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The Relationship Between Collaborative Innovation Risk and Performance of Industrial Parks

Xiaofei Wang, School of Economics and Management, Tongji University, China
Yuchun Sun, School of Economics and Management, Tongji University, China
Guoqiang Li, School of Economics and Management, Tongji University, China*

ABSTRACT

From the perspective of collaborative innovation risk, the relationship between different risks and IP is explored based on the BPNN (back propagation neural network) model. Then, the SE (synergy effect) and the DC (dynamic capability) are introduced as intermediary and moderating variables. Following specific enterprise data input, the relationship between collaborative innovation risk and IP is analyzed based on deep learning and its endogenous mechanism. The analysis model of enterprise IP based on deep learning BPNN can well process enterprise data, and different types of collaborative innovation risks in industrial parks have significant negative effects on IP. The negative effect of organizational collaborative risk on IP is −0.268. Apart from market risk factors, the other collaborative innovation methods further hinder the improvement of IP by inhibiting SE. Apart from the risk of benefit distribution, the other collaborative innovation risks and IP are negatively regulated by DC, and the regulation effect on the risk of innovative factor input is the largest.

KEYWORDS

Collaborative Innovation, Deep Learning, Dynamic Capability, Industrial Park, Innovation Performance

1. INTRODUCTION

Innovation is the core driving force of social and economic development. Nowadays, abnormal development of science and technology makes the competition between enterprises fierce. The core competitiveness of enterprises, global economic and the uncertainty of new technologies make innovative activities particularly complex (Chen, J. et al., 2017). Concurrently, knowledge, technology and capital can be easily shared worldwide through the Internet and the life cycle of technology and products has been significantly shortened. Many enterprises have realized the necessity of cooperation in enterprise innovation (Yang, Z. et al. 2018). Therefore, industrial parts are informed of the significance of enterprise cooperation. These enterprises try to seek common ground, integrate their supply chains and industrial terminals, and innovate through cooperation to improve competitiveness (Hanif, M. et al., 2017). Risk can be burdened among partners, thereby reducing the risk of enterprises in collaborative innovation. Besides, there may be new risks in innovation cooperation, affecting the Synergy effect (SE) of enterprises, reducing their performance and making

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*Corresponding Author

it difficult for enterprises to give full play to their competitive advantages (Najafi-Tavani, S. et al. 2018). In dynamic environment, high-tech enterprises can use resource-based theory and Dynamic Capability (DC). Gradually, innovation activities will require more and more resources, and simple resource accumulation will be difficult to use for innovation, economic efficiency or risk reduction of collaborative innovation (Zhang, Z. et al. 2020). Therefore, the risk of collaborative innovation is of great significance to the intellectual property rights of enterprises. Risk may directly affect intellectual property rights or be adjusted by the stock exchange intermediaries.

Fan, Y. et al. (2020) believed that industrial parks, while driving the regional economy, posed a great threat to the natural environment due to large resource consumption and intensive pollutant emissions. Eco-industrial development, including cleaner production, biological products or waste exchange and infrastructure sharing, is the key to improve the environmental quality and sustainability of the industry park, which can improve the intellectual property (innovation performance) and competitive advantage of enterprises. In terms of the relationship between cooperative innovation and intellectual property rights, David et al (2021) pointed out that the internal interaction between subordinate members and independent members of cooperative enterprises had a positive impact on their "innovation performance". Subordinate members are more involved in innovation construction than independent members. Internal social factors are important assets for effective innovation of cooperatives, and a new research path is established from an empirical perspective. Su et al. (2021) proved that under the knowledge economy, organizational risk could be avoided through network and cooperation, which could use social resources to improve the innovation ability and competitiveness of enterprises. While collaborative innovation can benefit both sides, there are potential risks, with instability as high as 30% ~ 50%. These potential risks may reduce enterprise performance and competitive advantage. At present, few scholars have studied the mediating effect of risk, especially the relationship between new collaborative innovation risk of industrial parks and enterprise intellectual property rights (Wang, C., & Hu, Q.2020). Therefore, the research on the relationship between collaborative innovation risk and intellectual property rights has important referencing value for understanding enterprise innovation and decision-making from the perspective of policy. As a conclusion, research aims to identify and analyze the risk factors in enterprise collaborative innovation, clarify the relationship between different risks and enterprise intellectual property, and reveal the influence mechanism of collaborative innovation risk on intellectual property.

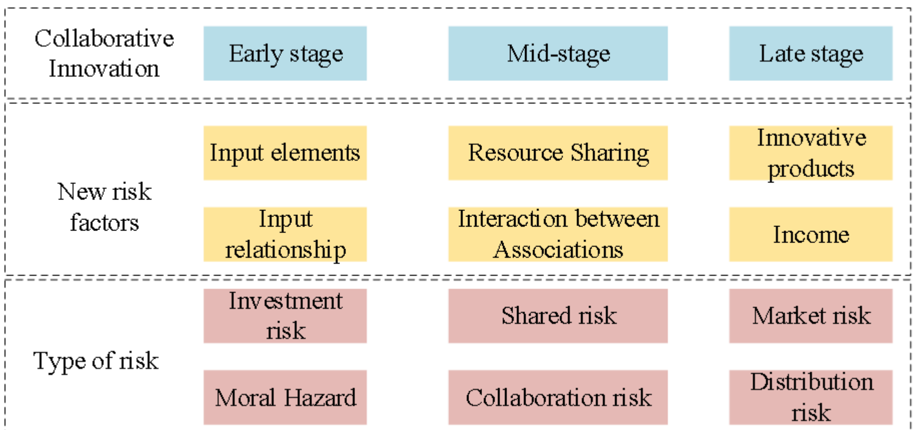
The innovation is to construct the research hypothesis and put forward the theoretical analysis model based on synergy, innovation and resource value theory. Through statistical analysis and hypothesis testing, the relationship between collaborative innovation risk and enterprise intellectual property rights is clarified. The research results have important referencing significance for preventing and controlling the risk of collaborative innovation and improving the intellectual property rights of enterprises, and put forward new ideas for studying the mediating effect of risk.

2. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESES

2.1 Collaborative Innovation Risks

Risk refers to the uncertainty of actual results concerning the expected goal (Wei, L., et al.2019). Particularly, the uncertainty of partners and the external environment in collaborative innovation may result in a wide discrepancy in results (Torfing, J.2019). Enterprises can complement each other in technology, capital, and management through the cooperation of different units and partners, while inappropriate enterprise behaviors may induce risks (Benhayoun, L. et al.2020). Here, a collaborative innovation model with endogenous mechanisms is constructed, and the model develops over three stages, including the early stage, mid-stage, and late-stage, as shown in Figure 1. In the early stage, enterprises and partners need to invest capital, technology, human resources, and material resources for innovation. The quality and quantity of investment embody an enterprise's innovation ability, and investment differences of the partners become a new risk factor (Sørensen, E., & Torfing, J.2017). Due to information asymmetry, trust crisis, and different interest demands, every partner thinks that they are unfairly treated in terms of investment return ratio. In the mid-stage, members should cooperate to effectively transfer and integrate resources, such as knowledge, technology, the capital. Unsmooth resource transmission channel hinders resource sharing, affects effectively collaborative innovation, and inflicts risk. In the late stage, innovative products are one of the important outputs (Xue, X., et al.2018). Technological innovation should be combined with the market for applicability. But in the output stage, factors, such as the mismatch between innovative products and market demand, and changes in consumer demand may lead to Market Risk (MR). Member enterprises participate in collaborative innovation to gain profits. The collaborative innovation benefits are diverse and not predictable and may induce Distribution Risk (DR) (Becker, M., & Tickner, J. A.2020).

