IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received November 27, 2020, accepted December 18, 2020, date of publication December 22, 2020, date of current version January 4, 2021.

Digital Object Identifier 10.1109/ACCESS.2020.3046641

How Does the External Integration and Internal Sharing of Big Data Influence Organizational Innovation? The Roles of Strategic Learning and Market Responsiveness

XIAOHONG XIAO[1], YUQI ZHU[1], YUXI ZHU[2], AND QING ZHAO[1]
[1]School of Business Administration, Guizhou University of Finance and Economics, Guiyang 550025, China
[2]School of Economics and Finance, South China University of Technology, Guangzhou 510006, China

Corresponding author: Qing Zhao (jonysweet@126.com)

ABSTRACT The issue of how the external integration and internal sharing of big data influence organizational innovation has attracted extensive attention worldwide. The existing literature rarely addresses the relationship between big data integration/sharing and organizational innovation from the strategic perspective at a higher level. Consequently, in this study, big data integration and sharing were employed as external and internal influencing factors to explore the origin of organizational innovation from the perspective of the mediating role of strategic learning and the moderating role of market responsiveness. Simultaneously, an online questionnaire survey was conducted to gather data from 237 research staff working in Chinese firms. The empirical analysis indicated that big data integration and sharing promoted organizational innovation. Specifically, strategic learning played a partial mediating role in the correlation between big data integration/sharing and its innovative capability. Moreover, the innovation-promoting degree of big data integration varied among organizations with market response levels. This study has specific theoretical and managerial implications.

INDEX TERMS Big data integration, big data sharing, strategic learning, organizational innovation.

I. INTRODUCTION

After the outbreak of COVID-19, companies worldwide have actively reshaped their businesses, and many Chinese corporations have attempted to implement strategic reforms. In this process, big data integration and sharing have been integrated into enterprises in an unprecedented manner and played an immeasurable role in enterprises' innovation ability. Judging from the case of Chinese corporations, the epidemic has not only spawned many new forms of business but also promoted attaching importance to big data integration and sharing.[1] For example, through applying a market data mining and supporting decision system, Haier rapidly achieved a daily production capacity of 100,000 protective suits and masks during the epidemic, occupying the top position in the market.[2] Nonetheless, these scattered, disordered, and standard-varying data were not utilized to a high degree in organizations [1]–[3]. However, extensive data have created challenges for companies, leading to blind innovation or even strategic misdirection [4], [5]. Above all, the external integration and internal sharing of big data appear to be critical for survival and development in a changing environment and have raised the concerns of practitioners and scholars.

Existing theories and studies have revealed the critical role of big data in organizational innovation [6]–[11]; mostly, social information processing theory provided theoretical support for this study to some extent. In the view of most scholars, big data would inevitably promote the innovation activities of organizations; however, other scholars held different opinions [4], [5], [9]. Therefore, different contexts, methods, samples, and purposes achieve different results. Above all, the influencing mechanism remains unclear because some crucial factors, such as strategic learning and

The associate editor coordinating the review of this manuscript and approving it for publication was Jenny Mahoney.

[1]As the first country to suffer the outbreak of COVID-19, Chinese enterprises' survival has been seriously affected by this public health incident. In the first quarter of 2020, China's macroeconomy shrank by 6.8%.

[2]https://www.mckinsey.com/featured-insights/china

market responsiveness, have been neglected. Furthermore, the current research in this field failed to attach importance to the role of strategic learning, which refers to the ability to acquire knowledge from past strategic actions and the subsequent application of the knowledge in future strategic adjustments [12], [13], as a bridge linking digitization and creative ability. For instance, big data bring strategic learning to the forefront for organizations, thereby strengthening strategic management. Accordingly, improving the strategic learning ability is particularly vital for the survival of domestic corporations [14]. However, some scholars believe that big data may negatively affect the market's judgment, thereby affecting the innovative behavior of organizations [9], [15]. In other words, as a bridge between the two constructs, whether the connection is reinforced or weakened under the influence of strategic learning remains unclear. Moreover, organizations vary in their responses to markets. Are the market responses a moderating factor or do they vary in mediating strategic learning? Nothing is clear; thus, these issues are the focus of this study.

A relatively complete framework can be constructed, and a preliminary discussion on the relation of big data integration/sharing with organizational innovation can be made by exploring the influence of the critical variables in big data integration and sharing on organizational innovation ability with the market response as the moderating variable and strategic learning as the mediating variable. The remainder of this paper is structured as follows. The related literature is initially revisited to identify the role of big data integration and sharing capability on organizational innovation, and the mediating and moderating mechanisms of strategic learning and the market response are explored. Subsequently, we measure each variable in the scales developed by predecessors and conduct an empirical analysis to examine six hypotheses. The results are presented in the next section and followed by a detailed discussion. The last section includes theoretical contributions, managerial implications, and limitations.

II. LITERATURE REVIEW AND HYPOTHESES

A. BIG DATA INTEGRATION AND ORGANIZATIONAL INNOVATION

Katsuki [6] once stated that enterprise innovation depends on knowledge acquisition from outside organizations in the new economy. As a knowledge source, big data integration mostly occurs outside an organization. It is defined as the process in which enterprises gather external data to achieve independent innovation through a formal relationship with organizations and organizational members' social contact with other organizations and nonorganized individuals. Woodman *et al.* [16] defined organizational innovation as the creation of valuable and useful new products/services within an organizational context. Prusak and Davenport [17] and Wei [18] believed that the external integration of data is based on the existing big data of enterprises, and it is a process of digestion and absorption of external knowledge caused by the intense shock of external data sources.

Enterprises conduct business in the market, and they undoubtedly accumulate abundant data assets. The capability of gathering market data from customers and competitors efficiently promotes organizations' responses to opportunities and threats [19]. Nevertheless, big data integration is equivalent to external information gathering in strengthening an organization. Integrated efficiency is mainly rooted in information transmission efficiency among various departments in the organization, which implies gathering and applying invisible knowledge and data scattered within and outside the organization.

Formal and informal big data integration between individuals and organizations can be regarded as data interaction to some extent [20], enabling better communication and coordination among different departments inside an organization, thus improving the learning ability together and indirectly increasing the effectiveness of innovation [7]. Meanwhile, through intensive access to external data, enterprises can effectively alleviate the constraints of limited internal resources, decrease R&D costs, speed up innovation and avoid the problem of a rigid innovation capability caused by the accumulation of simple internal homogeneous data [7]. Conversely, good integration ability can promote the externalization and internalization efficiency of big data in interorganizational interactions [21]. A new data system can be obtained after data integration [22]. When the enterprise's internal and external data are activated, the enterprise's innovation ability is presented as their data integration ability and their value realization [23].

In summation, big data integration serves organizations through conducting continuous innovation and overcoming environmental uncertainty. In a highly evolving industry, an organization that is good at data integration can explore more innovation opportunities amid dynamic environmental changes and form more rare competitive traits in the industry. Therefore, the following hypothesis is proposed:

H1: Big data integration can positively promote the improvement of organizational innovation capability.

