Optimization of Multi-agent Innovation System and Its Knowledge-Syncretism Path Based on the Neural Network

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Abstract

The innovation nodes in the regional multi-agent innovation system are similar to the neurons in the neural network. The dynamic collaborative process between different innovations has significant information processing characteristics, such as nonlinearity, adaptability and fault-tolerance, and analysis-design consistency. In the knowledge innovation network, the constraint mechanism among the nodes is the foundation of the interests and risk balance, is also the necessary condition for the transfer and integration of knowledge. Through the exploration analysis of the knowledge conduction mechanism, the goal that describes the transition process of knowledge transmission and knowledge-flow state among the innovation nodes can be achieved. Finally, the back propagation network structure based on cluster innovation output and the selection method of knowledge-syncretism path are presented.

Keywords

Innovation node; multi-agent innovation system; neural network; knowledge-syncretism path.

1. Introduction

As the foundation and platform of the regional innovation, the multi-agent innovation system is a knowledge symbiosis collection that encompasses multiple innovation nodes and their associated application nodes. The essence of multi-agent innovation process is the self-improvement process of the information organization system based on the own knowledge of innovation nodes. In the collaborative innovation process, it is necessary to improve the structural constraints of innovation network and obtain heterogeneous knowledge by carrying out knowledge exchange and integration [1]. Knowledge-syncretism is the basic form of the knowledge exchange and innovation relationship optimization between innovation nodes, and the efficiency of knowledge-syncretism ultimately determines the level and quality of multi-agent innovation system. The knowledge-syncretism path is chosen to control the knowledge redundancy, and it is the key to the knowledge flow enhancement of regional multi-agent innovation system and the development of regional collaborative innovation [2].

At present, the research on the multi-subject innovation and knowledge-syncretism is mainly focused on the model of knowledge-syncretic ferment and the selection of the knowledge-syncretism path based on the bionics [3-4]. Some studies also focus on the feedback mechanism of the technological innovation process[5]. In regard to the information sharing and service platform, relevant scholars have explored the information sharing mechanism of collaborative innovation process based on game of chance, and put forward the stable cooperative model of multi-agent innovation, and discussed the reciprocity principle of information resource sharing[6-7]. Through the combination of social psychology and information system theory, the relevant theoretical research also reveals that there are three factors that affect the willingness to share information in the network environment, namely, social factors, information factors, individual factors, and construct the integration model of knowledge search and sharing behavioral [8].

In the knowledge-syncretism process, multi-agent innovation is always accompanied by the symbiosis and fusion of knowledge. In order to understand the diffusion and melting mechanism of innovative knowledge, it is beneficial to analysis the synergetic relationship between innovation nodes. In addition, the process optimization will improve the effectiveness of knowledge-syncretism, and then achieve the comprehensive upgrade of collaborative innovation system[9]. Therefore, this paper analyzes the knowledge transmission relationship and the activation function of the innovation network node, and then draws on the BP neural network hierarchical association mechanism to realize the optimization of innovation network and knowledge flow state.

2. Knowledge conduction mechanism of multi-agent innovation system

Multi-agent collaborative innovation is achieved based on the knowledge-syncretism relationship. Knowledge-syncretism is not only the sharing and diffusion of knowledge, but also the mapping value conversion of innovative knowledge flow. The features of innovation network usually include the relationship, social network structure and characteristics of social actors. The collaborative mechanism of innovation network is essentially the interactive process of social network structure, service innovation and knowledge diffusion[10], and the knowledge conduction relationship determines the basic situation of regional innovation.

Within the characteristics of the innovation network constraints, the state of knowledge exchange is limited by the characteristics of the subject's own absorptive capacity and knowledge gap, but also by the factors such as the new knowledge quantity of the relevant innovation subjects, the type of knowledge, the structural relationships and so on[11]. Among them, the knowledge absorptive ability and gap feature of the innovation subject determine the type of new knowledge element that needs to be acquired, and the factors such as the knowledge of the relevant subject, the type of knowledge and the structural relationships affect the efficiency of knowledge acquisition. Therefore, the construction of effective knowledge relations and linking mechanism will help reduce the transaction cost of the innovation process, so that the node innovation activities break through the time and space constraints of the subject innovation and enhance the cluster innovation level (Fig. 1).

