# Research on Regional Collaborative Network Innovation and Enterprises' Innovation Performance in the Sustainable Development of Yangtze River Delta, China

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**Abstract.** As one of the most dynamic and sustainable economic regions in China, Yangtze River Delta has been forming an innovation cluster of high-quality development. To explore the driving force during the integration of Yangtze River Delta, this article constructs a driving force model and makes an empirical study by the structural equation modeling method. The model proves that heterogeneity knowledge will positively affect innovation, that innovation performance has a strong positive impact on regional collaborative network innovation, that regional collaborative network innovation exerts a positive effect on knowledge spillover, and that organizational learning can affect innovation performance positively. Based on the above research results, some recommendations are proposed. Those recommendations consist of: (a) to forge a dynamic sustainable and innovative regional collaborative network system lay a foundation of high-quality development; (b) while the two driving forces of heterogeneity knowledge and organizational learning activated, the indices of enterprise innovation performance should be optimized.

**Keywords:** regional collaborative network innovation; innovation performance; sustainable; high-quality; SEM.

## 1. Introduction

An unprecedented drastic change is undertaking in the world economy. Favorable and unfavorable factors of economic development are constantly impacting the world economy, such as the new round of scientific and technological revolution, industrial revolution, Sino-US trade conflict, COVID-19 and so on. People all over the world have always been reflecting on how economic development should be carried out in order to ensure it orderly, healthy and sustainable. Regardless of the internal and external factors, the momentum of China's economic development remains strong. The 14th Five-Year Plan for Economic and Social Development of the People's Republic of China and the Outline of the Long-range Goals for 2035 clearly outlines high-quality development of China's economy. The Outline of the Development Plan for Regional Integration in the Yangtze River Delta, one of China's national strategies, also stipulates that we should uphold the concept of integrated high-quality development, promote deeper regional integration in the Yangtze River Delta through high-quality development, and form a regional cluster featuring high-quality development. Quality reform, efficiency reform and driving force reform needs to be achieved first during the integration in the Yangtze River Delta. Innovation, a driving force to increasingly maintain one regional economy sustainable growth, has already played an irreplaceable role in breaking through the current unfavorable challenges during the process of regional integration development in the Yangtze River Delta. It is urgent to study the mechanism and driving force behind how enterprises in the region have been effectively integrated and realized higher start point reform and open at a higher level.

Based on a review of existing literatures and pertinent hypotheses, this paper constructs a driving force model including factors like regional collaborative network innovation and enterprises' innovation performance from the perspective of the integration of the Yangtze River Delta, China. Then researchers conducted a questionnaire survey on respondents of typical enterprises in emerging industries in the Yangtze River Delta. These respondents are mainly managers and technology researchers. The empirical study is carried out by structural equation modeling method. With the help of the model, two research questions are expected to be explored. First, in order to promote the development of regional collaborative network effectively and to maximize the innovation performance of individual enterprises, what is the relationship among heterogeneity knowledge, innovation performance and regional collaborative network innovation in the Yangtze River Delta needs to be researched; Second, how do knowledge spillover, organizational learning and heterogeneity knowledge push forward innovation performance of firms? Whether they can help firms stand at a higher start point of innovation and achieve high-quality innovation performance during the sustainable development.

## 2. Theory and Hypotheses

### 2.1 Knowledge heterogeneity and innovation performance

In the era of knowledge economy, enterprises increasingly expect to promote their own knowledge innovation and obtain the unique competitiveness by means of expanding knowledge heterogeneity. Rodan and Galunic (2004) [1] believed it true that knowledge heterogeneity involves the diversity of knowledge, skills and expertise obtained by team members in a team. Beckman (2005) [2] indicated that firms which is made up of diverse background team members will have higher levels of performance because the knowledge heterogeneity is beneficiary to have a deeper insight into the industrial development trend and the various change of marketing demand. Pablo (2005) [3] held that the root of intra-industry heterogeneity lies on the difference of knowledge reserve of the firms. On the other hand, some scholars hold different viewpoints that knowledge heterogeneity goes against the promotion of the firms' innovation performance in view of interpersonal relationship conflict. Yang and Wang (2017) [4] empirically verified that knowledge heterogeneity has a strong positive impact on the innovation performance. Based on those above analysis, we could assume as follows.

