Behavioral Selection Strategies of Members of Enterprise Community of Practice—An Evolutionary Game Theory Approach to the Knowledge Creation Process

DAN WANG AND BAIZHOU LI
School of Economics and Management, Harbin Engineering University, Harbin 150001, China
Corresponding author: Baizhou Li (baizhouliheu@126.com)

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ABSTRACT The development of a community of practice may play an important role in promoting knowledge creation and knowledge sharing economics. However, due to the nature of humanity, community members must cope with collaboration and conflicts in order to achieve knowledge creation in the community of practice. Based on the evolutionary game theory, this article analyzes and simulates the behavioral selection of community members in the knowledge creation process, in order to clarify how the selection strategies of community members evolves with time and related parameters, and to help us to further understand the game process and influencing factors. The results show that the consequences of a comprehensive game of community members are determined by the location of the saddle point, which will evolve to the evolutionary stable strategy. The closer the position of the saddle point is to the origin, the greater the probability that the community members will select the collaboration strategy. The probability of one member selecting a collaboration strategy will have an impact on the probability of another member selecting a collaboration strategy. Factors such as the coefficient of benefit distribution ($\alpha$), the cost of knowledge creation ($S$), and the additional benefit obtained by the conflicting member ($G$) have an impact on the evolution of the selection strategy of community members in the knowledge creation process.

INDEX TERMS Enterprise community of practice, collaboration, conflict, evolutionary game theory, knowledge creation.

I. INTRODUCTION

With the development of knowledge sharing economics, scholars have begun paying more attention to smart cities and communities of practice [1], [2]. The community of practice is increasingly defined as an informal and self-organizing network of members with different skills and experience in practice or in the professional field, and the members of the informal network are connected by the sharing of knowledge [3], to which knowledge resources are important [4]. In the informal type of learning process, the desired knowledge is often created during the execution of the learning process itself [5]. The community of practice encourages members to share knowledge, exchange ideas and present controversial issues [6], and their interactions can help to cultivate new knowledge, promote knowledge creation, and improve the level of innovation further [7]. However, with the development of the community of practice, there are more and more activities of knowledge creation that need to be completed by the community members. In the process of knowledge creation, there may be some knowledge blind spots that cannot solve the problem on their own. The community of practice provides members with a platform for collaborative innovation, members decide whether to collaborate by considering knowledge cost and benefit distribution [8]. At the same time, it is inevitable that there will be disputes and conflicts in the process of knowledge creation, which generates competition and makes it difficult.
to collaborate. A certain degree of conflict and competition will help promote knowledge creation in the community, but too much conflict and competition will hinder knowledge creation and the favorable development of the community of practice. Therefore, the issue of community members’ behavior selection in the process of community knowledge creation has gradually attracted the attention of scholars.

However, as the subject of knowledge creation of community of practice, the community members’ behavioral selection in the process of knowledge creation will have an important impact on knowledge creation in the community. That is, the essence of the process of selecting collaboration or conflict with the goal of knowledge creation is the game between community members.

Therefore, considering the dynamic behaviors of the community members in the knowledge creation process, it is necessary to use the method of evolutionary game theory to research the knowledge creation process of the community members. Consequently, by exploring the behavioral selection of community members in the knowledge creation process in depth and clarifying the variation of selection between community members over time and related parameters, we can understand the evolutionary game of strategy selection of community members in the knowledge creation process.

II. LITERATURE REVIEW

A. COMMUNITY OF PRACTICE

Since scholars pioneered research on the integration of members in the community of practice, the research on the community of practice has continued to develop, and more and more scholars recognize the important role of the community of practice in knowledge management [9].

Scholars have conducted research on how to effectively promote the knowledge sharing and knowledge flow in the community of practice in order to maximize the knowledge level of its members and whether the cultivation of a community of practice requires management [10]–[13]. Knowledge flow is the process of knowledge diffusion, knowledge transfer, knowledge sharing and related knowledge growth, which are generated by the interaction between different participants [14], [15]. Vidgen pointed out that the members of a community of practice are linked by learning and knowledge sharing, driven by development of member value and generated individual members’ learning, the desire to share knowledge and the development of common practice [10]. Regarding the cultivation and management of a community of practice, some scholars suggest that the community of practice needs careful planning [11], and some scholars believe that the community of practice cannot be deliberately enforced by a top-down approach, but rather must be generated by loose organizational relationships [12]. Through case studies, Watkins determined that a well-designed and well-funded community of practice can facilitate knowledge exchange to enhance individual, collective, and domain outcomes. Additionally, community of practice need time, money and leadership to function well, and they may trigger conflicts to challenge assumptions and habits of its members [13].

B. COLLABORATION AND CONFLICT

The interaction between collaboration and conflict is critical to the quality of decision-making in multiparty systems [16]. Members of a community of practice have a common interest in a problem and are willing to collaborate with others for a period of time [17], [18]. However, the conflict is a natural part of human interaction, it is a part of collaborative learning. Rogat pointed out that when conflicting interactions occur, they can be reflected in various interactions, such as overthrowing or destroying the opinions and expertise of others, or interactions emphasizing the knowledge of certain group members and sacrificing others’ knowledge [19]. Petru et al. exploited the complex dynamics of conflict and collaboration through realistic behavioral simulation and explored the positive effects of task conflicts on multiparty systems [20]. Scholars also use the evolutionary game method to analyze the collaboration and conflict strategies of innovation team members, but there is a lack of simulation analysis [21], [22].

