Ecological Innovation Decision Behavior of Enterprises in the Strategic Emerging Industrial Clusters Based on Cognitive Neuroscience

Xing Li[1,2*], Lin Liu[2]

ABSTRACT

For the decision makers of eco-innovation in the strategic emerging industrial clusters, the behavioral preference function is formed during their previous cognitive practice and learning process. The processes of Learning and memory can shape the structure and function of the brain. Meanwhile, the specific structure and function of the brain also affects and optimizes the learning behavior and cognitive process. Therefore, it is of great significance to grasp and explain the decision-making behavior of the enterprise's eco-innovation in the strategic emerging industrial clusters from the perspective of neuroscience. Firstly, we analyzed the influence of the mental model of the entrepreneurs in the strategic emerging industrial clusters on the choice of decision-making mode for company's eco-innovation. Secondly, we analyzed the process of decision of company's eco-innovation in the strategic emerging industrial clusters based on the mental model, and established an benefit model of eco-technology R&D, and analyzed the eco-innovation decision-making process of companies in the strategic emerging industrial clusters by simulation. The result shows that companies in the strategic emerging industrial clusters will decide whether to adopt eco-innovation behaviors according to their own mental model. At the same time, the knowledge accumulation obtained by the enterprises in the strategic emerging industrial clusters is inversely related to the average path length of the cluster eco-innovation network and is positively related to knowledge spillover benefits under the influence of the entrepreneurs' mental model. The R&D revenue obtained by enterprises is inversely related to the average path length of the cluster eco-innovation network and is positively related to the average degree and aggregation coefficient of the cluster eco-innovation network.

Key Words: Cognitive Neuroscience, Strategic Emerging Industry, Eco-innovation, Decision-Making Behavior

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Introduction

The relationship of brain-cognition-behavior is the core issue that we must solve in the process of self-cognition. Recognizing the brain and understanding ourselves has become the most challenging and active scientific frontier, cognitive neuroscience is particularly prominent among a large number of branches in brain science (Li, 2011). Particularly, with the rapid development of cognitive neuroscience techniques and theories, and the rapid integration of cognitive neuroscience with management and economics, the new inter-disciplinary disciplines and decision neuroscience have gradually emerged, it means that it is possible to explore the cognitive processing behind people's economic and management decisions from the cognitive level (Ma *et al.,* 2012; Meng, 2016). Therefore, the research on the brain imaging of economic decision-making has become the focus of the

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domestic and foreign scholars. Luo *et al.,* (2008) found that most of the brain activity was enhanced when the decision may improve the income and was declined when the decision may lead to increase the loss.

In a situation with highly uncertain of decision environment, decision makers often need to formulate corresponding measures based on the interpretation and judgment of the environment, and the function of the mental model during the process of making decisions received widespread attention (Levy, 2005). Bucciarelli (2007) presented a framework where possible relations between learning and mental model are explored. Wu and Hu (2007) discussed the assumptions and beliefs behind entrepreneur's decision, that is, the influence of entrepreneur's mental model on the development of enterprises. Jonassen (2008) described how Mind tools could be used by learners to externalize their mental model using different tools that represent different kinds of knowledge. Luo (2008) proposed a system and its composition of higher-level managers' mental model based on the dynamic view, namely the knowledge system, belief system and improvement system of higher-level managers. Yao and Chen (2009) believed that the heterogeneous mental model has a corresponding impact on the psychological process of entrepreneurial diversified strategic decision, which determined whether the entrepreneur chooses diversification and what type of diversification to choose. Li (2013) proposed a conceptual model that expressed the relationship among team processes, shared mental model, and quality of strategic decisions, as well as empirically analyzed the influence of team processes and shared mental model on the quality of strategic decisions. Li (2013) analyzed the influence of mental model on the ability of entrepreneurs' strategic decisions. Dong *et al.,* (2013) presented advances to two complementary research methods, latent semantic analysis and reflective practice analysis, to provide a way to model design team cognition over time so as to identify which aspects are relevant to design performance based on the construct of the team mental model. Cincotta (2013) created a model to explore the effect of dominant group status on stigmatization of mental illness and on moral relativism and the interactive effect of dominant group status on stigmatization of mental illness through moral relativism. Shi (2014) analyzed the function mechanism about the influence of the mental model of grassroots employees on the service quality, as well as the relationship of mental model of grass-roots employees and service quality. Butcher (2015) analyzed two experiments which investigated learning outcomes and comprehension processes when students learned about the heart and circulatory system. Xiang *et al.,* (2015) claimed that designers often collaborate to explore creative ideas, especially during the early stages of conceptual design, and their mental model, as the framework of design tasks, greatly influence the collaborative sketching process. Nathan and Martinez (2015) analyzed the relationship between gesture production and mental model was explored in three experiments focusing on inference making when learning from reading a scientific text. Bressan (2018) analyzed the influences of the executive's personal characteristics on the strategic decision-making Process based on mental model. Therefore, according to the research results, the entrepreneurs' mental model is the way of thinking and behavior formed in the process of their production and business activities, which based on their past experiences, habits, knowledge accomplishment and values. It affects the choice of entrepreneurs' decision. Once the mental model is formed, entrepreneurs will recognize and think about problems in a fixed mode of thinking and solve problems in the way they are used to (Wu and Hu, 2007).