B. BIG DATA SHARING AND ORGANIZATIONAL INNOVATION

Big data sharing generally stems from an internal organization, which refers to various interactive knowledge/information exchange activities conducted by organization members to enhance the understanding or replication of information and disseminate successful experience [24]. When the data information can flow freely within the organization, innovative performance can be promoted through the entire organization based on a shared understanding [11].

The data resources discovered and identified from the external environment are often implicit. Through scientific classification and effective integration, new market information can be continuously communicated and shared among organization members, enhancing the professionalism of knowledge. Consequently, the barriers to innovation caused by organizational hierarchical differences can be weakened, and the team's creative behavior is bound to be promoted [23]. In data sharing, the sharer needs to interpret, reorganize, and transfer the recipients' knowledge in a clear and valuable form rather than simply delivering it. While avoiding the blind position of inappropriate knowledge, the members can grasp the opportunity to reform more actively and ultimately improve the entire organization's innovation ability. Therefore, big data sharing within an organization can speed up knowledge transmission, further motivate innovative thinking, and thus lead to innovative activities. Thus, the previous research concerning this issue has enlightened our work.

On the basis of the above discussion, this study confirms that if all departments of an organization can share big data resources openly during innovation, each department can effectively obtain the required information to accelerate innovation. When the parties in the innovation process are familiar with the requirements and constraints of other groups, the innovation efficiency will be enhanced. Therefore, we expect the following:

H2: Big data sharing can positively influence the improvement of organizational innovation capability.

C. MEDIATING ROLE OF STRATEGIC LEARNING

According to strategic entrepreneurship theory, strategic learning refers to a corporation's dynamic ability to acquire, bundle, leverage, and renew its strategic knowledge to enrich the corporation's valuable knowledge [1], [25]. In this manner, a favorable data utilization capability can be the foundation of organizational innovation, which is more critical than the rich data obtained for organizations. Since strategic learning effectively institutionalizes scattered knowledge, we assumed that the transformation of internal and external data to organizational innovation could be realized through strategic learning.

Briefly, access to diverse data information gives entrepreneurs more strategic knowledge and influences strategic renewal [3]. Strategic learning can integrate organizational learning focused on data acquisition and management processes that emphasize data applications. Furthermore, the core of strategic learning lies in further taking enterprises' understanding of indirect experience, especially the transformation of basic knowledge, as a critical link to guide organizational innovation. Through strategic learning, organizations can capture various and dispersed knowledge elements, which are conducive to creating new products and making new efforts [26]. Strategic learning can also facilitate the integration process of valuable data for innovative purposes because it enhances the likelihood of institutionalization to gain more available organizational-level big data that promote innovation [1].

Undeniably, abundant data resources generate interaction and knowledge sharing among individuals and promote further mutual learning within an organization. Although most scholars support the positive effect of data sharing on organizational innovation, the input and sharing of excessive information within an organization will also slow down organizational innovation [5], [27], [29], [30]. Handling excessive information in the innovation process will also overwhelm the cognitive capabilities of decision-makers [4], [28]. Moreover, a large amount of data costs considerable time and may cause the data to be outdated at the time of its integration. The lack of accurate information in the innovation process further affects product and process design modifications and extends innovation development [28]. However, when strategic learning intervenes, corporations can institutionalize the knowledge that is embedded in individuals or scattered around the corporation into available knowledge [1], [2], [13], thereby creating the possibility of developing advanced products and services [3].

Consequently, as corporations integrate and share big data in the organization, strategic learning is considered a spread-and-incorporate approach that emphasizes the advantage of heterogeneous knowledge, enabling the application of strategic knowledge in developing more novel technologies, products, and services [2], [26]. This phenomenon is due to effective strategic learning not only enabling individuals to recombine and create more novel knowledge [2] but also guiding members in coping with new challenges via the recombination of valuable strategic knowledge [31]. Nevertheless, limited research has explored the mediating effect of strategic learning on the relationship between big data sharing and organizational innovation. Nevertheless, we are convinced that strategic learning plays a critical mediating role in this process. Consequently, we propose the following hypotheses:

H3: Strategic learning mediates the relationship between knowledge integration and organizational innovation.

H4: Strategic learning mediates the relationship between knowledge sharing and organizational innovation.

D. MODERATING EFFECT OF MARKET RESPONSIVENESS

Market responsiveness can be regarded as enterprises' ability to apply internal knowledge to handle dynamic local market conditions. In short, market responsiveness can be defined as the extent to which a corporation reacts to market signals and potential market opportunities and threats [18]. Thus, market responsiveness and product innovation are two particularly important strategic capabilities in the international marketing field (Ruby P. Lee). If a company can timely and rapidly respond to the changes of customer needs in the market and gain a foothold in new markets faster than competitors, then it has a crucial survival marketing strategy [33]. Thus, a quick market response enables an organization to gather more external valuable data resources, leading to the creation of advanced and useful products/services.

Most previous studies have indicated that market responsiveness positively affects organizational performance. A sensitive response to a variation in market demand promotes effective behavior (such as innovation) within an organization [34]. Carbonell and Escudero [9] defined market responsiveness as a mediator and found that it influenced the effects of intelligence generation and dissemination on

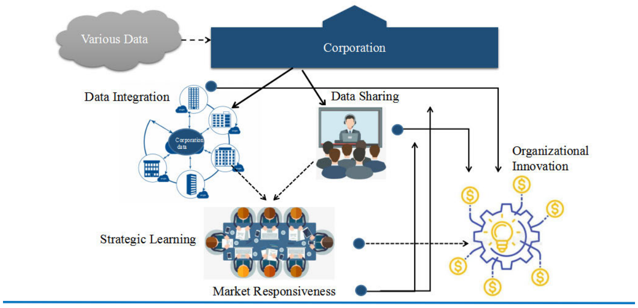

FIGURE 1. Schematic logic process.

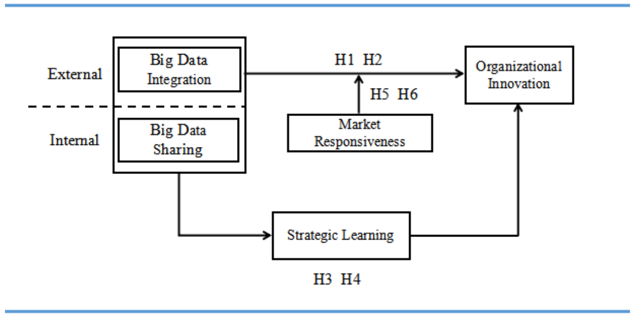

FIGURE 2. Research model.

innovation speed and new product performance. Some scholars have also deemed that the interaction of the external environment and market responsiveness will affect individual behavior. For example, the interaction of market sensitivity and information diversity will cause organizations to make changes [35]. Similarly, enterprises equipped with advanced big data information systems can quickly locate the resource requirements to respond to the market. By integrating data resources acquired externally, a series of market big data can be acquired to precisely enhance the team's innovation in response to the changing market. Although researchers have realized the role of internal and external factors in moderating organizational behavior, few have focused on the moderating effect of market responsiveness toward big data integration/sharing.

