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Relationship between Ambidexterity Learning and Innovation Performance: The Moderating Effect of Redundant Resources

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Abstract

Researchers have confirmed the relationship between ambidexterity learning and innovation performance, but according to the resource-based theory, the relationship between ambidexterity learning and innovation performance is also affected by the internal resources of the organization. Internal resources are an important factor affecting the transformation of learning outcomes into performance. In addition, few scholars have pointed out whether different types of learning have different effects on different types of innovation performance. This study collects data from 170 High-tech enterprises in Shandong, china, and discusses the effects of exploitative learning and explorative learning on management innovation performance and technological innovation performance .This study further examines the moderating role of slack resource on the relationship between ambidexterity learning and innovation performance. Results show that ambidexterity learning has positive effect on innovation performance. Compared with exploitative learning, explorative learning has a greater impact on management innovation performance; compared with explorative learning, exploitative learning has a greater impact on technological innovation performances. Slack resource has positive moderating role between the relationship of exploitative learning, explorative learning and technology innovation performance. But Slack resource has no moderating role between the relationship of exploitative learning, explorative learning and management innovation performance.

Keywords: Exploitative Learning, Explorative Learning, Technological Innovation, Management Innovation, Redundant Resources.

JEL Classification Code: M1, M10, M19.

1. Introduction

March (1991) defines dualistic learning as exploitative learning and explorative learning. Exploitative learning is characterized by "refining, screening, production, efficiency, selection, implementation and execution", while explorative learning is characterized by "searching, variation, adventure, experiment, attempt, adaptation, discovery and innovation. Former emphasizes the use and deep development of the existing knowledge, while the latter focuses on the pursuit of new knowledge (Lin, Iii, Lin, & Lin, 2013). In the constantly changing market environment, the enterprises' survival not only need the exploitative learning to development their own knowledge, but also need the explorative learning to pushing the old to bring forth the new, creating a new market or reshaping the current market. Enterprises need to achieve different types of innovation performance through different organizational learning methods, so as to gain competitive advantage (Kitapçi & Çelik, 2014); the study of the relationship between different learning styles and different types of innovation performance is insufficiency. Few scholars have discussed the relationship between exploratory learning and exploitative learning on different types of innovation performance, and the results are different(Aarons & Sommerfeld, 2012; Zhang, Zhao, Management, & University, 2017).

Raj and Srivastava (2013) showed that knowledge search from first-line managers has a negative impact on management performance. The reason may be that first-line managers can not accurately grasp the direction of industry technology and market development, which will lead enterprises to a wrong direction. Katila and Ahuja (2002) found that there was an inverted U-shaped relationship between depth of knowledge search and technological

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innovation, while there was a linear relationship between breadth of knowledge search and technological innovation. However, the results of Atuahene-Gima and Murray (2007) showed that there is a positive U-shaped relationship between exploitative learning and technological performance, not an inverted U-shaped relationship; and explorative learning have a positive curve relationship with technological performance. Existing studies have found that there are both positive and negative, as well as linearity and nonlinearity relationship between exploitative learning, explorative learning and technological innovation performance and management innovation Performance. Then, how does the affection of exploitative learning and explorative learning to the technological innovation performance and management innovation performance .The relationship is positive or negative or linear and curvilinear?

The main reason for the inconsistency research results on the effects of exploitative learning and explorative learning on management innovation performance and technological innovation performance is the lack of discussion on the regulation mechanism in the process of implementation and the research on the moderating effect of the relationship is still basically at the level of theoretical analysis, lacking empirical research. Based on the resource theory, this study introduces the variables of slack resource and explores the regulatory mechanism of slack resource in the relationship between exploitative learning, explorative learning and innovation performance. This study focusing on the following two questions: Are the effects of exploitative learning and explorative learning on different types of innovation performance? Will slack resources regulate the relationship between exploitative learning and explorative learning on technological innovation performance and management innovation performance?

2. Literature Review and Hypothesis

The present study investigates the relationship between different organizational learning styles and different types of innovation. Many scholars only explore the relationship between ambidexterity learning and technological innovation performance, or the relationship between ambidexterity learning and management innovation performance. Some researchers classify innovation performance into long-term innovation performance and short-term innovation performance, and discuss the relationship between explorative learning, exploitative learning and long-term and short-term innovation performance. This research divides innovation performance into technological innovation performance and management innovation (Lin et al., 2013). This study integrates explorative learning, exploitative learning, management innovation performance and technological innovation performance into a framework. Empirically examine the differences in the impact of different learning styles on the different innovation performance.

