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THE RELATIONSHIP BETWEEN AMBIDEXTROUS KNOWLEDGE SHARING AND INNOVATION WITHIN INDUSTRIAL CLUSTERS: EVIDENCE FROM CHINA

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ABSTRACT

Aim/Purpose	This study examines the influence of ambidextrous knowledge sharing in industrial clusters on innovation performance from the perspective of knowledge-based dynamic capabilities.
Background	The key factor to improving innovation performance in an enterprise is to share knowledge with other enterprises in the same cluster and use dynamic capabilities to absorb, integrate, and create knowledge. However, the relationships among these concepts remain unclear. Based on the dynamic capability theory, this study empirically reveals how enterprises drive innovation performance through knowledge sharing.
Methodology	Survey data from 238 cluster enterprises were used in this study. The sample was collected from industrial clusters in China's Fujian province that belong to the automobile, optoelectronic, and microwave communications industries. Through structural equation modeling, this study assessed the relationships among ambidextrous knowledge sharing, dynamic capabilities, and innovation performance.
Contribution	This study contributes to the burgeoning literature on knowledge management in China, an important emerging economy. It also enriches the exploration of innovation performance in the cluster context and expands research on the dynamic mechanism from a knowledge perspective.
Findings	Significant relationships are found between ambidextrous knowledge sharing and innovation performance. First, ambidextrous knowledge sharing positively influences the innovation performance of cluster enterprises. Further, knowledge absorption and knowledge generation capabilities play a mediating role in this relationship, which confirms that dynamic capabilities are a partial mediator in the relationship between ambidextrous knowledge sharing and innovation performance.

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Recommendations for Practitioners: The results highlight the crucial role of knowledge management in contributing to cluster innovation and management practices. They indicate that cluster enterprises should consider the importance of knowledge sharing and dynamic capabilities for improving innovation performance and establish a multi-agent knowledge sharing platform.

Recommendations for Researchers: Researchers could further explore the role of other mediating variables (e.g., organizational agility, industry growth) as well as moderating variables (e.g., environmental uncertainty, learning orientation).

Impact on Society: This study provides a reference for enterprises in industrial clusters to use knowledge-based capabilities to enhance their competitive advantage.

Future Research: Future research could collect data from various countries and regions to test the research model and conduct a comparative analysis of industrial clusters.

Keywords: industrial cluster, ambidextrous knowledge sharing, innovation, dynamic capabilities, China

INTRODUCTION

In today's knowledge economy, knowledge management has become a critical factor for a business's survival and for the development of industrial clusters (Ai & Wu, 2016; Zhang & Hu, 2017). As one of the core activities of knowledge management, knowledge sharing is the fundamental means by which a cluster member can contribute to knowledge application, innovation, and, ultimately, its own competitive advantage (Olaisen & Revang, 2017; Sergeeva & Andreeva, 2016; Zimmermann, Oshri, Lioliou, & Gerbasi, 2018). Knowledge sharing among enterprises in an industrial cluster has important practical significance for reducing the costs of knowledge transmission, enhancing the synergy between the enterprises in the cluster, improving the ability of cluster innovation, and promoting innovation in all cluster enterprises (Loebbecke, Van Fenema, & Powell, 2016; R. H. Wang, Lv, & Duan, 2016).

Knowledge sharing enables cluster enterprises to overcome the barriers to exploiting best practices and innovation (Kyoon Yoo, 2014; Loebbecke et al., 2016). With advances in research, an increasing number of scholars are realizing the importance of ambidextrous knowledge sharing, which refers to explorative and exploitative knowledge sharing. Explorative knowledge sharing is the pursuit of new knowledge, whereas exploitative knowledge sharing refers to the use and refinement of existing knowledge (Im & Rai, 2008). Given the heavy investment needed to develop a cluster, policymakers may be particularly keen for it to succeed and may thus put specific measures in place to promote knowledge sharing to improve performance (Connell, Kriz, & Thorpe, 2014). Hence, there is a need to better understand the relationship between ambidextrous knowledge sharing and innovation performance.

In recent years, scholars have begun to gradually combine knowledge sharing, dynamic capabilities, and innovation performance (Estrada, Faems, & de Faria, 2016; Zhou & Li, 2010). The combination of knowledge management and dynamic capabilities has led to the concept of knowledge-based dynamic capabilities (Han & Li, 2015; Nieves, Quintana, & Osorio, 2016). Knowledge sharing provides solutions and thus enhances learning, enabling businesses to respond to environmental changes at an increased pace and with lower costs. Enterprises therefore benefit from improved dynamic capabilities and competitiveness. In the information age, with its dynamic environmental changes, knowledge-based dynamic capabilities are hence an important source of innovation (Cheng, Yang, & Sheu, 2016; Falasca, Zhang, Conchar, & Li, 2017; Han & Li, 2015).

In addition, although knowledge sharing and dynamic capabilities are a widely recognized catalyst to improving innovation among cluster enterprises in a knowledge-based economy, the relationship between these concepts remains unclear. This is partly because only a few empirical studies have examined the interactions among the three (Cheng et al., 2016; Lin & Chen, 2017). Another reason is that most studies have focused on the bilateral relationships between knowledge sharing and innovation performance or between dynamic capabilities and innovation performance (Lin & Chen, 2017; Nieves et al., 2016; Olaisen & Revang, 2017), while failing to explore the determinants of innovation in a more holistic and structural manner. This study attempts to further clarify this issue by exploring how knowledge sharing and dynamic capabilities can promote innovation. The results of this study show that dynamic capabilities play a mediating role between knowledge sharing and innovation performance in cluster enterprises.