Hypothesis 1 (H1): Heterogeneity knowledge has a positive influence on the innovation performance.

### 2.2 Regional collaborative network innovation, knowledge heterogeneity and innovation performance

The knowledge flow among enterprises is increasingly becoming fast. External sources of knowledge are posing more and more impact on regional collaborative network. Thomas (2009) [5] discussed that supplier involvement in new product development affects the effectiveness and efficiency of the cooperation among enterprises. In the view of Powell et al. (2005) [6], enhanced flows of ideas and skills can appeal more various economic actors to join the network. Gao et al. (2011) [7] revealed that the major patterns of knowledge exchange in China are within-province and international collaborations. Daniela et al. (2015) [8] pointed out that the development of macro-network level of innovation will be influenced by the actors' heterogeneity. Various heterogenous knowledge can obviously strengthen the creative ability of the industrial cluster. Paul et al. (1999) [9] find it possible that the degree of knowledge localization will vary across regions and that the interfirm mobility of engineers can have an impact on the local knowledge transfer. Ari et al. (1996) [10] put forward a finding that a positive and statistically significant spillover effect will exist in different firms with moderate technology gaps. ALMEIDA and PHENE (2004) [11] developed a hypothesis that the characteristics of the heterogenous knowledge will have a positive influence on subsidiary technological innovation and the validity of the hypothesis is proved. Thus:

Hypothesis 2 (H2): Heterogeneity knowledge can positively influence regional collaborative network innovation.

An efficient regional collaborative innovation can not only enhance the innovation ability of one region, but also improve the innovation performance of actors in the network. Individual enterprises can obtain both knowledge spillovers from other actors in the network and the information & resource necessary to carry out innovation activities. From the network perspective, Guan et al. (2015) [12] discussed that the inventor collaboration networks have an impact on the individual enterprise's performance. The firms can benefit from diverse knowledge from different partners in a network, and the efficiency and output of their innovation will get to be improved through joining the inter-regional collaborative innovation network. Liao et al. (2016) [13] took 191 firms in high-technology industries as a sample and discussed how a firm's diverse knowledge base and knowledge processing capabilities affect knowledge creation when spanning multiple structural holes. Wu and Gu (2017) [14] constructed a model of industry-university-research innovation network and demonstrated the positive relationship between the characteristics of actors and innovation based on the social network analysis. Based on these arguments, we could create the third hypothesis.

Hypothesis 3 (H3): Innovation performance will positively impact on the regional collaborative network innovation.

### 2.3 Knowledge spillovers

Many scholars like Chesbrough (2003) [15], Hastbacka (2004) [16], West and Gallagher (2006) [17] thought it important that firms should consciously combine their internal and external resources with marketing development for innovation. Knowledge spillover refers to a process of knowledge and technology which flows across the economic and business activities among regions or industries because of their different knowledge stock. The production and transmission of knowledge have very strong features of strong self-accumulation and path dependence. The innovation of enterprise knowledge chain can gain the vitality of innovation during the process of the integration of real economy and the knowledge chain. Some scholars like Peri (2004) [18] constructed models to measure knowledge spillover effect. Some firms' R&D departments realize the spillover effect by means of knowledge spillover effect measurement model. More outer knowledge can be learned by firms through the knowledge spillover effect of inter-region cooperative network. Liu and Bai (2021) [19] suggested that the technology spillover of quasi-public goods make firms' innovation lack initiative in many aspects. Based on the above literature review, the following hypothesis was proposed.

Hypothesis 4 (H4): The regional collaborative innovation will have a positive influence on knowledge spillover.