In addition, scholars have inconsistent or even contradictory conclusions on the relationship between exploitative learning, explorative learning and innovation performance, indicating that the impact of these two types of learning activities on innovation performance may be affected by other factors. Schildt, Keil, and Maula (2012) pointed out that the regulatory mechanism should be further explored in the study of the relationship between exploitative learning, explorative learning and innovation performance. Gupta, Smith, and Shalley (2006) pointed out that factors such as resource endowment, resource management ability, absorptive capacity, organizational size and structure, as well as the industry environment, all have certain effects on the relationship between Ambidexterity organizational learning and innovation performance. The main reason for the conflict between exploitative learning and explorative learning is that the coexistence of exploitative learning and explorative learning will compete for resources within the organization, so the resource-based view holds that the size of the organization, the availability of resources, the abundance of resources and other factors will affect the relationship between exploitative learning and explorative learning and innovation performance. Therefore, this study adds the factor of redundant resources to discuss whether the relationship between organizational learning and innovation performance will change under the adjustment of redundant resources.

In conclusion, in order to better explain the relationship between organizational learning and innovation performance, this study constructs a theoretical model, and examines the model with firm data from China's high-tech industries in order to further enrich the existing research on the relationship between organizational learning and innovation performance. It will provide useful theoretical reference for China's high-tech enterprises.

2.1. Effect of Explorative Learning between Innov ation Performances

Explorative learning is an organizational learning behavior characterized by "search, variation, adventure, experiment, attempt, contingency, discovery and innovation". It requires increasing variation, taking risks and emphasizing the pursuit of new knowledge. Explorative learning refers to organizational learning behavior characterized by "search, variation, adventure, experiment, attempt, contingency, discovery and innovation", which requires increasing variation, taking risks and emphasizing the pursuit of new knowledge. Lin et al. (2013) pointed out explorative learning need to introduce new and heterogeneous knowledge into the existing knowledge base by searching for new technologies, new business opportunities, and even experimenting with new options, so as to improve the ability of enterprises to integrate search to promote new product development performance. Schildt et al. (2012) argues that explorative learning breeds innovations that have a significant impact on the industry, which are designed to help companies introduce new products, create new markets or reshape the current market, and meet potential customer needs. Gao, Meng, and Xie (2012) pointed out that the results of explorative learning promote technological innovation, because the knowledge acquired by explorative learning is often quite different from the existing knowledge of enterprises, and technological innovation means the introduction of new technologies and the development of new products, which require enterprises to carry out explorative learning to acquire new technologies and knowledge, so as to promote the technological innovation of enterprises.

Explorative learning is related to new and differentiated new product ideas and product concepts. Explorative learning can lead to breakthrough product changes and develop new products that lead the market. Customer demand diversification and differentiation are becoming higher and higher. In this case, leading products with differentiated performance are more likely to create user requirements and be accepted by customers. Explorative learning can integrate new ideas and new knowledge into product design, and therefore design new products with new characteristics and utility (Tsai, 2009). Explorative learning can not only promote the breakthrough development of new products, but also have self-enhancing learning effect. The self-reinforcing effect of explorative learning can bring the new product development into the track of the virtuous circle; therefore, explorative learning has a positive impact on organizational technological innovation performance. On the other hand, Explorative learning can also encourage team members to incorporate new knowledge and experience into their knowledge reserves, thereby increasing team members' knowledge accumulation and learning ability. Explorative learning has a positive impact on organizational technological innovation performance. In view of this, the following hypothesizes are proposed.

Although explorative learning encourages enterprises to pursue breakthrough innovation, explorative learning can constantly expand and enrich the organizational knowledge base, enhance enterprises perception of market environment changes, help managers seize external market opportunities, adjust enterprise strategies or internal processes, therefore, explorative learning helps to improve management innovation performance.

H1: Explorative learning positively impact on management innovation performance

H2: Explorative learning positively impact on technological innovation performance

2.2. Effect of Explorative Learning between In novation Performances

According to the resource-based theory, internal knowledge is more likely to be a sustainable competitive advantage, and internal knowledge is path dependent. In the process of exploitative learning, the use of new knowledge will face smaller conflicts and resistance than the use of new external knowledge (March, 1991). The exploitative learning focuses primarily on the firms' existing core Competences to deepen and refine their product advantages. Examples include upgrading current techniques or processes, fulfilling current customer needs, and extending current market segments. Firms may benefit from explorative learning through the expansion of knowledge scope, and the variation in technology and market information may contribute to differentiating firms from the rivals and gains in product distinctiveness (Tsai, 2009). Firms may take advantage of exploitative learning by strengthening knowledge depth. The thorough and detailed processing of extant knowledge in technology and the market may facilitate experience effects and secure cost-efficiency in production and transactions (He & Wong, 2004). In view of this, the following hypothesizes are proposed.

