

Simulation of collaborative product development knowledge diffusion using a new cellular automata approach

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ABSTRACT

In order to quantitatively examine the diffusion process and pattern of collaborative product development (CPD), this paper puts forward a quantitative research model of CPD knowledge diffusion based on improved cellular automata. In light of the idea of SIS epidemic model and the local knowledge interaction characteristic of CPD knowledge diffusion, the influencing factors of knowledge diffusion are abstracted into the parametric variables in the process of knowledge diffusion, and the knowledge-SIS (K-SIS) model is constructed based on improved cellular automata for CPD knowledge diffusion. Finally, the K-SIS model is simulated to study the diffusion process and pattern of CPD knowledge, revealing the influence mechanism of CPD knowledge diffusion influencing factors on the diffusion process. The research results provide valuable reference for improving the efficiency of CPD knowledge diffusion.

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1. Introduction

With the increasingly fierce competition in the product market, especially IT industry, pharmaceutical industry and automobile industry, enterprises are attaching more importance to the integration of suppliers, customers and other potential collaborators into product development. Owing to the deep integration of the collaborators' knowledge, collaborative product development (CPD) has become a new product innovation mode practiced by many enterprises, such as Apple, Xiaomi and LEGO, etc. The collaborative product development system (CPDS) consists of such collaborative members as suppliers, customers, other potential collaborators and enterprise professional product developers. Knowledge exchange and diffusion are prevalent in the CPDS owing to the asymmetry of the members in the structure of collaborative production development knowledge (CPD knowledge) and imbalance between them in the level of knowledge stock [1]. CPD knowledge diffusion enables each member to fully access and acquire the knowledge of others, thereby increasing the CPD knowledge stock of individual member and the entire CPDS. Meanwhile, the diffusion of CPD knowledge helps the members complement each other's advantages through the diffusion of CPD knowledge, optimizes the allocation of CPD knowledge resource, enhances the technical content of the CPD and accelerate the process of knowledge innovation and product development [2]. Therefore, the efficient knowledge diffusion opens up an important way to improve the product development capacity of the enterprises, and provides a key support to the successful development of new products.

As an integral part of knowledge management, knowledge diffusion has been followed and studied by many scholars. Probing into the effect of social cohesion and network size on knowledge diffusion, Reagans and McEvily argue that it is easier to diffuse knowledge if the members of society keep closer ties and shorter distances [3]. Kim and Park explore the relationship between the structure of collaborative organization network and knowledge diffusion, suggesting that the small-world network is the most fair and efficient collaborative network structure for knowledge diffusion [4]. Setting out from the motive and impetus to knowledge diffusion, Li et al. point out that the knowledge potential is an important determinant of the speed and breadth of knowledge diffusion [5]. Based on the philosophy of epidemiology, Bass establishes the “epidemic” model innovation diffusion, and expresses the model with mathematical equations [6]. From the perspective of NW small-world network, Sun and Wei build the knowledge diffusion model of high-tech enterprise alliance, and explore the effect of network clustering coefficient, characteristic path length and exchange frequency on the knowledge diffusion of the enterprise alliance [7]. Meng et al. adopt the multi-agent model of disease transmission to simulate the knowledge diffusion process in the network environment [8].