Based on the summary and analysis of existing research, we can find that scholars focused on the related research of community of practice. They also concentrated on promoting the knowledge sharing and knowledge flow in the community of practice. The collaboration and conflict are also the research issue, but the research set as the community of practice is lacked. Generally, it is agreed that members of an enterprise community of practice face collaboration, conflicts and challenges in the knowledge creation process. That is, collaboration and conflict issues exist in the interactions of community members, even though the community of practice works well on the surface. However, there is a lack of research on how community members develop their behavioral selection strategies and how the influencing factors affect the behavioral selection strategies. Moreover, empirical research is adopted mostly, causing the results to have limitations at a certain point. The application of evolutionary game theory is limited, there is a lack of simulation analysis based on evolutionary game model.

Therefore, in the knowledge creation process of a community of practice, community members use evolutionary game theory to seek information and to better understand the strategic space of other members [8]. Through evolutionary game theory, we can research the collaboration and conflict between members of the community of practice, and provide theoretical support for further promoting the knowledge creation of community members.

III. METHOD

A. HYPOTHESIS AND VARIABLES

Under the premise of limited rationality, members of an enterprise community of practice are prone to collaborate or conflict in the knowledge creation process. The members of
a community of practice continue to select and adjust to the optimal strategy because it is difficult to find one optimal strategy for one time [23, 24].

Therefore, the behavioral selection strategies of members of an enterprise community of practice is a dynamic evolutionary process in accordance with the characteristics of the evolutionary game theory, and it is applicable to select the evolutionary game model as the research method. Moreover, any member of an enterprise community of practice may be confronted with the behavioral selection strategies of collaboration and conflict in the knowledge creation process. Thus, the evolutionary game model of behavioral selection strategies of members of an enterprise community of practice is replicable. According to the evolutionary game model and the analysis of the knowledge creation process of community of practice, we propose the assumptions as follows:

**Assumption 1:** The set of strategies for community member $i$ and member $j$ in the knowledge creation process are {collaboration, conflict}, and both of them have limited rationality. If the conflicts between the community members are within a certain range, they will select a collaboration strategy for knowledge creation. Otherwise, a conflict strategy will be selected, and each member will create knowledge to compete.

**Assumption 2:** Generally, the evolutionary game theory mainly involves benefit and the coefficient of benefit distribution, cost and the coefficient of cost allocation, loss and compensation [25]. According to the theoretical basis, related references and research experience, we make the following assumptions regarding benefit and coefficient of benefit distribution, cost and coefficient of cost allocation, loss and compensation [8], [21]. $G_1$ and $G_2$ represent the benefit obtained respectively by the community member $i$ and $j$ selecting a conflict strategy. $\Delta G$ represents the excess benefit obtained by the two members selecting a collaboration strategy, $\alpha$ is the coefficient of benefit distribution which is between 0 and 1. $G$ represents the additional benefit for the member selecting conflict when one member selects collaboration and the other selects a conflict strategy. $S$ is the required cost for knowledge creation, if both of two members select the cooperation strategy, they will allocate the cost and the coefficient of cost allocation is $\beta$. $\beta$ is between 0 and 1. If one of members selects conflict strategy or both them select conflict strategy, the two members pay the cost of knowledge creation respectively. $L$ is the loss suffered by one member selecting the collaboration strategy alone. $M$ is the compensation that the member selecting conflict strategy to the member selecting collaboration strategy when one of members selects collaboration strategy and the other member selects the conflict strategy.

**Assumption 3:** The strategy selection of community members is random, and the selection strategies of member $i$ and member $j$ are not determined in advance, but rather adjust according to the reaction of the other member during the evolutionary game. At the same time, it is also a process of multiple games. The probability of the community member

| Community Member $j$ | Collaboration | Conflict |
|----------------------|---------------|----------|
| $\text{Community}$ $i$ | $(G_1+\alpha \Delta G - \beta S) + (1-\alpha)(G_1 - L - S + M)$ | $(G_2 - G - S + M)$ |
| $\text{Collaboration}$ | $(G_1+\alpha \Delta G - \beta S)$ | $(G_2 - G - S + M)$ |
| $\text{Conflict}$ | $(G_1+\alpha \Delta G - \beta S)$ | $(G_2 - G - S + M)$ |

$\gamma$ selects the collaboration strategy is $x$, so the probability of selecting conflict strategy is $(1 - x)$, and $x$ is between 0 and 1. The probability of the community member $j$ selects collaboration strategy is $y$, so the probability of selecting conflict strategy is $(1 - y)$, and $y$ is between 0 and 1.

**B. EQUATION SOLVING**

Based on the assumptions and evolutionary game theory, the game payoff matrix of the knowledge creation process of an enterprise community of practice can be obtained as shown in Table 1 [26], [27].