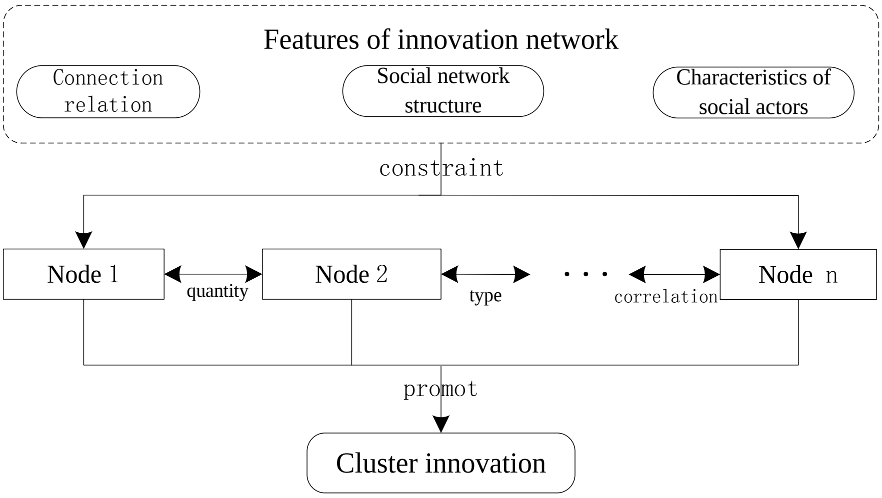

Fig. 1 Knowledge structure of regional multi-agent innovation system

In the regional multi-agent innovation system, any innovation node P_i absorb the knowledge element $x_j(j=1,2,\cdots,m)$ of the related node P_j within the constraints of its own absorptive capacity and effective knowledge stock θ_i, and the innovation process also is influenced by the innovation system network structure and correlation strength $w_{ij}(j=1,2,\cdots,m)$ [12-13]. Innovative knowledge that the innovation node P_i may incorporate is a linear combination μ_i of the external knowledge elements $x_j(j=1,2,\cdots,m)$ and the knowledge stock θ_i. The transformation of the knowledge element and the state transition of the knowledge flow about node P_i are shown in Fig. 2.

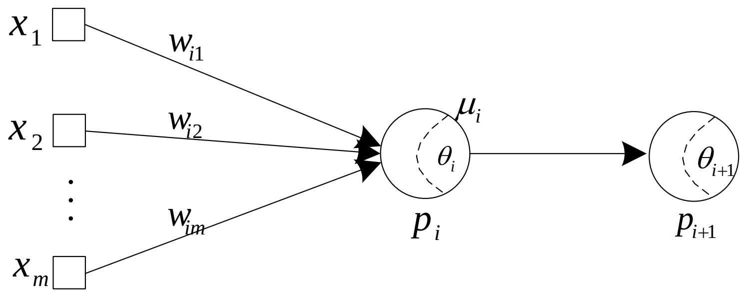

Fig. 2 Transformation of knowledge element and state transition of knowledge flow

In the process of knowledge integration, transformation and output of nodes, the knowledge-syncretism process is a kind of knowledge flow state transition based on the conduction relation of innovative knowledge elements. As an independent knowledge processing unit, the innovation node P_i with multi-input and single-output characteristics acquire various new knowledge to make up the knowledge gap and realize the process of knowledge fusion [14-15]. The knowledge element conduction and knowledge flow state transition generally has three basic features.

① Correlation strength of nodes. For innovation nodes, the correlation strength causes the difference of knowledge elements and makes some new knowledge elements more important than other ones. That is to say, certain correlative node has an influence on the knowledge fusion of the node through some kind of correlation. At the same time, the new knowledge element x_j that spreads to it is subject to the correlation strength w_{ij} between nodes.

② Linear summation unit. The so-called linear summation unit, that is, the innovation node is always constructing the knowledge fusion relationship by a certain linear process based on its own knowledge characteristics. It is the total amount of knowledge that the node P_i can absorb in the knowledge-syncretism process, which contains not only the knowledge structure characteristics but also its own knowledge gap characteristics.

③ Incentive relationship. A certain degree of knowledge-syncretism incentive will ultimately determine the innovation strength of the node P_i. From a certain scope, the new knowledge increment as the innovation output plays a non-linear mapping function to the various kinds of knowledge received by the node P_i, and also determines its ability and motivation to send new knowledge to the downstream node.

