariance. Then, we analyzed the path coefficients, R2 values, and p-values. According to Hair et al. (2016) [76], signs of covariance exist when the variance inflation factor is >5 (VIF >5). None of the VIF values obtained in this study exceeded the maximum value.

The results of the empirical analysis of knowledge management on innovative behavior are shown in Table 8. The findings show that knowledge acquisition, knowledge transformation, and knowledge exploitation have a significant positive effect on exploratory innovation (β=0.124, P<0.05; β=0.155, P<0.001; β=0.342, P<0.001), and this result supports hypotheses H1a, H1b, and H1c, which state that knowledge acquisition, knowledge transformation, and knowledge exploitation can effectively promote exploratory innovation. It can be seen that external sources of knowledge provide key resources and knowledge support for small and medium-sized enterprises (SMEs), and play an important role in exploratory innovation in particular. While exploratory innovation emphasizes the identification and experimentation with new markets, technologies and opportunities [77], SME are usually relatively limited in terms of internal resources and R&D capabilities and therefore rely more on external networks for new knowledge and inspiration [78].

Table 8. Structural equation model test path parameter table

	Estimate	S.E.	C.R.	P	Standardized Regression Weights	R^2
EI←KA	0.131	0.057	2.293	*	0.124	
EI←KT	0.159	0.056	2.863	***	0.155	0.213
EI←KE	0.362	0.059	6.152	***	0.342	
EXI←KA	0.132	0.058	2.280	*	0.128	
EXI←KT	0.197	0.056	3.486	***	0.197	0.139
EXI←KE	0.204	0.057	3.555	***	0.197	
EIP←KA	0.121	0.055	2.218	*	0.115	
EIP←KT	0.139	0.054	2.574	*	0.136	
EIP←KE	0.251	0.059	4.241	***	0.239	0.271
EIP←EI	0.139	0.054	2.560	*	0.140	
EIP←EXI	0.172	0.053	3.256	*	0.169	

* Significant at p< 0.05; ** significant at p < 0.01; *** significant at p< 0.001.

Knowledge acquisition, knowledge transformation, and knowledge exploitation have a significant positive effect on exploitative innovation (β=0.128, P<0.05; β=0.197, P<0.001; β=0.1972, P<0.001), and this result supports hypotheses H2a, H2b, and H2c, which state that knowledge acquisition, knowledge transformation, and knowledge exploitation have a positive effect on exploratory innovation. Knowledge acquisition, knowledge transformation, and knowledge exploitation have a significant positive effect on enterprise innovation performance (β=0.115, P<0.05; β=0.136, P<0.05; β=0.239, P<0.001), and this result supports hypotheses H3a, H3b, and H3c. From the above data analysis, it can be seen that knowledge transformation and knowledge exploitation have higher path coefficients for exploitative innovation than knowledge acquisition. This is because exploitative innovation emphasizes optimizing, improving, and partially updating an existing product, process, or market. For example, improving efficiency, reducing costs, and improving user experience. This type of innovation itself relies on deepening the understanding and effective use of existing knowledge, rather than the pursuit of new knowledge [79]. Therefore, the greater the ability to transform and exploit existing knowledge, the more likely it is that this type of "incremental" innovation will be facilitated.

Exploratory innovation and exploitative innovation have a significant positive effect on enterprise innovation performance (β= 0.140, P < 0.05; β = 0.169, P < 0.05); this result supports hypotheses H4 and H5. The results of the analysis show that exploitative innovation has a higher impact on enterprise innovation performance than exploratory innovation. This is most likely because this study is based on a predominantly traditional manufacturing industry, and such firms themselves are better at exploiting established resources and tend to improve their performance through iterative optimization [80].

Figure 2 summarizes the results obtained for each of the hypotheses.