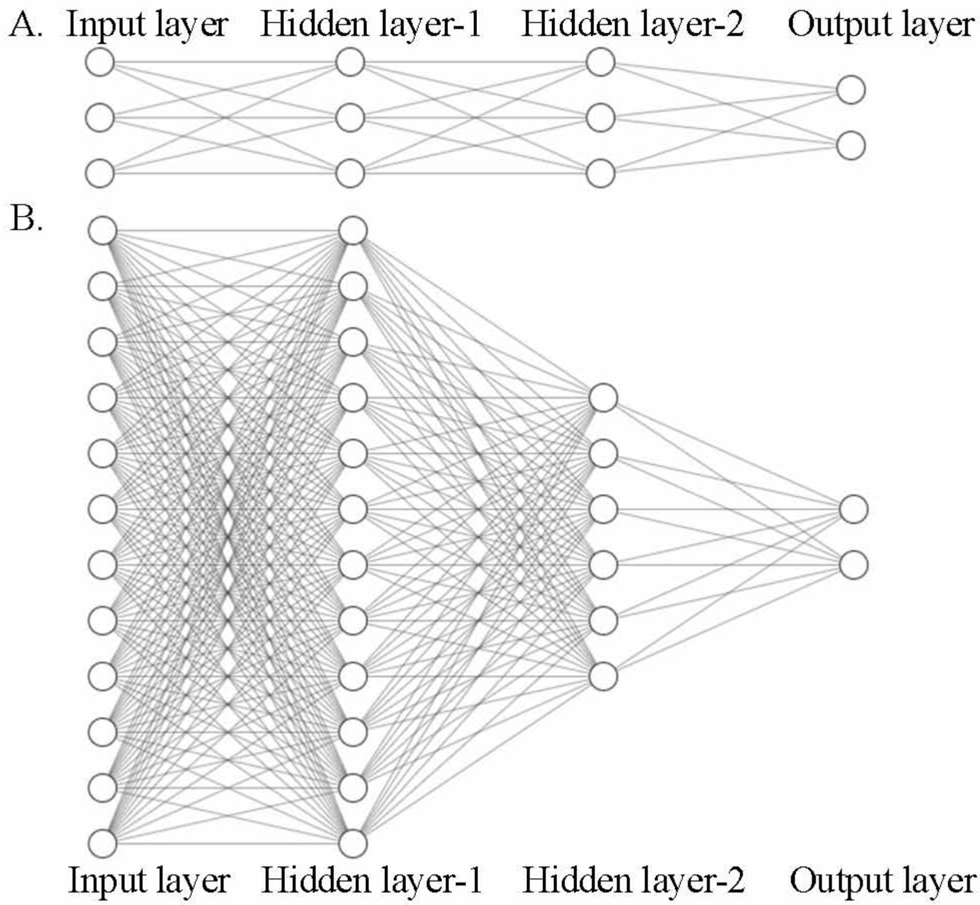
Figure 1. Endogenous mechanism model of collaborative innovation risks for enterprises



2.2 Deep Learning Backpropagation Neural Network (BPNN)

Deep learning is an algorithm based on data representation learning in machine learning. Observations can be represented in various ways, such as the vector of each pixel strength value, or more abstractly as a series of edges, regions of specific shapes. Specific representation methods can facilitate learning from instances. The neural network is an important branch of machine learning, which consists of many interconnected neurons and has strong learning ability and nonlinear mapping ability. While neurons, connections, and weights are a simulation of biological neurons, axons, and dendrites. During information dissemination, the network performance is adjusted through the size of connection weights. Figure 2 displays single neuron structure. Figure 2A referes to a single layer Back Propagation Neural Networks (BPNN), and Figure 2B signifies a deep BPNN. Specifically, an enterprise organization construction is studied here using the Back Propagation (BP) algorithm in the big data neural network, based upon which the evaluation model of enterprise organization construction is implemented. Finally, the model is trained through the neural network development kit based on Tensorflow. According to the evaluation results, evaluation can be made on the status of enterprise organization construction, and corresponding preventive measures can be adopted, which has a positive effect on enterprise management in the future.

Figure 2. Structure diagram of deep learning BPNN

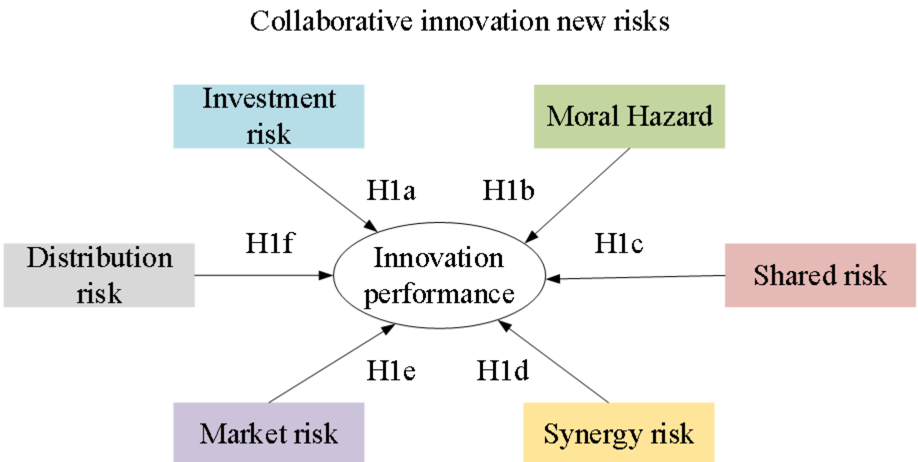


2.3 Research Hypothesis

2.3.1. The Relationship Between Enterprise Collaborative Innovation Risks And IP And Hypotheses

The endogenous mechanism model shows that inappropriate enterprise behaviors during collaborative cooperation may lead to many new risks. Firstly, Investor Relations (IR) hampers the improvement of Intellectual Property (IP), reduces resource allocation efficiency, and causes a serious imbalance in the supply chain. As a result, an enterprise's innovation ability may be doubted, and the collaborative innovation effectiveness will be weakened (Roper, S., et al.2017). Secondly, Shared Risk (SR) may emerge during the acquisition, transfer, or creation of innovative resources, such as knowledge and technology. Poor knowledge exchange and conservative technology transfer reduce the efficiency of cooperation and information exchange. Thirdly, the Cooperation Risk (CR) is caused by poor organizational coordination and weak collaboration mechanism. It hinders the interaction between innovation subjects (Agostini, L., et al.2017). Fourthly, the market is the decisive factor and it can directly embodies the success of collaborative innovation. MR comes from the uncertainty of the market environment of innovative products. Finally, when the partner enterprises think that they deserve more than the distributed resources, DR comes about. Accordingly, here propose several hypotheses.