On the basis of the analysis of the above two aspects, companies with a better market response-ability can respond to the emerging customer needs and the challenges of competitors faster and better than their competitors and subsequently enhance the external and internal effects on organizational innovation. Accordingly, two hypotheses are proposed as follows:

H5: Market responsiveness moderates the positive effect of big data integration on organizational innovation.

H6: Market responsiveness moderates the positive effect of big data sharing on organizational innovation.

Based on the theoretical reasoning summarized above, a schematic logic process is presented in Figure 1, and we further abstract it into a research model, as shown in Figure 2.

III. METHODOLOGY AND MEASUREMENT

A. MEASUREMENT OF VARIABLES

The questionnaire was divided into two sections. The first section measured five variables, including big data integration, big data sharing, strategic learning, market responsiveness, and organizational innovation, with mature scales. In the second section, we collected demographic information, including gender, age, education, and job position, through the questionnaires. A seven-point Likert scale, ranging from strongly disagree to strongly agree, was used to measure the questionnaire items. To ensure the validity of the scale used in the survey, the items were adapted from the relevant research and existing literature to fit this study's theme and context. Since the participants involved in our study were Chinese, the questionnaires were in Chinese to ensure that our questions were accurately understood. The original English questions were translated and then back-translated, and experienced researchers were invited to improve the questions to further enhance the reliability of the scales, which were used for the formal investigation.

Following Kleinschmidt *et al.* [36], big data integration is measured with a ten-item scale. The typical items include "Colleagues act in strict accordance with the rules and regulations" and "The company has a system for how to spread its expertise."

Big data sharing is assessed with the scale developed by Bart and De Ridder [37], which consists of five items, including "If I get some information, I will share it with my colleagues" and "I will not hesitate to teach my colleagues the skills I have acquired."

We follow Cordero [38] to measure organizational innovation. The scale consists of six items, such as "Our Company has recently improved its product quality through technological innovation."

To measure market responsiveness, we adopted the two-item scale developed by Anderson *et al.* [1], that is, (1) We will respond quickly to changes in the market demand, and (2) We are more responsive to changes in the market demand than our primary competitors.

Strategic learning was measured using a six-item scale adopted from Anderson *et al.* [1] and Covin *et al.* [39], including "We can learn from wrong strategies and make fewer mistakes," "We can conclude the reasons for the failure of the strategy," and "We will regularly adjust our strategy and put it into action."

B. DATA COLLECTION AND SAMPLE

To determine the reliability and validity of the measurement tools, we first conducted a small-scale preliminary test of the questionnaire in Guizhou and Shanghai. The enterprises involved were mainly high-tech enterprises that had long-term cooperation with our university. Then, structured questionnaires were distributed to collect data from Chinese corporations, and a total of 321 questionnaires were obtained in this study. We filtered the questionnaires based on the completeness of the information and whether the answers

TABLE 1. Respondent demographics (N=237).

Items	Classification	Number of Samples	Percentage (%)
Gender	Male	115	48.5
	Female	122	51.5
Age	≤30	49	20.7
	31–40	64	27.0
	41–50	78	32.9
	51–60	41	17.3
	61 and above	5	2.1
Education	Primary school or below	1	0.4
	Junior high school	6	2.5
	Senior high school	43	18.1
	Bachelor's degree	130	54.9
	Master's degree or above	57	24.1
Industry	Manufacturing	36	15.2
	Trading	8	3.4
	Finance	35	14.8
	Traditional services	16	5.61
	Agriculture	2	0.93
	Construction	26	9.35
	Real estate	2	1.25
	Internet	3	1.25
	Others	109	47.66
Corporation Size	≤1000	129	40.19
	1000–2000	56	17.45
	2000–3000	16	4.98
	3000 and above	120	37.38
Is the corporation a high-tech enterprise?	Yes	77	23.99
	No	244	76.01
Has the corporation received strategic guidance from a third party?	Yes	135	42.06
	No	186	57.94

to the options were regular. Finally, 237 valid questionnaires remained with an effective response rate of 73.83%. As shown in Table 1, nearly half of the participants (48.5%) were male, and most of the respondents were aged from 41 to 50, accounting for 32.9%. The majority of the participants (79%) had a bachelor's degree or above, and the remaining respondents were below the undergraduate level. In addition, most of the surveyed enterprises are located in western China, but few of them have been certified as high-tech enterprises.[3] Moreover, nearly half of these enterprises (42.06%) had strategic consultants overseeing their strategy design and implementation.

[3]. The Chinese government reduces the income tax of enterprises with a high-tech enterprise certificate by 10% every year. Many enterprises seek to obtain a certificate by enhancing their technological innovation capability.

IV. EMPIRICAL RESULTS

A. RELIABILITY AND VALIDITY ANALYSIS

This study used Mplus 8.0 to analyze the reliability and validity of each part of the construct. Table 2 shows the factor loading of each latent variable, the composite reliability (CR), the convergent validity (AVE), and the discriminant validity. Regarding the reliability test, the composite reliability of all variables was greater than 0.8, which was consistent with the criterion suggested by Fornell and Larcker (CR>0.6), indicating that the reliability of the measurements was acceptable. The construct validity of the scale was analyzed using the convergent and discriminant validity. According to Fornell and Larcker, evidence for discriminant validity is present when the square root of the average variance extracted (AVE) for each construct exceeds the corresponding correlations between that construct and the other constructs. The results show that the discriminant validity of the measurements was acceptable. The AVEs of the five constructs were approximately 0.5 or over 0.5, and the CRs were all above 0.7. Thus, convergent validity was significant. (It is acknowledged that items with AVE>0.5 or CR>0.7 are considered to have good convergent validity.)

Furthermore, compared with other four-factor and three-factor models, the five-factor model has a better model fit, indicating that the model with five variables is the best.

B. COMMON METHOD VARIANCE

The business-completed questionnaires may produce a common method variance problem. To avoid this problem, we designed reverse questions for each scale. Following Podsakoff's practice, we used the single-factor exploratory analysis method of Harman to test our work's effect. We found that the first factor's initial eigenvalue was 46.492%, which is less than the 50% that Hair suggested. The result showed that the common method problem was not serious. Simultaneously, regarding the correlation coefficients of the structure, as shown in Table 4, the maximum value of the coefficient was 0.897, which is less than 0.9. Thus, the common method variance was in a comparative acceptable range.

C. DESCRIPTIVE STATISTICS AND CORRELATION ANALYSIS

Before conducting the regression analysis, upon which we base our hypothesis tests, in Table 4, we present the descriptive statistics of the investigated corporations in our study. As seen from the means, maximums, and minimums of the variables, strategic consultation has not been widely adopted (less than 50%) by Chinese corporations, though more than half of the involved corporations are high-tech corporations. The skewness and kurtosis indexes indicate that the respondents' corporations are generally normally distributed, supporting that our sample is representative in the Chinese context. Table 5 presents the correlation coefficient matrix.