3. Dynamic analysis of innovative knowledge flow based on knowledge-syncretism

Based on the analysis of the knowledge transmission relationship and the knowledge flow state, the basic motivation of innovation knowledge flow is to make up the knowledge gap, or innovation efficiency improvement caused by heterogeneous knowledge fusion. The knowledge transmission behavior of the innovation nodes is generally caused by the innovation efficiency or the innovation output incentive, which is a kind of conditional reflection and feedback process similar to the nerve trigger.

The knowledge-syncretism process of the node P_i may need new knowledge element $x_j(j=1,2,\cdots,m)$ from another related node P_j. Then, based on the self knowledge stock θ_i and the correlation strength w_{ij}, the linear combination of P_i can be written as follows:

$$\mu_i = \sum_{j=1}^{m} w_{ij} x_j + \theta_i . \quad (1)$$

At this time, the incentive relationship function $f(\mu_i)$ of the innovation node P_i reflects the mapping relationship between the node's knowledge stock and the innovation output. According to the neural network conduction rule, the innovation knowledge increment of every node in the innovation network is normalized, and then the incentive function $f(\mu_i)$ indicates the incremental knowledge of the node P_i.

When the node P_i does not acquire new knowledge from its associated innovation nodes, the probability of its knowledge-syncretism is related to its own knowledge and knowledge innovation ability. With the continuous integration of new knowledge, the probability of successful innovation is growing, and the incentive function $f(\mu_i)$ is on the rise. When the new knowledge absorbed by the node P_i trends to meet its own innovation knowledge gap, the knowledge redundancy trend is gradually formed, and the incentive effect of innovation process tends to decline, and the incentive function $f(\mu_i)$ gradually becomes stable.

Taking into account the neural network conduction rules and the numerical variation trend of the incentive function $f(\mu_i)$ with the combination of innovative knowledge elements, the incentive function of the node P_i possesses the characteristic of the sigmoid function, and then the incremental knowledge of P_i can be written as follows:

$$f(\mu_i) = \frac{2}{1+e^{-\mu_i}} - 1 = \frac{1-e^{-\mu_i}}{1+e^{-\mu_i}} . \quad (2)$$

When $\mu_i \geq 0$, there are $f(\mu_i) \in [0,1)$, $f'(\mu_i) \geq 0$ and $f''(\mu_i) \leq 0$.

Before the new knowledge is acquired by, the node P_i associated with its downstream node P_{i+1} is usually in a relatively stable state [16]. That is to say, prior to to obtaining innovative knowledge from outside, the node P_i won't send out knowledge. If the function $g(\mu_i)$ is used to indicate the total amount of output knowledge that P_i can provide with the downstream node, the function is different from the incentive function $f(\mu_i)$ when stimulated by the new input knowledge. The new knowledge element quantity the node P_i can send to P_{i+1} is the sum of the incremental innovation knowledge and the input knowledge $(\mu_i - \theta_i)$ received from outside, which can be written as follows:

$$g(\mu_i) = \frac{1-e^{-\mu_i}}{1+e^{-\mu_i}} + \mu_i - \theta_i . \quad (3)$$

When $g(\theta_i) = f(\theta_i) = \frac{1-e^{-\theta_i}}{1+e^{-\theta_i}}$, there is $\mu_i - \theta_i = 0$.

Optimization of knowledge conduction in innovation process

Innovation node P_i can use or rely on the input and output mapping of certain given innovation network in the process of knowledge, without having to know the mapping in advance. Therefore, the knowledge-syncretism network based on arbitrary innovation node P_i is a multilayer feed forward network with the characteristics of error propagation. The knowledge-syncretism process can draw on the experience of the conduction rules of BP neural network. Keep adjusting the correlation strength between the nodes and the amount of their own knowledge in the network structure by using the reverse error propagation, in order to achieve the incentive relationship optimization of the innovation process.

The nodes that only output new knowledge to other nodes in the network are defined as the knowledge output layer, the nodes that receive the new knowledge and pass new knowledge to the other nodes are defined as the transition layer, the remaining nodes that only received new knowledge are defined as the knowledge input layer. According to this, we can draw the BP network structure based on knowledge conduction (Fig. 4). Among them, the whole layer is connected with the layer, and there is no interconnection in the same layer.