This research takes place in the Chinese context. China is an indispensable member of the global economy as it is the world's largest developing country and the second largest economy. It also shares many characteristics with other emerging economies. In recent years, China has been constantly changing its economic development mode, shifting from extensive growth to intensive growth and paying increasing attention to the use of knowledge resources (Zhou & Li, 2010). The knowledge economy has enabled the high-tech industry to lead China's industrial development, and knowledge resources have become the mainstay of industrial clusters. Therefore, conducting research in the Chinese context can help clarify the importance of knowledge sharing and the impact of dynamic capabilities in other emerging economies.

The rest of this paper is structured as follows. Section 2 presents the theoretical background and research hypotheses. Section 3 discusses the study methodology, including methods and data. The empirical results are presented in Section 4. Finally, Section 5 provides a discussion and conclusions, including theoretical and practical implications, limitations, and future research directions.

THEORY AND HYPOTHESES

AMBIDEXTROUS KNOWLEDGE SHARING

Knowledge sharing is defined as the exchange of skills, know-how, and information across the enterprises involved (Im & Rai, 2008). It is one of the most important knowledge management processes (Wu & Zhang, 2015). Knowledge sharing aims to provide knowledge where it is needed, thus contributing to the achievement of a sustainable competitive advantage (S. Wang & Noe, 2010). With effective knowledge sharing, the strategic intent of inter-organizational collaborations for sustainable competitive advantage can be achieved by combining the relevant organizational resources and capabilities of all parties (M. Wang, Vogel, & Ran, 2011). In general, scholars have recognized knowledge sharing as a source of innovation and value creation in both intra- and inter-organizational contexts (Olaisen & Revang, 2017; Ritala, Olander, Michailova & Husted, 2015; R. H. Wang et al., 2016).

The idea of ambidexterity has steadily gained importance in business, management, and organizational studies (Kauppila & Tempelaar, 2016; Nosella, Cantarello, & Filippini, 2012; Turner, Swart, & Maylor, 2013). Scholars originally interpreted the concept of ambidexterity as the ability to pursue two contrasting objectives, which inherently leads to the creation of a tension that must be reconciled or accommodated (Andriopoulos & Lewis, 2010). Nosella et al. (2012) argued that ambidexterity is an organizational capability, which makes it possible to resolve the different tensions that arise within organizations (p. 450). Turner et al. (2013) argued that the use of the word *ambidexterity* does not reflect managerial "activity," it reflects "capability" (p. 319). The work of Im and Rai (2008), for the first time, applied the concept of ambidexterity to the context of explorative and exploitative knowledge sharing. As mentioned earlier, exploitation refers to the use and refinement of existing knowledge, while exploration refers to the pursuit of new knowledge and opportunities (March, 1991). Exploitative knowledge sharing is thus the exchange of knowledge between enterprises, using existing technical conditions and environmental factors, to carry out knowledge sharing behavior; while explorative knowledge sharing is the exchange of knowledge between enterprises, using new technology and new methods, to achieve knowledge accumulation and realize knowledge sharing behavior (Im & Rai, 2008). Inspired by the ideas and insights from those early studies, ambidexterity has recently been considered a balancing act between exploration and exploitation (Benavides & Ynalvez, 2018). Thus, ambidextrous knowledge sharing requires enterprises to balance the use of explorative and exploitative knowledge sharing.

Knowledge Sharing and Innovation Performance

The literature on the diffusion of innovation has made some contributions to the definition of knowledge sharing (Connell et al., 2014; Olaisen & Revang, 2017; Ritala et al., 2015; Zappa, 2011). Knowledge sharing offers an excellent opportunity to explore and test the potential value of the knowledge shared and potential markets for that knowledge, which are important for enterprise innovation. If enterprises do not share knowledge externally, they may never achieve the full potential of their intended strategies. This would mean not only that enterprises might miss an opportunity to gain access to external knowledge but also that an enterprise's own knowledge might remain unused (Ritala et al., 2015). Hence, enterprises that share knowledge externally are more likely to establish and engage in increased inter-organizational collaborations specifically aimed at enhancing innovation.

It seems that exploration and exploitation are both necessary for innovation within cluster enterprises. High explorative knowledge sharing should reduce uncertainties about technological changes, raise the generation potential of the relationship, and lower the risks of a lock-in with inferior technologies. In addition, sharing explorative knowledge should contribute to the innovation of products, services, and processes to coordinate the exchange (Im & Rai, 2008). In addition, high levels of exploitative knowledge sharing should improve the recognition of bottlenecks, such as the leakage of confidential knowledge, a lack of innovation, and knowledge lock-ins (Ritala et al., 2015; Wei, Zhou, Greeven, & Qu, 2016). It provides new opportunities for innovation, enhances the ability to perform routine tasks, and reduces innovation costs. These two types of knowledge sharing not only enlarge the enterprise knowledge pool but also uncover problems and improve innovation. Moreover, both explorative and exploitative processes can be carried out simultaneously, leading to cycles of reinforcement. Thus, simultaneous explorative and exploitative knowledge sharing between cluster enterprises should improve the success rate of innovation. Therefore, ambidextrous knowledge sharing, measured by explorative and exploitative knowledge sharing, can improve enterprise innovation performance. Hence, this study puts forward the following hypothesis:

H1. Ambidextrous knowledge sharing is positively related to innovation performance.