Focusing on the influencing factors, processes and models of knowledge diffusion, the above-mentioned literatures share two common defects: Firstly, most of them concentrate on the social network, the interior and exterior of enterprises, industrial clusters, R & D team, etc. but few pays attention to the diffusion of product development knowledge in the collaboration environment (e.g. CPDS). Secondly, based on mathematical methods, system dynamics and other theoretical methods, the majority of knowledge diffusion models lay too much stress on the macro features like the speed and process of knowledge diffusion, and largely ignore the microscopic basis that the knowledge diffusion is the result of the knowledge activities between the knowledge subjects. Knowledge diffusion is a complex process in which organized and complex knowledge behaviors are formed through the local knowledge interaction between the knowledge subjects [9]. In light of the above, this paper intends to study the CPD knowledge diffusion by the complex system modeling method: cellular automata (CA). Targeted at the complex and inenarrable process of CPD knowledge diffusion, the author draws on the idea of SIS epidemic model, describes the knowledge exchange activities between knowledge subjects and collaborative teams, and illustrates the macro knowledge diffusion phenomenon of the entire CPDS. From the micro-level to the macro-scale, the description and illustration are clear and intuitive. On this basis, the traditional CA model is improved, and the quantitative model of CPD knowledge diffusion is constructed based on improved CA. The model is used to examine the process and pattern of CPD knowledge diffusion, revealing the influence mechanism of CPD knowledge diffusion influencing factors on the diffusion process.

This paper aims to quantitatively analyze the CPD knowledge diffusion process and effectively predict the diffusion trend, which can help managers to better improve the management performance of CPD.

2. Analysis of CPD knowledge diffusion process

Knowledge diffusion refers to the transfer and sharing of knowledge between different subjects across time and space. In the context of CPD, the knowledge in the CPDS is diffused between different knowledge subjects, between knowledge subjects and collaborative teams, and between different collaborative teams [10, 11]. During the diffusion of CPD knowledge, the knowledge exchange happens between knowledge receivers and knowledge transmitters. Based on their own demand of knowledge and understanding of transmitters’ knowledge resources, receivers seek for in-depth exchange with transmitters to acquire valuable knowledge. Then, the receivers digest and absorb the acquired knowledge, internalize it into their own knowledge, and transform themselves into knowledge transmitters, aiming to spread the acquired knowledge to other subjects. In addition, the CPDS is a virtual organization involving multiple units and subjects. In the system, the CPD activities are mainly implemented by virtual teams that closely collaborate with each other. Thus, knowledge exchanges also take place between subjects belonging to different teams, that is, knowledge diffusion occurs both inside the teams

and between the teams. In this way, the CPD knowledge is eventually diffused and shared across the CPDS.

3. Construction of CPD knowledge diffusion model

3.1 Cellular automata

Cellular automata (CA) is a network dynamics model discrete in time and space. The CA is composed of a finite number of locally interacting cells. At a certain moment, the state of a cell only depends on its own state and the state of neighborhood cells. As time goes, the simple local rule between the cells can evolve into the complex global behavior of the macro system [12-14]. The "evolution from simple local rule to complex global behavior" is one of the unique strengths of the CA model. Once it is applied to knowledge diffusion, the model will be able to depict the phenomenon of knowledge diffusion in real system from the microscopic angle: simulate the local knowledge exchanges between subjects with simple rules and evolve into the macroscopic results of global knowledge diffusion. Through the control of the initial parameters, the model can simulate the diffusion process of different types and forms of knowledge, and explain the influence of factors like organizational characteristics and knowledge subject features in the knowledge diffusion process. Therefore, the CA model is an ideal choice for CPD knowledge diffusion simulation.

The CA can be expressed by a four-tuple:

$$CA = (C, Q, V, F) \quad (1)$$

where C is the cell space; Q is the cell state set; V is the cell neighborhood; F is the cell state transition rule.

3.2 CA model of CPD knowledge diffusion

A large number of studies have shown that the spread of social phenomena is an infection process [15]. In this research, the CPDS members in possession of a specific piece of CPD knowledge are regarded as "infectors" and those who do not possess such knowledge are viewed as "susceptibles". For a specific type of CPD knowledge, the "infectors" can "infect" the "susceptibles" with the knowledge so that the latter acquire the knowledge and the ability to "infect" others with the knowledge. In the meantime, the knowledge "infectors" may give up the knowledge because of their memory ability. There is a certain probability for the "infectors" to transform into "susceptibles" by forgetting the knowledge. The transformation is the "restoration of health". Here, an "infector" is denoted as I and a "susceptible" is denoted as S . In light of the CA model proposed above, this paper names the CPDS knowledge diffusion model as the Knowledge-SIS (K-SIS) model.