In the ear of knowledge economy, knowledge spillovers of clustered firms have positive and negative effects on cluster innovation performance. More and more enterprise practices show that the higher the conscious knowledge spillover is, the more beneficial it is to accelerate the transformation of tacit knowledge and explicit knowledge. Bell and Zaheer (2005) [20] proved that the prominent reason for clustered firms' higher innovation performance lies in the knowledge spillover effect brought by multidimensional proximity, which forms a specific shared knowledge pool and improves the efficiency of knowledge utilization. Zucker et al. (1998) [21] found it significant that contributor spillover can greatly speed up knowledge transfer among clustered enterprises and it can accelerate the reorganization of existing enterprises. Knowledge spillover is one of the indispensable factors which can play a key role in the upgrade of advanced manufacturing cluster and the development of high-quality economy. Hájek and Stejskal (2018) [22] pointed out that intra-cluster knowledge acquisition can effectively promote intra-cluster knowledge flow and play a positive role in industrial cluster upgrade. Thus:

Hypothesis 5 (H7): Knowledge spillover effect can positively impact on innovation performance.

### 2.4 Mediating effect of organizational learning

March (1991) [23] outlined the concept of exploration learning and exploitation learning. Both have different learning features and are differential in essence, but they belong to the same concept organizational learning. Christopher J. Medlin et al. (2015) [24] noted that exploration learning can be beneficiary to promote the holistic effect brought by absorbing outer knowledge for organization development. With its great risk and uncertainty, exploration learning can acquire novel, diverse and non-redundant knowledge in a broader range. Nguyen (2018) [25] suggested that top-down knowledge flows significantly influence both incremental and radical innovations but bottom-up knowledge flows do not have any effect on incremental and radical innovations. Radical innovation askes for the organizations to carry on exploration learning. The innovation performance can be promoted by consciously pushing knowledge spillover effect in the development of the enterprises. Breschi et al. (2003) [26] claimed that knowledge-relatedness is a key factor in affecting firms' technological diversification. Exploration research and development prior to the acquisition of external technology can help firms improve their ability to identify and evaluate external technology and facilitate the acquisition of external learning sourcing. Thus:

Hypothesis 6 (H6): Knowledge spillover can exert a positive effect on organizational learning.

The balance between exploitation learning and exploration learning as the twin concepts will play an important role in acquiring long-term competitive advantage for firms. Blome et al. (2013) [27] put forward that exploitation learning can help organizations improve efficiency, better utilize resources and stay competitive. Asheim et al. (2011) [28] indicated that it is easier to realize inter-industry knowledge spillover among industries with high-tech and high relevance. Different types of enterprises can reorganize the acquired knowledge through interactive learning and knowledge spillover, thus the industrial innovation can be promoted. Exploitation learning can better help R&D teams strengthen the recognition and assimilation of knowledge structure and make full use of it. Liu et al. (2016) [29] suggested that knowledge spillover can reduce the cost of enterprises' technological learning through the recipient's exploitation learning ability. With different views on exploitation learning, Some of scholars like Lichtenthaler (2009) [30] thought it possible that exploitation learning may go against the latent enterprise innovation as it may prevent the introduction of external heterogeneity knowledge and technology to some extent. From the above literature, we could infer the following hypothesis.

Hypothesis 7 (H7): Organizational learning will affect innovation performance positively.

Based on the above literature reviews and hypotheses, the driving force model including the factors of regional collaborative network innovation, heterogeneity knowledge, organizational learning, knowledge spillover effect and innovation performance was constructed in this paper.