Knowledge Sharing and Dynamic Capabilities

In the knowledge-based economy era, the concept of knowledge-based dynamic capabilities has been introduced, and its typologies, dimensions, and relationship with knowledge management and performance have been explored (Denford, 2013; Han & Li, 2015; Nieves et al., 2016). From a knowledge-based view, Teece (1998) defined dynamic capabilities as "the ability to sense and then to seize new opportunities, and to reconfigure and protect knowledge assets, competencies, complementary assets, and technologies to achieve sustainable competitive advantages" (p. 72). Zheng, Zhang, Wu, and Du (2011) proposed knowledge acquisition, generation, and combination as three sub-capabilities of knowledge-based dynamic capabilities. Denford (2013) divided knowledge-based dynamic capabilities into knowledge creating, knowledge integrating, knowledge reconfiguring, knowledge replicating, knowledge developing, knowledge assimilating, knowledge synthesizing, and knowledge imitating. Therefore, based on the literature, knowledge-based dynamic capabilities can be defined as an enterprise's potential to solve problems through a more dynamic application of knowledge. Moreover, from the perspective of process, it is the ability of an enterprise to absorb and adjust its knowledge bases formed by three types of capabilities: knowledge absorption, knowledge integration, and knowledge generation (Cheng et al., 2016; Denford, 2013; Li & Liu, 2014; Teece, 2007).

Knowledge sharing provides employees with shortcuts to solutions when they encounter similar decisions. This enhances learning and enables them to respond to environmental changes at an increased pace while incurring lower costs. Enterprises thus benefit from improved dynamic capabilities. Indeed, by maintaining such a learning process, they can engage in knowledge sharing and reuse, which enhances their dynamic capabilities to adapt and respond to changing environments (Tseng & Lee, 2014). An organization can promote knowledge sharing to enhance knowledge management capabilities as well as positively influence its dynamic capabilities (Lin & Chen, 2017). Hence, this study puts forward the following hypothesis:

H2. Knowledge sharing is positively related to (a) knowledge absorption capability, (b) knowledge integration capability, and (c) knowledge generation capability.

Dynamic Capability and Innovation

Dynamic capabilities emphasize an enterprise's constant pursuit of absorbing, generating, and reconfiguring its resource bases (Weerawardena, Mort, Salunke, Knight, & Liesch, 2015). The literature on innovation has widely addressed the contribution of dynamic capabilities to enable successful innovation (Falasca et al., 2017). Dynamic capabilities, in fact, are said to create both a temporary and a long-term competitive advantage, thus having a preeminent function in enhancing innovation (Breznik & Hisrich, 2014; Janssen, Castaldi, & Alexiev, 2016). Ulusoy (2003) mentioned some dynamic capabilities that could foster innovation, including continuous improvement, learning, problem solving, and product development. Teece's (2007) views of dynamic capabilities were constructed to capture the set of capabilities that drive innovation and early internationalization. Hence, the role of dynamic capabilities in developing new knowledge resource configurations is necessary for innovation and enhanced goal achievement (Teece & Leih, 2016). Thus, by governing the change rate of knowledge, dynamic capabilities become the ultimate organizational capabilities, which are conducive to increasing long-term performance. Hence, this study puts forward the following hypothesis:

H3. (a) Knowledge absorption capability, (b) knowledge integration capability, and (c) knowledge generation capability have a positive impact on innovative performance.

The Mediating Role of Dynamic Capabilities

Knowledge sharing alone is insufficient to improve innovation. Resources must also be transformed into outputs through transformational capabilities (Han & Li, 2015). As they enable this process, dynamic capabilities are demonstrable mediating factors between the drivers of innovation and different innovation implementations within an enterprise (Liying, Wang, & Ning, 2016). It has been concluded that knowledge sharing and knowledge-based dynamic capabilities are important sources of innovation in the information age with its accompanying dynamic environmental changes (Falasca et al., 2017). In brief, knowledge-based dynamic capabilities are higher-level abilities created through knowledge sharing, which determines how they can be aligned and realigned to match environmental requirements (Han & Li, 2015). This leads to the following hypothesis:

H4. (a) Knowledge absorption capability, (b) knowledge integration capability, and (c) knowledge generation capability mediate the positive relationship between knowledge sharing and innovation performance.

Figure 1 provides an overview of the theoretical model to be tested, including ambidextrous knowledge sharing (explorative and exploitative knowledge sharing), knowledge-based dynamic capabilities (knowledge absorption capability, knowledge integration capability, and knowledge generation capability), and innovation performance. The model relates the influence of ambidextrous knowledge sharing on innovation performance, specifically how simultaneous explorative and exploitative knowledge sharing affect innovation performance through knowledge-based dynamic capabilities.