According to the four elements of the four-tuple expression of the CA, the K-SIS model is constructed as below.

Cell space C : Let C be a 2D cell space containing $n \times n$ cells, representing the entire CPDS. The cells in C are expressed as $c(i, j)$, representing the CPD teams in the CPDS. Hence, can be expressed as:

$$C = \{c(i, j) | 1 \leq i \leq n, 1 \leq j \leq n\} \quad (2)$$

As discussed before, the CPD are mainly implemented by virtual teams in the CPDS, and knowledge exchanges occur between different subjects and collaborative teams. Hence, this paper sets each cell as a CPDS collaborative team, each containing a certain number of knowledge subjects.

Cell state set Q : By the above definition, each cell represents a collaborative team containing a certain number of knowledge subjects. Thus, the cell state can be expressed by the proportions of knowledge infectors and susceptibles in the cell. Let $S_{c(i, j)}^t$ be the proportion of knowledge

susceptibles in cell $c(i, j)$ at the moment t , and $I_{c(i, j)}^t$ be the proportion of knowledge infectors, and we have:

$$S_{c(i, j)}^t + I_{c(i, j)}^t = 1 \tag{3}$$

The state of a cell can be expressed by a two-tuple $q_{c(i, j)}^t = (S_{c(i, j)}^t, I_{c(i, j)}^t) \in Q$.

Neighborhood V : This paper uses a Moore neighborhood with a 2-radius. As shown in Fig. 1, the neighborhood of the central black cell is expressed by the area of the grids marked by dotted lines.

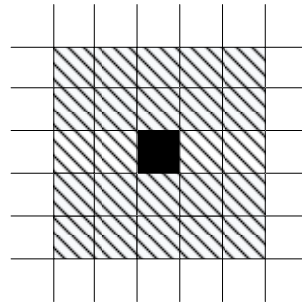


Fig. 1 Moore neighborhood with a 2-radius

Transition rule F : During the diffusion of CPD knowledge, there is a certain probability for the susceptibles to transform into infectors after acquiring knowledge from the infectors via knowledge exchanges. The infectors are either internal or external to the team. Meanwhile, the infectors are transforming into susceptibles at a certain probability by forgetting the knowledge. For the K-SIS model, the core objective is to obtain the proportions of susceptibles and infectors $S_{c(i, j)}^t$ and $I_{c(i, j)}^t$ in the cell $c(i, j)$. Through the analysis of CPD knowledge diffusion process and its influencing factors, the cell state transition rule F can be expressed as:

$$S_{c(i, j)}^t = S_{c(i, j)}^{t-1} + \delta \cdot I_{c(i, j)}^t - \frac{\rho_{In} \cdot S_{c(i, j)}^{t-1} \cdot I_{c(i, j)}^{t-1}}{v_{In}} - S_{c(i, j)}^{t-1} \cdot \sum_{c(i+\alpha, j+\beta) \in V} \frac{N_{c(i+\alpha, j+\beta)}}{N_{c(i, j)}} \cdot \mu_{\alpha\beta}^{ij} \cdot I_{c(i+\alpha, j+\beta)}^{t-1} \tag{4}$$

$$I_{c(i, j)}^t = (1 - \delta) \cdot I_{c(i, j)}^t + \frac{\rho_{In} \cdot S_{c(i, j)}^{t-1} \cdot I_{c(i, j)}^{t-1}}{v_{In}} + S_{c(i, j)}^{t-1} \cdot \sum_{c(i+\alpha, j+\beta) \in V} \frac{N_{c(i+\alpha, j+\beta)}}{N_{c(i, j)}} \cdot \mu_{\alpha\beta}^{ij} \cdot I_{c(i+\alpha, j+\beta)}^{t-1} \tag{5}$$