Figure 3. The relationship between enterprise collaborative innovation risks and IP



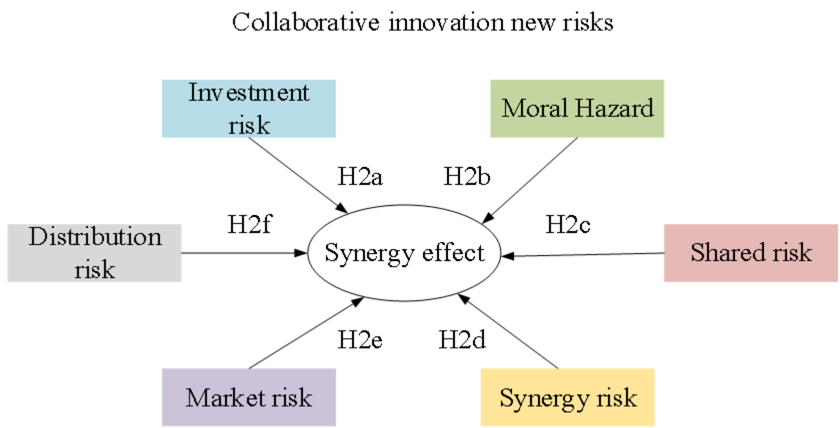
H1: The collaborative innovation risks have a significant inhibition on IP.
H1a: The IR has a significant inhibition on IP.
H1b: The Moral Hazard (MH) has a significant inhibition on IP.
H1c: SR has a significant inhibition on IP.
H1d: Synergy risk has a significant inhibition on IP.
H1e: MR has a significant inhibition on IP.
H1f: DR has a significant inhibition on IP.

2.3.2. The Mediating Effect Of Synergy On The Risk And Performance Of Collaborative Innovation

During the collaboration, enterprises integrate external resources according to their strategic objectives for practical achievement. SE effectively integrates and allocates innovative factors, and requires nonlinear interaction and coupling mechanisms among collaborative partners (Hong, J., et al.2019). Only when the innovation resources, especially the hidden resources, are fully utilized, can the SE be maximized. Good and efficient cooperation can provide information for partner-enterprises, accelerate the mutual trust in technology and knowledge, and significantly increase the enterprise value, concurrently, the frequent interaction and deepening cooperation can improve the SE in turn (Li, X.2020). However, in the actual operation process, conflicts and contradictions often occur among innovation subjects due to factors, such as the distribution of rights and interests, division of costs, organization management, communication, and trust, which hinders the friendly cooperation and interaction between the subjects, causes collaborative innovation risks, and reduce the SE. Accordingly, some hypotheses are proposed.

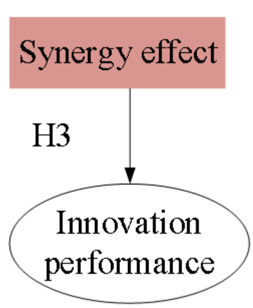
H2: The enterprise collaborative innovation risks have an obvious hindrance to the SE.
H2a: IR has an obvious hindrance to the SE.
H2b: MH has an obvious hindrance to the SE.
H2c: SR has a significant hindrance to the SE.
H2d: SR has a significant hindrance to the SE.
H2e: MR has a significant hindrance to the SE.
H2f: DR has a significant hindrance to the SE.

Figure 4. The relationship between enterprise collaborative innovation risks and SE



The synergetic effect comes from the close interaction among innovation partner enterprises and the complex role of resource factors. The research on knowledge flow shows that collaborative innovation helps innovation enterprises filter information from the shared resources, accelerates technological innovation, and provides enterprises with more innovation profits (Yu, S., & Yuizono, T.2021). The research on the resource-based view theories indicates that collaborative innovation helps the innovation enterprises integrate internal and external resources to promote IP. When partner-enterprises set the same goal as each other, make synchronized decisions, communicate frequently, exchange information, share resources, innovate knowledge, and form supply chain collaboration, then cost and response time in the innovation will be reduced (Fang, W., et al.2018). Accordingly, the following hypotheses are proposed.

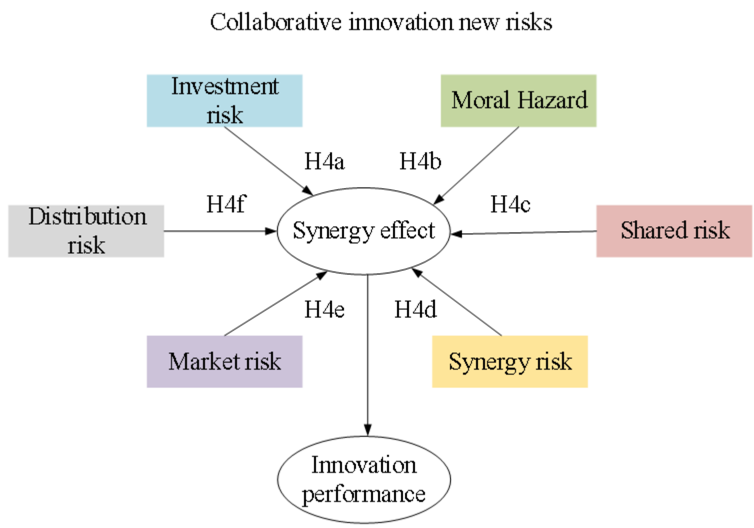
Figure 5. The relationship between SE and IP



H3: SE has a significant positive impact on IP.

Collaborative innovation connects enterprises closely with the outside world, circulates internal and external resources for enterprises, producing a SE. Collaboration mode is the key to improve collaborative innovation, can enhance cooperation willingness, and deepens the trust of partner enterprises (Zouaghi, F., et al.2018). However, insufficient innovation resources, untimely communication, imperfect coordination mechanism, and improper interest distribution may spread risks among enterprises, weaken the SE, and thus blocking knowledge and technology sharing, and product renewal. Under the worst conditions, the collaboration among enterprises ruptures (Marasco, A., et al.2018). Accordingly, the following hypotheses are proposed.

Figure 6. The effect of enterprise collaborative innovation risks and SE on IP



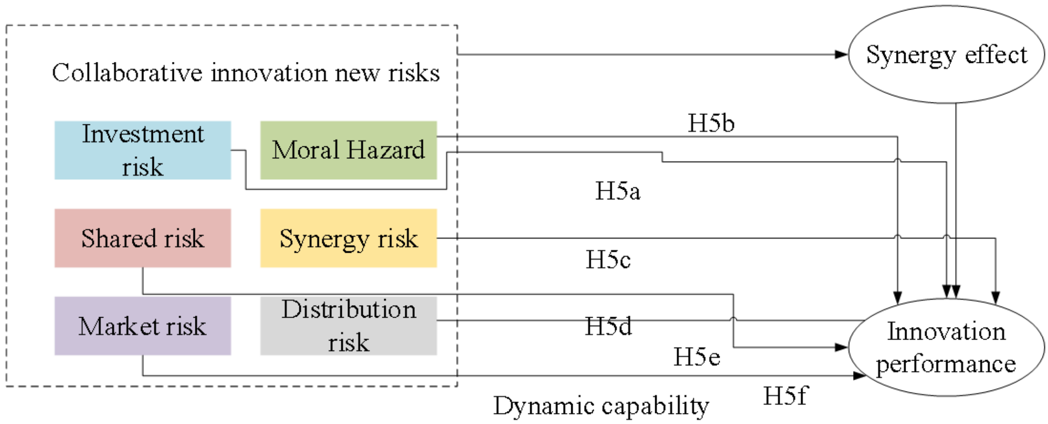
H4: The SE plays a mediating role in the relationship between collaborative innovation risk and IP.
H4a: The SE has a mediating effect on the relationship between IR and IP.
H4b: SE has a mediating effect on the relationship between MH and IP.
H4c: SE plays a mediating role in the relationship between SR and IP.
H4d: SE has a mediating effect on the relationship between CR and IP
H4e: SE plays a mediating role in the relationship between MR and IP.
H4f: SE plays a mediating role in the relationship between DR and IP.