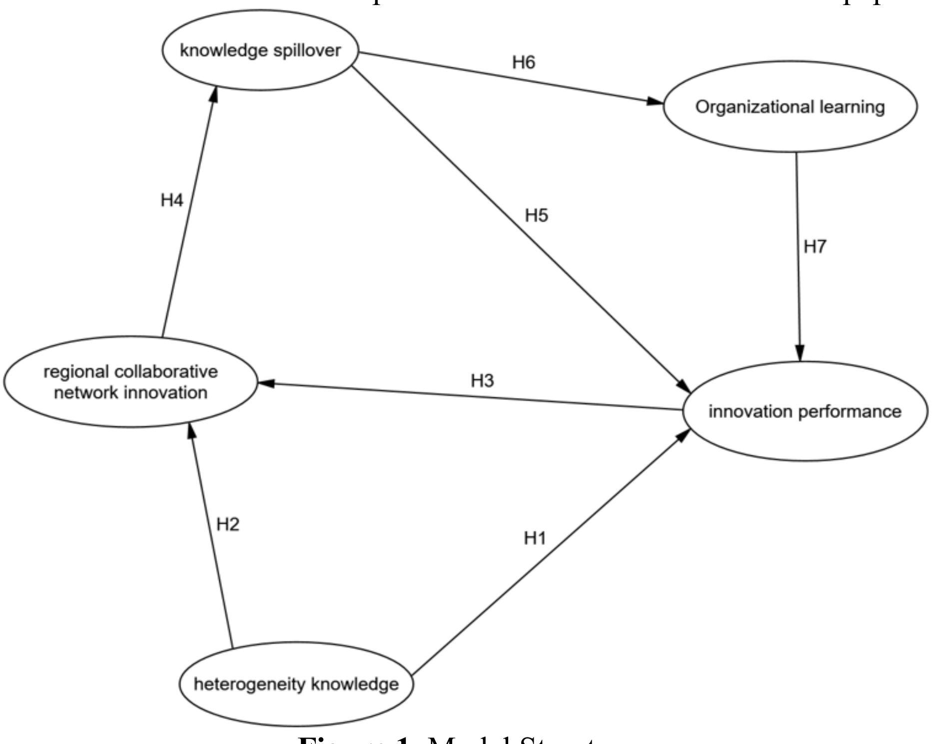


**Figure 1.** Model Structure

As shown in Figure 1, the relationship between regional collaborative network innovation and innovation performance would be affected by the two intermediary variables heterogeneity knowledge and knowledge spillover. Moderator variables, organizational learning can have effects on the relationship between knowledge spillover and innovation performance.

# 3. Materials and Methods

### 3.1 Questionnaire Design and Data Collect

Centering on the above research model and the corresponding literatures, a questionnaire with the item related to the latent variables and observed variables was carefully designed. The questionnaire was divided three sections. First, the purpose and meaning of the questionnaire was described in the first section. That could make it clear that the investigation objects know how to respond to the questionnaire, so the survey work might be completed with high quality. In the second sector, the basic information of the respondents would be investigated to get the control variables in the questionnaire. Lastly, the survey items in the section were designed by Likert 5 scale. Respondents could complete the questionnaire by his own judgement with his working experience and acknowledge of the enterprise.

This study mainly investigated the typical strategic new rising industries which were located in the areas consisting of Shanghai, Hangzhou, Ningbo, Nanjing, and so on. The number of samples from those above areas accounted for 87.56 percent of the total. For the purpose of the research, we chose the related industry categories which came from the strategic new rising industry category issued by China. They included the next generation information technology industry, High-end equipment manufacturing, new material industry, new energy vehicle industry, digital creativity industry and related service industries. Most of the selected enterprises from those industries were located in the areas like Science and Technology Park, Pioneer Park and High-Tech Development Zone. The number of firms surveyed was 83. Each enterprise filled in five questionnaires, two by mangers and three by research teams. A total of 439 questionnaires were used, 45 invalid and information-missing of which were excluded, and 394 valid questionnaires were collected, with an effective response rate of 89.75%. That met the requirement of the number of samples for hierarchical regression method. According to the requirements of structural equation model (SEM), the sample size must be more than 10 times of the total number of the observations. There were 6 latent variables which consisted of 33 observed variables in the questionnaire. There were 394 efficient sample size, which was consistent with the requirement of the SEM. From the descriptive statistical value of the samples in Table 1, those sample data could be applied to the study. We would carry out the following empirical analysis and research by SPSS and AMOS software.

### 3.2 Variable Measurement

There were the six latent variables in the research, including regional collaborative network innovation, heterogeneity knowledge, knowledge spillover, innovation performance, exploration learning and exploitation learning. On the basis of the empirical mature scales from the literatures at home and abroad and the specific characteristic of the study, the items of the observation variables related to the above latent variables were modified and designed correspondingly. Table 1 outlines the related information of the observation variables and the latent variables.