H2: Exploitative learning positively impact on management innovation performance

H3: Exploitative learning positively impact on technological innovation performance

2.3. Regulation of Redundant Resources

The relationship between ambidexterity learning and organizational innovation performance is affected by the use and integration of internal resources. Creative use of redundant resources can play a synergistic effect (complementary relationship) between exploitative learning and explorative learning, thereby enhancing and influencing the innovation performance of enterprises. The organization can make use of Redundant resources creatively through process management (Benner & Tushman, 2003), team structure and executive teams (Jansen, Tempelaar, Bosch, & Volberda, 2009) strategic alliance and external relations

(Lee, 2001), knowledge management and R&D management (Drongelen, Weerd-Nederhof, & Fisscher, 2010; Greve, 2007) and organization structure design of "sub-organization" structure (Fang, Lee, Sun, & Zhang, 2005; Gardner, Susong, Solomon, & Heasler, 2006), etc., take both the exploitative learning and explorative learning into account, enhancing the competitive advantage and cultivate a new competitive advantage. He and Wong (2009) used a sample of Singapore and Malaysian's companies, investigating S&P500 companies, found that for large firms with redundant resources, ambidexterity learning and innovation performance is positively correlated, and it also implies that the redundancy of the abundance of resources has a regulatory effect on the relationship between the binary learning and innovation performance. In view of this, the following hypothesis is proposed.

H4: Redundant resources regulate the relations between ambidextrous learning and innovation performance

H4a: Redundant resources regulate the relations between explorative learning and management innovation performance

H4b: Redundant resources regulate the relations between explorative learning and technology innovation performance

H4c: Redundant resources regulate the relations between exploitative learning and management innovation performance

H4d: Redundant resources regulate the relations between exploitative learning and technology innovation performance

3. Method

This study collects data in the form of questionnaire survey, and carries out statistical analysis for the collected questionnaires, like reliability and validity validation, multiple regression analysis, etc. This research uses statistical analysis software SPSS and AMOS, where SPSS software is used for the measurement of variable reliability and verification of proposed assumption, AMOS software is used for confirmatory factor analysis and model fitting degree analysis.

3.1. Data Collection

The core topic of this paper is to explore the relationship between innovation climate and performance, so the research object must have high intensity of R&D activities and innovative practice. The innovative team in high-tech enterprises, as high-intensive economic entity of knowledge, technology and investment, is capable of continuing the new technology and product development, with product high-tech, and on behalf of the most advanced and cutting-edge development direction in the technological field of enterprise. Compared with other general organizations, high-tech enterprises need to carry out innovative activities to construct core innovation ability (Schilling, Jones, Gareth, Hill, & Charles, 2001) in order to handle internal and external environment change. Therefore, high-tech enterprises match with this research issues. At the same time, the technological innovative activities of high-tech enterprises are of great strategic significance to the construction of an innovative country, promote the industrial transformation and upgrading whose results can also bring beneficial practical enlightenment to the enterprises and regional development.

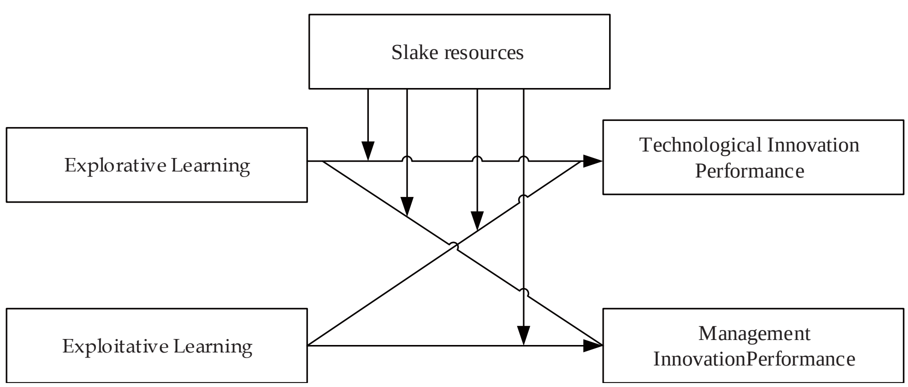

Figure 1: Theoretical Model

Benefit from the development of high-tech enterprises, Shandong Province ranks the third in GDP in 2015. Taking the convenience of information collection, research costs and data aggregation problems into account, this study choose high-tech manufacturing enterprises in Shandong Province as a research object. There are a total of 1516 high-tech enterprises in Shandong Province with 1374 manufacturing among them. In this study, stratified random sampling was used to sample 1374 high-tech manufacturing industries. One of the main problems of this study focuses on the impact of the external innovation climate on the innovation performance of enterprises. In order to ensure that the research results can fully reflect the influence of different external environment, this study proceed sampling according to the administrative region division of Shandong Province, which divided into 17 layers and sampled in accordance with 20% proportion in each layer to reduce the influence of data variability in every sampling layer, so as to make sure the extracted samples with sufficient representation.

In this study, 275 questionnaires are distributed in total, and 215 questionnaires are returned in fact, with the return rate of 78%. Besides, 45 invalid or poor-quality questionnaires are removed. The final number of valid questionnaires is 170, with the valid questionnaire return rate of 61.8%. State-owned and joint venture enterprises account for about 89%; the enterprises with more than 300 employees approximately account for 50% of the total number of enterprises;63.2% of enterprises have a development period of over 15 years, and the large-scale enterprises with high resource accumulation account for above 50% of the samples. 77% of respondents hold medium/senior management posts, and 56% of respondents have more than 5 years of work experience in respective enterprises. Thus, they have a better understanding of their enterprise status, and can provide better help for this study to obtain valid data. To sum up, the data in the table can meet the data requirements for the research issue, and can be analyzed.