2.3.3. The Moderating Effect of DC

According to the dynamic performance theory, the best innovation effect can be achieved only through the enterprise capability innovation strategy. Enterprises with high vitality can quickly adapt to the competitive market environment, adjust organizational structure, and plan marketing for scarce resources, and spontaneously integrate enterprise reserves with innovation resources (Mu, Y., & He, X.2021). The moderating effect can promote the transformation of new knowledge and technology into markets and diversifies the product distribution, improving the IP of enterprises. Particularly, in collaborative communication, information communication barriers lead to waste of resources, without proper adjustment, collaboration risks will sprawl, and collaboration may be interrupted. Accordingly, the following hypotheses are proposed.

H5: DC negatively moderates the relationship between collaborative innovation risk and IP.
H5a: DC negatively moderates the relationship between IR and IP.
H5b: DC negatively moderates the relationship between MH and IP.
H5c: DC negatively moderates the relationship between SR and IP.
H5d: DC negatively moderates the relationship between CR and IP.
H5e: DC negatively moderates the relationship between MR and IP.

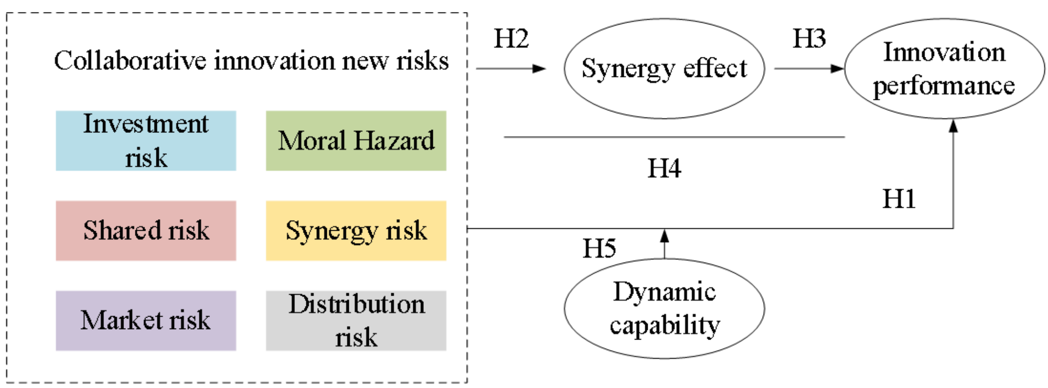
Figure 7. The relationship between DC and collaborative innovation risks, and DC and IP



H5f: DC negatively moderates the relationship between DR and IP.

Based on the proposed hypotheses, a relational model is constructed as shown in Figure 8. Here, collaborative innovation risks are divided into six categories. Among them, the CR can indirectly affect IP through moderating the SE. Meanwhile, the DC is used as an intermediate moderator.

Figure 8. Relational model based on theoretical hypotheses



3. SCALE DESIGN AND MODEL CONSTRUCTION

3.1 Scale Design

3.1.1 Collaborotive Innovation and IP Rights Scale

Collaborative innovation can reduce innovation costs, improve intellectual property rights and gain competitive advantages for enterprises. Here, the risk of collaborative innovation is analyzed from perspectives of IR, MH, SR, CR, MR and DR, and the scale (Agger, A., & Lund, D.H.2017) is designed based on relevant literature. Bustinza, O. F., et al. 2019). Specifically, the scale includes

17 items. The results can be scored with the 5 - level Likert scale. 1-5 points represent five levels: extremely poor, poor, common, good, excellent. Besides, the inverse integral method is also used.

IP refers to a manifestation of innovation activities or projects, which has attracted the attention of scholars from all walks of life. Due to the complexity of innovation projects, IP indicators are not uniform. However, with the deepening of research, IP indicators are being standardized. Here are some literature on IP measurements (Hameed, W. U., et al. 2018. Shen, J., et al. 2020), where three indicators sre selected.

3.1.2 SE Scale and DC Scale

Currently, the research on SE measurement has been unanimously recognized by academia. Referring to the measurement scale of Zhang et al. (2021), four measurement items are designed: collaborative surplus, knowledge search, absorption cost and product innovation efficiency.

DC has no unified definition, so the measurement of DC varies. Some researchers measured DC through five dimensions: market potential, organizational flexibility, strategic isolation, organizational learning and organizational change, and designed a DC scale containing eight items. Based on the scale of Yu et al. (2020), a scale is designed, which includes dimensions of resource integration, organizational restructuring, perception and innovation.

3.2 Data Sources

Here, a sample survey is conducted on innovative high-tech enterprises in China. Considering data availability and convenience for practical research, some enterprise data of some listed companies in instrumentation and pharmaceutical industry are selected according to the industry classification standards of "*Industry Classification Guidelines of Listed Companies*" and "*Classification of High-tech Industries*". Data from electronic equipment companies, such as computers and communications, are collected through e-mail and interviews. A total of 500 quality assurances are issued. 35 assurances are eliminated, which are incomplete and difficult to identify; 465 assurances are restored, and 12 assurances are deleted, which are withdrawn from the survey. Finally, 453 valid questionnaires are collected, and the effective rate is 90.6%.

3.3 Sample Statistics

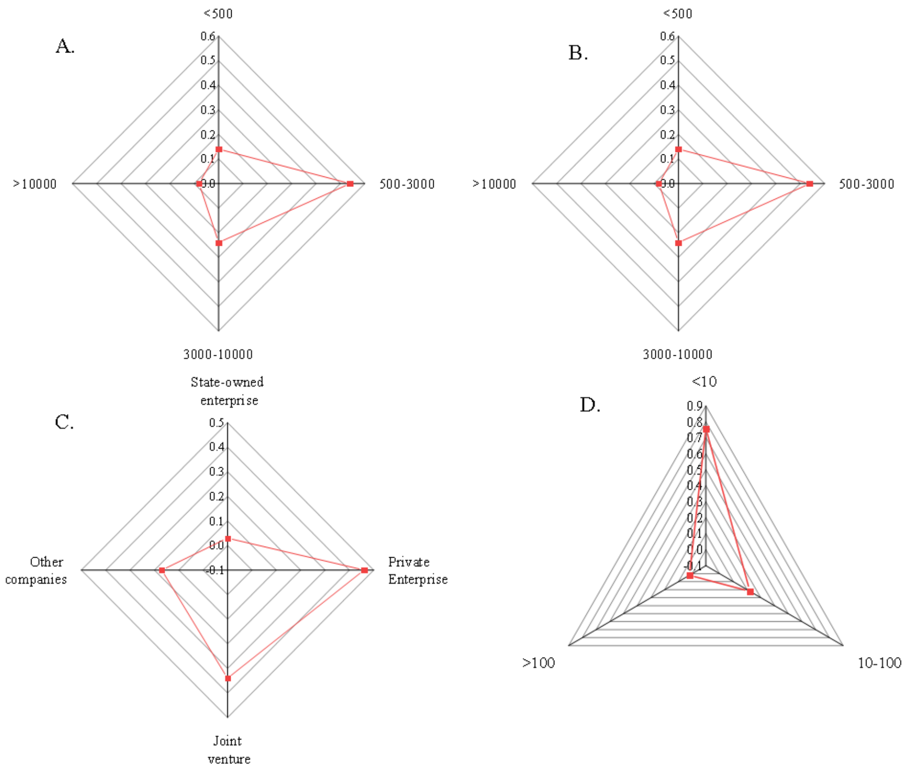
Figure 9A denotes the enterprise size distribution. Among all subjects, 14% have less than 500 people, 54% have 500-3000 people, and 24% have 3000–10000 people. Figure 9B displays the enterprise business years distribution. Among all subjects, 3% have been established less than 9 years, 52% have been established 10-20 years, and 45% have been established over 20 years. Figure 8C illustrates the enterprise nature distribution. Among all subjects, private enterprises, joint enterprises, and state-owned enterprises account for 3%, 34%, and 46%, respectively. Figure 8D demonstrates the registered capital distribution. Enterprises with registered capital less than 100,000 Renminbi (RMB) is 76%, and those between 100,000 RMB and 1,000,000 RMB are 22%. Overall, the sample distribution is extensive and representative.