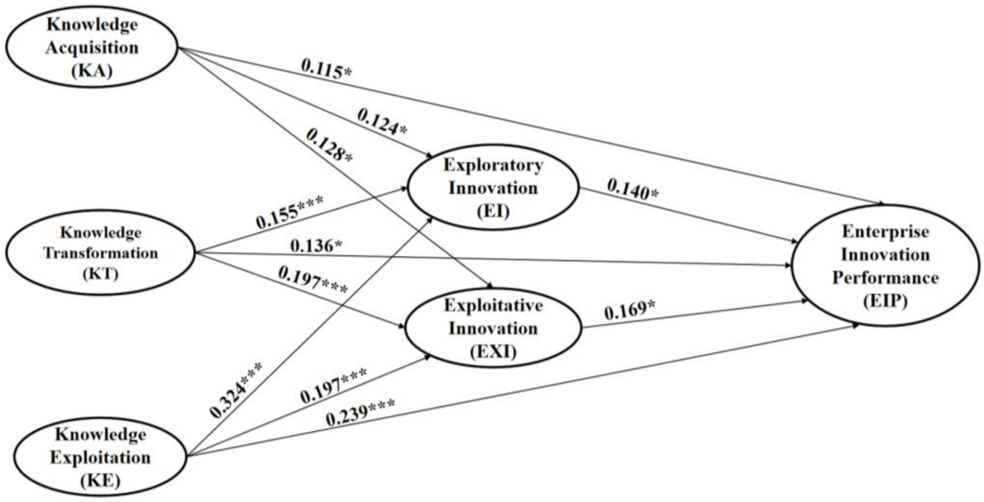

Figure 2. **Path coefficient**

To further explore the mediating role of the model, this study uses a bootstrap mediation effect test to assess the mechanism of innovation behavior in the relationships among knowledge acquisition, knowledge transformation, knowledge exploitation and enterprise innovation performance. To ensure the credibility and robustness of the results, this study used the bootstrap maximum likelihood (ML) method and set up 5000 replicated samples.

The results in Table 9 indicate that there is a significant mediating effect of both exploratory innovation and exploitative innovation between knowledge acquisition, knowledge transformation, knowledge exploitation and enterprise innovation performance and that the confidence interval of the mediation path does not contain zero ($P < 0.05$), which indicates that the mediation effect is statistically significant and that hypotheses H6 and H7 are valid. This shows that enterprises not only need to improve the knowledge management mechanism, but also should encourage employees to actively transform the acquired and converted knowledge into specific innovative behaviors, so as to truly promote the improvement of innovation performance.

Table 9. **Bootstrap mediation effect test**

Path	Indirect effect coefficient	P	Bias Corrected (95%)	
			Lower bounds	Upper bounds
KA→EI→EIP	0.020	0.019	0.003	0.055
KT→EI→EIP	0.025	0.005	0.007	0.058
KE→EI→EIP	0.056	0.004	0.020	0.103
KA→EXI→EIP	0.024	0.016	0.004	0.056
KA→EXI→EIP	0.036	0.001	0.013	0.072
KA→ExI→EIP	0.037	0.001	0.015	0.074

5- Discussion

The results of this study show that the key dimensions of knowledge acquisition, knowledge transformation, and knowledge exploitation all have a significant positive effect on enterprise innovation performance, a conclusion that fits with theory of knowledge creation [81], which emphasizes that the dynamic flow of knowledge in the organization has an important role in promoting innovative outcomes. In addition, all three dimensions of knowledge acquisition, knowledge transformation, and knowledge exploitation have a significant positive effect on the innovation behavior of the enterprise ($p < 0.01$), and at the same time, innovative behavior also shows a significant positive effect on enterprise innovation performance ($p < 0.001$). Further mediation effect tests showed that innovative behavior played a partial mediating role between all dimensions of knowledge management and innovation performance. This finding is also consistent with Zhang et al. (2024) [36], who found that “knowledge sharing helps stimulate employees' innovative behaviors, which in turn enhances product innovation”. This study further reveals that, in the context of the knowledge economy, innovative behavior not only acts as a bridge between knowledge management and innovation performance but also strengthens the synergistic effect between the two, highlighting the important mediating value of innovative behavior.