TABLE 2. Reliability and validity analysis.

Dim.	Items	Item Reliability	Composite Reliability	Convergence Validity	Discriminant Validity				
		Std. Loading	CR	AVE	BDI	BDS	OI	SL	MR
BDI	8	0.744–0.910	0.937	0.652	**0.807**				
BGS	3	0.716–0.877	0.846	0.648	0.563	**0.805**			
OI	4	0.883–0.926	0.945	0.811	0.783	0.516	**0.901**		
SL	3	0.823–0.869	0.881	0.712	0.728	0.478	0.771	**0.844**	
MR	2	0.881–0.883	0.875	0.778	0.709	0.475	0.897	0.825	**0.882**

Note: BDI represents big data integration, BDS represents big data sharing, OI represents organizational innovation, SL represents strategic learning, and MR represents market responsiveness.

TABLE 3. Structural validity analysis.

Model	X^2	DF	X^2/DF	CFI	TLI	RMSEA	SRMR
Five-factor model (BDI, BDS, SL MR, and OI)	401.324	160	2.508	0.942	0.931	0.080	0.044
Four-factor model (BDI+BDS, SL, MR, and OI)	594.355	164	3.624	0.896	0.880	0.105	0.059
Four-factor model (BDI, BDS+MR, SL, and OI)	627.076	164	3.824	0.888	0.870	0.109	0.066
Four-factor model (BDI+MR, BDS, SL, and OI)	642.724	164	3.919	0.884	0.866	0.111	0.067
Three-factor model (BDI+BDS+SL, MR, and OI)	812.725	167	4.867	0.844	0.823	0.128	0.073
Three-factor model (BDI+BDS+MR, SL, and OI)	830.036	167	4.970	0.840	0.818	0.129	0.076
Two-factor model (BDI+BDS+SL+MR and OI)	979.301	169	5.795	0.804	0.780	0.142	0.078
One-factor model (BDI+BDS+SL+MR+OI)	1183.427	170	6.961	0.755	0.726	0.159	0.081

The correlation analysis indicated that big data integration and big data sharing were significantly positively correlated with both organizational innovation ($r = 0.739, p < 0.01$ and $r = 0.475, p < 0.01$, respectively) and strategic learning ($r = 0.668, p < 0.01$ and $r = 0.423, p < 0.01$, respectively). Furthermore, strategic learning was also positively correlated with organizational innovation ($r = 0.709, p < 0.01$).

D. HYPOTHESIS TESTING

1) MAIN EFFECT ANALYSIS

To examine the main effects of the model, we used the regression analysis tool in the Mplus 8.0 software to construct a series of structural equation models to conduct the hypothesis testing, and the estimator was the maximum likelihood (ML). The regression equation is followed by Functions M1 and M2. Table 6 shows the results of the main effect analysis in our study, and most of the fitting indexes were acceptable except for a slightly higher one, but it did not affect the goodness of fit. H1 proposed that big data integration can positively promote organizational innovation capability, which was supported ($\beta = 0.777, p < 0.01$). Simultaneously, big data sharing positively affected organizational innovation ($\beta = 0.549, p < 0.01$), consistent with H2. The findings indicated that enhancing organizational big data integration and sharing is conducive to organizational innovation capability.

$$OI = \alpha_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + \beta_6 BDI + \varepsilon \ (M1)$$

$$OI = \alpha_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + \beta_6 BDS + \varepsilon \ (M2)$$

$$OI = \alpha_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + \beta_6 BDI + \beta_7 SL + \varepsilon \ (M3)$$

$$OI = \alpha_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + \beta_6 BDS + \beta_7 SL + \varepsilon \ (M4)$$

2) MEDIATING EFFECT ANALYSIS

To examine whether the relationships between big data integration/sharing and organizational innovation were mediated by strategic learning, the bootstrap (1000 times) confidence interval test method in the Mplus 8.0 software was applied (see Functions 3 and 4, as well as M3 and M4, in Tables 6 and 7).

Tables 7 and 8 show the results of the mediating effect of the strategic learning concerns in this study. A bootstrap analysis with 1000 resamples indicated that the indirect effect of big data integration on organizational innovation via strategic learning (effect=0.304, $p < 0.05$) with a confidence interval that did not include zero (bias-corrected 95% CI=0.132–0.660; percentile 95% CI=0.118–0.617), supported H3.

Similarly, the indirect effect of big data sharing on organizational innovation through the path of strategic learning was also significantly positive (effect=0.348, p<0.01; bias-corrected 90% CI=0.229–0.520; percentile 90% CI=0.214–0.534), which supported H4. As shown in Tables 6 and 7, big data integration/sharing positively and directly affected organizational innovation and positively and indirectly affected organizational innovation through the

TABLE 4. Descriptive statistics of the responding corporations' information.

Items	Classification	Mean	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
Corporation Size	≤1000 1000-2000 2000-3000 >3000	2.44	1.34	1	4	0.13	-1.77
Corporation Age	<1 year 1-5 years (excluding 5 years) 5-10 years (excluding 10 years) ≧10 years	3.73	0.63	1	4	-2.51	6.11
Corporation Property	solely state-owned state-owned holding private holding private sole foreign company	3.24	1.95	1	6	0.40	-1.45
Is the corporation a high-tech enterprise?	Yes No	1.74	0.438	1	2	-1.12	-0.76
Has the corporation received strategic guidance from a third party?	Yes No	1.57	0.50	1	2	-0.27	-1.95

Note: There are several categories for each variable and we assigned different numbers to quantify each category. 1 represents the first category, and the numbers increase in turn.

TABLE 5. Pearson correlation coefficients.

Variables	1	2	3	4	5	6	7	8	9	10
Corporation Size	-									
Corporation Age	0.280^{***}	-								
Corporation Property	-0.373^{***}	-0.130^{**}	-							
High-tech Enterprise	−0.117	−0.027	0.191^{***}	-						
Strategic Consultant	-0.330^{***}	−0.085	0.290^{***}	0.321^{***}	-					
BDI	0.109	−0.112	−0.053	0.051	−0.091	(0.936)				
BDS	0.002	-0.177^{***}	0.082	0.087	−0.075	0.526^{***}	(0.837)			
SL	0.091	−0.092	−0.015	0.072	−0.029	0.668^{***}	0.423^{***}	(0.881)		
OI	0.014	-0.130^{**}	0.019	0.129^{**}	0.059	0.739^{***}	0.475^{***}	0.709^{***}	(0.944)	
MR	0.057	−0.093	0.036	0.158^{**}	0.031	0.647^{***}	0.430^{***}	0.724^{***}	0.817^{***}	(0.875)

Note: $^{***}p<0.01$, $^{**}p<0.05$, and $^{*}p<0.1$

TABLE 6. Results of the main effect analysis.