4. EMPIRICAL RESULTS ANALYSIS

4.1 Reliability and Validity Analysis

Reliability analysis, also known as reliability analysis, is used to measure whether the sample answer results are reliable, that is, whether the sample has really answered the scale items. When the same object is measured and the results of multiple measurements are very close, it will be considered that the result is credible and true, that is, the reliability is high. If the results of each measurement are very different, it indicates that the reliability is low. There are many methods to measure reliability.

Figure 9. Sample statistical analysis



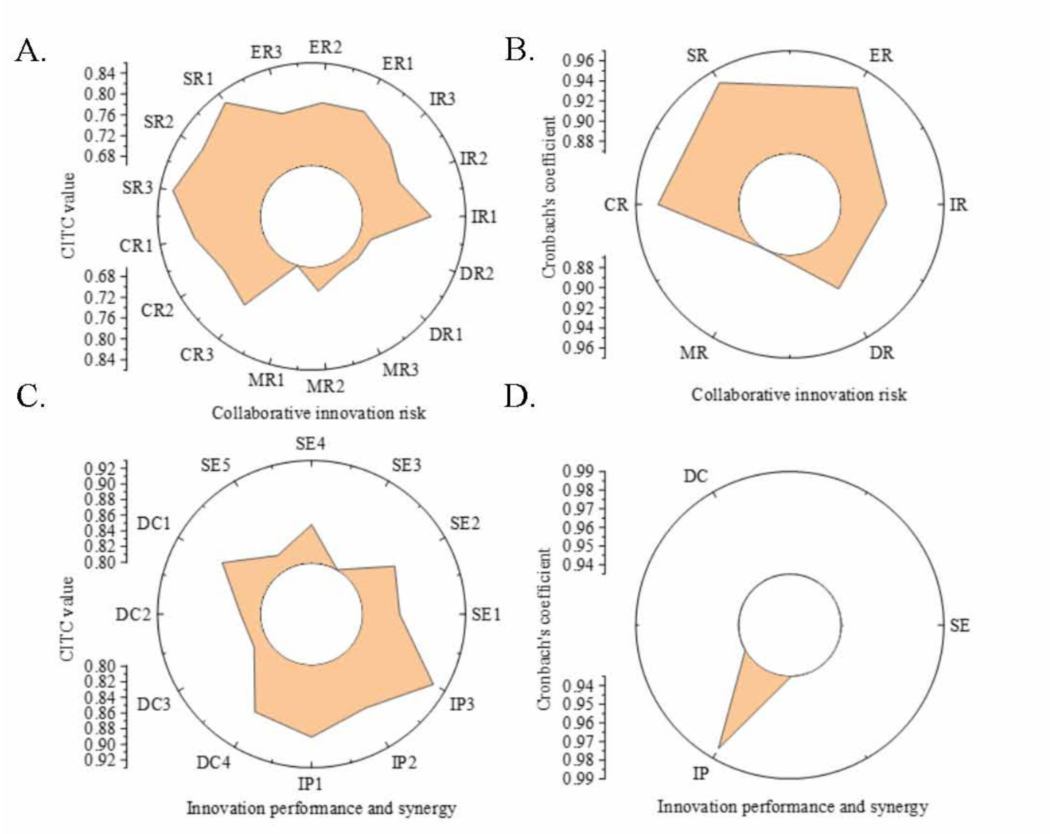
The commonly used reliability coefficients include: Clonbach α coefficient, half coefficient, and test-retest reliability, which can be analyzed in SPSS12.0.

Figure 10A shows that the Corrected Item Total Correlation (CITC) value of the cooperative innovation risk scale is > 0.5, and Figure 9B indicates that Clonbach α coefficient introducing six dimensions is > 0.8. Figure 9C shows that the CITC value of intellectual property and skill level is > 0.5, and Figure 9D shows that the Cronbach coefficient of intellectual property and skill level is > 0.7.

According to the Cronbach coefficient of the above scales, the CITC values of all items are greater than 0.5. The model proposed has good reliability.

Validity analysis is used to measure whether the item design is reasonable. Validity can be divided into content validity, structure validity, and criterion validity. Content validity is usually used to explain the effectiveness of the questionnaire by words. For example, explain the authority and effectiveness of the questionnaire through references or authoritative sources or fully illustrate the effectiveness of the questionnaire through the pre-test of the questionnaire and the correction of the items combined with the results. Structure validity refers to the corresponding relationship between measurement items and measurement dimensions. There are two measurement methods, exploratory factor analysis and confirmatory factor analysis. Among them, exploratory factor analysis is the most widely used structure validity measurement method at present. Figure 11A shows the Kaiser-Meyer-Olkin (KMO) value, and the KMO values of enterprise collaborative innovation risk, SE, DC, and IP are higher than 0.7. Figure 11B shows the approximate chi square, and Figure 10C shows the results of Sig test. The value of Bartlett spherical test is less than 0.05, so it meets the conditions of factor analysis. The model analysis structure meets the validity test criteria.

Figure 10. Statistical analysis of variable reliability test



4.2 Description and Correlation Analysis

Figure 12A-12C are the scores of different scale indicators. The results of the six dimensions of collaborative innovation risk are nearly the same. The mean value of the SE is 3.06, and the Standard Deviation (SD) is 1.18, indicating that the synergistic effect is at a moderate to low level during collaborative innovation. The mean value of IP is 3.14, and the SD is 1.10, indicating that IP is affected by risk factors during collaborative innovation. The mean value of DC is 2.98, and the SD is 1.14, indicating that the DC level of enterprises is at the lower-moderate level.

Table 1 implies that there is a significant correlation between each variable. The correlation coefficient of collaborative innovation is between 0.55 and 0.73, which is a moderate correlation. There is a significant negative correlation between CR and IP ($p<0.01$), which is a moderate correlation. There is a significant positive strong correlation between SE and IP ($p<0.01$), which is consistent with the proposed theoretical hypotheses.