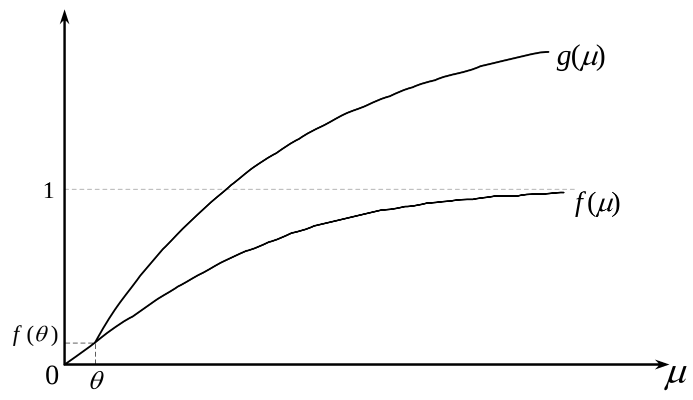

Fig. 3 Differences between incentive function $f(\mu)$ and output function $g(\mu)$

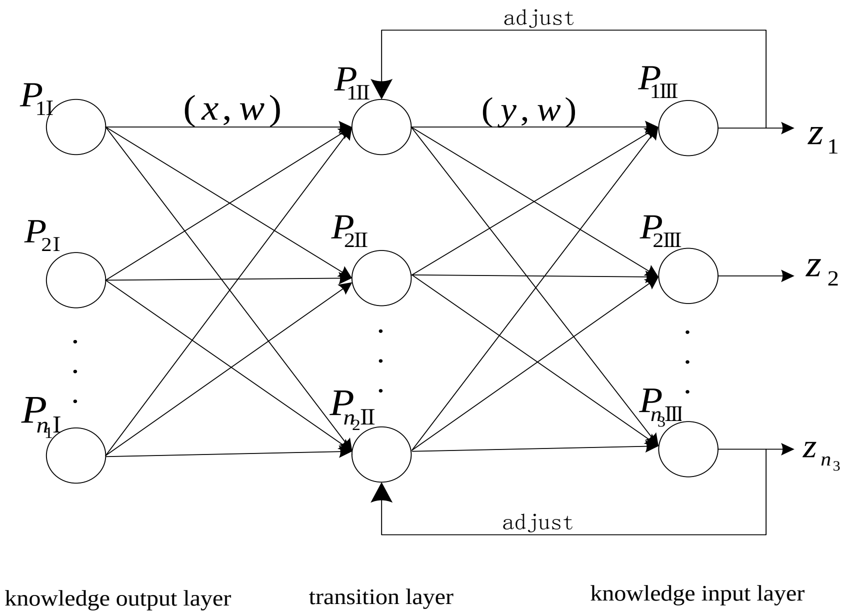

Fig. 4 BP network structure based on knowledge conduction

In the BP network structure based on knowledge conduction, there are two kinds of information between layers. One is the informational knowledge, that is, the output knowledge of the output layer is forward propagated to the input layer; the other is the error signal, that is, the difference calculated between the new knowledge increment and the expected value, which is propagated back by layer from the knowledge input layer, in order to adjust the correlation strength and the knowledge stock.

Suppose any node P_i of the output layer can provide the new knowledge x_i, any node P_k of the output layer generates certain expected output s_k, and then the linear combination of knowledge elements that could be absorbed by any node P_j of the transition layer can be written as follows:

$$\mu_j = \sum_{i=1}^{n_1} w_{ij} x_i + \theta_j \,. \tag{4}$$

According to the above dynamic analysis of the knowledge flow, the original storage knowledge of any node P_j of the transition layer is not involved in knowledge transmission. Then, the new knowledge that the node P_j can provide for downstream nodes is the sum of the fetched knowledge and the innovation knowledge increment, which is denoted by

$$y_j = g(\mu_j) = \frac{1-e^{-\mu_j}}{1+e^{-\mu_j}} + \mu_j - \theta_j \,. \tag{5}$$

At this point, the linear combination of knowledge elements that could be absorbed by any node P_k can be written as follows:

$$\mu_k = \sum_{j=1}^{n_2} w_{jk} y_j + \theta_k \,. \tag{6}$$

According to the above dynamic analysis of the knowledge flow, the output knowledge of any node P_k in the input layer is the sum of the new knowledge elements and the innovation knowledge increment, which is denoted by

$$z_k = g(\mu_k) = \frac{1-e^{-\mu_k}}{1+e^{-\mu_k}} + \mu_k - \theta_k \,. \tag{7}$$