However, some of the results also differ from previous studies. For example, unlike Liang & Li (2024) [82], who concluded that “exploratory innovation has a stronger impact on innovation performance than exploitative innovation” [83], exploitative innovation shows a stronger impact in this study. This difference may be attributed to the fact that most of the sample enterprises are in the manufacturing industry, which is highly dependent on external knowledge and technological information, thus enhancing the impact of exploitative innovation on innovation performance. In addition, this study also found that innovative behavior can more significantly strengthen the role of KM on performance when there is a stronger culture of innovation within the enterprise, suggesting that organizational context variables may cause differences in results across studies. Therefore, future studies may further introduce contextual variables, such as organizational learning culture and level of technological capability, to more comprehensively explain the differences and similarities between the results of different studies.

The results of the study empirically validate the role of knowledge management in enhancing enterprise innovation performance by stimulating innovative behavior, confirming the internal logic of the resource-based theory and the knowledge-based view. This finding is a useful supplement to the previous knowledge management research that ignored behavioral factors, and also provides new management insights for enterprises in the process of promoting innovation performance improvement. It is not only important to pay attention to the effective management of knowledge resources, but also to the incentives and support of innovative behavior.

In addition, the study also found that there are differences in the intensity of the role of knowledge management in different dimensions, and the influence of knowledge exploitation is greater than that of knowledge acquisition and transformation, suggesting that the transformation of knowledge on the ground into practical actions is the key to driving innovation performance. This suggests that enterprises should shift from single knowledge accumulation to knowledge practice-oriented management thinking to further open up the transformation path from knowledge to behavior to performance.

6- Conclusion

Based on the mediating role of innovative behavior, this study systematically explores the influence mechanism of knowledge management on enterprise innovation performance, constructs a theoretical model containing knowledge acquisition, knowledge transformation, knowledge exploitation, innovative behavior and innovation performance, and empirically verifies it through questionnaires and structural equation modeling. It is found that all three elements of knowledge management significantly and positively affect innovation behavior, and innovative behavior further positively affects innovation performance. Meanwhile, innovative behavior plays a partial mediating role between knowledge management and innovation performance. This finding reveals that the impact of KM on innovation performance is not only the direct path, but also the behavioral mechanism cannot be ignored.

In terms of theoretical significance, this study has deepened the understanding of the relationship between knowledge management and innovation performance, and expanded the study of mediation paths under the behavioral perspective. In terms of practical significance, it provides action suggestions for enterprises to improve innovation performance, especially emphasizing the transformation process from knowledge management to behavioral incentives and innovation practices.

Future research can be expanded in the following two directions further. One is to introduce external environmental variables to explore the moderating effect of environmental dynamics on the model path. The second is to use longitudinal data tracking analysis to verify the timeliness and dynamics of the causal relationship between variables in order to improve the robustness and generalization value of the research findings.

7- Declarations

7-1- Author Contributions

Conceptualization, Q.J. and H.B.; methodology, Q.J.; software, H.B.; validation, Q.J., H.B., and K.U.; formal analysis, Q.J.; investigation, Q.J.; resources K.U.; data curation, H.B.; writing—original draft preparation, Q.J.; writing—review and editing, H.B.; visualization, Q.J.; supervision, H.B.; project administration, K.U. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the author.

7-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7-4- Institutional Review Board Statement

The study was approved by the Institutional Review Board of the Walailak University with the IRB certificate number WUEC-25-056-01.

7-5- Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

8- References

[1] Yang, J., Zhang, X., & Pei, Y. (2025). Digital transformation of the business models of Chinese sporting goods enterprises in the post-COVID-19 era: a knowledge-management perspective. Journal of Knowledge Management, 29(3), 723–734. doi:10.1108/JKM-12-2022-0946.

[2] Gao, J., Zhang, W., Guan, T., Feng, Q., & Mardani, A. (2023). Influence of digital transformation on the servitization level of manufacturing SMEs from static and dynamic perspectives. International Journal of Information Management, 73, 102645. doi:10.1016/j.ijinfomgt.2023.102645.

[3] Chopra, M., Saini, N., Kumar, S., Varma, A., Mangla, S. K., & Lim, W. M. (2021). Past, present, and future of knowledge management for business sustainability. Journal of Cleaner Production, 328, 129592. doi:10.1016/j.jclepro.2021.129592.