Model and Path		M1 BDI→OI	M2 BDS→OI
Path Coefficients	BDI→OI	0.777***	
	BDS→OI		0.543***
Model Fit Index	χ^2/df	2.866	2.353
	CFI	0.961	0.986
	TLI	0.952	0.978
	RMSEA	0.089	0.076
	SRMR	0.038	0.040

TABLE 7. Results of the mediating effect of BDI.

Path	Effect	Point Estimate	S.E.	Est./S.E.	p-Value	Bootstrapping 1000 Times: Bias-corrected 95% CI		Percentile 95% CI	
M3						Lower	Upper	Lower	Upper
BDI->SL->OI	TOTAL	0.774	0.067	11.50	***	0.650	0.914	0.655	0.918
	TOTAL INDIRECT	0.304	0.130	2.328	**	0.132	0.660	0.118	0.617
	DIRECT	0.471	0.159	2.965	***	0.106	0.741	0.131	0.749

partial mediator—strategic learning.

$$OI = \alpha_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + \varepsilon \ (M5)$$

$$OI = \alpha_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + + \beta_6 BDI + \beta_7 MR + \varepsilon \ (M6)$$

$$OI = \alpha_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + \beta_6 BDI + \beta_7 MR + \beta_8 BDI \times MR + \varepsilon \ (M7)$$

$$OI = \alpha_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + + \beta_6 BDS + \beta_7 MR + \varepsilon \ (M8)$$

$$OI = \alpha_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 + \beta_6 BDS + \beta_7 MR + \beta_8 BDS \times MR + \varepsilon \ (M9)$$

3) MODERATING EFFECT ANALYSIS

This study used hierarchical regression to examine the moderating effect of market responsiveness. The regression equations were followed by M5–M9.

As shown in Table 9, M5 represented that the younger organizations or the organizations with high-tech enterprise certificates (awarded by China's Ministry of Science and Technology every year) performed more innovatively, which indicated that the government's policy of promoting enterprises to obtain high-tech enterprise certificates helps improve innovation capability. Regarding M6 and M8, when the moderating variable is added, the significance of path a (effect=0.313, $p < 0.01$) and path b (effect=0.131, $p < 0.05$) showed that big data integration and sharing positively affected organizational innovation. Regarding M7 and M9, the interaction of big data integration and market responsiveness was positive and significant ($\beta = 0.079$, $p < 0.01$), indicating that market responsiveness moderated the relationship between big data integration and organizational innovation such that when an organization was more sensitive to the market, the relationship between big data integration and organizational innovation would be promoted, which supported H5. Nevertheless, the interaction of big data sharing and market responsiveness was nonsignificant; thus, H6 was not supported. These findings imply that organizations with big data integration capability can effectively adopt valuable market information to promote innovation capability. However, regarding big data sharing, the probable reason may be that organization members hardly share worthy information timely or effectively, resulting in a lower degree of innovation. Unexpectedly, as shown in M7, a strategic consultant could also significantly affect organizational innovation capability together with data integration, manifesting that a strategic consultant improves the innovation process.

Furthermore, we examined the moderating effect of market responsiveness on the relationship between big data integration/sharing and organizational innovation via strategic learning; however, the results were nonsignificant, indicating that these moderated mediating effects we proposed did not exist.

V. GENERAL DISCUSSION

This study aims to shed light on how big data integration and sharing promote organizational innovation capability. First, empirical analysis results revealed that the process of big data integration and sharing significantly affects the organizational capability of innovation, that is, organizations with more robust big data integration and sharing capability will be more innovative. Second, strategic learning plays a partial mediating role in the effect of big data integration and sharing on innovation, indicating that the promotion of innovation can be realized by strengthening organizational concerns and attitudes toward strategic issues. Third, market responsiveness plays a moderating role in the integration and innovation context. When organizations are highly responsive to market changes, they will accelerate the transformation from big data integration to the creation of valuable products/services, thereby improving the competitiveness of organizations. However, market responsiveness fails to moderate the positive relationship between big data sharing and innovation. Finally, we also found that the organization's age and whether it is a high-tech enterprise will also significantly affect its innovation capability. Based on the results, organizations perform more innovatively when they are younger and possess high-tech qualifications.

A. THEORETICAL CONTRIBUTIONS

The findings of this study extend the empirical research of social information processing theory in four critical ways. First, the results reveal a positive effect of big data integration on organizational innovation capability rather than merely emphasizing knowledge. Currently, data is gradually replacing the traditional factors of production of labor, capital and

TABLE 8. Results of the mediating effect of BDS.

Path	Effect	Point Estimate	S.E.	Est./S.E.	p-Value	Bootstrapping 1000 Times			
						Bias-corrected 90% CI		Percentile 90% CI	
M4						Lower	Upper	Lower	Upper
BDS->SL ->OI	TOTAL	0.551	0.105	5.264	***	0.406	0.749	0.405	0.748
	TOTAL INDIRECT	0.348	0.086	4.059	***	0.229	0.520	0.214	0.534
	DIRECT	0.203	0.108	1.878	*	0.038	0.384	0.043	0.438

TABLE 9. Results of the moderating effect analysis.

Step	Variables and Models		OI				
			M5	M6	M7	M8	M9
①	Control Variables	Corporation Size	0.067	−0.036	−0.043	−0.023	−0.023
		Corporation Age	-0.258^{**}	−0.021	−0.031	−0.032	−0.032
		Corporation Property	−0.002	−0.007	−0.013	−0.024	−0.024
		High-tech Enterprise	0.313^{*}	−0.015	−0.032	−0.053	−0.053
		Strategic Consultant	0.086	0.165	0.166^{**}	0.140	0.141
②	Path a	Independent Variable: BDI		0.313^{***}	0.308^{***}		
		Moderator: MR		0.651^{***}	0.639^{***}		
	Path b	Independent Variable: BDS				0.131^{**}	0.130^{**}
		Moderator: MR				0.808^{***}	0.809^{***}
③	Moderating Effect a	BDI×MR			0.079^{***}		
	Moderating Effect b	BDS×MR					0.002

Note: *** p<0.01, ** p<0.05, and * p<0.1.