According to relevant theories, literature and experts’ consultation results, as well as the comprehensive consideration of the variables and influencing factors that may be involved (because the real scenario of knowledge creation is so complex, there may be other influencing factors we did not take into account), we conduct a simulation analysis to show the complex behavioral selection strategy of community members in the knowledge creation process as much as possible. Compared with related literature [21], [28], it is remarkable that we believe each of members will pay the cost of knowledge creation ($S$) when both community members select conflict strategy and carry out knowledge creation independently.

(1) Based on the payoff matrix, we can calculate the expected benefit $U_{i1}$ and $U_{i2}$ if community member $i$ selects the collaboration and conflict strategy respectively:

$$U_{i1} = \gamma(G_1 + a \Delta G - \beta S) + (1 - \gamma)(G_1 - L - S + M) \quad (1)$$

$$U_{i2} = \gamma(G_1 + G - S - M) + (1 - \gamma)(G_1 - S) \quad (2)$$

Thus, the average expected benefit for selecting the collaboration and conflict strategy is $E(U_{i1})$.

$$E(U_{i1}) = xU_{i1} + (1 - x)U_{i2}$$

$$= xy(a \Delta G - \beta S + L - G + S) + x(M - L)$$

$$+ \gamma(G - M) + G1 - S \quad (3)$$

The dynamic replication equation of community member $i$ is as follows:

$$F_1(x) = \frac{dx}{dt} = x(U_{i} - E(U_{i1}))$$

$$= x(1 - x)[\gamma(a \Delta G - \beta S - G + S + L) + M - L] \quad (4)$$

That means the speed of the dynamic change of the probability of community $i$ selecting collaboration and conflict strategies.

(2) Similarly, based on the payoff matrix, we can calculate the expected benefit $U_{j1}$ and $U_{j2}$ if community member $j$
selects the collaboration and conflict strategy respectively:

\[
U_{ij} = x[G_2 + (1 - a)\Delta G - (1 - b)S] + (1 - x)(G_2 - L - S + M) \\
U_{j2} = x(G_2 + G - S - M) + (1 - x)(G_2 - S)
\]

(5) (6)

Thus, the average expected benefit for selecting the collaboration and conflict strategy is \( E(U_j) \).

\[
E(U_j) = yU_{j1} + (1 - y)U_{j2} \\
= xy[(1 - a)\Delta G + \beta S + L] + x(G - M) + y(M - L) + G_2 - S
\]

(7)

The second derivation to \( x \) is obtained as follows:

\[
g_1(x) = (1 - 2x)[y(1 - a)\Delta G - \beta S - G + S + L] + M - L
\]

and command \( g_1(x) < 0 \).

I. If \( y = (L - M)/(a\Delta G - \beta S - G + S + L) \), \( F_1(x) \) always equal to 0, then all values of \( x \) are stable, and the diagram of evolution phase is shown in Figure 1.

II. If \( y > (L - M)/(a\Delta G - \beta S - G + S + L) \), according to \( g_1(x) < 0 \), we can obtain \( x > 1/2 \), \( x = 1 \) is the evolutionary stabilization strategy, and the diagram of evolution phase is shown in Figure 2.

III. If \( y < (L - M)/(a\Delta G - \beta S - G + S + L) \), according to \( g_1(x) < 0 \), we can obtain \( x < 1/2 \), \( x = 0 \) is the evolutionary stabilization strategy, and the diagram of evolution phase is shown in Figure 3.

IV. RESULTS

A. STABILITY ANALYSIS

Learning from the reasoning process and the stability of game strategy [21], [30], the stability analysis of the game strategy of community members is as follows.

1) STABILITY OF GAME STRATEGY FOR COMMUNITY MEMBER I

If \( F_1(x) = 0 \), the following three stable points are available:

\[
x_1 = 0, \quad x_2 = 1, \quad x_3 = (L - M)/(a\Delta G - \beta S - G + S + L)
\]

The second derivation to \( x \) is obtained as follows:

\[
g_1(x) = (1 - 2x)[y(1 - a)\Delta G - \beta S - G + S + L] + M - L
\]

I. If \( y = (L - M)/(a\Delta G - \beta S - G + S + L) \), \( F_1(x) \) always equal to 0, then all values of \( x \) are stable, and the diagram of evolution phase is shown in Figure 1.

II. If \( y > (L - M)/(a\Delta G - \beta S - G + S + L) \), according to \( g_1(x) < 0 \), we can obtain \( x > 1/2 \), \( x = 1 \) is the evolutionary stabilization strategy, and the diagram of evolution phase is shown in Figure 2.

III. If \( y < (L - M)/(a\Delta G - \beta S - G + S + L) \), according to \( g_1(x) < 0 \), we can obtain \( x < 1/2 \), \( x = 0 \) is the evolutionary stabilization strategy, and the diagram of evolution phase is shown in Figure 3.