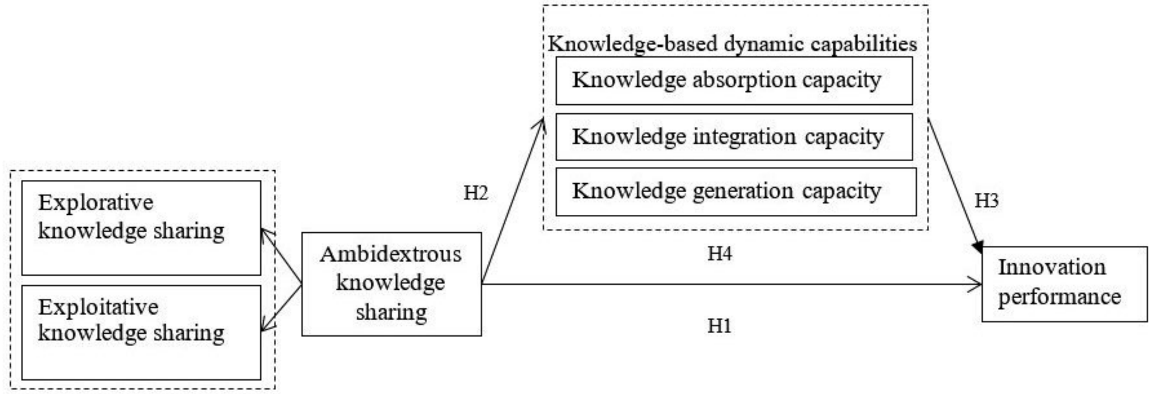

Figure 1. Research framework

RESEARCH METHODOLOGY

DATA COLLECTION AND SAMPLE

To test the research model, we conducted a survey study. The survey was administered in China's Fujian province. The study sample comprised enterprises in industrial clusters, including Qinkou automobile cluster, Quanzhou microwave communication cluster, and Fuqing optoelectronic cluster. A preliminary draft of the questionnaire was developed through an extensive literature review. Subsequently, five professors with expertise in strategic management and knowledge management fields were invited to check the content validity. Afterward, six CEOs from the target industrial clusters were consulted to revise the measurement items. The feedback from these scholars and CEOs was used to create a revised version of the questionnaire. The items were randomly shuffled and correlated with various structures to reduce common method biases in the questionnaire design. The revised questionnaire was sent to 30 manufacturing enterprises for a pilot study.

After these adaptations, 200 questionnaires were sent out in 2010 and another 200 questionnaires in 2016. The final questionnaire was thus sent to 400 cluster enterprises in total. Each enterprise received one questionnaire, and 263 questionnaires were returned (response rate = 65.8%). Among the returned questionnaires, 25 were excluded, as the information provided was incomplete. Thus, 238 valid questionnaires were completed (completion rate = 59.5%).

These questions were translated and presented in the manuscript in English. The study used three translators to ensure the instrument's reliability. The first translator translated the English version into Chinese. The second translator reverse translated the Chinese version into English. The third translator compared the English and Chinese versions and modified the final draft. Further, other experts also examined the items to ensure content validity.

MEASURES AND VARIABLES

Innovation performance is the dependent variable in this research. The independent variable is ambidextrous knowledge sharing, and the mediating variables are knowledge absorption capability, knowledge integration capability, and knowledge generation capability. To test the hypotheses, the dependent, independent, and mediating variables were measured using five-point Likert scales from "strongly disagree" to "strongly agree." Table 1 shows the measured variables.

Table 1. Measured variables

LATENT VARIABLE	MEASURED VARIABLE
Explorative knowledge sharing	The enterprise management attaches importance to an atmosphere of sharing innovative knowledge.
	There are many informal communication opportunities for cluster enterprises to share their knowledge.
	For this enterprise, the rewards for sharing innovative knowledge are higher than for peer enterprises.
	This enterprise considers knowledge sharing a means to gain competitive advantage.
Exploitative knowledge sharing	The enterprise shares its work reports and official documents with other enterprises.
	The enterprise shares its manuals and methodologies with other enterprises.
	The enterprise shares its experiences and know-how with other enterprises.
Knowledge absorption capability	The enterprise can gain market development skills from other enterprises or institutions in its industrial cluster.
	The enterprise can gain management development skills from other enterprises or institutions in its industrial cluster.
	The enterprise can gain new technology skills from other enterprises or institutions in its industrial cluster.
Knowledge integration capability	The enterprise can apply its expertise to bring new projects or initiatives to fruition.
	The enterprise can learn to effectively pool ideas and knowledge.
	The enterprise can assimilate ideas in ways that help find solutions to problems.
Knowledge generation capability	The enterprise can buy new technology and equipment as well as bring in new technology and knowledge.
	The enterprise can introduce new employees who can bring in new technology and knowledge.
	The enterprise can acquire new knowledge from scientific research institutions, colleges, universities, and intermediary service agencies.
Innovation performance	The enterprise has a higher number of new products.
	The enterprise has a faster speed for launching new products.
	The enterprise has lower operating costs for new products.

Knowledge sharing

As this study focuses on how enterprises in industrial clusters are encouraged to share knowledge, all the constructs were measured using multiple-item scales adapted from related studies. In particular, explorative and exploitative knowledge sharing were measured by a four-item scale and a three-item scale, respectively, which were drawn from the works of Kyoon Yoo (2014) and Ritala et al. (2015).

Knowledge-based dynamic capabilities

As mentioned earlier, this study defines knowledge-based dynamic capabilities as knowledge absorption capability, knowledge integration capability, and knowledge generation capability (Roberts & Grover, 2012; Zheng et al., 2011). As mediators, the strength of knowledge absorption capability, knowledge integration capability, and knowledge generation capability were measured using three multi-item sets. Regarding these three dimensions of dynamic capabilities, these items were adapted from the works by Mu and Di Benedetto (2012) and Caridi-Zahavi, Carmeli, and Arazy (2016).

Innovation performance

Most scholars in developed countries obtain data on innovation performance from public databases, but it is not as easy to get accurate data from enterprises in China (Li & Liu, 2014). Therefore, questionnaires were used to measure innovation, with three items designed to reflect the number of new products, the speed of new product launches, and new product operating costs from the sampled enterprises in the past three years (Cheng, Yang & Sheu, 2016).