[4] Jiang, H., Yang, J., & Liu, W. (2022). Innovation ecosystem stability and enterprise innovation performance: the mediating effect of knowledge acquisition. Journal of Knowledge Management, 26(11), 378–400. doi:10.1108/JKM-04-2022-0275.

[5] Hanifah, H., Abd Halim, N., Vafaei-Zadeh, A., & Nawaser, K. (2021). Effect of intellectual capital and entrepreneurial orientation on innovation performance of manufacturing SMEs: mediating role of knowledge sharing. Journal of Intellectual Capital, 23(6), 1175–1198. doi:10.1108/jic-06-2020-0186.

[6] Zhao, Y., Wen, S., Zhou, T., Liu, W., Yu, H., & Xu, H. (2022). Development and innovation of enterprise knowledge management strategies using big data neural networks technology. Journal of Innovation & Knowledge, 7(4), 100273. doi:10.1016/j.jik.2022.100273.

[7] Hael, M., Belhaj, F. A., & Zhang, H. (2024). Organizational learning and innovation: A bibliometric analysis and future research agenda. Heliyon, 10(11), 31812– 31812. doi:10.1016/j.heliyon.2024.e31812.

[8] Fan, M., Huang, W., & Xiong, S. (2023). How enterprise interactions in innovation networks affect technological innovation performance: The role of technological innovation capacity and absorptive capacity. PLOS ONE, 18(3), e0282540. doi:10.1371/journal.pone.0282540.

[9] Wang, C., Ren, X., Jiang, X., & Chen, G. (2024). In the context of mass entrepreneurship network embeddedness and entrepreneurial innovation performance of high-tech enterprises in Guangdong province. Management Decision, 62(8), 2532–2557. doi:10.1108/MD-04-2023-0531.

[10] Alkaraan, F., Elmarzouky, M., Hussainey, K., Venkatesh, V. G., Shi, Y., & Gulko, N. (2024). Reinforcing green business strategies with Industry 4.0 and governance towards sustainability: Natural-resource-based view and dynamic capability. Business Strategy and the Environment, 33(4), 3588–3606. doi:10.1002/bse.3665.

[11] Yeboah, A. (2023). Knowledge sharing in organization: A systematic review. Cogent Business & Management, 10(1), 2195027. doi:10.1080/23311975.2023.2195027.

[12] Atapattu, M. M., & Huybers, T. (2022). Motivational antecedents, employee engagement and knowledge management performance. Journal of Knowledge Management, 26(3), 528–547. doi:10.1108/JKM-12-2020-0898.

[13] Islam, M. T., & Chadee, D. (2023). Stuck at the bottom: Role of tacit and explicit knowledge on innovation of developing-country suppliers in global value chains. International Business Review, 32(2), 101898. doi:10.1016/j.ibusrev.2021.101898.

[14] Rampa, R., & Agogué, M. (2021). Developing radical innovation capabilities: Exploring the effects of training employees for creativity and innovation. Creativity and Innovation Management, 30(1), 211–227. doi:10.1111/caim.12423.

[15] Von Krogh, G., Ichijo, K., & Nonaka, I. (2000). Enabling Knowledge Creation: How to Unlock the Mystery of Tacit Knowledge and Release the Power of Innovation. Oxford University Press, Oxford, United Kingdom. doi:10.1093/acprof:oso/9780195126167.001.0001.

[16] Abbas, J., Zhang, Q., Hussain, I., Akram, S., Afaq, A., & Shad, M. A. (2020). Sustainable innovation in small medium enterprises: The impact of knowledge management on organizational innovation through a mediation analysis by using SEM approach. Sustainability (Switzerland), 12(6). doi:10.3390/su12062407.

[17] Ungureanu, P., Cochis, C., Bertolotti, F., Mattarelli, E., & Scapolan, A. C. (2020). Multiplex boundary work in innovation projects: the role of collaborative spaces for cross-functional and open innovation. European Journal of Innovation Management, 24(3), 984–1010. doi:10.1108/EJIM-11-2019-0338.