3.2. Measurement of Variables

In order to ensure the reliability and validity of the variables of this study, the scale used in this study is derived from the mature scale developed by the previous scholars. This study used the Likert 5 point scale to measure these items.

Innovation Performance: The measurement of innovation performance is measured for the reference of Damanpour and Aravind (2012) scale from technical innovation and management innovation. The retest value of Cronbach'a in the scale is 0.83 (A patent-based study of the relationships among technological portfolio, ambidextrous innovation, and firm performance, 2015).Four indicators to measure technological innovation performance: companies develop more new products than competitors; companies develop new products faster than competitors; new products of companies exist difference compared to similar new products of competitors; new products of companies have a higher market acceptance. Management innovation is measured by four indicators: Company has successfully put forward new development ideas; Company has made effective innovations or improvements in some work processes; Company has made effective reforms to the establishment of the organization; Leaders have made effective innovations or improvements in the way and style of management.

Redundant Resources: This paper uses the scale of Li (2013), adopting six items to measure redundant resources. Enough financial resources to be dominated freely; Save enough profits to support market expansion; Gain bank loan or funds of other financial institution when needing; The use of advanced process equipment but not fully utilized; There are more specialized personnel, there is a certain potential to explore; Operational ability lower than design ability currently(or intended target).

Organizational Learning: Exploitative learning and explorative learning were measured by the scale of March (1991). Five indicators to measure explorative learning: The company obtains new technologies and skills for itself within three years; The company learn the new product development technology and development process for industry; The company get new management and organizational skills that are important to innovation; The company have access to new technologies in investing, R&D deployment, R&D, training and development of engineer; The company strengthen innovative skills in previously inexperienced areas; Five indicators to measure exploitative learning: Upgrade the existing knowledge and skills in familiar products and technology field; Enhance skill investment to improve productivity when using mature technology; Enhanced the ability to find solutions to customer problems that are not new but resemble existing methods; Enhance your skills further in new product development processes that already have some experience; Strengthen project knowledge and experience to improve the efficiency of existing innovative activities.

Control Variable: The economic nature of firms has an impact on innovation performance. Compared with state-owned enterprises and foreign-funded enterprises, private enterprises are more likely to develop high innovation performance because their small-scale organization has flexibility in responding to the changing competitive environment. Longer-established enterprises can accumulate the necessary innovation experience, which has a positive impact on innovation activities, but such enterprises do not focus too much on situation outside enterprise or even ignore information from customers (Sorensen & Stuart, 2000). Scale is closely related to innovation activities of enterprise. Scale has influence on the adoption of managerial innovation and a strong relationship with explorative learning. Therefore, this paper places the scale, economic nature, establishment time, into the control variable category.

3.3. Common Method Bias Test

In this study, Harman single factor test was used to test the common method bias. By the Harman single factor test, 4 factors have been analyzed. (Characteristic root > 1). The rate of variance of the greatest common factor before rotation was 39.275% (< 40%). so there is no common method bias problem in this study data.

4. Results

4.1. Reliability Analysis

In this study, Cronbach's α is used to test the internal consistency of scales. Nunnally (1978) indicated that the estimated Cronbach's α should be above 0.7 as a high reliability value of a construct. Melchers (1987)indicated that the coefficient of internal consistency at the lowest level should be above 0.5, preferably above 0.6, and the lowest coefficient of internal consistency of the entire scale should be above 0.7, preferably above 0.8.

The Cronbach's α values of explorative learning and exploitative learning are respectively 0.876 and 0.795. The Cronbach's α value of technology innovation performance is 0.724. The Cronbach's α value of management innovation performance is 0.813. That shows the reliability of each scale is within an acceptable range, with good internal consistency.

4.2. Confirmatory Factor Analysis

To test the discriminant validity among key variables and the corresponding measurement parameters of each measurement scale, AMOS17.0 is adopted in this study to carry out confirmatory factor analyses (CFA) on key variables, and the model comparison method is used to investigate the discriminant validity and convergent validity of each scale (Gatignon, 2010). AMOS is tested on the basis of chi-square statistic value (X^2). In general, the chi-square value P>0.05 is deemed as a criterion to judge that a model has a good fit effect (Gefen, Straub, & Boudreau, 2000; Rong, Scholz, & Martin, 2009). However, the chi-square statistic is susceptible to the sample size. Thus, in addition to chi-square statistic, other fit indexes need to be considered as well (Zhu, 2008). The judgment criteria for fit indexes are listed in Table 1.