**Table 1.** The measurement scale and source of the variables

| Latent Variables | Observed Variables | Source |
| --- | --- | --- |
| Heterogeneity knowledge (HK) | The difference of the degree levels (HK1)<br>The difference of the knowledge levels (HK2)<br>The difference of professional fields (HK3)<br>The difference of working experience (HK4)<br>The difference of understanding ability (HK5) | Derived from the viewpoints of Shi et al. (2019) [31], Louadi (2008) [32], Felin and Hesterly (2007) [33] and other scholars |

| | | |
|---|---|---|
| | The difference of insight ability (HK6) | |
| Regional collaborative network innovation (RCNI) | Number of the invention patents authorization (RCNI1)<br>Number of R&D team members(RCNI2)<br>Expenditure of R&D (RCNI3)<br>The constraint system of the structural hole (RCNI4)<br>Network and embeddedness (RCNI5)<br>Cooperation intensity (RCNI6) | Derived from the viewpoints of Nandkeolyar (2008) [34], Guo et al. (2019) [35] and other scholars |
| Innovation performance (IP) | The quantity of innovations (IP1)<br>The quality of innovations (IP2)<br>R&D speed of the innovative achievements (IP3)<br>Success rate of innovative projects (IP4)<br>The earning rate of the innovations' conversion (IP5) | Derived from the viewpoints of Shi et al. (2019) [31], Chung et al. (2013) [36], Matson et al. (2003) [37] and other scholars |
| Knowledge spillover (KS) | New knowledge promotes the development of the firm's main business (KS1)<br>Direct economic benefits are due to new knowledge (KS2)<br>Effectively promote the product market development (KS3)<br>To promote the improvement or upgrade of production technology (KS4)<br>Speed up the R&D of new technologies or new product (KS5)<br>Accelerating the integration of patent technology and the firm' know-how (KS6) | Derived from the viewpoints of Xu et al. (2007) [38], Andrea and Cinzia (2007) [39], Jiang et al. (2019) [40] and other scholars |
| Organizational learning (ORL) | To explore the new production technology and technique (ORL1)<br>Actively learning the new innovative methods and process from the industry (ORL2)<br>Actively learning new management and organization methods (ORL3)<br>To take the lead in mastering the new know-how in some fields (ORL4)<br>The application attitude of the existing knowledge (ORL5)<br>The problem-solving ability for the existing customers (ORL6)<br>Maturity of production development process (ORL7)<br>The optimized integration of the existing knowledge and technology (ORL8) | Derived from the viewpoints of Jiang et al. (2019) [40], Atuahene (2005) [41], He and Wong (2004) [42] and other scholars |

In the software AMOS 24, we drew the model diagram which included latent variables and their corresponding observation variables, as shown in Figure 2.

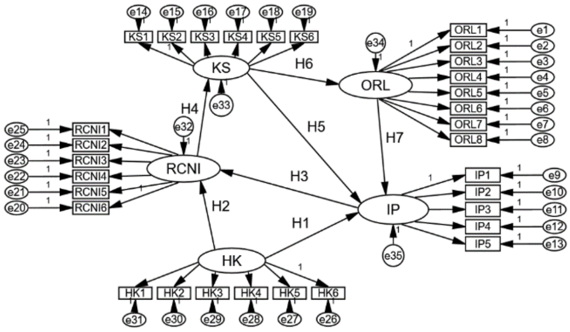

**Figure 2.** The research model with various types of variables.

The abbreviated names of latent and observation variables could be found in Table 1.

## 4. Results

### 4.1 Reliability and Validity of the Measurement

To effectively demonstrate how validly, accurately and reliably the questionnaire was designed, by the software SPSS 26, we analyzed the reliability of the measurement based on the 394 data and the results were shown in Table 2.