For the decision makers of eco-innovation behavior in the strategic emerging industrial clusters, the behavioral preference functions are formed based on their past cognitive practices and learning processes and are often revealed in their brain "unconsciously" before they make decisions. (Ma and Wang, 2006), therefore, grasping and interpreting the decision behavior of eco-innovation in the strategic emerging industrial clusters from the perspective of neuroscience will undoubtedly be able to know and understand the process of eco-innovation more objectively and deeply.

Related description

Mental Model

The mental model is a structured knowledge framework and value system (or hypothetical belief) formed by the accumulation of knowledge, experience, emotions and practices. It is a basic hypothesis for specific things that hides behind our reflections, and it is the individual's ideas or beliefs (Yao and Chen, 2009) which stems from the individual's learning. Learning is accomplished by the brain, and the process of learning and memory can shape the structure and function of the brain. At the same time, the specific structure and function of the brain also affects and optimizes the learning behavior and cognitive processes. In addition, Learning is achieved through social interactions, and the learners quickly learn from interactions with other people and tend to focus on and imitate the behavior of others (Hu *et al.,* 2016).

In the strategic emerging industrial clusters, the occurring of the eco-innovation among enterprises is a complex and nonlinear process. With the complexity and uncertainty of ecological innovation, increasingly fierce market competition, and increasingly shortened product production cycles, the enterprises in the strategic emerging industrial clusters cannot have all the knowledge and information owning to the constraints of small scale, backward technology, and limited resources and other constrains of factors, so they need to have a multi-directional, multi-level interaction with the other actors in the industrial clusters to achieve the goal of learning (Li, 2014), and the mental model of the entrepreneurs in the industrial clusters is formed through this interactive behavior. The entrepreneurs received a great deal of knowledge and information and constructed its own knowledge network by interacting with other actors in the industrial clusters. And this kind of belief or understanding is the basis of decision and it can filter information and select information which is important to entrepreneurs and must be processed urgently. In addition, it can deal with and analyze the information based the entrepreneurs' original experience and knowledge, and then an effective management decision schemes is formed.

For the enterprises in the strategic emerging industrial clusters, the environment of eco-innovation decision is filled with a large number of complex and uncertain information, and there exists a great difference in the degree of mastering information among different corporate decision-makers. In fact, this difference is a reflection of the differences in entrepreneurs' mental model, and the entrepreneur's mental model will help the entrepreneur to make decision, such as whether the company has the need to implement eco-innovation, the judgment of opportunities or threats of eco-innovation, and the judgment of its own ability in the process of ecological innovation and evaluation of the eco-innovation performance. The individual's cognitive function will be activated if the received information is in line with the existing knowledge framework, and it will lead to the decision-making behavior (Yao and Chen, 2009). We assumed that the decision-making behaviors of eco-innovation of different agents mainly include two kinds of decision-making behavior model which is following (ecological innovation) and not following (non-ecological innovation). Here, we define two kinds of decision-making behavior model as following (Fan and Li, 2009; Li, 2014).