Where $c(i + \alpha, j + \beta)$ is a neighborhood cell of the cell $c(i, j)$; $N_{c(i+\alpha, j+\beta)}$ and $N_{c(i, j)}$ are the number of knowledge subjects in the cell; $\delta \in [0,1]$ is the knowledge forgetting rate of CPD knowledge subjects; $\rho_{In} \in [0,1]$ is the intra-team trust level between the CPD knowledge subjects; $v_{In} \in [1,9]$ is the intra-team knowledge stickiness; $\mu_{\alpha\beta}^{ij} = \frac{\rho_{out} \cdot c_{\alpha\beta}^{ij}}{v_{out}}$ is the inter-team transfer and diffusion ability of CPD knowledge; $\rho_{out} \in [0,1]$ is the inter-team trust level between the CPD knowledge; $v_{out} \in [1,9]$ is the inter-team knowledge stickiness; $c_{\alpha\beta}^{ij} \in [0,1]$ is the inter-team collaboration strength.

For the inter-team collaboration strength, this paper adopts the second-order extended Moore neighborhood, which naturally leads to the concept of “cell distance”. If the coordinates of a cell in the cell space is represented with a pair of integers (x, y) , the distance between the cells $c(i, j)$ and $c(i + \alpha, j + \beta)$ can be expressed in Euclidean distance.

$$d_{\alpha\beta}^{ij} = \sqrt{(x_i - x_{i+\alpha})^2 + (y_i - y_{i+\alpha})^2} \tag{6}$$

The inter-team collaboration strength in the CPDS is defined as the reciprocal of the cell distance.

$$c_{\alpha\beta}^{ij} = 1 / d_{\alpha\beta}^{ij} \tag{7}$$

4. Simulation analysis of CPD knowledge diffusion

4.1 Settings of simulation parameters

Based on the K-SIS knowledge diffusion model, the trust level between CPD knowledge subjects, knowledge stickiness, the inter-team collaboration strength and knowledge forgetting rate are set as the parameters of the simulation experiment. The simulation aims to explore the effect of these influencing factors on CPD knowledge diffusion. Suppose the CPD knowledge diffusion cell space contains 20×20 cells, each of which has 30 knowledge subjects; at the initial moment of knowledge diffusion, the cell $c(10,10)$ is the only one that contains knowledge infectors, i.e. only one team in the CPDS possesses a specific type of CPD knowledge. The initial state is denoted as $q_{c(10,10)}^0 = (0.3, 0.7)$, and the simulation time $T = 100$.

In this research, the level of CPD knowledge diffusion performance is measured by the average knowledge level and the standard deviation of knowledge level [16, 17]. At the moment, the average knowledge level of the collaborative teams within CPDS is:

$$KP_t = \frac{1}{N} \sum_{i \in V} l_{i,t} \quad (8)$$

where N is the number of collaborative teams; $l_{i,t}$ is the amount of knowledge possessed by team i at the moment t .

At the moment t , the standard deviation of knowledge level $K\sigma_t$ reflecting the uniformity of knowledge possessed by each team is:

$$K\sigma_t = \sqrt{\frac{1}{N} \sum_{i \in V} l_{i,t}^2 - KP_t^2} \quad (9)$$

4.2 Analysis of the effect pattern of influencing factors on CPD knowledge diffusion

(1) The effect of trust level between knowledge subjects on CPD knowledge diffusion

In the CPDS, assume that the intra-team trust level between knowledge subjects $\rho_{in} = 0.9$, the inter-team trust level between knowledge subjects $\rho_{out} = 0.6$, the intra-team knowledge stickiness $v_{in} = 3.5$, the inter-team knowledge stickiness $v_{out} = 4.5$, and the knowledge forgetting rate $\delta = 0.1$. To disclose the effect of trust level on CPD knowledge diffusion, the simulation is conducted with the initial trust levels of 60 %, 70 %, 80 %, 90 % and 100 %. The simulation results are exhibited in Fig. 2.