land as the core resources and key elements of enterprises. Integrated big data constitute the essence of enterprises' core capabilities and expand the boundary of competition. Sun *et al.* [7] stated that for organizations, data integration can effectively exchange and recombine data resources from various channels, which results in optimizing innovation costs and cycles. Accordingly, it is necessary to make full use of big data in the technological innovation process through integration [44]. Moreover, as increasingly more enterprises are involved in digital transformation, the stimulating effect of data integration on organizational innovation becomes more prominent. Furthermore, it will arouse organizations' attention to integration capabilities, which may result in innovative breakthroughs. Second, big data sharing can also enhance organizational innovation capability. Although the influential coefficient ($\beta = 0.543$) is lower than that of data integration, it still significantly boosts the intention for innovation, indicating that data sharing should also be a great concern of the academic domain. That is, interactions among individuals who possess diverse and different data resources will augment the organization's capacity for making novel associations—innovating—far beyond the reach of one individual [24]. However, most existing studies have mixed data integration with sharing as one latent variable and deem data sharing as one part of integration [7], [22] whereas our work contributes to an emergent realm to distinguish the two constructs. We held that data integration is the process of involving new external resources in internal organizations while data sharing mainly occurs within organizations, emphasizing that these two constructs should not be confused. Third, this study proposes an important mechanism to explain the positive effect of data integration and sharing on organizational innovation, which explicitly reveals that strategic learning is considered to be a vital bridge in linking big data integration/sharing and promoting the capacity for organizational innovation. Particularly, both of the indirect effects of strategic learning accounted for nearly 50% (0.3040.774=39.2%; 0.3480.551=63.2%) of the total effects. Thus, nearly half (39.2%) of the transmission from integration to innovation can be realized through strategic learning whereas over half of the effect (63.2%) from sharing to innovation occurs via this path. However, studies on the mediating mechanism of strategic learning are still scarce, especially at the organizational level [58], and few of them have separated strategic learning from the traditional concept of organizational learning. Furthermore, the empirical results show that using strategic consultants will influence organizational innovation together with market responsiveness. Although effectively adopting big data is essential, strengthening cooperation with professional consultants is nearly as important in modern China. Last, this study contributes to other existing studies by investigating the moderating role

TABLE 10. Constructs and their measurement.

Construct	Items	Reference
Big Data Integration	BDI1: Our corporation encourages us to share new information and has established a reward system.	[38]
	BDI2: All of my colleagues like our corporation's culture and institutions.	
	BDI3: My colleagues act in strict accordance with the rules and regulations.	
	BDI4: The corporation has clear rules about what everyone should do.	
	BDI5: The corporation has a system for how to spread its expertise.	
	BDI6: The corporation's products need our joint efforts to be completed.	
	BDI7: There is a high degree of coordination between the various departments of the corporation.	
	BDI8: The corporation provides training or job rotation to improve our cooperative capability.	
Big Data Sharing	BDS1: If I receive some information, I will share it with my colleagues.	[39]
	BDS2: I will not hesitate to teach my colleagues the skills I have acquired.	
	BDS3: When I ask my colleagues some questions, they will tell me what they know.	
Strategic Learning	SL1: We can summarize the reasons for the failure of a strategy.	[1],[41]
	SL2: When we know which strategy works and which does not work, we will regularly adjust our strategies and put them into action.	
	SL3: When we find that a strategy does not work, we will adjust our strategic goals and find an alternative strategy.	
Market Responsiveness	MR1: We will respond quickly to changes in market demand.	[1]
	MR2: We are more responsive to changes in market demand than our primary competitors.	
Organizational Innovation	OI1: Our corporation has improved the profitability of its products through innovation.	[40],[42]
	OI2: Our corporation can reduce product development costs through innovation. OI3: Our corporation has introduced new technology and equipment that accelerate the speed of product updates.	
	OI4: Our corporation innovates new technology and optimizes its operating flow.	

of market responsiveness in organizational innovation. That is, this study provides empirical evidence that organizations that sensitively respond to the market are likely to promote the transmission from data integration to innovative capability, though it failed to moderate the relationship between data sharing and organizational innovation. We speculate that when organizations are overly responsive to the market, excessive data sharing may lead to information redundancy, thus offsetting the significant positive impact of data sharing on organizational innovation. Nevertheless, the current study mainly focused on the effect of market responsiveness on organizational performance, and its moderating role has not been fully discussed [1], [35].

B. MANAGERIAL IMPLICATIONS

Since the start of the 21st century, the global era of big data has inevitably followed, thereby promoting digitization to an unprecedented level. How does big data influence organizational innovation? If an effect exists, what is the mechanism? Scholars have not fully discussed these problems. An entire organization is handling data all the time, which are derived from various channels, such as mobile apps, massive media, and conference platforms. Excessive data may not only enrich the source of information and knowledge but also increase organizations' confusion and blindness in their thinking and behavior [4], [5].

On the basis of the empirical analysis results, this study raises the following suggestions for organization managers. Above all, organizations should not be afraid that rich information will burden their cognition and processing ability. In contrast, they should fully enjoy the positive effect caused by the information. Leaders should be aware of the positive effect of big data integration ability on organizational innovation. Data integration in the context of the big data economy should break through the constraints of organizational frontiers. The training of members within the organization should focus on strengthening their ability to capture market information data and establishing an institutionalized process to integrate and synthesize external information. Moreover, creating an intense atmosphere of big data sharing is a necessity within an organization. The corporate strategic direction, active sharing, and the application of internal and external data resources can strengthen various departments' cooperation and accelerate the flow of innovation consciousness in the organizational hierarchy. Finally, due to the rapidly changing market information and radical dynamic competition, organization members should deepen their sense of strategic learning and insight into the market information. Learning from experience and a consultant helps create more effective organizational routines and determine suitable strategies. In this manner, a practical decision can be made and mistakes can be avoided, thereby promoting innovation capability.

VI. LIMITATIONS AND FUTURE RESEARCH OPPORTUNITIES

This study has two specific limitations. The first limitation is related to the cross-sectional design of this study. Although our conclusions are consistent with most scholars' results, the cross-sectional nature of the data did not permit the causal inference of the links between big data integration/sharing and organization innovation. Future research could use a longitudinal design that may better ascertain the causal basis of the relationships examined. The second one is that the market responsiveness's moderating effect on the positive relationship between big data sharing and organizational innovation is nonsignificant, which does not agree with our previous assumption. For the explanation of the above phenomenon, we believe that the process of big data sharing generally occurs within the organization. If organization members are extremely sensitive to market information, then the information may be redundant during the sharing process, and excessively rich data may reduce the speed of understanding. A probable reason is that there would be an upper limit on an organization's ability to accept shared data beyond which new product development may slow down.

APPENDIX

See Table. 10.

REFERENCES

[1] B. S. Anderson, J. G. Covin, and D. P. Slevin, "Understanding the relationship between entrepreneurial orientation and strategic learning capability: An empirical investigation," *Strategic Entrepreneurship J.*, vol. 3, no. 3, pp. 218–240, Sep. 2009.

[2] C. A. Sirén, M. Kohtamäki, and A. Kuckertz, "Exploration and exploitation strategies, profit performance, and the mediating role of strategic learning: Escaping the exploitation trap," *Strategic Entrepreneurship J.*, vol. 6, no. 1, pp. 18–41, Mar. 2012.

[3] J. Zhao, Y. Huang, X. Xi, and S. Wang, "How knowledge heterogeneity influences business model design: Mediating effects of strategic learning and bricolage," *Int. Entrepreneurship Manage. J.*, pp. 1–31, Feb. 2020.