Definition 1. For $\phi \neq S \subseteq N, B \in \theta$, under the influence function B, the set of following agents of ecological innovation decision behavior of any group S in the strategic emerging industrial clusters can be expressed as:

$$F_B(S) := \{ j \in N \mid \forall i \in I_S [(Bi)_j = i_S] \}$$

Similarly, the set of non-following agents of ecological innovation decision behavior of any group S in the strategic emerging industrial clusters can be expressed as:

$$\bar{F}_B(S) := \{ j \in N \mid \forall i \in I_S [(Bi)_j = -i_S] \}$$

Theorem 1. If $B \in \theta$, S, T are two unrelated and nonempty subsets of N, then the following relationship is true:

(1) $S \cap T = \phi, F_B(S) \cap F_B(T) = \phi.$

(2) $B \in \theta_{S \to T}, F_B(S) = S \cup T, \bar{F}_B(S) = \phi.$

Proof: (1) Assuming $F_B(S) \cap F_B(T) \neq \phi$, then for $j \in F_B(S) \cap F_B(T)$, $(Bi)_j = i_S = i_T$ is satisfied. And because $S \cap T = \phi$ and $i \in I_S \cap I_T$, so $i_S = -i_T$ is satisfied, which contradicts the previous equation $(Bi)_j = i_S = i_T$, so the original hypothesis is not satisfied, so $F_B(S) \cap F_B(T) = \phi$.

(2) Assuming $t \in S \cup T$. If $t \in T$, then for any $i \in I_S$, $(Bi)_t = i_S$ is satisfied. If $t \in S$, then for any $i \in I_S$, $(Bi)_t = i_t = i_S$ is satisfied, so $t \in F_B(S)$. In turn, Assuming $t \in F_B(S)$, then for any $i \in I_S$, $(Bi)_t = i_S$, so $t \in S \cup T$, $F_B(S) = S \cup T$. Assuming $\bar{F}_B(S) \neq \phi$, $(Bi)_j = i_S = i_T$ exists, if $j \in \bar{F}_B(S)$, then for any $i \in I_S$, $(Bi)_j = -i_S$.This

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also contradicts the previous assumption, so the original hypothesis is not true, so $\bar{F}_B(S)=\phi$.

Next, we analyze the influence function B in the above equation. Four influencing functions have been proposed by some researchers (Handcock, 2003; Rusinowoska, 2006, 2008). Combined with the actual research, we mainly used the majority influence function and the dominant influence function. In the strategic emerging industrial clusters, the agents always have a tendency when they make the final decisions about eco-innovation, that is they will consider the behavior of the groups is right and follow it when the majority of the groups (or communities) in the industrial clusters take a certain type of behavior based on their own mental model, and we name this influence function as the majority influence function $B^{Maj}_{S\to j}$. On the other hand, in the strategic emerging industrial clusters, there often exists a special kind of subjects which have strong capabilities and are convinced by many other agents, so if they adopt certain behavior, the other agents in the group will also adopt this behavior, and we named this affect function as dominant influence function.

In the strategic emerging industrial clusters, we used $i_k=+1$ to represent the agents who adopt the eco-innovation behavior and used $i_k=-1$ to represent the agents who do not adopt eco-innovation behavior. Then, the set of agents who adopt ecological innovation behavior can be expressed as $i^+:=\{k\in N\mid i_k=+1\}$, and the set of agents who do not adopt ecological innovation behavior can be expressed as $i^-:=\{k\in N\mid i_k=-1\}$.