RELIABILITY AND VALIDITY TESTS

Before hypothesis testing, this study used SPSS v. 21.0 to test the reliability and validity of the measurements. As shown in Table 2, the Cronbach's α coefficient relates to the latent variables, namely explorative knowledge sharing, exploitative knowledge sharing, knowledge absorption capability, knowledge integration capability, knowledge generation capability, and innovation performance, ranging from 0.796 to 0.892, which were all greater than the threshold of 0.7. In addition, the results show that the factor loadings of all the observed variables ranged from 0.630 to 0.899. All were above 0.6, indicating that each latent variable was significant ($p < 0.01$). These results suggest that the measures had good convergent validity.

Table 2. Variable reliability tests

LATENT VARIABLE	MEASURED VARIABLE	CRONBACH'S α	FACTOR LOADING
Explorative knowledge sharing	Explor1	0.836	0.694
	Explor2		0.715
	Explor3		0.610
	Explor4		0.630
Exploitative knowledge sharing	Exploi1	0.860	0.830
	Exploi2		0.825
	Exploi3		0.664
Knowledge absorption capability	Abs1	0.892	0.870
	Abs2		0.899
	Abs3		0.835

LATENT VARIABLE	MEASURED VARIABLE	CRONBACH'S α	FACTOR LOADING
Knowledge integration capability	Int1	0.796	0.761
	Int2		0.782
	Int3		0.781
Knowledge generation capability	Gen1	0.817	0.804
	Gen2		0.847
	Gen3		0.852
Innovation performance	Inn1	0.885	0.786
	Inn2		0.884
	Inn3		0.850

Table 3 presents the descriptive statistics of the variables. The means of the main measures ranged from 3.172 to 3.943. The composite reliability (CR) values are presented along with the average variance extracted (AVE) values for each latent variable. The results indicated that all the CR values were larger than the threshold of 0.70. The data suggest that innovation was significantly correlated with both knowledge sharing and knowledge-based dynamic capabilities ($p < 0.01$). Moreover, knowledge sharing, knowledge-based dynamic capabilities, and innovation performance had a positive relationship. Meanwhile, the square roots of the AVE values listed diagonally in the matrix exceeded the correlations between the constructs, which indicated acceptable discriminant validity (Hair, Anderson, Tatham & William, 1998). These results indicate that the reliability and validity of the measurement instrument meet the requirements for model testing using structural equation modeling (SEM) procedures. Additionally, the Kaiser Meyer Olkin (KMO) value of each scale exceeded the recommended value of 0.857, and Bartlett's test of sphericity was statistically significant ($p < 0.01$). Thus, the results appear to be valid. These results confirm the internal consistency and reliability of the measures.

Table 3. Descriptive statistics of the measured variables

	MEAN	SD	CR	AVE	SQUARED CORRELATION COEFFICIENTS					
					(1)	(2)	(3)	(4)	(5)	(6)
Explorative knowledge sharing (1)	3.800	0.552	0.837	0.565	0.752	—	—	—	—	—
Exploitative knowledge sharing (2)	3.789	0.622	0.871	0.694	.636**	0.806	—	—	—	—
Knowledge absorption capability (3)	3.943	0.712	0.900	0.752	0.378*	0.284**	0.867	—	—	—
Knowledge integration capability (4)	3.489	0.700	0.797	0.569	0.537**	.527**	0.262**	0.754	—	—

	MEAN	SD	CR	AVE	SQUARED CORRELATION COEFFICIENTS					
					(1)	(2)	(3)	(4)	(5)	(6)
Knowledge generation capability (5)	3.172	0.896	0.817	0.599	0.279**	0.204**	0.113	0.256**	0.774	—
Innovation performance (6)	3.672	0.702	0.862	0.677	0.426**	0.360**	0.422**	0.378**	0.277**	0.823

A series of goodness-of-fit tests was used to justify the model design (Hair, Black, Babin, & Anderson, 2010). Ambidextrous knowledge sharing capability, knowledge absorption capability, knowledge integration capability, knowledge generation capability, and innovation performance were included in a confirmative factor analysis (CFA). The results for Model 3 in Table 4 show that the baseline five-factor model fits the data. First, the value of the normed chi-square (χ^2/df) was 1.778. This was less than the threshold criteria of 3, thus indicating a good model fit. In addition, the value of the comparative fit index (CFI) was 0.956, which was greater than the threshold value of 0.9, and again supported the fitness of the model. The value of the adjusted goodness-of-fit index (AGFI) was 0.872, which was greater than the model's acceptable level of 0.80 or above. Moreover, the value of the root mean square residual (RMR) was 0.039, and this satisfied the criteria of $p < 0.05$. Finally, the value of the root mean square error of approximation (RMSEA) was 0.066, which again fell within an acceptable range. Overall, these results suggest that the model is suitable. Additionally, the study tested two alternative models: a null model in which all the indicators were independent (Model 1) and a four-factor model combining knowledge absorption capability, knowledge integration capability, and knowledge generation capability into one factor (Model 2). The results show that the baseline model fits the data better than these two alternative models, supporting the structural distinctiveness of the variables.