4.3 SEM (Standard Error of Mean) Analysis

After software fitting, the ratio of chi-square and degree of freedom is less than 3, the value of Comparative Fit Index (CFI) is greater than 0.9, the value of Goodness-Of-Fit (GFI) is greater than 0.8, the value of Tucker-Lewis index (TLI) is greater than 0.9, and the value of Root-Mean-Square Error of Approximation (RMSEA) is less than 0.08, which meets the model conditions. Therefore, the SEM model is implemented as shown in Figure 13.

Figure 11. KMO and Bartlett's spherical test results

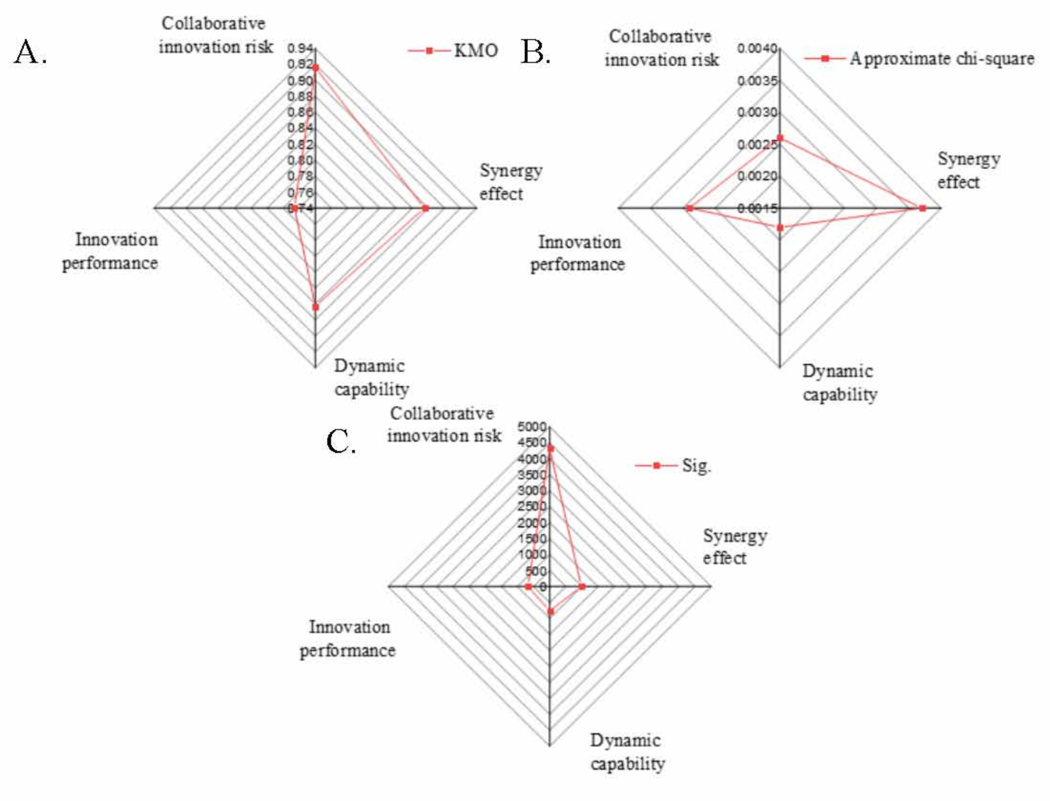


Figure 14A shows the result of standardized and non-standardized paths, and Figure 14B displays the result of fitting indicators. The results suggest that the standardized path coefficients of IP to SR, IP to CR, and IP to DR are -0.171, -0.268, and -0.239, respectively, and that all indexes reach the significant levels. The standardized path of IP to IR, IP to ER, IP to MR are -0.137, -0.126, and -0.134, respectively, which meet the significant level of $p<0.05$. The coefficients of the six paths are all negative and significant, indicating that the six types of risks of enterprise collaborative innovation significantly hinder the improvement of IP. Thus, hypotheses H1, H1a, H1b, H1c, H1d, H1e, and H1f hold. Among them, CR has the most significant impact on IP.

4.4 Mediating and Moderating Effects

Figure 15 indicates that mediating effect can be observed only when there is a significant correlation between independent variables and dependent variables. Test results show that the CMIN/df value is less than 2, the CFI, GFI, TLI,values are greater than 0.8, and the RMSEA value is less than 0.08. The model fitting index meets the requirements.

Figure 16A shows the result of standardized and non-standardized paths, and Figure 16B displays the result of fitting indicators. The results imply that the standardized path coefficients of IR, ER, SR, CR, and DR to the SE are all negative and satisfy significant conditions, so hypotheses H2a, H2b, H2c, H2d, and H2f are established. The negative effect of MR on synergy is not significant, so H2e and H2 are not established. The standardized path coefficient of MR on IP is 0.741, which is significant at 0.01 level, so hypothesis H3 is true. The standardized coefficient of IR to IP is 0.038, the standardized coefficient of ER to IP is 0.014, the standardized coefficient of SR to IP is 0.059,