Definition 2. Given $\left\lfloor \frac{n}{2} \right\rfloor \le m \le n$, for any $i\in I$, the majority influence functions $B^{Maj}_{S\to j}$ can be defined as:

$$B^{Maj}_{S\to j} i := \begin{cases} +1_N & if\ |i^+|\ge m \\ -1_N & if\ |i^-|< m \end{cases}$$

Theorem 2. Given $\left\lfloor \frac{n}{2} \right\rfloor \le m \le n$, we consider the majority influence function $B^{Maj}_{S\to j}$, and the following formulate is satisfied:

For $\phi\ne S\in N$, $j\in N\setminus S$,

$$D_\alpha(B^{Maj}_{S\to j},S\to j)=\begin{cases}1, s\ge m\\ \dfrac{\sum_{i\in I^-_{S\to j}}\alpha_i^{S\to j}+\sum_{i\in I^+_{S\to j}}\alpha_i^{S\to j}}{\sum_{i\in I_{S\to j}}\alpha_i^{S\to j}}, s<m\end{cases}$$

Proof: for $\phi\ne S\in N$, $j\in N\setminus S$, $s\ge m$. If $i_s=+1$, then $|i^+|\ge m$, therefore, $(B^{Maj}_{S\to j}i)_j=+1+i_S$. If $i_S=-1$, then $|i^-|<m$, and $(B^{Maj}_{S\to j}i)_j=-1+i_S$. It means $I^{pos}_{S\to j}(B^{Maj}_{S\to j}i)_j=I_{S\to j}$, and $D_\alpha(B^{Maj}_{S\to j},S\to j)=1$. For $\phi\ne S\in N$, $j\in N\setminus S$, $s<m$.

So we can get:

$$D_\alpha(B^{Maj}_{S\to j},S\to j)=\frac{\sum_{i\in I^{pos}_{S\to j}}\alpha_i^{S\to j}}{\sum_{i\in I_{S\to j}}\alpha_i^{S\to j}}=\frac{\sum_{i\in I^-_{S\to j,s<m}}\alpha_i^{S\to j}+\sum_{i\in I^+_{S\to j,s<m}}\alpha_i^{S\to j}}{\sum_{i\in I_{S\to j}}\alpha_i^{S\to j}}$$

Definition 3. Given $k\in N$, k is a subject with dominant ability, and the dominant influence function $B^k_{S\to j}$ can be defined as $(B^k_{S\to j}i)_j=i_k$. That is, if there is an agent with dominant ability in the group, no matter what behavior the agent adopts, other subjects will follow this behavior.

Theorem 3. Given $k\in N$, we consider the dominant influence function $B^k_{S\to j}$. Then the following relationship is true:

For any $\phi\ne S\in N$, $k\in S$, $j\in N\setminus(S\cup\{k\})$, $D_\alpha(B^k_{S\to j},S\to j)=1$, $D^{neg}_\alpha(B^k_{S\to j},S\to j)=0$.

Proof: for $\phi\ne S\in N$, $k\in S$, $j\in N\setminus(S\cup\{k\})$. Therefore, for $i\in I_S$, $(B^k_{S\to j}i)_j=i_k=i_S$, so it makes $D_\alpha(B^k_{S\to j},S\to j)=1$. And $\bar{I}^{neg}_{S\to j}(B)=\phi$, so $D^{neg}_\alpha(B^k_{S\to j},S\to j)=0$

Enterprise's Eco-innovation Decision based on Mental Model

In the strategic emerging industrial clusters, there exists the difference in the influence and the ability to obtain the resources among the agents owning to the differences in the location of their structure holes in the industrial clusters which leads to the agents will be influenced by other groups or individual's decision behavior in the industrial clusters when they make eco-innovation decisions, and whether they will adopt eco-innovation decision-making behavior depends on their evaluation on R&D performance of eco-technology based on their own mental model.