Table 4. Comparison of the measurement models for the main variables

Model	X2	Df	X2/DF	CFI	AGFI	RMR	RMSEA
Model 1	1393.876	152	9.170	0.510	0.508	0.098	0.186
Model 2	799.005	146	5.473	0.742	0.605	0.127	0.137
Model 3	254.185	143	1.778	0.956	0.872	0.039	0.066

RESULTS

MODEL SPECIFICATION

SEM is being increasingly adopted for concept and theory development in the social sciences (Hair, Gabriel, & Patel, 2014). It has been used in several prior studies of knowledge management to illustrate complicated relationships between latent variables (Kline, 2016). For SEM analysis, while LISREL used to be the first choice among researchers, Analysis of Moment Structure (AMOS) by IBM is a powerful software program used mainly for the analysis of means and covariance structures, which is the essence of SEM analysis (Byrne, 2016). Thus, the hypotheses were tested using the SEM method in AMOS 21.0 software. Figure 2 illustrates the expanded model, which demonstrates the predicted direct and indirect effects of knowledge sharing on innovation performance through the mediator of dynamic capabilities. The model was then estimated using the maximum likelihood estimator, which generated parameter values producing a model-implied covariance matrix.

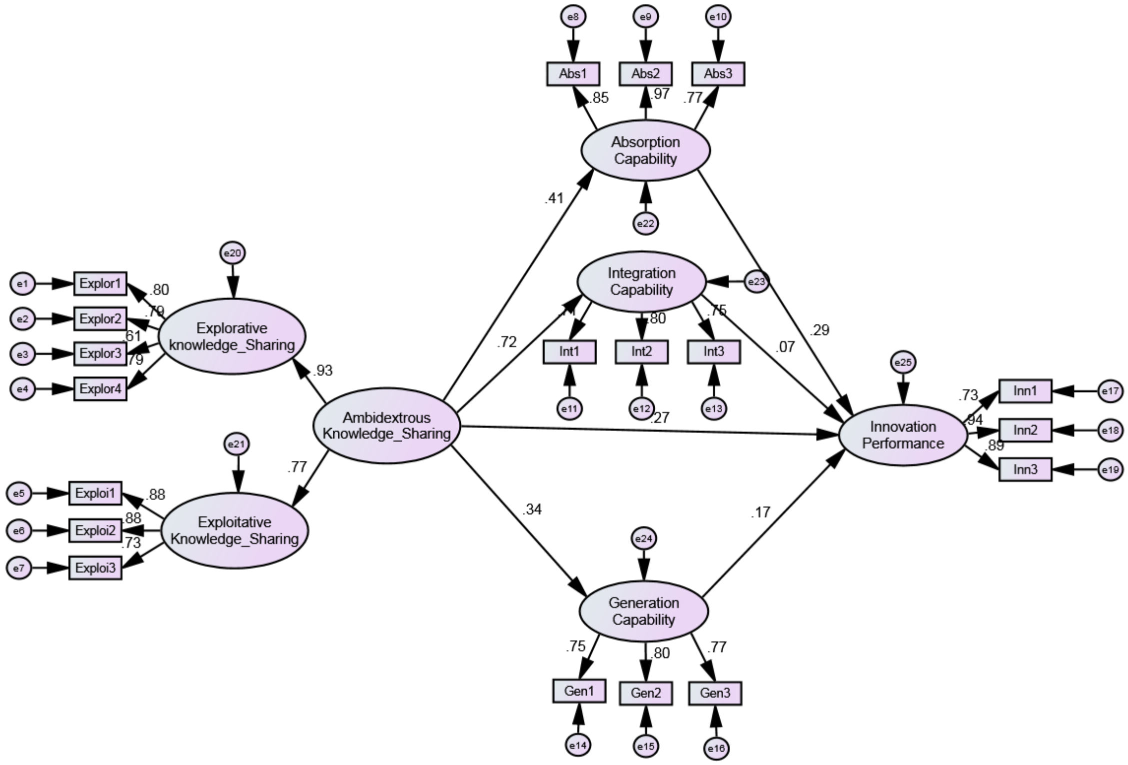

Figure 2. Amos results of the model with full sample

Main Effect Hypothesis Testing

SEM is an appropriate method since it can simultaneously estimate the complex relationships among cluster-wide knowledge sharing, dynamic capabilities, and innovation. This is especially important for the mediating effects within the three components of dynamic capabilities. Moreover, SEM can accommodate the measurement error of the survey data. Table 5 presents the results of the path coefficient estimates, including both the standardized and unstandardized estimates, as well the standard errors and p values. Several indices are also provided to determine the overall fit of the estimated model.

Table 5. Path coefficient estimates of the impact of ambidextrous knowledge sharing on innovation performance

PATH	UNSTANDARDIZED ESTIMATE	STANDARDIZED ESTIMATE	S.E.	C.R.	P
Explorative knowledge sharing←Ambidextrous knowledge sharing	0.93	1.000			
Exploitative knowledge sharing←Ambidextrous knowledge sharing	0.77	0.935	0.105	8.887	0.000**

PATH	UNSTANDARDIZED ESTIMATE	STANDARDIZED ESTIMATE	S.E.	C.R.	P
Ambidextrous knowledge sharing←Innovation performance	0.27	0.295	0.136	2.162	0.031*
Knowledge absorption capability←Ambidextrous knowledge sharing	0.41	0.526	0.097	5.433	0.000**
Knowledge integration capability←Ambidextrous knowledge sharing	0.72	0.795	0.110	7.212	0.000**
Knowledge generation capability←Ambidextrous knowledge sharing	0.34	0.543	0.136	3.988	0.000**
Innovation performance←Knowledge absorption capability	0.29	0.243	0.060	4.061	0.000**
Innovation performance←Knowledge integration capability	0.07	0.072	0.109	0.656	0.512
Innovation performance←Knowledge generation capability	0.17	0.117	0.049	2.404	0.016*

Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

The path value shows a positive and significant relationship between ambidextrous knowledge sharing and innovation performance, as H1 postulates (H1: $\beta = 0.27$, $t = 2.162$, $p = 0.031$). The path value provides support for H2 as well: there is a significantly positive relationship between knowledge sharing and knowledge-based dynamic capabilities (H2a: $\beta = 0.41$, $t = 5.433$, $p < 0.001$; H2b: $\beta = 0.72$, $t = 7.212$, $p < 0.001$; H2c: $\beta = 0.34$, $t = 3.988$, $p < 0.001$). The results also partially confirm a positive relationship between knowledge-based dynamic capabilities and innovation performance, providing support for H3a and H3c (H3a: $\beta = 0.29$, $t = 4.061$, $p < 0.001$; H3c: $\beta = 0.17$, $t = 2.404$, $p = 0.016$). However, the expectation that the relationship between knowledge integration capability and innovation performance would be positive was not supported (H3b: $\beta = 0.007$, $t = 0.656$, $p = 0.512$).

MEDIATING EFFECT HYPOTHESIS TESTING

Figure 3 presents the direct and indirect effects as well as the total effects of ambidextrous knowledge sharing on innovation performance. As shown in Figure 3, the tests for the intermediary effect can be traced to Baron and Kenny (1986), who tested the significance of a and b to judge whether there were any intermediary effects. As a supplement, the Sobel test (Sobel, 1982), which is more widely used than Baron and Kenny's method, checked the significance of $a \times b$ to determine whether a mediating effect existed. However, the Sobel test has some shortcomings. For example, it assumes that the indirect influence of a sample distribution is normal, whereas the sample distribution is often asymmetric (Bollen & Stine, 1990; Stone & Sobel, 1990). Since then, MacKinnon and Dwyer (1993) have improved the measure. This study adopted Mackinnon, Fritz, Williams, and Lockwood's (2007) method to test the mediating effect of dynamic capabilities. The bootstrap method for sampling was selected and simulated 1,000 times with a 95% confidence interval. This method can effectively avoid estimation deviation as well as address the problem of a limited sample size (Fritz & MacKinnon, 2007).

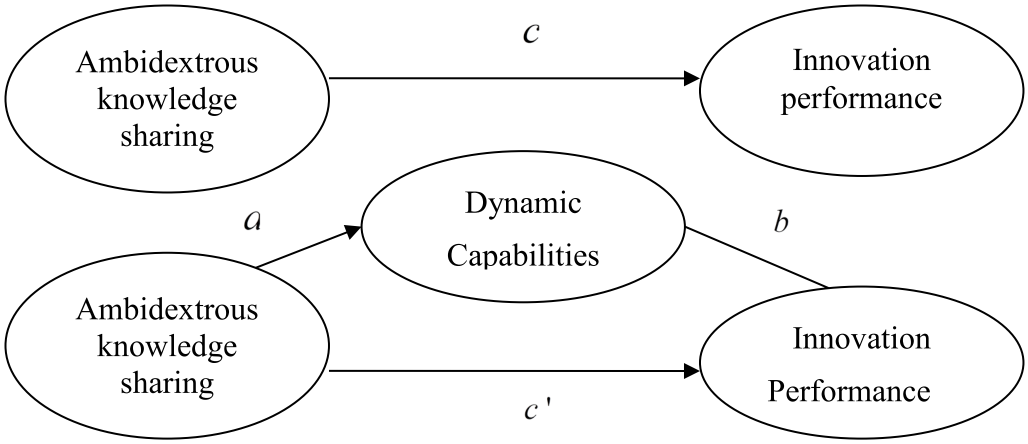

Figure 3. The principle diagram of the intermediary effect

As shown in Table 6, the confidence intervals of knowledge absorption capability and knowledge generation capability did not contain a zero. Therefore, the null hypothesis is rejected. This finding suggests that knowledge absorption capability and knowledge generation capability have a mediating effect between knowledge sharing and innovation performance. Hence, there is support for H4a and H4c. Meanwhile, the confidence interval of knowledge integration capability contained a zero. Thus, it appears that knowledge integration capability did not play a mediating role. Therefore, H4b is not supported.

Table 6. The mediating effects of knowledge-based dynamic capabilities

Intermediary Variable	PATH A		PATH B		Correlation Coefficient	Confidence Interval	
	Coefficient	Standard Error	Coefficient	Standard Error		Lower	Upper
Knowledge absorption capability	0.526	0.079	0.243	0.060	0.413	0.051	0.232
Knowledge integration capability	0.795	0.110	0.072	0.109	0.717	-0.090	0.272
Knowledge generation capability	0.543	0.136	0.117	0.049	0.345	0.009	0.146

DISCUSSION AND CONCLUSION

Existing literature posits that knowledge sharing and innovation are positively related; however, the question of what contributes to the achievement of knowledge sharing in a dynamic environment and in this information era has remained largely unanswered (Chang, Liao, & Wu, 2017; Keszey, 2018; Kim & Shim, 2018). This study therefore investigated the relationship between knowledge sharing, innovation, and the concept of knowledge-based dynamic capabilities in the Chinese context. A SEM model was developed consisting of both the main and mediating effects. From the results, it can be seen that ambidextrous knowledge sharing positively affects innovation (H1) and knowledge-based dynamic capabilities (H2). Knowledge-based dynamic capabilities have a positive impact on innovative performance (H3). Specifically, knowledge absorption capability and knowledge generation capability acted as mediators in the relationship between ambidextrous knowledge sharing and innovation performance in our study, whereas knowledge integration capability did not act as a mediator (H4). These findings provide several theoretical contributions and practical implications.