Table 1: Goodness of Fit Analysis of Model

Index	x^2	x^2/df	GFI	AGFI	RMSEA	NFI	CFI
Standard Value	>0.5	<5	>0.9	>0.9	<0.08	>0.9	>0.9
Model	231.361	1.216	.917	.942	.033	.921	.934

According to the judgment criteria for fit indexes (Gatignon, 2010) listed in Table 2 a confirmatory factory analysis on model is carried out. The results show that the verification indexes such as X^2/df, RMSEA, NFI and CFI in the model basically reach the acceptable level, indicating that model has good fit.

Table 2: CFA of Model

	Route		λ	C.R.	AVE
S11	<---	S1	.801	.918	.799
S12	<---	S1	.841		
S13	<---	S1	.835		
S14	<---	S1	.894		
S15	<---	S1	.893		
S21	<---	S2	.868	.927	.802
S22	<---	S2	.899		
S23	<---	S2	.755		
S24	<---	S2	.917		
S25	<---	S2	.883		
C11	<---	C1	.987	.906	.766
C12	<---	C1	.940		
C13	<---	C1	.776		
C14	<---	C1	.713		
C21	<---	C2	.815	.869	.751
C22	<---	C2	.833		
C23	<---	C2	.717		
C24	<---	C2	.871		
R1	<---	R	.575	.882	.714
R2	<---	R	.576		
R3	<---	R	.855		
R4	<---	R	.744		
R5	<---	R	.797		
R6	<---	R	.729		

Note: S1, S2, C1, C2 and R stand for explorative learning, exploitative learning, technological innovation performance, management innovation performance and slack resource

For the convergent validity of each dimension, the average variance extraction (AVE value) is adopted to reflect the value, and generally used to reflect the convergent validity of scales, which can directly display how much variance explained by latent variables that comes from measurement errors. The bigger the AVE value is, the larger the variation percentage of the measured variable explained by latent variables will be. Accordingly, the measurement error will be smaller. The average variance extraction values all conform to the criterion of 0.50+ suggested by Fornell and Larcker (1981). The above data show that the model is within an acceptable range. Composite reliability (CR) as one of the judgment criteria for intrinsic quality of the model reflects whether the observation item in each latent variable consistently explains the latent variable. Seen from Table 3, CR is above 0.7, which is above the criterion of more than 0.60 suggested by Fornell and Larcker (1981), with good internal consistency.

4.3. Effect of Organizational Learning on Innovati on Performance

The partial least squares regression analysis provides multiple-to-multilinear regression modeling, especially when the number of variables is large and multiple correlations exist and the sample size is small, the model established by partial least squares regression has the advantage that traditional classical regression analysis methods do not have. Because partial least squares regression analysis concentrates the characteristics of principal component analysis, canonical correlation analysis, and linear regression analysis methods in the modeling process, in addition to providing a more reasonable regression model, it can also complete some research contents similar to principal component analysis and canonical correlation analysis at the same time, which can provide some richer and deeper information.

For t dependent variables y_1, y_2,..., y_t with the modeling problem of m independent variables x_1, x_2,..., x_m, the basic approach of partial least partial square regression is: firstly, propose the first component u_1 in the set of independent variables (u_1 is linear combination of x_1, x_2, …, x_m, and extracting as much variation information as possible from the original set of independent variables); Meanwhile, the first component v_1 is also extracted in the dependent set of variables, and the degree of correlation between u1 and v_1 is required to be maximized. Then establish the regression of dependent variables y_1, y_2,..., y_t with u1, the algorithm is terminated if the regression equation has achieved satisfactory accuracy. Otherwise, the extraction of the second pair of components is continued until satisfactory accuracy can be achieved. If we finally extract r components u_1, u_2,..., ur, partial least squares regression will be performed by building the regression of y_1, y_2,..., y_t with u_1 , u_2..., u_r, then y_1, y_2,..., y_t are expressed as the regression equation of the original independent variable, i.e., the partial least squares regression equation.

Because the internal innovation climate and the external innovation climate of this study are composed of multiple dimensions and there are interdependent relationships among multiple variables, it is an effective method to use the partial least squares regression method to verify the multiple relationships of innovation climate, organizational learning, and innovation performance.

4.4. The Effect of Organizational Learning on Technological Innovation Performance

Table 3 is the result of the variance ratio explained by the potential factors of independent and dependent variables, which reflects the comprehensive explanatory power of the information of potential factors. From the results presented in Table 3, the 1st latent factor can explain 94.9% of the information on the independent variable and 61.9% of the information on the dependent variable, while the first two latent factors cumulatively can explain 100% of the information on the independent variable and 63.1% of the information on the dependent variable. This shows that a good information extraction effect can be achieved with the first two latent factors.