For the enterprises in the strategic emerging industrial clusters, they require a certain amount of knowledge reserves to carry out eco-technology R&D activities, and this needs the learning among the enterprises in the industrial clusters, and this learning behavior will have an important effect on the mental model of entrepreneurs. In the eco-innovation network of the strategic emerging industrial clusters, we assumed that the knowledge capability of the enterprise is σ_i , and the cumulative knowledge of the enterprise i at the moment t is defined as $g_i(t)$: $g_i(t) = \sigma_{i(t)} + \sum_j \gamma^{l(i,j)} \max\{0, \sigma_{j(t)} - \sigma_{i(t)}\}$

Among them, node j refer to enterprise that has a direct or indirect connection with the enterprise i at time t; γ is knowledge spillover efficiency, $0 \le \gamma \le 1$, which represents the speed of technological decline among enterprises, the smaller the value is, the faster the knowledge declines, and the knowledge spillovers obtained by enterprises i decreases with the increase of network distance among enterprises, so we also call called γ as the distance attenuation coefficient. Enterprises obtain income by carrying out eco-innovation activities through the knowledge created by themselves or acquired directly or indirectly. Assuming that enterprise i obtains the income $S_i(t)$ has the following functional relationships with knowledge stock $S_i(t)$ during the time $[t, t+1]$ (Zhang *et al.,* 2012):

$$S_i(t) = \sqrt{g_i(t)}$$

At the same time, it is necessary for the enterprise to pay the corresponding cost to carry out eco-technology R&D activities which includes fixed cost, cooperation cost and environmental cost. In addition, the average path length, the average degree of network, and the aggregation coefficient of the eco-innovation network also have an impact on its cost. Therefore, the innovation cost $H_i(t)$ paid by the enterprise i during the time $[t, t+1]$ can be expressed as:

$$H_i(t) = H_0 + \sum_{j \in P} [h \cdot l(i,j)]^{c_i \bar{d}(k)} + \mu$$

Among them, H_0 is the fixed cost, h is the unit distance cost coefficient, μ is the environmental cost, $l(i,j)$ is the length of the path among enterprises, $\bar{d}(k)$ is the average degree of the network, and c_i is the aggregation coefficient of the enterprise i .

Therefore, the R&D revenue function of the company i during the time $[t, t+1]$ can be expressed as (Zhang *et al.,* 2012):

$$s_i(t) = \sqrt{g_i(t)} - H_0 - \sum_{j \in P} [h \cdot l(i,j)]^{c_i \bar{d}(k)} - \mu$$

Test results and analysis

We assume that the largest scale of eco-innovation network enterprise at the initial stage is $N = 40$ in the strategic emerging industrial clusters, and the knowledge ability σ_i of the enterprise i follows uniform distribution, that is $\sigma_i \sim U(0,1)$, and the knowledge spillover efficiency $\gamma \in (0,1)$, and we set $H_0 = 0.5$, $h = 0.001$, $\mu = 0.5$. When $t = 0$, there is no cooperation relationship among the agents in the eco-innovation network of the strategic emerging industrial clusters, and this eco-innovation network is empty network.

Changes in the accumulation of knowledge of the enterprise i

Assuming that at time t, the knowledge ability of the enterprise j which has a connection relationship with enterprise i is not as good as the enterprise i. The amount of knowledge $g_i(t)$ by the enterprise i at the time t is the knowledge ability σ_i of the enterprise i itself. The simulation result is shown in Figure 1.

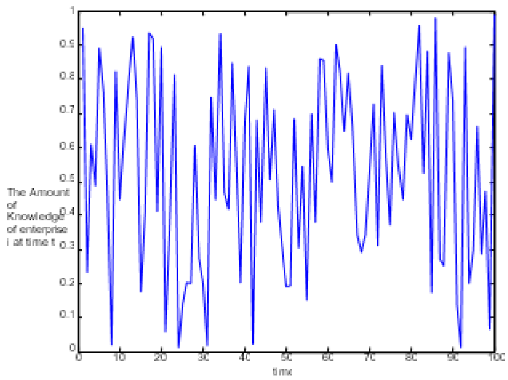

Figure 1. Changes of the accumulation of knowledge of enterprises i

When T=100, we can see from Fig.1 that the amount of knowledge $g_i(t)$ accumulated by the company i at the time t is the knowledge

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ability of the enterprise i itself, and it follows uniformly distributed interval, that is $\sigma_i \sim U(0,1)$, and it means that it is realistic to assume that the knowledge ability σ_i of the enterprise i follows uniformly distributed.