According to the BP neural network rule, under the dual role of knowledge flow propagation and the expected output s_k of knowledge input layer, the knowledge information error function of the input layer can be written as follows:

$$\gamma = \frac{1}{2}\sum_{k=1}^{n_3} (s_k - z_k)^2 \,. \tag{8}$$

When the initial set values are $w_{ij}(0)$, $w_{jk}(0)$, $\theta_j(0)$ and $\theta_k(0)$, the adjustment quantity stored in the t-th incentive and conduction iteration is $\Delta w_{ij}(t)$, $\Delta w_{jk}(t)$, $\Delta\theta_j(t)$ and $\Delta\theta_k(t)$. Then, when the knowledge information error function $\gamma(t_0)$ reaches the minimum value or less than the predetermined value, there are

$$w(t_0) = w(0) + \Delta w(1) + \Delta w(2) + \cdots + \Delta w(t_0) \,, \tag{9}$$

$$\theta(t_0) = \theta(0) + \Delta\theta(1) + \Delta\theta(2) + \cdots + \Delta\theta(t_0) \,. \tag{10}$$

Thus, the incentive functions about any innovation node P_j of the transition layer and any innovation node P_k of the input layer respectively are

$$f(\mu_j) = \frac{1-e^{-\mu_j(t_0)}}{1+e^{-\mu_j(t_0)}} = \frac{1-e^{-\sum_{i=1}^{n_1} w_{ij}(t_0)x_i - \theta_j(t_0)}}{1+e^{-\sum_{i=1}^{n_1} w_{ij}(t_0)x_i - \theta_j(t_0)}} \,, \tag{11}$$

$$f(\mu_k) = \frac{1-e^{-\mu_k(t_0)}}{1+e^{-\mu_k(t_0)}} = \frac{1-e^{-\sum_{j=1}^{n_1} w_{jk}(t_0)y_j - \theta_k(t_0)}}{1+e^{-\sum_{j=1}^{n_1} w_{jk}(t_0)y_j - \theta_k(t_0)}} \,. \tag{12}$$

4. Choice of knowledge-syncretism path

The knowledge transfer process is not only the binary structure relation accompanied by the knowledge-syncretism process between knowledge input nodes and output nodes, but also the structural adjustment of the innovation network and the change of the incentive function. Innovative nodes generally have the tendency of improving the relationship or state of knowledge connection, so as to break the structural constraint of the knowledge-syncretism process. The pattern that is similar to the feedback mechanism and utilitarian following of the neural triggering is the incentive relationship of the innovation process. In the practice of innovation, the adjustment of the incentive relationship determines directly the choice of the knowledge-syncretism path[17].

It is assumed that the collection of innovation nodes of certain multi-agent innovation system is $P=\{P_1,P_2,\cdots,P_n\}$. Among them, innovation node P_s is a knowledge source which provide new knowledge elements for the system at some point. Firstly, the innovation nodes in the system are divided into knowledge output layer, transition layer and input layer according to their different orders and function in knowledge transmission, and construct the BP network structure of knowledge transmission.

Assuming that the BP network structure has two transition layers, the innovation nodes can be written as $P=\{P_1,P_2,\cdots,P_s;P_{11},P_{21},\cdots,P_{n_1 1};P_{12},P_{22},\cdots,P_{n_2 2};P_{13},P_{23},\cdots,P_{n_3 3}\}$, where there is $(n-n_1-n_2-n_3-1)$ nodes that have no direct or indirect knowledge exchange between the innovation node P_s and the nodes of the input layer. By adjusting to determine the final correlation strength w and effective knowledge stock θ of the any associated innovation nodes P_i and P_j, we can figure out the incentive function $f(x)$ of any innovation node.

It is generally believed that the linear combination of knowledge elements that any downstream node P_i could absorb can be written as $\mu_i = w_{si}x_s + \theta_i$. If

$$f(\mu_i)=\frac{1-e^{-\mu_i}}{1+e^{-\mu_i}}=\frac{1-e^{-(w_{si}x_s+\theta_i)}}{1+e^{-(w_{si}x_s+\theta_i)}}>0.6,$$

it shows that the node P_i has sufficient ability to absorb and utilize the knowledge element, that is, the node P_s should provide new knowledge elements to the node P_i.