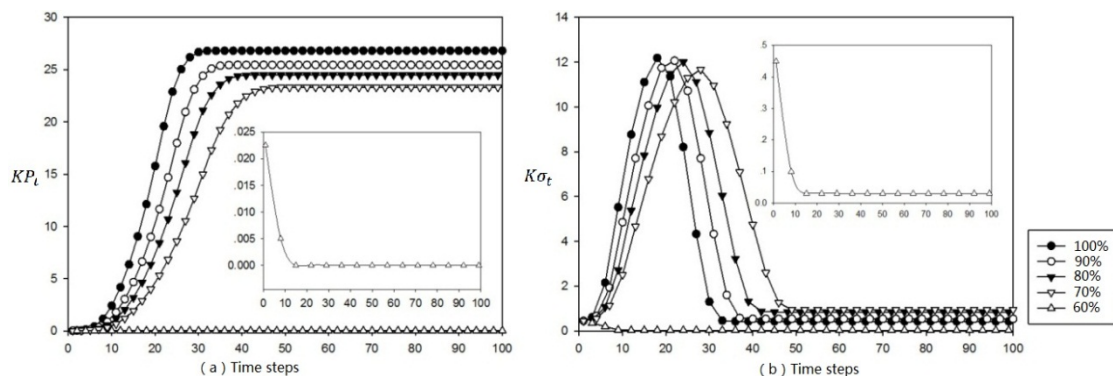


Fig. 2 The effect of trust level between knowledge subjects on CPD knowledge diffusion

Under the same knowledge stickiness, inter-team collaboration strength and knowledge forgetting rate, the average knowledge level of CPDS teams grows higher and faster with the increase of the trust level between the knowledge subjects in the CPDS, Fig. 2(a). This means the trust level between knowledge subjects is positively correlated with the average knowledge lev-

el and the diffusion rate of CPD knowledge diffusion. At the beginning of knowledge diffusion, higher trust level between knowledge subjects is accompanied by wider gaps on the knowledge levels of different teams; when it comes to the later stage of knowledge diffusion, however, the gaps narrow down rapidly and eventually converge to a low variance, Fig. 2(b). Thus, higher trust level helps CPDS teams to achieve more uniform distribution of knowledge. Summing up the simulation results of Figs. 2(a) and 2(b), it is concluded that: when the knowledge subjects maintain a high level of trust, the CPDS teams would possess high knowledge levels and achieve uniform knowledge distribution at a fast knowledge diffusion rate. In practice, the CPDS managers should recognize that the effective knowledge diffusion is the outcome of trust, cooperation and other emotional factors, and the foundation of knowledge interaction and collaboration is trust. Therefore, the managers should take organizational, institutional and cultural measures to boost the trust between CPDS members on knowledge sharing, encourage them more willing to cooperate and share knowledge with each other, promote them to build closer ties, and arouse their interests in actively exchanging and sharing knowledge.

(2) The effect of knowledge stickiness on CPD knowledge diffusion

In the CPDS, assume that the intra-team knowledge stickiness $v_{In} = 3.5$, the inter-team knowledge stickiness $v_{out} = 4.5$, the intra-team trust level between knowledge subjects $\rho_{In} = 0.9$, the inter-team trust level between knowledge subjects $\rho_{out} = 0.6$, and the knowledge forgetting rate $\delta = 0.1$. To study the effect of knowledge stickiness on CPD knowledge diffusion, the simulation is conducted with the initial trust levels of 60 %, 70 %, 80 %, 90 % and 100 %. The simulation results are displayed in Fig. 3.