IMPLICATIONS FOR THEORY

This research contributes to the theory in this field in the following three ways. First, it demonstrates how the effects of ambidextrous knowledge sharing are realized. Although there is rich academic research on knowledge sharing and its effect, researchers have rarely explored ambidextrous knowledge sharing (Im & Rai, 2008). This paper shows that both explorative and exploitative knowledge sharing significantly influence innovation performance. Exploration without exploitation is likely to lead to an investigation of many innovative projects without any benefits. Exploitation without exploration may reduce a firm's chances of maintaining any competitive advantage (Im & Rai, 2008). This study theoretically divided knowledge sharing by clustering it into exploitative and exploratory knowledge sharing, as well as investigated and identified the specific dimensions of each of them through qualitative research, thereby examining knowledge sharing from a more holistic perspective.

Second, this study adds to the literature by suggesting that the effectiveness of knowledge sharing depends on dynamic perspectives and by distinguishing "static" knowledge sharing from "dynamic" leveraging capabilities. Specifically, in a dynamic environment, knowledge sharing is a key driver of dynamic capabilities. The integration of knowledge sharing and dynamic capabilities illustrates how knowledge sharing affects the transformation of knowledge resources into capabilities (Chien & Tsai, 2012), which highlights the importance of fully understanding how cluster enterprises adapt to changing circumstances.

Third, the survey results show that dynamic capabilities promote the innovation performance of cluster enterprises. This finding is consistent with previous research, indicating that dynamic capabilities enable enterprises to quickly and efficiently reconfigure their innovation resources to respond to changing environments (Cheng, Yang & Sheu, 2016; Han & Li, 2015; Nieves et al., 2016). While previous research has often assumed a link between dynamic capabilities and innovation performance (Falasca et al., 2017; Janssen et al., 2016; Zheng et al. 2011), little attention has been paid to examining the mediating effects. Our study results confirm that knowledge-based dynamic capabilities positively influence enterprise performance. Specifically, our empirical results also support the idea that knowledge absorption and generation capabilities play a mediating role that transforms the benefits of knowledge sharing into innovative performance. This finding clarifies the debate on the role that knowledge-based dynamic capabilities play in terms of knowledge sharing and innovation.

IMPLICATIONS FOR PRACTICE

From a practical perspective, the results hold important implications for managers. First, the findings suggest that enterprises must focus on ambidextrous knowledge sharing to enhance their dynamic capabilities and must create a context that enhances ambidextrous knowledge sharing, which in turn leads to new knowledge and innovation. To develop superior capabilities in both explorative and exploitative knowledge sharing, enterprises should establish well-organized routines and processes (Im & Rai, 2008). In particular, cluster enterprises should construct knowledge management systems. They need to strengthen their exploitative knowledge sharing capabilities and seek homogeneous knowledge from other cluster members to help improve their innovation performance. In addition, cluster enterprises should aim to achieve moderate levels of explorative knowledge sharing to introduce new knowledge and technologies, seize innovation opportunities, and improve innovation performance (Zhang & Hu, 2017).

Second, the importance of developing knowledge-based dynamic capabilities can never be neglected. Therefore, enterprises must foster and make full use of knowledge-based dynamic capabilities, be sensitive to tiny changes in the external environment, be equipped with the abilities of knowledge searching and interpreting, be able to discover opportunities and threats, be flexible in strategic decision-making based on demand, and be efficient in the integration of their knowledge-based resources (Falasca et al., 2017; Liying, Wang & Ning, 2016; Weerawardena et al., 2015).

Third, the Chinese industrial clusters need to adjust and establish appropriate governance mechanisms to promote effective development (Wei et al., 2016). There is a causal link between cluster governance and innovation: good governance allows innovative cluster enterprises to foster their knowledge management capabilities. The government should steer cluster development at the local level by establishing a multi-agent knowledge sharing platform to help cluster enterprises contact scientific research institutions, universities, and other organizations, share public technologies, avoid repeating developments made by others, provide financial services to reduce the cost of enterprise knowledge sharing, and effectively guarantee the innovation activities of industrial clusters (Chen, Wang, & Wang, 2018). In addition, Chinese cluster enterprises should rely on global knowledge networks, as both knowledge absorbers and transmitters, that develop technology-driven innovation and create stronger competitive advantage.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Despite these contributions and implications, this study has several limitations, which warrant future research. First, in exploring when and how knowledge sharing was related to innovation, only the effects of knowledge-based dynamic capabilities were investigated. However, many other context variables such as culture, environmental uncertainty, and industry growth were not examined. New research designs could be developed to examine these factors and obtain a more comprehensive understanding of the mechanisms and conditions involved in enterprise innovation.

Second, the concepts utilized for reference are from Western perspectives, while the context of this study was China. Thus, more attention should be paid to cross-context theorizing. In addition, this study only sampled cluster enterprises in Fujian province. Expanding the sample selection to the entire nation could enable researchers to test the generalizability of the findings. Thus, selecting cluster enterprises using strictly random sampling procedures for a nationwide survey study should be considered.

Third, the theoretical model was examined in a cross-sectional study rather than using longitudinal data. This research design may not be capable of reflecting the actual causal relationships because of the time-lag effect. Thus, panel data should be considered to examine these relationships in future research. In addition, although the samples are from three industrial clusters, the current project did not involve a comparative study. Thus, future research should aim to compare data from different clusters.

Fourth, as the questionnaires were sent in 2010 and 2016, there could have been some changes during these six years. Thus, future research should avoid collecting data in different years or over a long time period to prevent any possible significant differences between the data sets caused by the time effect.

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