Figure 12. Results of descriptive statistical analysis

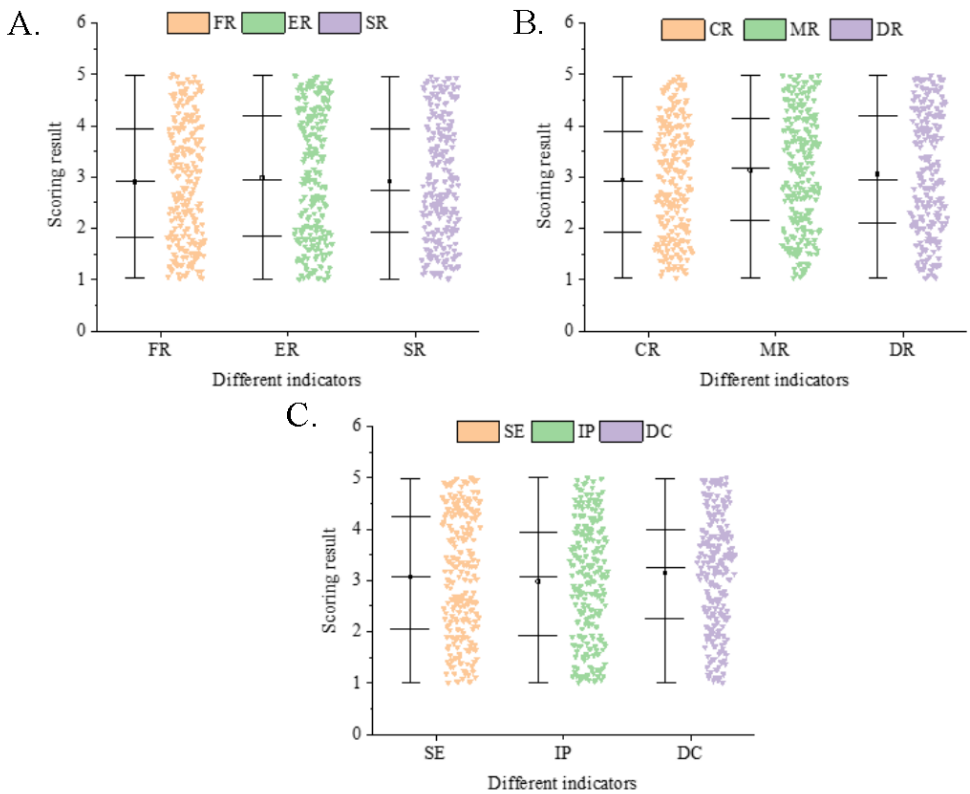


Table 1. Results of correlation statistical analysis

Variables	FR	ER	SR	CR	MR	DR	SE	DC	IP
FR	1								
ER	0.728**	1							
SR	0.698**	0.712**	1						
CR	0.658**	0.613**	0.727**	1					
MR	0.634**	0.627**	0.669**	0.586**	1				
DR	0.594**	0.536**	0.589**	0.613**	0.596**	1			
SE	-0.738**	-0.715**	-0.813**	-0.797**	-0.689**	-0.612**	1		
DC	-0.415**	-0.375**	-0.496**	-0.469**	-0.458**	-0.479**	0.618**	1	
IP	-0.713	-7.112**	-0.786**	-0.714**	-0.692**	-0.712**	0.891**	0.672**	1

Figure 13. Direct effect path diagram of SEM model

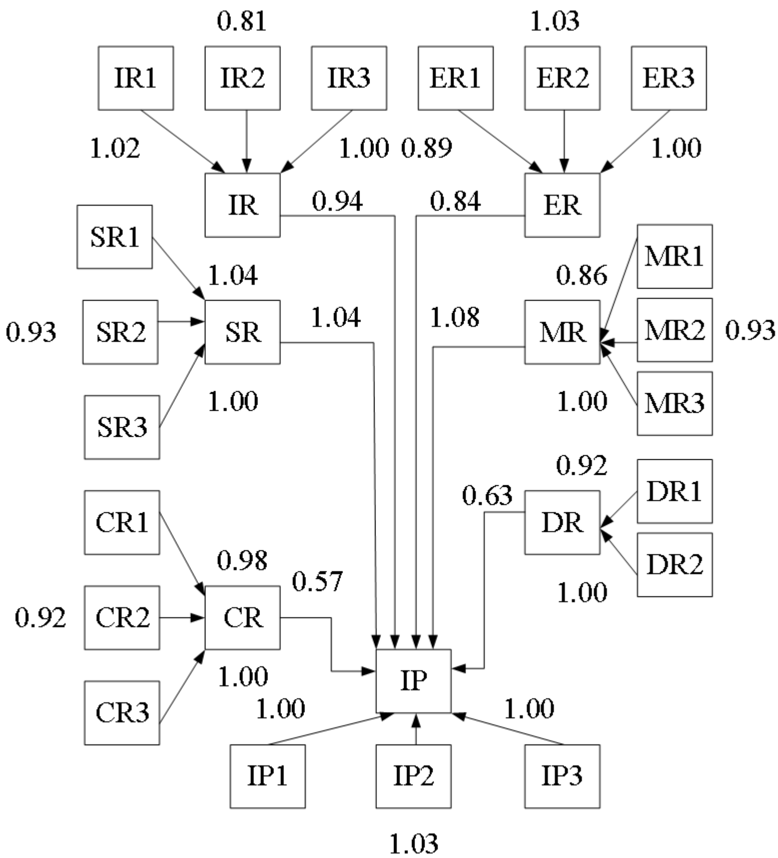


Figure 14. Direct effect path coefficients of SEM model

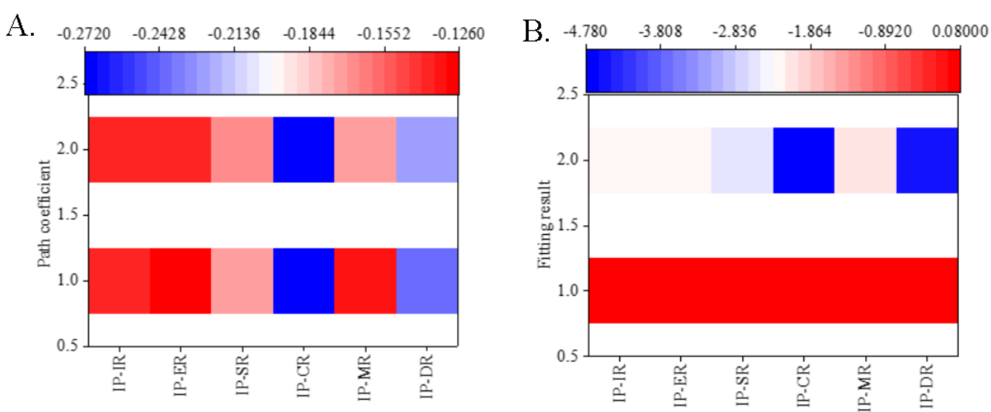


Figure 15. SEM Path diagram of SEM model mediating effect

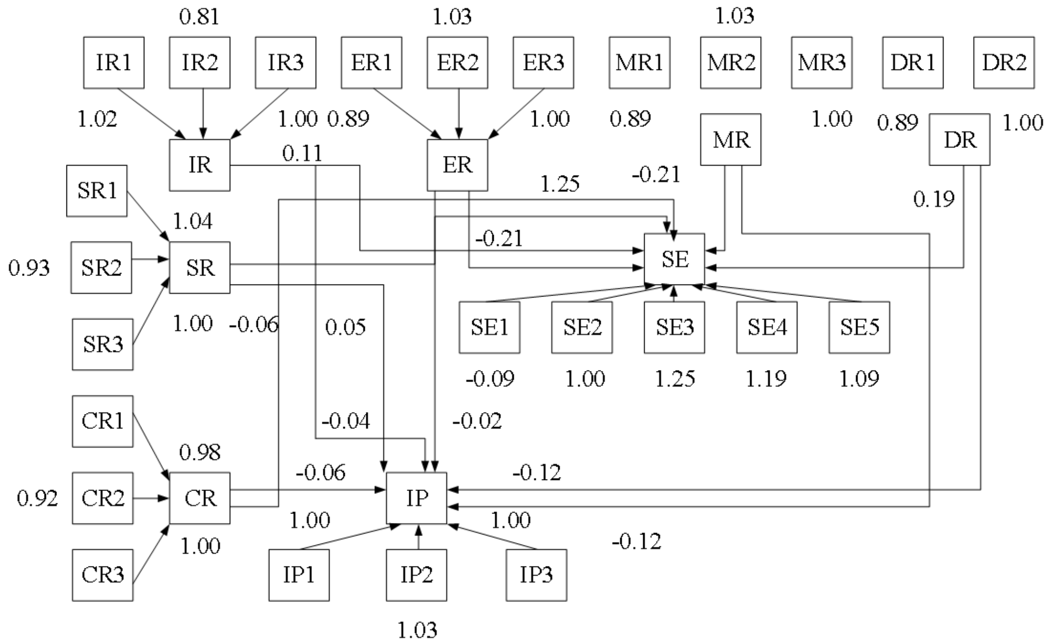
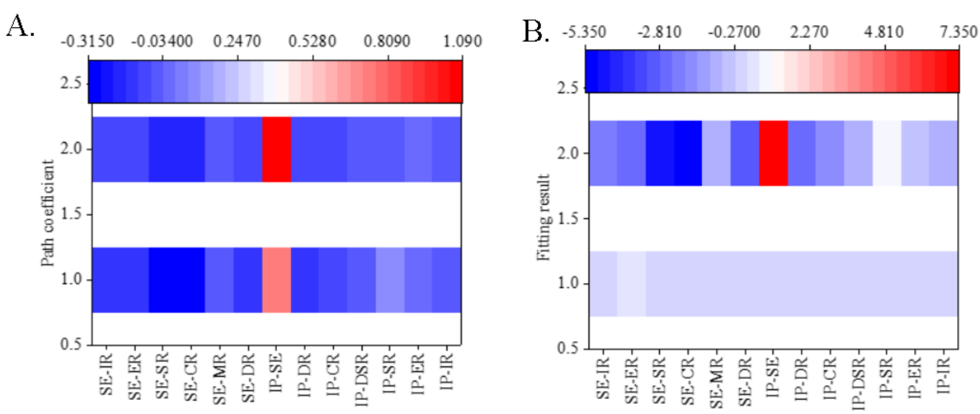