Table 3: Variance Proportion by Latent Factors

Latent Factors	Statistics				
	Variance of X	R^2	Variance of Y	R^2	Adj R^2
1	.949	.949	.619	.619	.612
2	.051	1.000	.013	.631	.618

Columns3–7 in Table4 is the VIF values, which represent the role of the independent variables in explaining the latent factors. VIF value of less than 0.5 was not significant, VIF value between 0.5-1 is not significant, and it has a significant effect greater than 1. The VIF values of each variable in table 4 are basically greater than 1, which represents the role of independent variables in explaining the latent factor. From table 4, we can get the regression result of the standardized variable of the dependent variable on the latent factors.

$$C_1^{*}=0.571t_1+.0.356t_2 \quad \text{Formula 1}$$

The linear combination of its latent factors on the standardized variables of independent variables is expressed as follows:

$T1=0.731s_1^*+0.682s_2^*$ Formula 2

$T_2=0.706s1^*-0.709s2^*$ Formula 3

The results of formula 2, formula3 are brought to formula 1, and the results are as follows:

$$C_1^*=0.613^*(0.731s_1^*+0.682s_2^*)+0.254^*(0.706s_1^*-0.709s_2^*) =0.6688S_1+0.1373S_2 \quad \text{Formula 4}$$

Table 4: Results of Cumulative Variables and Factor Weight

Independent Variable	Cumulative Variables		Variable	Weight	
	T_1	T_2		T_1	T_2
			C1*	.571	.356
S1	.928	.950	S1*	.731	.706
S2	1.213	1.109	S2*	.682	-.709

Note : T_1, T_2 in the second row of the table indicate the first 2 Latent factors. The variable name plus "*" represents the standardized variable.

From the regression standardization coefficient, the coefficients of explorative learning and exploitative learning on technological innovation performance are 0.6688 and 0.1373, both of which have positive effects. Compared with exploitative learning, explorative learning has a greater impact on technological innovation performance.

4.5. Effect of Organizational Learning on Management Innovation Performance

Table5 are the results of the proportion of variance explained by the latent factor on the independent and dependent variables, embodying the information synthesis explanatory power of the latent factor. From the results presented in Table 5, the 1st latent factor can explain 95% of the information on the independent variable and 71.2% of the information on the dependent variable, while the first two latent factors cumulatively can explain 100% of the information on the independent variable and 71.9% of the information on the dependent variable. This shows that a good information extraction effect can be achieved with the first two latent factors.

Table 5: Variance Proportion by Latent Factors

Latent Factors	Statistics				
	Variance of X	R^2	Variance of Y	R^2	Adj R^2
1	.950	.950	.712	.712	.707
2	.050	1.000	.007	.719	.708

Columns 3–7 in Table 6 gives the VIF values, which represent the role of the independent variables in explaining the latent factors. VIF value of less than 0.5 was not significant, VIF value between 0.5-1 is not significant, and it has a significant effect greater than 1. The VIF values of each variable in Table 6 are basically greater than 1, which represents the role of independent variables in explaining the latent factor.

From table 6, we can get the regression result of the standardized variable of the dependent variable on the latent factors.

$C_1^*=0.613t_1+.0.254t_2$ Formula 5

The linear combination of its latent factors on the standardized variables of independent variables is expressed as follows:

$T_1=0.690s1^*-0.708s2^*$ Formula 6

$T_2=-0.708s1^*+0.706s2^*$ Formula 7

The results of formula 6, formula 7 are brought to formula 5, and the results are as follows:

$$C_2^* = 0.613^*(0.690s_1^*-708s_2^*) +0.254^*(-0.708s_1^*+0.706s_2^*) = 0.2429S_1+ 0.6226\ S_2 \quad \text{Formula 8}$$

Table 6: Results of Cumulative Variables and Factor Weight

Independent Variable	Cumulative		Variable	Weight	
	T_1	T_2		T_1	T_2
			C_2*	.613	.254
S_1	.976	.977	S_1*	.690	-.708
S_2	1.023	1.023	S_2*	.723	.706

Note : T_1, T_2 in the second row of the table indicate the first 2 Latent factors. The variable name plus "*" represents the standardized variable.

From the standardized regression coefficient, the coefficients of explorative learning and exploitative learning on management innovation performance are 0.2429 and 0.6226. Explorative learning and exploitative learning have a positive impact on management innovation performance. Compared with exploitative learning, explorative learning has a greater impact on management innovation performance.

4.6. Verification for the Moderating Effect of Unabsorbed Slack Resources on Explorative Learning and Innovation Performance

Models 1-3 verify the moderating effect of slack resources on explorative learning and technological innovation performance. There are only 3control variables in Model 1, including the nature, scale and founding time of enterprise. The results show that the nature, scale and founding time fail to reach the significance level in the regression analysis, i.e., the 4 control variables have no significant effect on explorative learning. On the basis of model 1, model 2 is added with 2 master variables, namely, explorative learning and slack resources. The results show that the entry of the two master variables significantly increases R^2 to 0.668 in the regression equation. The F-test value is 17.071 (p=0.000<0.001), which passes the T-test, with zero significant difference. The regression coefficients are respectively 0.819 (p=0.000<0.001) and 0.007 (p= 0.364>0.05), which show that the slack resources has no significantly positive effect on technological innovation performance. On the basis of model 2, Model 3 is added with the interaction of explorative learning and slack resources. It is found that the regression coefficient of the interaction is 0.361, passing the T-test (p=0.027>0.05). The specific results are shown in Table 7. Slack resources have a moderating effect on explorative learning and technological innovation performance.