The relationship between the amount of accumulated knowledge of enterprise i and the average path length of the network

Assuming that the enterprise's knowledge capacity is 1, the knowledge ability of enterprise j at the time t is stronger than that of of enterprise i, and the knowledge spillover efficiency γ is $1/2$. The simulation result is shown in Figure 2.

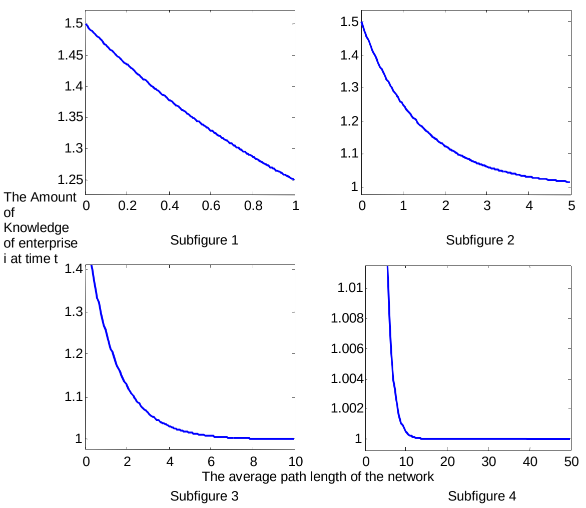

Figure 2. The relationship between the amount of accumulated knowledge and the average path length of the network of enterprise i.

In the Fig.2, the average path length of the eco-innovation network is $\bar{l} \in [0,1]$ in Subgraph 1, the average path length of the eco-innovation network is $\bar{l} \in [0,5]$ in Subgraph 2, the average path length of the eco-innovation network is $\bar{l} \in [0,10]$ in Subgraph 3, and the average path length of the eco-innovation network is $\bar{l} \in [0,50]$ in Subgraph 4. From the Figure 2, it can be seen that the amount of knowledge accumulated by enterprises decreases with the increase of the average path length of the eco-innovation network. At the same time, we can see from the Figure 3 that the knowledge accumulated by the enterprise is 1 and reaches a stable state when the average length of the eco-innovation network is 10.19.

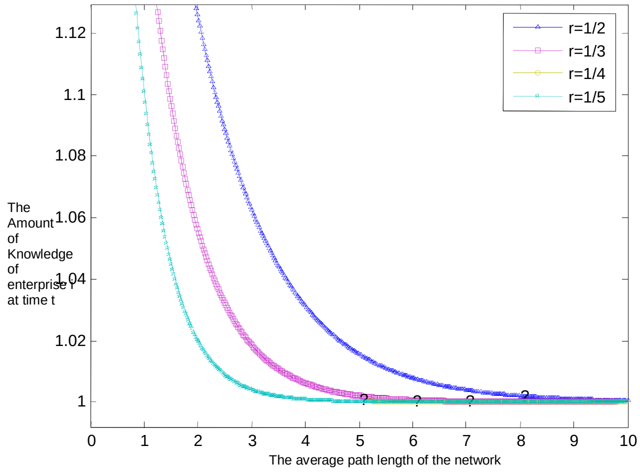

Figure 3. The relationship between the amount of accumulated knowledge and the average path length of the network of enterprise i.

It can be seen from the Fig .3 that when the knowledge spillover efficiency $\gamma \in (0,1)$ in the eco-innovation network, the knowledge accumulated by the enterprise decreases with the increase of the average path length of the eco-innovation network, but the amount of accumulated knowledge acquired by enterprises in the eco-innovation network is reduced more slowly when the knowledge spillover efficiency of the eco-innovation network is high. At the same time, under the same average path length of eco-innovation networks, the greater the knowledge spillover efficiency, the greater the amount of knowledge accumulated by enterprises.