[4] R. M. Cyert, E. A. Feigenbaum, and J. G. March, "March: A Behavioral Theory of the Firm," *Amer. Sociol. Rev.*, vol. 29, no. 2, pp. 81–95, Aug. 1964.

[5] B. J. Zirger and J. L. Hartley, "A conceptual model of product development cycle time," *J. Eng. Technol. Manage.*, vol. 11, nos. 3–4, pp. 229–251, Dec. 1994.

[6] F. Katsuki, "Empirical research of the relationship between relational networks, inter-organizational knowledge integration and innovation performance," *J. Ind. Technol. Econ.*, vol. 89, no. 8, pp. 4643–4647, Oct. 2012.

[7] B. Sun, Y. Liu, and Y. Liu, "The relationship among uncertainty, knowledge integration mechanisms and innovation performance in technology innovation alliance," *Sci. Sci. Manage. S.& T.*, vol. 33, no. 1, pp. 51–59, Jan. 2012.

[8] P. Zeng, T. Z. Deng, and X. B. Zeng, "IT infrastructure, knowledge sharing and organizational innovation-empirical evidence come from enterprises in Pearl Rive delta," *Stud. Sci. Sci.*, vol. 29, no. 11, pp. 1696–1708, Nov. 2011.

[9] P. Carbonell and A. I. Rodríguez Escudero, "The effect of market orientation on innovation speed and new product performance," *J. Bus. Ind. Marketing*, vol. 25, no. 7, pp. 501–513, Aug. 2010.

[10] S. Chang, Y. Gong, S. A. Way, and L. Jia, "Flexibility-oriented HRM systems, absorptive capacity, and market responsiveness and firm innovativeness," *J. Manage.*, vol. 39, no. 7, pp. 1924–1951, Nov. 2012.

[11] Q. C. Lu, L. L. Liang, and F. Jia, "How does strategic learning affect organizational innovation-from a dynamic competency perspective," *Manage. World*, vol. 34, no. 9, pp. 109–129, Sep. 2018.

[12] W. Pietersen, *Reinventing Strategy: Using Strategic Learning to Create and Sustain Breakthrough Performance*. New York, NY, USA: Wiley, 2002.

[13] J. B. Thomas, S. W. Sussman, and J. C. Henderson, "Understanding 'strategic learning': Linking organizational learning, knowledge management, and sensemaking," *Org. Sci.*, vol. 12, no. 3, pp. 331–345, Jun. 2001.

[14] R. P. Lee, "Extending the environment–strategy–performance framework: The roles of multinational corporation network strength, market responsiveness, and product innovation," *J. Int. Marketing*, vol. 18, no. 4, pp. 58–73, Dec. 2010.

[15] R. F. Rich, "Social science information and public policy making: The interaction between bureaucratic politics and the use of survey data," *J. Geophys. Res. Atmos.*, vol. 110, no. D24, p. 311, 1981.

[16] R. W. Woodman, J. E. Sawyer, and R. W. Griffin, "Toward a theory of organizational creativity," *Acad. Manage. Rev.*, vol. 18, no. 2, pp. 293–321, Apr. 1993.

[17] L. Prusak T. H. Davenport, *Working Knowledge: How Organizations Manage What They Know*. Cambridge, U.K.: Harvard Business School Press, 1998.

[18] J. Wei, *Knowledge Learning and Technological Capability Growth of Enterprises*. Beijing, China: Science Press, 2006.

[19] S. F. Slater and J. C. Narver, "Market orientation and the learning organization," *J. Marketing*, vol. 59, no. 3, pp. 63–74, Jul. 1995.

[20] A. C. Inkpen, "Creating knowledge through collaboration," *California Manage. Rev.*, vol. 39, no. 1, pp. 123–140, Oct. 1996.

[21] Z. Yuquan and L. Yuan, "Research on the relationship of organizational learning capability and choice of innovation type," *Stud. In Sci. Sci.*, vol. 23, no. 4, pp. 525–530, Apr. 2005.

[22] W. A. Pan, "The impact of relationship strength and knowledge integration capability on supply chain knowledge transfer," *Sci. Res. Manage.*, vol. 33, no. 1, pp. 147–153, Jan. 2012.

[23] C. Jin and L. F. Yu, "Social capital: Its sociological meanings to technological innovation," *Stud. Sci. Sci.*, vol. 19, no. 3, pp. 102–107, Mar. 2001.

[24] W. M. Cohen and D. A. Levinthal, "Absorptive capacity: A new perspective on learning and innovation," *Administ. Sci. Quart.*, vol. 35, no. 1, p. 128, Mar. 1990.

[25] M. A. Hitt, R. D. Ireland, D. C. Sirmon, and C. A. Trahms, "Strategic entrepreneurship: Creating value for individuals, organizations, and society," *Acad. Manage. Perspect.*, vol. 25, no. 2, pp. 57–75, Jan. 2012.

[26] C. Sirén, H. Hakala, J. Wincent, and D. Grichnik, "Breaking the routines: Entrepreneurial orientation, strategic learning, firm size, and age," *Long Range Planning*, vol. 50, no. 2, pp. 145–167, Apr. 2017.

[27] C. Moorman and G. Zaltman, "The Dynamics of Trust within and between Organizations," *J. Marketing Res.*, vol. 29, pp. 314–318, Jan. 1992.

[28] B. J. Zirger and J. L. Hartley, "The effect of acceleration techniques on product development time," *IEEE Trans. Eng. Manag.*, vol. 43, no. 2, pp. 143–152, May 1996.

[29] V. Blazevic, A. Lievens, and E. Klein, "Antecedents of project learning and time-to-market during new mobile service development," *Int. J. Service Ind. Manage.*, vol. 14, no. 1, pp. 120–147, Mar. 2003.

[30] M. Hyung-Jin Park, J. W. Lim, and P. H. Birnbaum-More, "The effect of multiknowledge individuals on performance in cross-functional new product development teams*," *J. Product Innov. Manage.*, vol. 26, no. 1, pp. 86–96, Jan. 2009.

[31] C. Welter, R. Mauer, and R. J. Wuebker, "Bridging Behavioral models and theoretical concepts: Effectuation and bricolage in the opportunity creation framework," *Strategic Entrepreneurship J.*, vol. 10, no. 1, pp. 5–20, Mar. 2016.

[32] Y. Wei, S. Samiee, and R. P. Lee, "The influence of organic organizational cultures, market responsiveness, and product strategy on firm performance in an emerging market," *J. Acad. Marketing Sci.*, vol. 42, no. 1, pp. 49–70, Jan. 2014.

[33] R. P. Lee and Q. Chen, "The immediate impact of new product introductions on stock price: The role of firm resources and size*," *J. Product Innov. Manage.*, vol. 26, no. 1, pp. 97–107, Jan. 2009.