[18] Shehzad, M. U., Zhang, J., Dost, M., Ahmad, M. S., & Alam, S. (2024). Knowledge management enablers and knowledge management processes: a direct and configurational approach to stimulate green innovation. European Journal of Innovation Management, 27(1), 123–152. doi:10.1108/EJIM-02-2022-0076.

[19] Houessou, A. M., Aoudji, A. K. N., Biaou, G., & Floquet, A. (2023). Tacit knowledge acquisition and incremental innovation capability: Proximity perspective. Journal of Open Innovation: Technology, Market, and Complexity, 9(3), 100085. doi:10.1016/j.joitmc.2023.100085.

[20] Sahoo, S., Kumar, A., & Upadhyay, A. (2023). How do green knowledge management and green technology innovation impact corporate environmental performance? Understanding the role of green knowledge acquisition. Business Strategy and the Environment, 32(1), 551–569. doi:10.1002/bse.3160.

[21] Lam, L., Nguyen, P., Le, N., & Tran, K. (2021). The relation among organizational culture, knowledge management, and innovation capability: Its implication for open innovation. Journal of Open Innovation: Technology, Market, and Complexity, 7(1), 1–16. doi:10.3390/joitmc7010066.

[22] Yang, M., Luu, T. T., & Wang, D. (2024). The effect of internal knowledge transfer on the relationship between personality traits and employee service performance: a multilevel model. Journal of Knowledge Management, 28(3), 799–826. doi:10.1108/JKM-10-2022-0827.

[23] Ononye, U. H. (2021). Tacit Knowledge and Innovation: Insights from the Public Sector in Delta State, Nigeria. Journal of Information & Knowledge Management, 20(3). doi:10.1142/S0219649221500325.

[24] Işık, C., Aydın, E., Dogru, T., Rehman, A., Alvarado, R., Ahmad, M., & Irfan, M. (2021). The nexus between team culture, innovative work behaviour and tacit knowledge sharing: Theory and evidence. Sustainability (Switzerland), 13(8), 4333. doi:10.3390/su13084333.

[25] Gu, M., Shu, C., & Urbano, D. (2024). Knowledge creation and knowledge exploitation influencing employee venturing behaviours at the national level: the moderating role of national entrepreneurial values. Entrepreneurship & Regional Development, 36(7–8), 1118–1144. doi:10.1080/08985626.2024.2310109.

[26] Davenport, T. H., & Prusak, L. (2000). Working knowledge: How organizations manage what they know. Harvard Business School Press. Brighton, United States.

[27] Neuländtner, M., & Scherngell, T. (2022). R&D networks and their effects on knowledge exploration versus knowledge exploitation: Evidence from a spatial econometric perspective. Industry and Innovation, 29(7), 847–878. doi:10.1080/13662716.2022.2063110.

[28] Antonelli, C., Crespi, F., & Quatraro, F. (2022). Knowledge complexity and the mechanisms of knowledge generation and exploitation: The European evidence. Research Policy, 51(8), 104081. doi:10.1016/j.respol.2020.104081.

[29] Azeem, M., Ahmed, M., Haider, S., & Sajjad, M. (2021). Expanding competitive advantage through organizational culture, knowledge sharing and organizational innovation. Technology in Society, 66. doi:10.1016/j.techsoc.2021.101635.

[30] Alavi, M., & Leidner, D. E. (2001). Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. MIS Quarterly, 25(1), 107. doi:10.2307/3250961.

[31] Rehman, S. U., Bresciani, S., Ashfaq, K., & Alam, G. M. (2022). Intellectual capital, knowledge management and competitive advantage: a resource orchestration perspective. Journal of Knowledge Management, 26(7), 1705–1731. doi:10.1108/JKM-06-2021-0453.

[32] Ferreira, N. C. M. Q. F., & Ferreira, J. J. M. (2025). The field of resource-based view research: mapping past, present and future trends. Management Decision, 63(4), 1124–1153. doi:10.1108/MD-10-2023-1908.