The moderating effect of slack resources on explorative learning and management innovation performance can be verified in a similar way (Models 4-6). The regression coefficient of the interaction is -0.118, failing to pass the T-test (p=0.721>0.05). The specific results are shown in Table 7. Slack resources have no moderating effect on explorative learning and management innovation performance.

4.7. Verification for the Moderating Effect of Slack Resources on Exploitative Learning and Innovation Performance

Models 1-3 verify the moderating effect of slack resources on exploitative learning and technological innovation performance. There are only 3 control variables in Model 1, including the nature, scale and founding time of enterprise. The results show that the nature, number of employees, development stage and founding time fail to reach the significance level in the regression analysis, i.e., the 4 control variables have no significant effect on exploitative learning. On the basis of model 1, model 2 is added with 2 master variables, namely, exploitative learning and slack resources. The results show that the entry of the two master variables significantly increases R^2 to 0.578 in the regression equation. The F-test value is 12.118 (p=0.000 <0.001), which passes the T-test, with zero significant difference. The regression coefficients are respectively 0.774 (p=0.000<0.001) and -0.026 (p=0.564>0.05), which show that the slack resources has significantly positive effect on technological innovation performance. On the basis of model 2, model 3 is added with the interaction of exploitative learning and unabsorbed slack resources. It is found that the regression coefficient of the interaction is 0.401, passing the T-test (p=0.008<0.001). The specific results are shown in table 8.Slack resources have a moderating effect on exploitative learning and technological innovation performance.

The moderating effect of slack resources on exploitative learning and management innovation performance can be verified in a similar way (models 4-6). The regression coefficient of the interaction is 0.043, failing to pass the T-test (p=0.721>0.05). The specific results are shown in table 8. Slack resources have no moderating effect on exploitative learning and management innovation performance.

Table 7: The Moderating Effects of Slack Resources on Explorative Learning and Innovation Performance

Variable	Technological Innovation Performance			Management Innovation Performance		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Nature	-.110	-.200	-.181	-.078	-.171	-.161
Scale	-.264	-.020	-.002	-.203	.059	.068
Time	-.013	.032	.026	-.136	-.087	-.090
Explorative Learning		.819***	.542***		.844***	.704***
Slack Resources		.007	-.162		-.033	-.118
Explorative Learning*Slack Resources			.361**			.183
F	1.036	17.071***	14.909***	1.036	18.835***	15.991***
R^2	.071	.668	.696	.073	.689	.691
ΔR^2	.071	.597.	.028	.117	.616	.003
$AdjR^2$	.001	.628	.631	.003	.652	.648

Note：* p<0.05; ** p<0.01; *** p<0.001

Table 8: The Moderating Effects of Slack Resources on Exploitative Learning and Innovation Performance

Variable	Technological Innovation Performance			Management Innovation Performance		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Nature	-.110	-.199	-.178	-.078	-.182	-.180
Scale	-.264	-.049	-.029	-.203	.070	.072
Time	.133	-.059	-.059	.100	-.148	-.148
Exploitative Learning		.774***	.464**		.914***	.881***
Slack Resources		-.026	-.200		-.107	-.126
Exploitative Learning* Slack Resources			.401**			.043
F	1.036	12.118***	10.679***	1.036	26.43***	22.223***
R^2	.071	.578	.599	.073	.757	.787
△R2	.071	.507	.021	.117	.684	.103
AdjR^2	.001	.539	.543	.003	.728	.723

Note：* p<0.05; ** p<0.01; *** p<0.001

5. Conclusions

Based on the empirical study, this paper analyzes the mechanism of the impact of ambidextrous learning on enterprise innovation performance and further examines the moderating role of slack resource on the relationship between ambidexterity learning and innovation performance. The conclusions are as follows.

5.1. Conclusions

First, both explorative learning and exploitative learning have significant positive effects on management innovation performance and technological innovation performance. This research results means that as long as organization learns, regardless of type of organizational learning, it will have a positive effect on organizational innovation performance.