2) STABILITY OF GAME STRATEGY FOR COMMUNITY MEMBER J

If \( F_2(x) = 0 \), the following three stable points are available:

\[
y_{j1} = 0, \quad y_{j1} = 1, \quad y_{j3} = (L - M)/[(1 - a)\Delta G + \beta S + L - G)]
\]

The second derivation to \( y \) is obtained as follows:

\[
g_2(x) = (1 - 2y)[y(1 - a)\Delta G + \beta S + L - G)] + M - L
\]

I. If \( x = (L - M)/[(1 - a)\Delta G + \beta S + L - G)] \), \( F_2(x) \) always equal to 0, then all values of \( y \) are stable, and the diagram of evolution phase is shown in Figure 4.

II. If \( x > (L - M)/[(1 - a)\Delta G + \beta S + L - G)] \), according to \( g_2(x) < 0 \), we can obtain \( y > 1/2 \), \( y = 1 \) is the evolutionary stabilization strategy, and the diagram of evolution phase is shown in Figure 5.
FIGURE 5. Diagram of evolution phase when \( x > (L - M)/(1 - \alpha \Delta G + \beta S + L - G) \).

III. If \( x < (L - M)/(1 - \alpha \Delta G + \beta S + L - G) \), according to \( g_2(x) < 0 \), we can obtain \( y < 1/2 \). \( y = 0 \) is the evolutionary stabilization strategy, and the diagram of evolution phase is shown in Figure 6.

3) STABILITY ANALYSIS OF THE EVOLUTIONARY GAME MODEL
The local equilibrium points constitute the boundary of the evolutionary game strategies for member \( i \) and member \( j \) in an enterprise community of practice. We obtain the matrix Jocobi by calculating the partial derivative of dynamic replication equation with respect to \( x \) and \( y \). Further, we can obtain the determinant \( \text{Det}(J) \) and trace \( \text{Tr}(J) \) of the matrix, respectively:

\[
\text{Det}(J) = (1 - 2\alpha)(1 - 2\gamma)[y(\alpha \Delta G - \beta S + G + S + L) + M - L] \\
\quad \times [x((1 - \alpha)\Delta G + \beta S + L - G) + M - L] \\
\quad - xy(1 - x)(1 - y)(\alpha \Delta G - \beta S - G + S + L) \\
\quad \times [(1 - \alpha)\Delta G + \beta S + L - G] \tag{9}
\]

\[
\text{Tr}(J) = (1 - 2\alpha)[y(\alpha \Delta G - \beta S - G + S + L) + M - L] \\
\quad + (1 - 2\gamma)[x((1 - \alpha)\Delta G + \beta S + L - G) + M - L] \tag{10}
\]

Based on the \( \text{Det}(J) \) and \( \text{Tr}(J) \) of the matrix, we calculate and analyze the stability of each local equilibrium point as shown in Table 2 [25], [29].

The stability results \( \text{ESS} \) means evolutionary stable strategy, which reflects the stable state of the evolution of community members. That is, both community member \( i \) and \( j \) will select collaboration strategy or conflict strategy.

![FIGURE 6. Diagram of evolution phase when \( x < (L - M)/(1 - \alpha \Delta G + \beta S + L - G) \).](image)

![FIGURE 7. Dynamic evolution of game strategies of member \( i \) and \( j \).](image)

The saddle point is not the evolutionary stability of the whole game. Once the member of enterprise community of practice deviates from the saddle point and enters the lower left or the upper right part, the game will move towards the \( \text{ESS} \).

According to the analysis above, the game strategies of community member \( i \) and community member \( j \) in the knowledge creation process are shown in Figure 7:

The five points in Figure 7 are \( E(\alpha \Delta G - \beta S - G + S + L) \), \( O(0, 0) \), \( O_1(1, 0) \), \( O_2(0, 1) \), and \( O_3(1, 1) \). Point \( E \) and \( O_1 \), \( O_2 \), and \( O_3 \) divide the quadrilateral formed by \( O_0O_1O_2O_3 \) into four areas A, B, C and D. In area A and area B, the common result of the evolutionary game for community member \( i \) and community member \( j \) tends to point \( O(0, 0) \). In area C and area D, the common result of evolutionary game for community member \( i \) and community member \( j \) tends to point \( O_3(1, 1) \).

B. INFLUENCE OF PARAMETER VARIATION
1) KNOWLEDGE CREATION PROCESS FOR MEMBER I
A. If \( (L - M)/(\alpha \Delta G - \beta S - G + S + L) = 0 \), \( y \) always equal to 0, then all values of \( x \) are stable. That is, when the cost of knowledge creation is equal to the compensation of conflict party to collaboration party, member \( i \) of the enterprise community of practice has two options, one is to select collaboration strategy, and the other is to select conflict strategy.

B. If \( (L - M)/(\alpha \Delta G - \beta S - G + S + L) < 0 \), always exists \( y > (L - M)/(\alpha \Delta G - \beta S - G + S + L) \), then \( x = 1 \) is the evolutionary stabilization strategy. That is, when the probability of community member \( j \) selecting collaboration is greater than a certain value, the community member \( i \) will select the collaboration strategy.