[33] Lei, H., Khamkhoutlavong, M., & Le, P. B. (2021). Fostering exploitative and exploratory innovation through HRM practices and knowledge management capability: the moderating effect of knowledge-centered culture. Journal of Knowledge Management, 25(8), 1926–1946. doi:10.1108/JKM-07-2020-0505.

[34] Awan, U., Arnold, M. G., & Gölgeci, I. (2021). Enhancing green product and process innovation: Towards an integrative framework of knowledge acquisition and environmental investment. Business Strategy and the Environment, 30(2), 1283–1295. doi:10.1002/bse.2684.

[35] Sarfo, C., Fakhar Manesh, M., & Caputo, A. (2024). Exploitative and exploratory search: Dynamic capabilities enhancing SME adaptation, new product development, and environmental performance. Journal of Small Business Management, 1–30. doi:10.1080/00472778.2024.2418026.

[36] Zhang, G., Zhang, X., & Wang, Y. (2024). Perceived insider status and employees' innovative behavior: the role of knowledge sharing and organizational innovation climate. European Journal of Innovation Management, 27(2), 589–607. doi:10.1108/EJIM-03-2022-0123.

[37] Xiao, J., & Bao, Y. (2022). Partners' knowledge utilization and exploratory innovation: the moderating effect of competitive and collaborative relationships. International Journal of Operations & Production Management, 42(9), 1356–1383. doi:10.1108/IJOPM-08-2021-0517.

[38] March, J. G. (1991). Exploration and Exploitation in Organizational Learning. Organization Science, 2(1), 71–87. doi:10.1287/orsc.2.1.71.

[39] Gao, Y., Hu, Y., Liu, X., & Zhang, H. (2021). Can Public R&D Subsidy Facilitate Firms' Exploratory Innovation? The Heterogeneous Effects between Central and Local Subsidy Programs. Research Policy, 50(4). doi:10.1016/j.respol.2021.104221.

[40] Tushman, M. L., & O'Reilly, C. A. (1996). Ambidextrous organizations: Managing evolutionary and revolutionary change. California Management Review, 38(4), 8–30. doi:10.2307/41165852.

[41] Allal-Chérif, O., Costa Climent, J., & Ulrich Berenguer, K. J. (2023). Born to be sustainable: How to combine strategic disruption, open innovation, and process digitization to create a sustainable business. Journal of Business Research, 154. doi:10.1016/j.jbusres.2022.113379.

[42] Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. Academy of Management Review, 27(2), 185–203. doi:10.5465/AMR.2002.6587995.

[43] Peiyao, Q., & Benrui, C. (2024). Research on the impact of digital technology applications on firms' dual innovation in the digital economy context. Scientific Reports, 14(1). doi:10.1038/s41598-024-57183-y.

[44] Gibson, C. B., & Birkinshaw, J. (2004). The Antecedents, Consequences, and Mediating Role of Organizational Ambidexterity. Academy of Management Journal, 47(2), 209–226. doi:10.2307/20159573.

[45] Alerasoul, S. A., Afeltra, G., Hakala, H., Minelli, E., & Strozzi, F. (2022). Organisational learning, learning organisation, and learning orientation: An integrative review and framework. Human Resource Management Review, 32(3), 100854. doi:10.1016/j.hrmr.2021.100854.

[46] Limaj, E., & Bernroider, E. W. N. (2019). The roles of absorptive capacity and cultural balance for exploratory and exploitative innovation in SMEs. Journal of Business Research, 94, 137–153. doi:10.1016/j.jbusres.2017.10.052.

[47] He, Z., & Hirshleifer, D. (2022). The Exploratory Mindset and Corporate Innovation. Journal of Financial and Quantitative Analysis, 57(1), 127–169. doi:10.1017/S0022109020000800.

[48] Jansen, J. J. P., Van den Bosch, F. A. J., & Volberda, H. W. (2005). Exploratory Innovation, Exploitative Innovation, and Ambidexterity: The Impact of Environmental and Organizational Antecedents. Schmalenbach Business Review, 57(4), 351–363. doi:10.1007/bf03396721.

[49] Zhong, X., & Chen, W. (2024). Learning through exploitative and exploratory overseas R&D: impacts on EMNEs' innovation performance. International Journal of Emerging Markets, 19(8), 2293–2314. doi:10.1108/IJOEM-12-2021-1811.