The relationship between knowledge accumulation and knowledge spillover efficiency

From the Fig.4, it can be seen that when the average length of the eco-innovation network express is $\bar{l} \in [0,1]$, the amount of knowledge accumulated by enterprises increases with the increase of knowledge spillover efficiency, and the shorter the average path length of the eco-innovation network, the faster the increment of knowledge gained by enterprises.

The relationship between eco-technology R&D revenue and various variables

Firstly, the relationship between the eco-technology R&D revenue and the average path length of the network

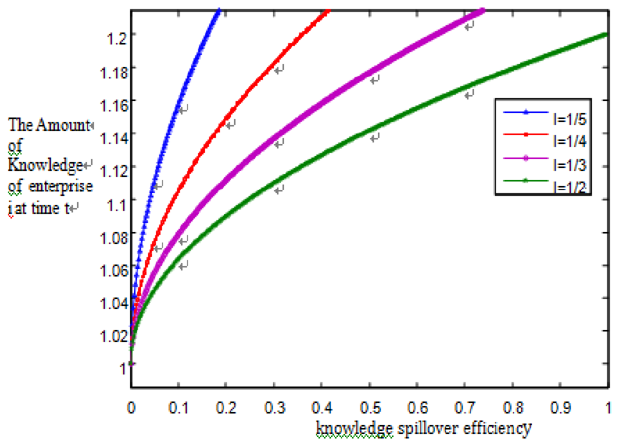

Figure 4. The relationship between the large amount of knowledge and knowledge spillover efficiency of enterprise i

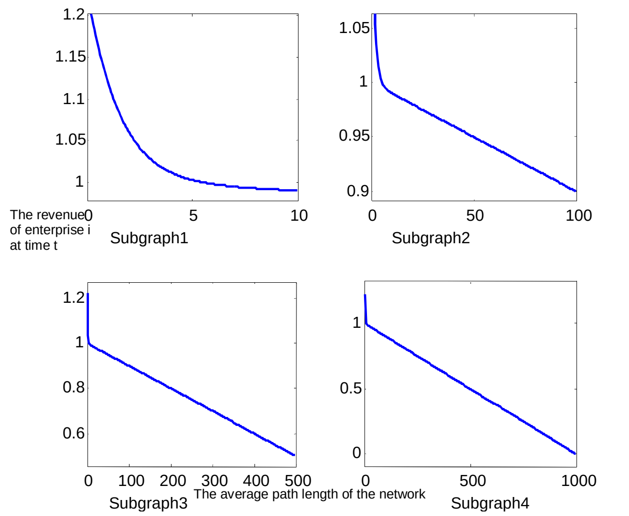

Figure 5. The relationship between the revenue earned by enterprise i and the average path length of the network

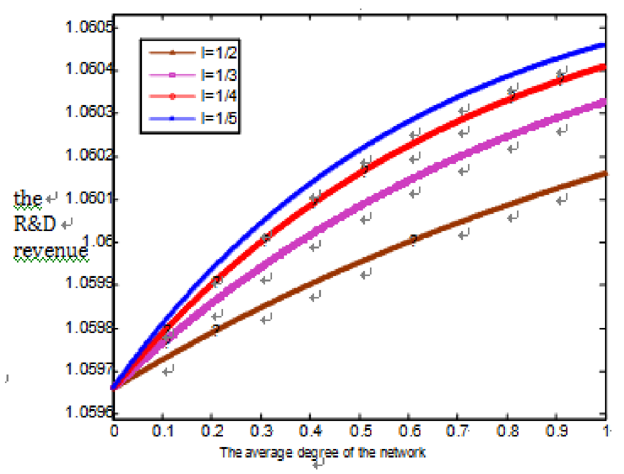

Figure 6. The relationship between the income and average degree of enterprise i at time t

From the Fig.5, it can be seen that the technology R&D revenue obtained by the enterprise shows a declining trend as the increases of the average length of the eco-innovation network, and when the average path length of the eco-innovation network is large enough, the technology R&D revenue obtained by enterprise is even negative.