If $P=\{P_s;P_{11},P_{21},\cdots,P_{n_1 1};P_{12},P_{22},\cdots,P_{n_2 2};P_{13},P_{23},\cdots,P_{n_3 3}\}$ is the set of innovative nodes that communicate with the innovation node P_s, the knowledge-syncretism path of the node P_s is summarized as follows.

① Node selection of the first associated layer of P_s

Considering the candidate set $P=\{P_s;P_{11},P_{21},\cdots,P_{n_1 1};P_{12},P_{22},\cdots,P_{n_2 2};P_{13},P_{23},\cdots,P_{n_3 3}\}$, the nodes belonging to the first associated layer of P_s may be in the first transition layer $\{P_{11},P_{21},\cdots,P_{n_1 1}\}$. Bringing these related parameters such as θ and w into the incentive function $f(\mu)>0.6$, the nodes satisfying the condition is identified as the first associated layer.

If $f(\mu_{i1})>0.6$ and $f(\mu_{j1})>0.6$, the first associated layer of P_s can be written as $\{P_{i1},P_{j1}\}$.

② Node selection of the second associated layer of P_s

The nodes of the first transition layer are discarded, and the remaining nodes are set as $P=\{P_{12},P_{22},\cdots,P_{n_2 2};P_{13},P_{23},\cdots,P_{n_3 3}\}$. In the set of remaining nodes, the nodes belonging to the second associated layer of P_s may be in the second transition layer $\{P_{11},P_{21},\cdots,P_{n_1 1}\}$. The amount of knowledge the node P_{i1} and P_{j1} are able to provide for the second transition layer are $g(\mu_{i1})=w_{s1}x_s+f(\mu_{i1})$ and $g(\mu_{j1})=w_{s1}x_s+f(\mu_{j1})$.

If $f(\mu_{k2})>0.6$, the second associated layer of P_s can be written as $\{P_{k2}\}$.

③ Node selection of the third associated layer of P_s

The nodes of the second transition layer are discarded, and the remaining nodes are set as $P=\{P_{13},P_{23},\cdots,P_{n_3 3}\}$. In the set of remaining nodes, the nodes belonging to the third associated layer of P_s may be in the input layer. The amount of knowledge the node P_{k2} is able to provide for the input layer is $g(\mu_{k1})=w_{i12}x_i+w_{j12}x_j+f(\mu_{k2})$.

If $f(\mu_{a3})>0.6$, $f(\mu_{b3})>0.6$ and $f(\mu_{b3})>0.6$, the final associated layer of P_s can be written as $\{P_{a3},P_{b3},P_{c3}\}$.

In conclusion, the best knowledge-syncretism path of the innovation node P_s has been shown in Fig.4.

$$P_s \leftrightarrow \begin{Bmatrix} P_{i1} \\ P_{j1} \end{Bmatrix} \leftrightarrow P_{k2} \leftrightarrow \begin{Bmatrix} P_{a3} \\ P_{b3} \\ P_{c3} \end{Bmatrix}$$

Fig. 4 Node matching and path selection

5. Conclusion

Knowledge fusion is a collaborative process of multiple nodes in an innovation network. In the knowledge transmission process, the correlation strength between nodes and their own effective knowledge stock cannot be assigned a value directly and accurately, but a predicted value. Then using a certain method to adjust the values is feasible. In this process, different nodes are to complete some related behaviors based on the accepted knowledge and their own knowledge, in order to enhance the cluster innovation level.

Based on the regional multi-agent innovation system, this study introduces the theory of neural network to determine the different roles of nodes playing in a similar network structure. By this means, it is feasible that For the node innovation to build efficient knowledge-syncretism relationships and an appropriate knowledge environment. Based on the selection process of knowledge-syncretism path, it not only constructs the best way of regional knowledge transfer, but also promotes the structural upgrading of knowledge network.

In the practice of regional innovation, the efficiency of knowledge exchange is not only related to the effort level of the innovation node, but also influenced by the exogenous variables of the innovation environment. Therefore, the government or the innovation management organizations should be acquainted with the correct knowledge transmission relationship and promote innovation nodes to contact high-quality knowledge, in order to improve the knowledge fusion efficiency of innovation nodes. At the same time, we should guide and promote the formation of regional knowledge exchange and sharing platform from the perspective of interest and risk equilibrium, and realize the sustainable development of regional knowledge innovation.Natural Science Foundation.

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