**Table 2.** Reliability statistics (n=394)

| variables | Measurement items | Cronbach's Alpha |
|---|---|---|
| Heterogeneity knowledge | 6 | 0.733 |
| regional collaborative network innovation | 5 | 0.756 |
| innovation performance | 5 | 0.756 |
| knowledge spillover | 6 | 0.744 |
| organizational learning | 8 | 0.654 |

From Table 2, we could see that the Cronbach's alpha value of all other than the variable organizational learning was greater than 0.7. Organizational learning's alpha value was 0.654, which was greater than 0.6, and that still lay in the acceptable range. KMO and Bartlett's Test was used for validity test. The results were shown in Table 3 below. The value of KMO test was 0.812, which was greater than 0.8. The significance probability was 0.000, less than 0.001, that represented those data were fit for factor analysis.

**Table 3.** KMO and Bartlett's Test

| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | 0.812 |
|---|---|---|
| Bartlett's Test of Sphericity | Approx. Chi-Square | 3402.977 |
| | df | 465 |
| | Sig. | 0.000 |

### 4.2 Model fit summary

Running the model, we could get the Figure 3 below. Model fit coefficients could be found in Table 4.

**Table 4.** Model fit coefficients.

| $\chi 2$/df | RMSEA | GFI | CFI | IFI | TLI |
|---|---|---|---|---|---|
| 2.641 | 0.065 | 0.838 | 0.769 | 0.772 | 0.749 |

As can be seen from Table 4, the value of $\chi 2$/df was 2.641, which was less than 3. The value of RMSEA was 0.065, which was less than 0.08. Both the indices above showed that the model fit well.

The coefficient GFI was 0.838, which was in the range of 0.8 to 0.9, indicating that the fitting effect of the model was general. The rest three indices of CFI, IFI and TLI were less than 0.8, suggesting that the model don’t fit well.

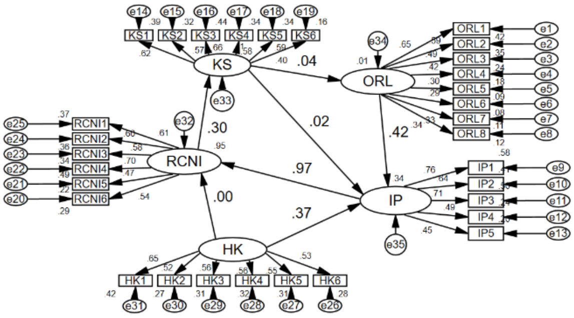


**Figure 3.** Result graph after model operation.

From Figure 3, there were several factors with factor loadings less than 0.36, so we needed to modify our model by deleting some observed variables. After deleting the variables like ORL4, ORL5, ORL6, ORL7, ORL8, KS6, IP4, IP5 and RCNI5, a new figure was able to be given, as shown in Figure 4.

After the revised model being run, the favorable model fit coefficients gave us a satisfactory result, and those indices could be seen from the Table 5.

**Table 5.** The first revised model fit coefficients

| χ2/df | RMSEA | GFI | CFI | IFI | TLI |
|---|---|---|---|---|---|
| 1.911 | 0.048 | 0.920 | 0.914 | 0.915 | 0.901 |

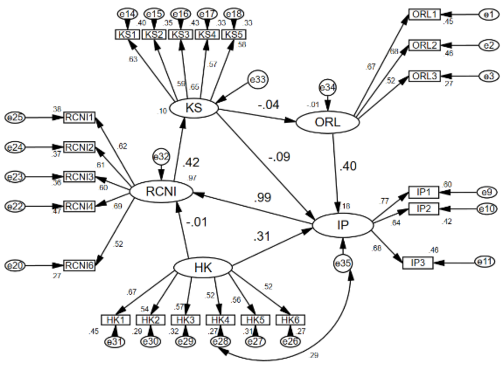


**Figure 4.** The first revised model graph.

### 4.3 Hypothesis testing

From Figure 4 and Table 6, we would see that there were several regression weights whose probability value was greater than 0.05. Statistically speaking, a probability value less than 0.05 meant that the causal relationship between two factors couldn’t be proved existing.