Secondly, compared with explorative learning, exploitative learning has a greater impact on technological innovation performance, while explorative learning has a greater impact on management innovation performance; this conclusion also verifies the view of Slater and Narver (1995). Explorative learning does not change organizational beliefs and rules, but only reflects market information, so it may have a significant impact on technological innovation performance. Exploitative learning will not only further adjust organizational beliefs and rules, but also require a higher level of knowledge, so it may have a greater impact on management innovation performance. This helps to take corresponding learning methods according to different stages of performance goals. For example, when managers are pursuing the goal of management innovation performance, managers can consider increasing the exploitative learning; while managers are pursuing the goal of technology innovation performance, managers can consider increasing explorative learning to achieve effective allocation and utilization of enterprise resources. At the same time, it also means that organizations can carry out different types of organizational learning according to the characteristics of each department. For example, R&D department should emphasize more explorative learning which has a greater impact on technological innovation performance, while business department may concentrate more on exploitative learning which has a greater impact on management innovation performance. The results of this study provide empirical support for the view that the adoption of explorative learning and exploitative learning requires different organizational structures and environments (Bierwerth, Schwens, Isidor, & Kabst, 2015)

Thirdly, slack resources positively regulate the relationship between explorative learning and exploitative learning on technological innovation performance, while redundant resources have no significant relationship with explorative learning and exploitative learning on management innovation performance. When enterprise has more slack resources, it can form a loose innovation environment within the organization, which is helpful to alleviate the pressure of resource competition between explorative learning and exploitative learning. Explorative learning is often faced with the search and test of new knowledge, new technology and new ideas, which will bring great uncertainty and high risk to the enterprise; however, more organizational slack resources can buffer the uncertainty of the enterprise in the dynamic environment and improve its ability to respond to the changes of the environment. This slack resource positively regulates the relationship between explorative learning and technological innovation performance. slack resource can provide enterprises with sufficient support from resources, it can help enterprises to improve flexibility and adaptability in the process of enterprise innovation, slack resource create favorable conditions for the exploitative learning , so slack resources are positively regulating the relationship between exploitative learning and technological innovation performance. Compared with the improvement of technological innovation performance, the improvement of management innovation performance requires more changes in organizational rules and organizational beliefs, and has less resource constraints. Therefore, redundant resources have no moderating effect between exploratory learning, exploitative learning and management innovation performance. Compared with the resources needed by technological innovation, management innovation performance requires more changes in organizational rules and organizational beliefs, and has less resource constraints. Therefore, slack resources have no moderating effect between explorative learning, exploitative learning and management innovation performance. This verifies Zhu (2008) research conclusion.

5.2. Limitations

The limitations of this study are as follow: first, this paper conducts the study only based on the data of Shandong Province in 2017, so the research results may have some limitations. For future researches, it's necessary to adopt data with longer time span and wider geographical scope to supplement and develop the results of this study. Second, this study uses the cross sectional data, which can't reflect the dynamic impact of ambidextrous learning on innovation performance. Therefore, dynamic analysis can be tried in the future. Third, this paper analyzes the impact of ambidextrous learning on innovation performance, but it may also be regulated by other factors during the process, such as environmental dynamics and redundant resources etc. Further studies on these aspects can be conducted in the future.

References

Aarons, G. A., & Sommerfeld, D. H. (2012). Leadership, innovation climate, and attitudes toward evidence-based practice during a statewide implementation. *Journal of the American Academy of Child & Adolescent Psychiatry, 51*(4), 423-431.

Bierwerth, M., Schwens, C., Isidor, R., & Kabst, R. (2015). Corporate entrepreneurship and performance: A meta-analysis. *Small Business Economics, 45*(2), 255-278.

Damanpour, F., & Aravind, D. (2012). Managerial Innovation: Conceptions, Processes, and Antecedents. *Management & Organization Review, 8*(2), 423-454.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39-50.

Gao, Y., Meng, X., & Xie, P. (2012). *Multi-Perspectives Integration on Exploitation and Exploration in Organizational Learning and Technological Innovation.*

Gatignon, H. (2010). *Statistical Analysis of Management Data.* New York, NY: Springer.

Gefen, D., Straub, D., & Boudreau, M.-C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems, 4*(1), 7. DOI: 10.17705/1CAIS.00407

Melchers, R. E. (1987). *Structural reliability:analysis and prediction*. Hoboken, NJ: Wiley & Sons.

Nunnally, J. C. (1978). Psychometric theory. *American Educational Research Journal, 5*(3), 83.

Raj, R., & Srivastava, K. B. (2013). The mediating role of organizational learning on the relationship among organizational culture, HRM practices and innovativeness. *Management and Labour Studies, 38*(3), 201-223.

Schildt, H., Keil, T., & Maula, M. (2012). The temporal effects of relative and firm-level absorptive capacity on interorganizational learning. *Strategic Management Journal, 33*(10), 1154-1173.

Slater, S. F., & Narver, J. C. (1995). Market Orientation and the Learning Organization. *Journal of marketing, 59*(3), 63-74.

Sorensen, J. B., & Stuart, T. E. (2000). Aging, obsolescence, and innovation. *Administrative Science Quarterly, 45*(2), 418-418.

Zhang, W., Zhao, W., Management, S. O., & University, X. J. (2017). *Study on the Relationship between Intra-and Extra-Industry Ties, Entrepreneurial Learning, and Entrepreneurial Performance.*

Zhu, C. H. (2008). Explorative learning,exploitative learning and innovation performance:moderating effects of environmental turbulence. *Studies in Science of Science, 26*(4), 860-867.