[34] R. A. Inman, R. S. Sale, K. W. Green, and D. Whitten, "Agile manufacturing: Relation to JIT, operational performance and firm performance," *J. Oper. Manage.*, vol. 29, no. 4, pp. 343–355, May 2011.
[35] J. C. Narver, S. F. Slater, and D. L. MacLachlan, "Responsive and proactive market orientation and new-product Success*," *J. Product Innov. Manage.*, vol. 21, no. 5, pp. 334–347, Sep. 2004.
[36] E. J. Kleinschmidt, U. de Brentani, and S. Salomo, "Performance of global new product development programs: A resource-based view," *J. Product Innov. Manage.*, vol. 24, no. 5, pp. 419–441, Sep. 2007.
[37] B. van den Hooff and J. A. de Ridder, "Knowledge sharing in context: The influence of organizational commitment, communication climate and CMC use on knowledge sharing," *J. Knowl. Manage.*, vol. 8, no. 6, pp. 117–130, Dec. 2004.
[38] R. Cordero, "The measurement of innovation performance in the firm: An overview," *Res. Policy*, vol. 19, no. 2, pp. 185–192, Apr. 1990.
[39] J. G. Covin, K. M. Green, and D. P. Slevin, "Strategic process effects on the entrepreneurial orientation-sales growth rate relationship," *Entrepreneurship Theory Pract.*, vol. 30, no. 1, pp. 57–81, Jan. 2006.
[40] V. Govindarajan and P. K. Kopalle, "Disruptiveness of innovations: Measurement and an assessment of reliability and validity," *Strategic Manage. J.*, vol. 27, no. 2, pp. 189–199, Feb. 2006.
[41] K. Kuwada, "Strategic learning: The continuous side of discontinuous strategic change," *Org. Sci.*, vol. 9, no. 6, pp. 719–736, Dec. 1998.
[42] R. Garud and P. R. Nayyar, "Transformative capacity: Continual structuring by intertemporal technology transfer," *Strategic Manage. J.*, vol. 15, no. 5, pp. 365–385, Jun. 1994.
[43] P. Hong, W. J. Doll, A. Y. Nahm, and X. Li, "Knowledge sharing in integrated product development," *Eur. J. Innov. Manage.*, vol. 7, no. 2, pp. 102–112, Jun. 2004.
[44] R. M. Grant, "Prospering in dynamically-competitive environments: Organizational capability as knowledge integration," *Org. Sci.*, vol. 7, no. 4, pp. 375–387, Aug. 1996.
[45] F. Wijnhoven, "Acquiring organizational learning norms: A contingency approach for understanding deutero learning," *Manage. Learn.*, vol. 32, no. 2, pp. 181–200, Jun. 2001.
[46] B. Kogut and U. Zander, "Knowledge of the firm, combinative capabilities, and the replication of technology," *Org. Sci.*, vol. 3, no. 3, pp. 383–397, Aug. 1992.
[47] G. Szulanski, "Exploring internal stickiness: Impediments to the transfer of best practice within the firm," *Strategic Manage. J.*, vol. 17, no. S2, pp. 27–43, Dec. 1996.
[48] I. Nonoka and H. Takeuchi, "The knowledge-creating company," *Nankai Bus. Rev.*, vols. 482–484, no. 2, pp. 175–187, Feb. 1998.
[49] M. Holmqvist, *Experiential Learning Processes of Exploitation and Exploration Within and Between Organizations: An Empirical Study of Product Development*. Annapolis, MD, USA: Informs, 2004.
[50] M. D. Lord and A. L. Ranft, "Organizational learning about new international markets: Exploring the internal transfer of local market knowledge," *J. Int. Bus. Stud.*, vol. 31, no. 4, pp. 573–589, Dec. 2000.
[51] A. C. Inkpen and E. W. K. Tsang, "Social capital, networks, and knowledge transfer," *Acad. Manage. Rev.*, vol. 30, no. 1, pp. 146–165, Jan. 2005.
[52] M. A. Hitt, R. D. Ireland, and C. D. L. Sexton, "Guest editors' introduction to the special issue strategic entrepreneurship: Entrepreneurial strategies for wealth creation," *Strategic Manage. J.*, vol. 22, nos. 6–7, pp. 479–491, Jan. 2001.
[53] C. Moorman, "Organizational market information processes: Cultural antecedents and new product outcomes," *J. Marketing Res.*, vol. 32, no. 3, pp. 318–335, Aug. 1995.
[54] G. Barczak and F. Sultan, "How marketing research affects cycle time: A case of the telecommunications industry," *J. Bus. Ind. Marketing*, vol. 16, no. 4, pp. 258–273, Jul. 2001.
[55] B. J. Jaworski, D. J. Macinnis, and A. K. Kohli, "Generating competitive intelligence in organizations," *J. Market-Focused Manage.*, vol. 5, no. 4, pp. 279–307, Dec. 2000.
[56] G. T. M. Hult, D. J. Ketchen, and S. F. Slater, "Market orientation and performance: An integration of disparate approaches," *Strategic Manage. J.*, vol. 26, no. 12, pp. 1173–1181, Dec. 2005.
[57] L. Zhen and Y. Hongtao, "The impact of absorptive capacity, relationship learning, and knowledge integration on the enterprise innovation performance–An empirical study on technology-based SMEs," *Sci. Res. Manage.*, vol. 30, no. 1, pp. 47–56, Jan. 2012.
[58] Z. Chunyang, X. Yan, and D. Kun, "A literature review and prospects of strategic learning," *Foreign Econ. Manage.*, vol. 42, no. 5, pp. 60–73, May 2020.

XIAOHONG XIAO is currently a Professor with the School of Business Administration, Guizhou University of Finance and Economics. She is also the Director of the Chinese Institute of Business Administration and the Managing Director of the Society of Chinese Commercial History. She is also a Senior Researcher of the Green Development Strategy Research Institute of Western China. Her research interests include strategy management, green innovation, and organizational behavior.

YUQI ZHU was born in Guiyang, Guizhou, China, in1997. She received the B.S. degree in financial management from the South China University of Technology, Guangzhou, in 2019. She is currently pursuing the master's degree with the School of Business Administration, Guizhou University of Finance and Economics.

Her research interests include big data application, organizational behavior, and strategic management.

YUXI ZHU was born in Guiyang, Guizhou. She received the bachelor's degree in international economics and trade from the South China University of Technology, Guangzhou, in 2019, where she is currently pursuing the degree in international business with the School of Economics and Finance. Her research interests include management of the multinational company and big data applications.

QING ZHAO was born in Guiyang, China, in 1979. He received the B.S. and M.S. degrees in economics and the Ph.D. degree in management science from the Shanghai University of Finance and Economics, Shanghai, in 2003 and 2007, respectively.

From 2010 to 2016, he was a Manager with the Department of Strategy and Investment, Wengfu Group Company Ltd. (the third largest corporation of fertilizer worldwide), Guiyang, China. From 2016 to 2018, he was an Entrepreneur in the field of big data and agriculture development. Since 2018, he has been an Associate Professor with the Department of Business and Management, Guizhou University of Finance and Economics, Guiyang. He is the author of five books and more than 11 articles. His research interests include development of big data processing, agriculture technology, and behavior science.