C. If \( 0 < (L - M)/(\alpha \Delta G - \beta S - G + S + L) < 1 \), there are two situations as follows:

| Equilibrium Point | \( \text{Det}(J) \) | \( \text{Tr}(J) \) | Stability Results |
|-------------------|-----------------|-----------------|------------------|
| \((0, 0)\)        | +               | +               | \text{ESS}       |
| \((0, 1)\)        | +               | -               | Instability Point|
| \((1, 0)\)        | +               | -               | Instability Point|
| \((1, 1)\)        | -               | -               | Saddle Point     |

TABLE 2. Stability analysis of the game equilibrium points.
C1: If \( y > (L - M)/(a\Delta G - \beta S - G + S + L), x = 1 \) is the evolutionary stabilization strategy. That is, when the probability of community member \( j \) selecting collaboration is greater than a certain value, the community member \( i \) will select the collaboration strategy.

C2: If \( y < (L - M)/(a\Delta G - \beta S - G + S + L), x = 0 \) is the evolutionary stabilization strategy. That is, when the probability of community member \( j \) selecting collaboration is less than a certain value, the community member \( i \) will select the conflict strategy.

D. If \((L - M)/(a\Delta G - \beta S - G + S + L) \geq 1\), always exists \( y < (L - M)/(a\Delta G - \beta S - G + S + L), x = 0 \) is the evolutionary stabilization strategy. That is, when the probability of community member \( j \) selecting collaboration is less than a certain value, the community member \( i \) will select the conflict strategy.

2) KNOWLEDGE CREATION PROCESS FOR MEMBER J

A. If \((L - M)/[(1 - \alpha)\Delta G + \beta S + L - G)] = 0, x \text{ always equal to } 0, \text{ then all values of } y \text{ are stable. That is, when the cost of knowledge creation is equal to the compensation of conflict party to collaboration party, member } j \text{ has two options, one is to select the collaboration strategy, and the other is to select the conflict strategy.}

B. If \((L - M)/[(1 - \alpha)\Delta G + \beta S + L - G)] < 0, x \text{ always equal to } 0, \text{ then all values of } y \text{ are stable. That is, when the probability of community member } x \text{ selecting collaboration is greater than a certain value, community member } j \text{ will select the collaboration strategy.}

C. If \( 0 < (L - M)/[(1 - \alpha)\Delta G + \beta S + L - G)]) < 1, \text{ there are two situations as follows:}

\( C1: \text{If } x > (L - M)/[(1 - \alpha)\Delta G + \beta S + L - G)], y = 1 \text{ is the evolutionary stabilization strategy. That is, when the probability of community member } i \text{ selecting collaboration is greater than a certain value, community member } j \text{ will select the collaboration strategy.}

\( C2: \text{If } x < (L - M)/[(1 - \alpha)\Delta G + \beta S + L - G)], y = 0 \text{ is the evolutionary stabilization strategy. That is, when the probability of community member } i \text{ selecting collaboration is less than a certain value, community member } j \text{ will select the conflict strategy.}

D. If \((L - M)/[(1 - \alpha)\Delta G + \beta S + L - G)] \geq 1, \text{ always exists } x < (L - M)/[(1 - \alpha)\Delta G + \beta S + L - G)], y = 0 \text{ is the evolutionary stabilization strategy. That is, when the probability of community member } i \text{ selecting collaboration is less than a certain value, community member } j \text{ will select the conflict strategy.}

Thus, based on the analysis above, the area of the quadrilateral \( O_2EO_1O_3 \) is composed of the areas of A and B in Figure 7. The area of the quadrilateral \( O_2EO_1O \) can be expressed as follow:

\[
S_{O_2EO_1O} = 1/2[(L - M)/(a\Delta G - \beta S - G + S + L) + (L - M)/[(1 - \alpha)\Delta G + \beta S + L - G)]
\] (11)

If the probability of community member \( i \) and community member \( j \) is within the quadrilateral \( O_2EO_1O_3 \), both members \( i \) and \( j \) will tend to select conflict. If the probability of community member \( i \) and community member \( j \) is within the quadrilateral \( O_2EO_1O_3 \), both members \( i \) and \( j \) will tend to select collaboration.

Therefore, if \( S_{O_2EO_1O} > S_{O_2EO_1O_3} \), the process of the evolutionary game converges to the point \( O(0, 0) \). If \( S_{O_2EO_1O} > S_{O_2EO_1O_3} \), the process of the evolutionary game converges to the point \( O_3(1, 1) \). If \( S_{O_2EO_1O} = S_{O_2EO_1O_3} \), the probability equals that evolving to the point \( O \) and point \( O_3 \).

Thus, according to the research methods of previous scholars, we can utilize \( S_{O_2EO_1O_3} \) to analyze the influencing factors that affecting the collaboration strategies of community members [30], [31]:

\[
S_{O_2EO_1O_3} = 1 - 1/2[(L - M)/(a\Delta G - \beta S - G + S + L) + (L - M)/[(1 - \alpha)\Delta G + \beta S + L - G)]
\] (12)

Then, the factors affecting the quadrilateral \( O_2EO_1O_3 \) are: \( L \) (the loss suffered by one member selecting the cooperation strategy alone), \( M \) (the compensation that the member selecting conflict strategy to the member selecting collaboration strategy), \( \alpha \) (the coefficient of benefit distribution), \( \Delta G \) (the excess benefit obtained by the two members selecting collaboration strategy), \( \beta \) (the coefficient of cost allocation), \( S \) (the required cost for knowledge creation), \( G \) (the additional benefit for the member selecting conflict when one member selects collaboration and the other selects conflict strategy).