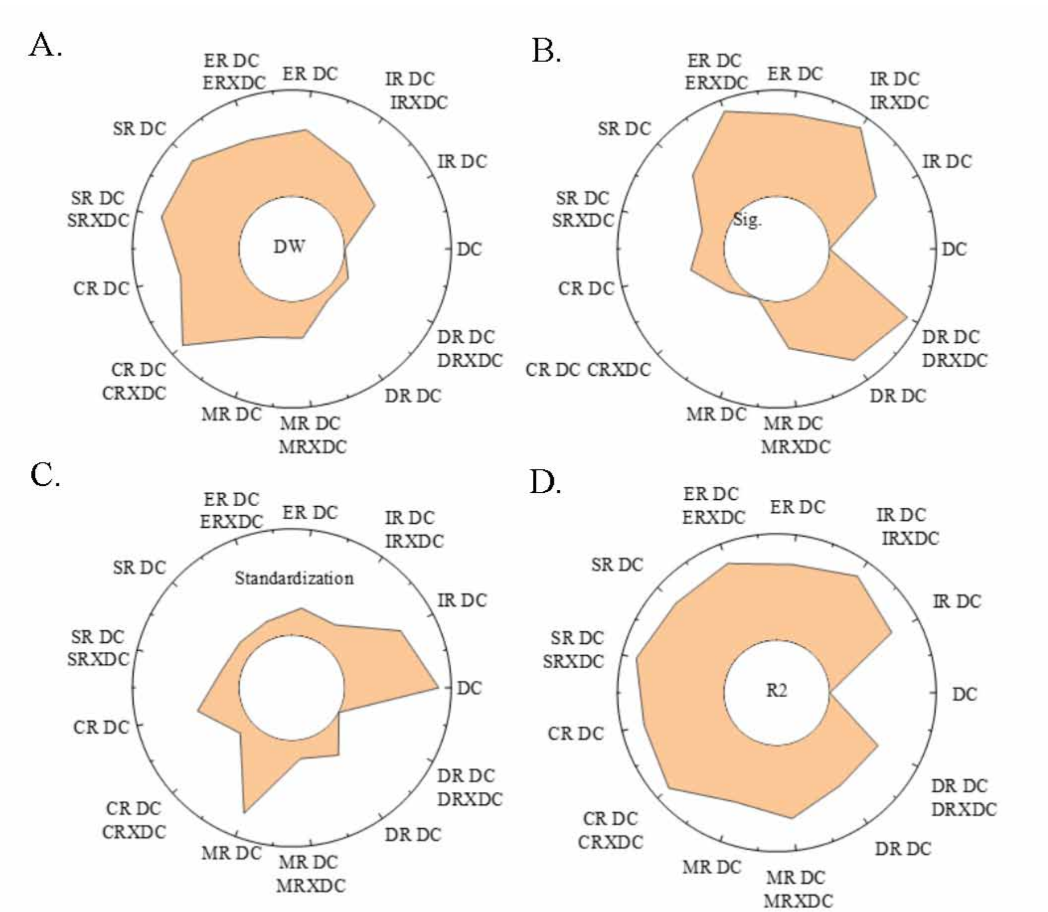
Figure 16. Mediating effect path coefficient and fitting index of SEM model



and the standardized coefficient of CR to IP is 0.055, indicating that the effect of these four types of risks on enterprise IP is mediating and is realized through SE. Thus, hypotheses H4a, H4b, H4c, H4d, and H4f hold. However, the mediating effect of synergy between MR and IP has failed the tests, so hypotheses H4e and H4 don't hold.

Figure 17A-17D shows all the hypothetical Durbin-Watson (DW), Sig., standardization, and R^2 results, respectively. The results show that the standardization coefficients of IR, ER, SR, CR, and MR are 0.234, 0.199, 0.208, 0.186, and 0.203 seperately, after the addition of independent variables and moderators, and they are all significant at the level of sig<0.01, indicating that DC positively moderates the relationship between IP and IR, ER, SR, CR, and MR. Hence, hypotheses H5a, H5b, H5c, H5d, and H5e hold. The moderating effects of DC on IR and SR are larger the that on ER, while the moderating effect of DC on DR and DC are not significant enough, so H5f and H5 do not hold.

Figure 17. Hierarchical regression results



5. CONCLUSIONS

The rapid development of science and technology makes competition among enterprises extremely fierce. Based on the endogenous mechanism of enterprise collaborative innovation risk, a risk identification model is implemented for enterprise collaborative innovation, and introduction is made on SE and DC as intermediaries and regulators. Based on the data of 226 high-tech enterprises, the impact of collaborative innovation risk on the intellectual property rights of industrial parks is discussed through hierarchical regression, modeling, and other statistical methods. The risk of enterprise collaborative innovation severly hinders IP rights, and SE plays an intermediary role in some risks. DC negatively regulates the relationship between enterprise collaborative innovation risk and IP rights. The results show that there is a significant correlation between the variables. The correlation coefficient of collaborative innovation is between 0.55 and 0.73, belonging to medium correlation. CR is significantly negatively correlated with IP ($P < 0.01$), and SE is significantly positively correlated with IP ($P < 0.01$), which is consistent with the proposed theoretical hypothesis. The result is of great significance for the long-term development of enterprise risk management, performance improvement, and collaborative innovation in China.

Although analyzation is made on the relationship between intellectual property rights and collaborative innovation risks here, there are still some shortcomings. First, only companies in the high-tech sector are sampled to yield clear results, but for universality, data from other sectors should be included. Additionally, the model effect needs to be further tested, and it is expected that more in-depth analysis will be carried out in the future to optimize the analysis model proposed here.

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Xiaofei Wang was born in Zoucheng, Shandong Province, P.R. China, in 1983. She received the master's degree from Qingdao University, P.R. China. Now, she studies in School of Economics and Management of Tongji University. Her research interest include innovation, business management.

Yuchun Sun, professor, doctor, doctoral supervisor of Tongji SEM. He graduated from the post-doctoral station of applied economics of Fudan University in 1999. His main research interests are multinational corporation empirical research, human resources, management communication, and management ethics.

Guoqiang Li is an Assistant Research Associate from the Institutes of Science and Development, Chinese Academy of Sciences, China. His research focuses on business management and technological innovation.