[50] Katila, R., & Ahuja, G. (2002). Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction. Academy of Management Journal, 45(6), 1183–1194. doi:10.5465/3069433.

[51] Ali, M. (2021). Imitation or innovation: To what extent do exploitative learning and exploratory learning foster imitation strategy and innovation strategy for sustained competitive advantage?. Technological Forecasting and Social Change, 165. doi:10.1016/j.techfore.2020.120527.

[52] Migdadi, M. M. (2022). Knowledge management processes, innovation capability and organizational performance. International Journal of Productivity and Performance Management, 71(1), 182–210. doi:10.1108/IJPPM-04-2020-0154.

[53] Arias-Pérez, J., Velez-Ocampo, J., & Cepeda-Cardona, J. (2021). Strategic orientation toward digitalization to improve innovation capability: why knowledge acquisition and exploitation through external embeddedness matter. Journal of Knowledge Management, 25(5), 1319–1335. doi:10.1108/jkm-03-2020-0231.

[54] Zhong, X., Ren, G., & Wu, X. (2023). Not all innovation is prioritized: economic policy uncertainty, industry environmental, and firms' relative exploitative innovation emphasis. European Journal of Innovation Management, 28(2), 166–186. doi:10.1108/ejim-01-2023-0006.

[55] Benner, M. J., & Tushman, M. L. (2003). Exploitation, exploration, and process management: The productivity dilemma revisited. Academy of Management Review, 28(2), 238–256. doi:10.5465/AMR.2003.9416096.

[56] He, P., Pei, Y., Lin, C., & Ye, D. (2021). Ambidextrous marketing capabilities, exploratory and exploitative market-based innovation, and innovation performance: an empirical study on China's manufacturing sector. Sustainability (Switzerland), 13(3), 1-21. doi:10.3390/su13031146.

[57] Lavie, D. (2006). Capability reconfiguration: An analysis of incumbent responses to technological change. Academy of Management Review, 31(1), 153–174. doi:10.5465/AMR.2006.19379629.

[58] Vrabcová, P., & Urbancová, H. (2023). Sustainable innovation in agriculture: Building competitiveness and business sustainability. Agricultural Economics (Zemědělská Ekonomika), 69(1), 1–12. doi:10.17221/321/2022-agricecon.

[59] Kotabe, M. M., & Helsen, K. (2022). Global marketing management. John Wiley & Sons, Hoboken, United States.

[60] Fithri, P., Hasan, A., Syafrizal, S., & Games, D. (2024). Enhancing Business Incubator Performances from Knowledge-Based Perspectives. Sustainability, 16(15), 6303. doi:10.3390/su16156303.

[61] Veiga, P. M., Ferreira, J. J., Zhang, J. Z., & Liu, Y. (2024). Exploring the Connections: Ambidexterity, Digital Capabilities, Resilience, and Behavioral Innovation. Journal of Computer Information Systems, 1–13. doi:10.1080/08874417.2023.2297031.

[62] Shenkar, O., & Li, J. (1999). Knowledge Search in International Cooperative Ventures. Organization Science, 10(2), 134–143. doi:10.1287/orsc.10.2.134.

[63] Szulanski, G. (1996). Exploring internal stickiness: Impediments to the transfer of best practice within the firm. Strategic Management Journal, 17(S2), 27–43. doi:10.1002/smj.4250171105.

[64] Jaworski, B. J., & Kohli, A. K. (1993). Market Orientation: Antecedents and Consequences. Journal of Marketing, 57(3), 53–70. doi:10.1177/002224299305700304.

[65] Jansen, J. J. P., Van Den Bosch, F. A. J., & Volberda, H. W. (2006). Exploratory Innovation, Exploitative Innovation, and Performance: Effects of Organizational Antecedents and Environmental Moderators. Management Science, 52(11), 1661–1674. doi:10.1287/mnsc.1060.0576.