Secondly, the relationship between the R&D revenue obtained by enterprise i and the average degree of the network.

Fig.6 shows the simulation results with $\bar{l}=1/2, \bar{l}=1/3, \bar{l}=1/4, \bar{l}=1/5$ respectively and the average path lengths of the cluster eco-innovation network is $\bar{l} \in [0,1]$. It can be seen from this figure that the greater the average degree of the cluster eco-innovation network, the greater the company's income from eco-technology research and development. The smaller the average path length of the network, the greater the growth rate of the eco-technology R&D revenues obtained by the company.

Thirdly, the relationship between the company's R&D revenue and the aggregation coefficient of enterprise i at time t

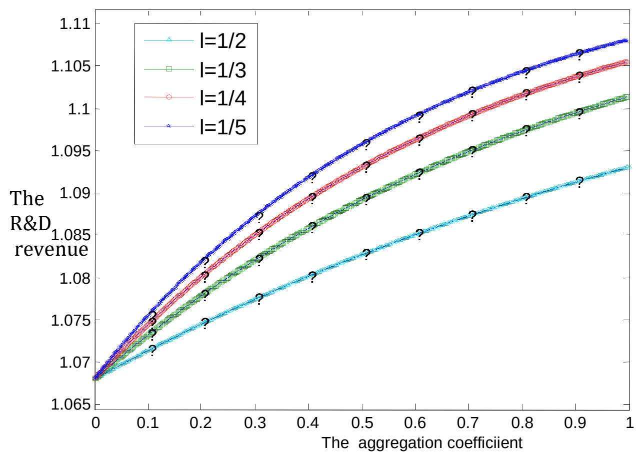

Figure 7. The relationship between the company's revenue and the aggregation coefficient of enterprise i at t

Assuming the average path length of the cluster eco-innovation network is $\bar{l} \in [0,1]$, selecting the, $\bar{l}=1/3$, $\bar{l}=1/4$, $\bar{l}=1/5$ respectively, we can see from Figure 7 that the larger the aggregation coefficient of the cluster eco-innovation network, the greater the eco-technology R&D income obtained by the enterprise, and the smaller the average path length of the network, the greater the growth rate of the R&D revenue of the eco-technology companies.

Conclusions

Based on the perspective of cognitive neuroscience, we firstly analyzed the decision-making model of eco-innovation in the strategic emerging industrial clusters, and built benefit model of eco-technology R&D, and then analyzed the process of eco-innovation decision-making in the strategic emerging industrial clusters by simulation, and we concluded:

(1) The behaviors of eco-innovation decision-making of enterprises in the strategic emerging industrial clusters will not only be affected by their own mental model, but also affected by the behaviors of other groups in the cluster eco-innovation network. That is, the agents often adopt the behavior based on their own mental model when the vast majority of certain groups take a certain behavior in the industrial cluster.

(2) The knowledge accumulated by the enterprise decreases with the increase of the average path length of the eco-innovation network, but the amount of accumulated knowledge acquired by enterprises in the eco-innovation network is reduced more slowly when the knowledge spillover efficiency of the eco-innovation network is high. At the same time, under the same average path length of eco-innovation networks, the greater the knowledge spillover efficiency, the greater the amount of knowledge accumulated by enterprises.

(3) The amount of knowledge accumulated by enterprises increases with the increase of knowledge spillover efficiency, and the shorter the average path length of the eco-innovation network, the faster the increment of knowledge gained by enterprises.

(4) The technology R&D revenue obtained by the enterprise shows a declining trend as the increases of the average length of the eco-innovation network, and when the average path length of the eco-innovation network is large enough, the technology R&D revenue obtained by enterprise is even negative. And the greater the average degree of the cluster eco-innovation network, the greater the company's income from eco-technology research and development. The smaller the average path length of the network, the greater the growth rate of the eco-technology R&D revenues obtained by the company.

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