C. SIMULATION ANALYSIS

To understand the process of evolutionary game and the stability of strategy selection of community members in the knowledge creation process more clearly, we use numerical simulation and the Octave software to analyze the comprehensive situation of the game process of community members \( i \) and \( j \).

(1) The relevant parameters are set according to related references, experts’ opinions and reality as follows [28], [32]. \( \alpha = 0.3, \beta = 0.4, \Delta G = 15, G = 10, S = 9, L = 10, M = 8 \), and substitute the parameters into the replication dynamic equation of community member \( i \) and member \( j \). The evolution diagram of the probability of game strategies of community members \( i \) and \( j \) is shown in Figure 8. The coordinate axes \( x \) and \( y \) represent the probability of selecting a strategy of community members \( i \) and \( j \), respectively. Evolution curves with different colors represent the evolution curves at different probability levels. It can be clearly seen that the common result of the evolutionary game between community members \( i \) and \( j \) will tend to point \((0,0)\) and point \((1,1)\) in Figure 8, which is related to the probability of members’ selection strategies. The evolution diagram is also consistent with the game results of the community members in Figure 7 above.

Figure 9 shows the evolution of the community member \( i \) at different probability levels. Evolution curves with different colors represent the evolution curves of member \( i \) at different probability levels. According to the
relevant parameter assignment, we can obtain that \((L - M)/(\alpha \Delta G - \beta S - G + S + L) = 0.202\). When \(y = 0.6 > 0.202\), the evolution curve of the community member \(i\) is a cluster of curves that approach to the top right, and the probability of selecting the collaboration strategy will eventually approach 1. Also, the convergence speed gets faster as the probability of selecting collaboration strategy increases, which means the evolution curve evolves to the ideal stable point more rapidly. When \(y = 0.1 < 0.202\), the evolution curve of the community member \(i\) is a cluster of curves that tend to be closer to 0, and the probability of selecting the collaboration strategy will eventually approach 0. Also, the convergence speed gets faster as the probability of selecting the collaboration strategy decreases.

Similarly, Figure 10 shows the evolution of the community member \(j\) at different probability levels. Evolution curves with different colors represent the evolution curves of member \(j\) at different probability levels.

According to the relevant parameter assignment, we can obtain \((L - M)/[(1 - \alpha) \Delta G + \beta S + L - G] = 0.142\). When \(x = 0.5 > 0.142\), the evolution curve of the community member \(j\) is a cluster of curves that approach to the top right, and the probability of selecting the collaboration strategy will eventually approach 1, also the convergence speed gets faster as the probability of selecting collaboration strategy increases. When \(x = 0.1 < 0.142\), the evolution curve of the community member \(j\) is a cluster of curves that tends to be closer to 0, and the probability of selecting the collaboration strategy will eventually approach 0. Additionally, the convergence speed gets faster as the probability of selecting the collaboration strategy decreases.

(2) To show the evolution curves of different community members more clearly, the comprehensive evolution of community members \(i\) and \(j\) in Figures 9 and 10 is decomposed to Figure 11 to Figure 14. Figure 11 assumes that the probability of community member \(j\) selecting the collaboration strategy is 0.6. Evolution curves with different colors represent the evolution curves of member \(i\) at different probability levels. The probability of the member \(i\) selecting the collaboration strategy converges to 1, and the time decreases as the probability of community member \(j\) selecting the collaboration strategy increases. Also, we can see that when the probability of the member \(i\) selecting collaboration strategy is close to the threshold 0.142, the member \(i\) will select collaboration strategy.

Figure 12 assumes that the probability of community member \(j\) selecting the collaboration strategy is 0.1. Evolution curves with different colors represent the evolution curves of member \(i\) at different probability levels. In particular, it will converge to 0 when the probability of the community member \(i\) selecting the collaboration strategy is less than 0.3, and the time increases as the probability of community member \(i\) selecting the collaboration decreases.
FIGURE 12. Evolution of community member $i$ when $y = 0.1$.

FIGURE 13. Evolution of community member $j$ when $x = 0.5$.

And, when the probability of the member $i$ selecting collaboration strategy is close to the threshold 0.142, the member $i$ will select conflict strategy.

It will converge to 1 when the probability of selecting the collaboration strategy is greater than 0.3, and the time decreases as the probability of community member $i$ selecting the collaboration increases. Due to the behavioral selection strategies of community members is a dynamic evolutionary process, and the community members continue to select and adjust to optimal strategy. At the beginning, the probability of the member $j$ selecting collaboration strategy is 0.1 < 0.202, the member $i$ tends to select conflict strategy, so the curves go down a little bit first. However, as time goes by, the benefits of member $i$ selecting collaboration strategy will be better than selecting conflict strategy, so member $i$ tends to adjust and select collaboration strategy, and the curve converges to 1.

Figure 13 assumes that the probability of community member $i$ selecting the collaboration strategy is 0.5. Evolution curves with different colors represent the evolution curves of member $j$ at different probability levels.