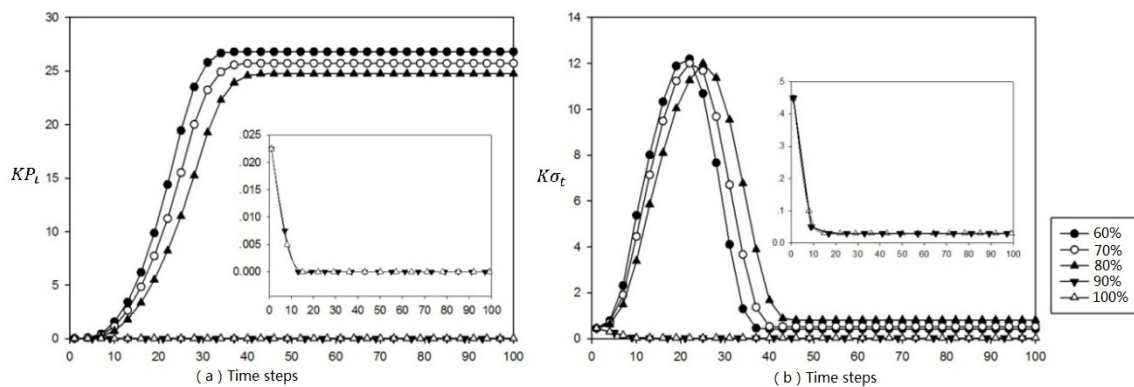


Fig. 3 The effect of knowledge stickiness on CPD knowledge diffusion

Under the same trust level, inter-team collaboration strength and knowledge forgetting rate, the average knowledge level of CPDS teams grows lower and slower with the increase of CPD knowledge stickiness, Fig. 3(a), that is, the knowledge stickiness is negatively correlated with the average knowledge level and the diffusion rate of CPD knowledge diffusion. The result bears testimony to the fact that: due to the objective nature of knowledge, stickier CPD knowledge is often more complex, ambiguous and specific, and harder to encode or transfer. The fact adds to the difficulty in knowledge diffusion. In the most severe cases, it would be too difficult for the CPD knowledge diffusion to occur. As shown in Fig. 3(b), the beginning of knowledge diffusion is marked by low CPD knowledge stickiness and wide gaps on the knowledge level between different teams. Upon entering the later stage of knowledge diffusion, however, the gaps shrink rapidly and finally converge to a low variance, Fig. 3(b), indicating that lower knowledge stickiness contributes to more uniform distribution of knowledge across the CPDS teams. Overall, the simulation results in Fig. 3 show the following practical implications: the less sticky the CPD knowledge is, the higher knowledge levels and faster knowledge diffusion rate the CPDS teams would possess. In real industrial environment, especially these high-technology industries with complex and quick-update knowledge, the CPDS should confer the members more permissions to contact and use its knowledge resource. On the other hand, the complex CPD knowledge should be described in simple, clear and versatile languages which can be effectively learned and

used by members, and the CPDS members should be trained to improve their comprehension and acceptance ability for the CPD knowledge. In these ways, managers can reduce the stickiness of knowledge transfer and raise the efficiency of knowledge diffusion.

(3) The effect of inter-team collaboration strength on CPD knowledge diffusion

According to the formula (6)-(7), the inter-team collaboration strength is a fixed value determined by "cell distance". To reveal the effect of inter-team collaboration strength on CPD knowledge diffusion, the simulation is conducted with the initial trust levels of 60 %, 70 %, 80 %, 90 % and 100 %. Assume that the trust level between the CPD knowledge subjects within a CPDS team $\rho_{In} = 0.9$, the inter-team trust level between knowledge subjects $\rho_{out} = 0.6$, the intra-team knowledge stickiness $v_{In} = 3.5$, the inter-team knowledge stickiness $v_{out} = 4.5$, and the knowledge forgetting rate $\delta = 0.1$. The simulation results are presented in Fig. 4.