**Table 6.** Standardized regression weights

| | Estimate | S.E. | C.R. | P |
|---|---|---|---|---|
| IP <--- HK | 0.313 | 0.121 | 4.229 | *** |
| RCNI <--- HK | -0.1 | 0.053 | -0.175 | 0.861 |
| KS <--- RCNI | 0.424 | 0.213 | 2.653 | 0.008 |
| IP <--- KS | -0.093 | 0.183 | -0.637 | 0.524 |
| IP <--- ORL | 0.397 | 0.094 | 4.737 | *** |
| RCNI <--- IP | 0.989 | 0.066 | 8.988 | *** |
| ORL <--- KS | -0.036 | 0.117 | -0.34 | 0.734 |

Note: *** indicates that P value is less than 0.001.

The probability value of the path from heterogeneity knowledge to regional collaborative network innovation was 0.861, which was greater than 0.05, so we could conclude that there was not enough evidence to prove the hypothesis H2. Based on the same consideration, we were able to infer that hypothesis H5 and H6 also did not hold. The regression weights of heterogeneity knowledge to innovation performance, innovation performance to regional collaborative network innovation, regional collaborative network innovation to knowledge and organizational learning were 0.51, 0.593, 0.566, 0.446 respectively, and they were significant at the level of probability p<0.001. Hypotheses H1, H3, H4 and H7 were effectively verified.

According to the above inference, we again designed our research model and ran it, the result was shown in Table 7, Table 8 and Figure 5. The indices of goodness of fit in Table 7 showed that the model was fit. From Table 8 and Figure 5, the model once again proved that heterogeneity knowledge would positively affect innovation performance, that innovation performance had a strong positive impact on regional collaborative network innovation, that regional collaborative network innovation exerted a positive effect on knowledge spillover, and that organizational learning could affect innovation performance positively.

**Table 7.** Model fit coefficients

| χ2/df | RMSEA | GFI | CFI | IFI | TLI |
|---|---|---|---|---|---|
| 1.887 | 0.048 | 0.915 | 0.908 | 0.909 | 0.901 |

**Table 8.** Standardized regression weights

| | Estimate | S.E. | C.R. | P |
|---|---|---|---|---|
| IP <--- HK | 0.397 | 0.107 | 5.608 | *** |
| KS <--- RCNI | 0.328 | 0.089 | 4.648 | 0.008 |
| IP <--- ORL | 0.335 | 0.072 | 5.210 | *** |
| RCNI <--- IP | 0.983 | 0.063 | 9.865 | *** |

Note: *** indicates that P value is less than 0.001.

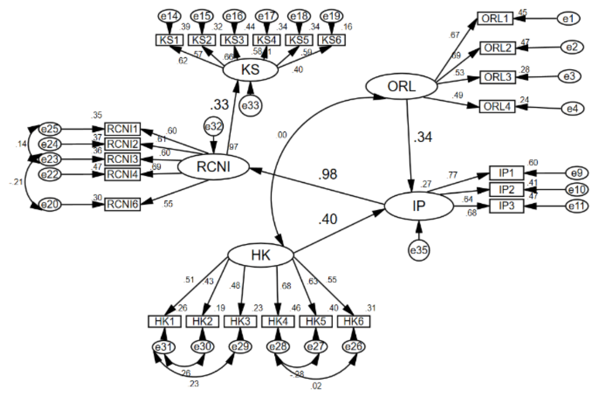


**Figure 5.** The final revised model graph.

## 5. Discussions

### 5.1 Discussions

Through the test and analysis of the above model, we've had a clear idea of the factors' relationship in the driving force model and the two research problems have also been solved effectively. The relevant conclusions are as follows.