The probability of member $j$ selecting the collaboration strategy converges to 1, and the time decreases as the probability of community member $i$ selecting the collaboration increases. Also, we can see that when the probability of the member $j$ selecting collaboration strategy is close to the threshold 0.202, the member $j$ will select collaboration strategy.

FIGURE 14. Evolution of community member $j$ when $x = 0.1$.

FIGURE 15. The probability of strategies selection with variation of $\alpha$.

Figure 14 assumes that the probability of community member $i$ selecting the collaboration strategy is 0.1. Evolution curves with different colors represent the evolution curves of member $j$ at different probability levels. In particular, it will converge to 0 when the probability of the community member $j$ selecting the collaboration strategy is less than 0.2, and the time increases as the probability that community member $j$ selecting the collaboration decreases. And, when the probability of the member $j$ selecting collaboration strategy is close to the threshold 0.202, the member $j$ will select conflict strategy.

It will converge to 1 when the probability of selecting the collaboration strategy is greater than 0.2, and the time decreases as the probability of community member $j$ selecting the collaboration increases. Similar to Figure 12, at the beginning, the probability of the member $i$ selecting collaboration strategy is 0.1 < 0.142, the member $j$ tends to select conflict strategy, so the curves go down a little bit first. However, as time goes by, the benefits of member $j$ selecting collaboration strategy will be better than selecting conflict strategy, so member $j$ tends to adjust and select collaboration strategy, and the curve converges to 1.

(3) The evolution of the variation of relevant parameters is as shown in Figure 15 to Figure 21.

In Figure 15, with the increase of the coefficient of benefit distribution $\alpha$, the speed of the community members tends to
stable point becomes faster and then slower. The coefficient of benefit distribution has a constraint on the evolution of both members. The higher the coefficient of benefit distribution $\alpha$, the more benefits will allocate for community member $i$ in the collaboration strategy, the more unfavorable it will be for the community member $j$ to select the collaboration strategy, so the community member $j$ will most likely select the conflict strategy and hinder the collaboration.

In Figure 16, with the increase of the cost of knowledge creation $S$, the speed of the community members tends to stable point becomes faster. Due to the increasing cost, the members select the collaboration strategy to share part of the cost, so the cost of knowledge creation $S$ will play a positive role in the evolution of community members.

In Figure 17, when the additional benefit of selecting conflict is low ($G = 9$ and $G = 10$) for the member, the final evolution of community members tends to 1, but with the increasing of additional benefit ($G = 13$ and $G = 15$), the community members will tend to select the conflict strategy more quickly. At this time, the stability of the collaboration strategy between two members is negatively correlated with the additional benefit obtained by the conflicting member. In addition, there is a certain degree of constraint that is an additional benefit to the behavior selection of community members.

In Figure 18, the stability of the collaboration strategy between two members is negatively correlated with the loss suffered by one member selecting the cooperation strategy alone. When the loss is low ($L = 6$, $L = 8$ and $L = 10$) for the member, the final evolution of community members tends to 1, but with the increasing of the loss ($L = 12$), the community members will tend to select the conflict strategy. That is, the loss has a restrictive effect on selecting collaboration strategy.

In Figure 19, the compensation $M$ plays a positive role in the evolution of community members. With the increase of the compensation that the member selecting conflict strategy to the member of selecting collaboration strategy, the speed of the community members tends to stable point becomes faster. That is, the compensation has a restrictive effect on selecting conflict strategy.

In Figure 20, the coefficient of cost allocation has a constraint on the evolution of community members. With the increase of the coefficient of cost allocation, the speed of the community members tends to stable point becomes slower. The higher the coefficient of cost allocation, the more cost
will be allocated to the community member $i$ in the collaboration strategy, and it will hinder the collaboration between community members.

In Figure 21, the excess benefit obtained by the two members selecting collaboration strategy also plays a positive role in the evolution of community members. With the increase of the excess benefit, the speed of the community members tends to stable point becomes faster.

**V. DISCUSSION**

**A. RESEARCH FINDINGS**

The results above demonstrate the following findings. First, the results of the comprehensive game of community members are determined by the position of saddle point $E$ in Figure 7. The closer the point $E$ is to the origin, the greater the probability that the community members will select the collaboration strategy. Second, the probability of one member selecting the collaboration strategy will have an impact on the probability of the other member selecting the collaboration strategy, which also proves the essence of the strategy selection of the game subject in the evolutionary game process [21], [25], [28]. When the probability of one member selecting the collaboration strategy is greater than a certain value, the probability of the other member selecting the collaboration strategy will eventually approach 1, and the convergence speed will get faster and faster with the increasing of the probability of selecting the collaboration strategy. When the probability of one member selecting the collaboration strategy is less than a certain value, the probability of the other member selecting the collaboration strategy will eventually approach 0, and the convergence speed will get faster and faster with the decreasing of probability of selecting the collaboration strategy.