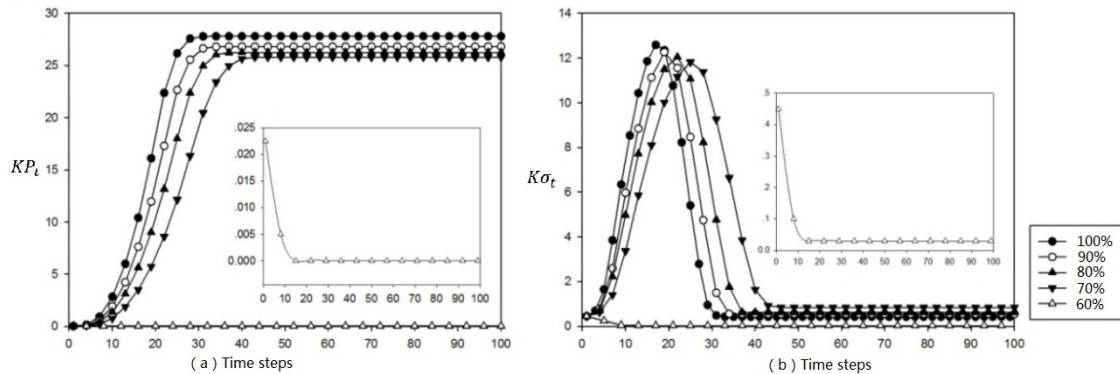


Fig. 4 The effect of inter-team collaboration strength on CPD knowledge diffusion

Fig. 4 shows the positive correlation between inter-team collaboration strength and the average knowledge level, diffusion rate and knowledge distribution uniformity in CPD knowledge diffusion. The revelation provides an evidence to the fact that: good inter-team collaboration strength improves the stability of CPDS so that the teams cooperate more closely in CPD tasks, and also offers knowledge subjects belonging to different teams more channels and chances for exchanges, thereby advancing the diffusion of knowledge across the collaborative teams. Thus, the practical conclusion can be drawn that: stronger inter-team collaboration enables CPDS teams to possess higher knowledge levels and achieve more uniform knowledge distribution at a faster knowledge diffusion rate. In the management of CPDS, the inter-team collaboration strength determines the effectiveness of knowledge exchange and collaboration among different teams, and then further affects the knowledge diffusion efficiency of the whole CPDS. Therefore, managers should strengthen the flat management of CPDS to make each team the centrality of CPDS by reducing organizational hierarchy and intensifying intra-team exchanges and collaborations in a relatively stable operating environment. On the other hand, managers also need to encourage members of different teams to actively communicate and collaborate with each other in formal and informal ways, in order to enhance the efficiency of knowledge exchange among members. Finally, the knowledge of individual team members can be elevated into team resources, and then turned into the knowledge resources of the entire organization, making knowledge a competitive edge over other groups and organizations.

(4) The effect of knowledge forgetting on CPD knowledge diffusion

Assume that the trust level between the CPD knowledge subjects within a CPDS team $\rho_{In} = 0.9$, the inter-team trust level between knowledge subjects $\rho_{out} = 0.6$, the intra-team knowledge stickiness $v_{In} = 3.5$, and the inter-team knowledge stickiness $v_{out} = 4.5$. To discover the effect of knowledge forgetting on knowledge diffusion, the simulation is conducted with $\delta = 0, 0.1, 0.2, 0.3, 0.4$. The simulation results are listed in Fig. 5.