[66] Stettner, U., & Lavie, D. (2014). Ambidexterity under scrutiny: Exploration and exploitation via internal organization, alliances, and acquisitions. Strategic Management Journal, 35(13), 1903–1929. doi:10.1002/smj.2195.

[67] Wang, S., M., Jing, R., T., & Shao, Y., F. (2019). Research on the influence mechanism of alliance routine on enterprise ambidexterity innovation capability. Journal of Management Science, 32(2), 19-32.

[68] Lopes, J., & Farinha, L. (2018). Measuring the Performance of Innovation and Entrepreneurship Networks. Journal of the Knowledge Economy, 9(2), 402–423. doi:10.1007/s13132-017-0487-8.

[69] Zhang, J. A., O'Kane, C., & Chen, G. (2020). Business ties, political ties, and innovation performance in Chinese industrial firms: The role of entrepreneurial orientation and environmental dynamism. Journal of Business Research, 121, 254–267. doi:10.1016/j.jbusres.2020.08.055.

[70] Qian, X. H., Yang, Y. F., & Xu, W. L. (2010). Firm network location, absorptive capacity and innovation performance-An interaction effect model. Management World, 13(5), 118-129. doi:10.1007/978-1-4419-5731-3_2.

[71] Akaraphan, S., Wiriyapinit, M., & Sinthupinyo, S. (2024). Global Perspectives on Management Consulting Competitiveness: Analyzing Knowledge Brokers' Components. Emerging Science Journal, 8(3), 1037–1059. doi:10.28991/ESJ-2024-08-03-014.

[72] Sürücü, L., Şeşen, H., & Maslakçı, A. (2023). Regression, mediation/moderation, and structural equation modeling with SPSS, AMOS, and PROCESS Macro. Livre de Lyon, Lyon, France.

[73] Ahire, S. L., Golhar, D. Y., & Waller, M. A. (1996). Development and validation of TQM implementation constructs. Decision Sciences, 27(1), 23–56. doi:10.1111/j.1540-5915.1996.tb00842.x.

[74] Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2014) Multivariate Data Analysi. (7th Ed.), Pearson Education, London, United Kingdom.

[75] Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39–50. doi:10.1177/002224378101800104.

[76] Hair Jr., J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Sage Publications, Thousand Oaks, United States.

[77] Zaragoza-Sáez, P., Marco-Lajara, B., Úbeda-García, M., & Manresa-Marhuenda, E. (2024). Exploratory and co-exploratory innovation. The mediating role of digitalization on competitiveness in the hotel industry. Technological Forecasting and Social Change, 199, 123069. doi:10.1016/j.techfore.2023.123069.

[78] Xie, X., Sun, J., Zhou, M., Yan, L., & Chi, M. (2024). Network embeddedness and manufacturing SMEs' green innovation performance: the moderating role of resource orchestration capability. Business Process Management Journal, 30(3), 884–908. doi:10.1108/BPMJ-08-2023-0676.

[79] Singh, K., Chatterjee, S., & Mariani, M. (2024). Applications of generative AI and future organizational performance: The mediating role of explorative and exploitative innovation and the moderating role of ethical dilemmas and environmental dynamism. Technovation, 133, 103021. doi:10.1016/j.technovation.2024.103021.

[80] Liu, Y., Zhang, Y., Xie, X., & Mei, S. (2024). Affording digital transformation: The role of industrial Internet platform in traditional manufacturing enterprises digital transformation. Heliyon, 10(7), 28772– 28772. doi:10.1016/j.heliyon.2024.e28772.

[81] Takeuchi, H., & Nonaka, I. (2000). Classic Work: Theory of Organizational Knowledge Creation. Knowledge Management, 139–182, The MIT Press, Cambridge, United States. doi:10.7551/mitpress/4075.003.0016.

[82] Liang, R., & Li, Y. (2024). How Digital Transformation Affects Exploitative and Exploratory Innovation: An Innovation Structure Perspective. IEEE Transactions on Engineering Management, 71, 10912–10923. doi:10.1109/TEM.2024.3408322.

[83] Gama, F., & Magistretti, S. (2025). Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. Journal of Product Innovation Management, 42(1), 76–111. doi:10.1111/jpim.12698.