First, from the perspective of mediating effect, if we take heterogeneity knowledge as an independent variable, regional collaborative network innovation as a dependent variable and innovation performance as a mediator, a complete mediating effect among them will be found. In Figure 5, that firms' innovation performance has a strong positive relationship with regional collaborative network innovation shows that the development and innovation of Yangtze River Delta is depending very strongly on the enterprises' innovation performance. There are no necessary connection between heterogeneity knowledge and regional collaborative network innovation. To activate heterogeneity knowledge in the area, we can only rely upon the relationship between heterogeneity knowledge and innovation performance, whose regression weight is only 0.4. It shows that we will have a very long road to go when enterprises want to consume their heterogeneity knowledge fully. If heterogeneity knowledge is regarded as a kind of stock resource and innovation performance is compared to an assessment index, the reason why their regression weight value is not high can be attributed to inadequate effectiveness of assessment indices. The observation variables of innovation performance consist of three indices, like quantity, quality and R&D speed of the innovations. If regarded as performance assessment index, they can't unleash the potential of heterogeneity knowledge fully to some extent. However, heterogeneity knowledge is still a driving force factor of innovation performance in the integration of Yangtze River Delta until now.

Second, Organizational learning can only influence innovation performance and has nothing to do with heterogeneity knowledge, regional collaborative network innovation and knowledge spillover. The value of regression weight between organizational learning and innovation performance is 0.34, and organizational learning can be seen as another driving factor of innovation performance. From the observation variables of organizational learning in Figure 5, we can find the fact that organizational learning is mainly concerned with explorable learning. It implies that the firms in the Yangtze River Delta focus on more explorable learning than exploitation learning. Major technological breakthroughs and major development needs will lay a solid foundation for the strategic emerging industries, the development of which keeps pace with that of major economies. There is neither space nor conditions for new technology import to develop itself and this inevitably askes enterprises to carry out exploration learning. It also gives us an explanation why the observation variables are mainly explorable learning indicators.

Last, regional collaborative network innovation has an positive effect on knowledge spillover which has nothing to do with organizational learning, innovation performance and heterogeneity knowledge. The value of regression weight is 0.33 in Figure 5. Regional collaborative network innovation has a complete mediating effect between innovation performance and knowledge spillover. It has been said that unconscious knowledge spillover is being replaced by conscious knowledge spillover among enterprises. Knowledge spillover in this model is one conscious knowledge spillover and it comes from the driving force factor of regional collaborative network innovation, that is, innovation performance consciously releases knowledge spillover with the help of mediator, regional collaborative network innovation. In other words, only when enterprises join the regional collaborative network actively, their innovation performance can lead to knowledge spillover through the mediator variable.

### 5.2 Management Recommendations

We can make some suggestions from the above research and expect to provide some help for sustainable and high-quality development of the integration strategy for Yangtze River Delta.

First, to forge a dynamic, sustainable and innovative regional collaborative network system lay a foundation of high-quality development. Local authorities should encourage the enterprises in the region to actively participate in the regional collaborative network, in which they have interested, in line with their desire of collaborative innovation. The administrative barriers should be broken and the operation information of different cooperative network organizations in the Yangtze River Delta should be integrated into a regional collaborative network database facilitating management. A set of simple and effective evaluation scale, whose relevant indicators can be designed by the observation variables from Table 3, should be established. The information collected and processed by that scale can be used as one of the competitiveness indicators for the cooperative network organizations. During the assessment period, a third-party agency should be engaged to dynamically evaluate the innovation and competitiveness of those organizations. The relevant aid policies should be initiated by different administrative authorities in Yangtze River Delta, encouraging and boosting local enterprises to join those regional collaborative network with significant innovation performance. In this way, the survival of the fittest mechanism will be established. Regional collaborative network will actively play a cluster effect on China emerging industries and help them meet global competition.

Secondly, while the two driving forces of heterogeneity knowledge and organizational learning activated, the indices of enterprise innovation performance should be optimized. Inter-regional technology innovation seminars should be encouraged to hold by different government agencies from different regions several times a year. Sub-sessions based on those seminars should be encouraged to host by leading enterprises in emerging industries at the same time. Through similar activities, the sources of heterogeneity knowledge within enterprises can be better activated and the knowledge, technology and skill horizons of their employees will be broadened. the policies of talent introduction and development should be updated every year for enterprises that have been in the regional cooperation network recognized. Thus, enterprises are encouraged to introduce more exploratory R&D talents and can strengthen their own ability of exploration learning, avoiding knowledge obsolescence and aging of their employees.

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