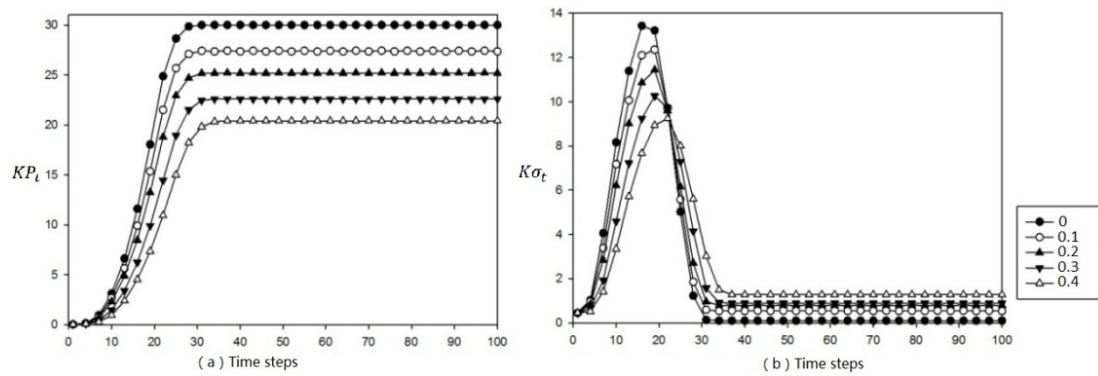


Fig. 5 The effect of knowledge forgetting on CPD knowledge diffusion

Fig. 5 showcases the negative correlation between knowledge forgetting and the average knowledge level, diffusion rate and knowledge distribution uniformity in CPD knowledge diffusion. It reflects the reality that: knowledge forgetting reduces the attachment of CPD knowledge to knowledge subjects, making it more difficult for knowledge subjects to possess CPD knowledge in the long run; meanwhile, the knowledge diffusion process is discretized due to the knowledge loss during knowledge forgetting, which hinders the effective diffusion of CPDS knowledge. Based on the simulation results in Fig. 5, it can be drawn the following practical conclusions: low knowledge forgetting rate allows CPDS teams to possess high knowledge levels and achieve uniform knowledge distribution at a fast knowledge diffusion rate. Therefore, managers should strictly control the introduced knowledge to avoid the waste or wrong guidance by introducing valueless knowledge. For the introduced knowledge with great value, managers should effectively promote the knowledge to improve members' cognition and recognition of the knowledge value. Secondly, the repeated backups and personnel trainings are necessary in the diffusion of the valuable CPD knowledge to lower the level of difficulty of the introduced knowledge. Moreover, the members possessing the knowledge should be regarded as key management object to give them more change to strengthen the memory through constant application of the knowledge, so as to minimize the loss of CPD knowledge caused by knowledge forgetting.

5. Conclusion

Effective knowledge diffusion plays a vital role for the success of CPD. Aiming to deeply understand the diffusion process and rule of CPD knowledge, this paper constructs the K-SIS model of CPD knowledge diffusion in the context of CPD based on an improved CA method. Compared with the traditional knowledge diffusion model, the proposed model makes the following innovations: (1) Based on the improved CA method, the model involves a “bottom up” examination of the CPD knowledge diffusion process from the perspective of microscopic knowledge exchange activities; (2) The traditional CA model is improved to fit the quantitative research of CPD knowledge diffusion in the context of collaboration. During the simulation on the proposed model, the author digs deep into the diffusion process and pattern of CPD knowledge, using the average knowledge level of the teams and the standard deviation of the knowledge level to measure the performance of CPD knowledge diffusion; Moreover, the author performs multiple simulations with the influencing factors of CPD knowledge diffusion given different parameter values, and compares and analyzes the simulation results to obtain the effect pattern of each influencing factor on CPD knowledge diffusion. The simulation results show that the proposed model can realize the quantitative analysis of the CPD knowledge diffusion process and the prediction of the diffusion trend. Moreover, different factors play different roles for the knowledge diffusion efficiency. Monitoring and managing these factors will help enterprises to optimizing the CPD knowledge diffusion process. This study offers theoretical guidance and methodological support for improving CPD knowledge diffusion efficiency.

This research provides a feasible reference for the study of the CPD knowledge diffusion mechanism and the prediction of CPD knowledge diffusion trend from the knowledge activities of micro individuals. Nevertheless, this paper fails to discuss the individual differences and the diffusion time delay in CPD knowledge diffusion. These issues are meaningful objects in further research.

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