Third, factors such as the coefficient of benefit distribution, the cost of knowledge creation, and the additional benefit obtained by the conflicting member have an impact on the evolution of the knowledge creation process of community members. The high coefficient of benefit distribution and cost allocation will hinder the collaboration strategy. The high cost of knowledge creation, the high compensation and the excess benefit will have positive impacts on collaboration. However, it may hinder collaboration behavior as the additional benefit obtained by the conflicting member increases, and the loss suffered by one member selecting the cooperation strategy alone has the negative effect on the evolution of community members. The findings support that conflicts are unavoidable but can be effectively controlled by adjusting and controlling related parameters [20], [21].

**B. IMPLICATION SUGGESTIONS**

The results provide some suggestions to the development of an enterprise community of practice in the knowledge creation process. First, controlling the probability of the community members selecting the collaboration strategy to maintain the mutual selection of collaboration strategy. The probability of the collaboration strategy selection of one community member has an influence on the strategy selection of the other member. Controlling the parameters related to the game behavior of community members can promote the selection of collaboration strategy of both members and achieve stability in the selection strategy game.

Second, it is beneficial to control the occurrence of conflicting strategy by adjusting the coefficient of benefit distribution and cost allocation, the cost of knowledge creation, the compensation and the excess benefit. Also, we should control the additional benefit of conflicting members and the loss suffered by collaboration members. The coefficient of benefit distribution and cost allocation should be balanced between the community members. One member could select the conflict strategy and hinder collaboration if a large deviation occurs. The additional benefit obtained by a conflict member could by controlled by increasing their compensation or by establishing a compensation mechanism to guide the community members to select collaboration strategy. The low threshold of the cultivation of a community of practice reduces the cost of knowledge creation to a certain extent and leads members to select the conflict strategy, further hindering collaboration. The cultivation of a community of practice should be strictly reviewed, and the community of practice with knowledge creation potential can be screened through an effective competition mechanism to improve its entry threshold and promote the collaborative behavior of community members.

Third, we must create a favorable atmosphere of collaboration and trust in community of practice. The original intention of the community of practice is to realize knowledge creation through collaboration and sharing between community members. To alleviate conflicts and challenges between community members, enterprises should create a favorable atmosphere of knowledge sharing and trust for the development of community, enable community members to share their expertise to the greatest extent, and achieve the goals of knowledge creation within the community of practice through knowledge collaboration.

**C. LIMITATIONS AND FUTURE RESEARCH**

There are still several limitations in the research. First, the empirical data of the knowledge creation process in community of practice is difficult to obtain; this article adopts only a numerical simulation analysis to research and analyze.
the evolutionary game process of collaboration and conflict strategies selection of community members in the knowledge creation process. However, in order to make the theoretical and numerical simulation analysis match real-world scenarios to the greatest extent, we analyze the applicability of the evolutionary game theory, and collect a great deal of literature and consult experts in the field of enterprise community of practice. Ultimately, the relevant parameters are set according to related references, experts’ opinions and reality situations. Second, the factors affecting the behavior selection of community members in the knowledge creation process are not limited to the coefficient of benefit distribution, the cost of knowledge creation, and the additional benefit obtained by the conflicting member, so we will improve the research further in the follow-up study.

VI. CONCLUSION

Based on knowledge collaboration and evolutionary game theory, we adopt the method of evolutionary game to analyze and numerically simulate the knowledge creation process of community members. Through exploration of the behavioral selection strategies of community members in the knowledge creation process in depth, the evolutionary game of community members’ strategies selection varying with time and related parameters are clear to understand, and we further clarify the influencing factors of different community members in the knowledge creation process.

The research makes some contribution to future research in knowledge creation and knowledge management. First, the cultivation of a community of practice is essential for knowledge management. The paper provides new research ideas and a theoretical framework for the knowledge creation and knowledge management of an enterprise community of practice. Second, the paper effectively makes up for the existing lack of research on the collaboration and conflict between community members in the knowledge creation process. Third, graphically using the simulation analysis method to show the evolutionary game process and the influence of the parameter variation for better understanding also provides, to a certain extent, a research method for knowledge management research.

The significance of the research for knowledge creation and knowledge management is as follows. The research provides a theoretical basis and foundation for the knowledge creation and knowledge management of community of practice, and it provides valuable suggestions for cultivating and developing the enterprise community of practice, which, in a sense, promotes the development of knowledge management. Based on the research results, members of an enterprise community of practice can better understand each other’s behavioral selection strategies and clarify the influencing factors that affect evolutionary game of behavioral selection strategies. Thus, a community of practice can adjust and control the relevant parameters to control its conflicts effectively in order to make the knowledge creation process proceed smoothly.

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**DAN WANG** is currently pursuing the Ph.D. degree with the School of Economics and Management, Harbin Engineering University, Harbin, China. During her studies, she has participated in research work with projects and has participated in conferences actively in China. Her research interests include knowledge management and innovation management.

**BAIZHOU LI** received the Ph.D. degree from the School of Economics and Management, Harbin Engineering University, Harbin, China, in 2004. He is currently a Professor and a Ph.D. Supervisor with the School of Economics and Management, Harbin Engineering University. He has presided over ten national and provincial research projects, and published more than 200 academic articles in journals. His research interests include regional innovation, technological innovation, and original innovation.

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