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Knowledge Sharing in R&D Teams: An Evolutionary Game Model

Jiuling Xiao [1], Yuting Bao [1], Jiankang Wang [2], Haiyun Yu [3], Zhenzhong Ma [1,4] and Lei Jing [5,*]

[1] School of Business, Nanjing Audit University, Nanjing 211815, China; xjl@nau.edu.cn (J.X.); mg1903009@stu.nau.edu.cn (Y.B.); maz@uwindsor.ca (Z.M.)
[2] School of Public Administration, Nanjing Audit University, Nanjing 211815, China; jiangkangyaya@nau.edu.cn
[3] School of Business, Jiangnan University, Wuxi 214122, China; yuhaiyun88@126.com
[4] Odette School of Business, University of Windsor, Windsor, ON N9B 3P4, Canada
[5] School of Marxism Studies, Faculty of Social Sciences, Jilin University, Changchun 130012, China
* Correspondence: jingl669@jlu.edu.cn

Abstract: Knowledge sharing plays an important role in promoting innovation and helping improve R&D team performance in the digital age. Based on the evolutionary game theory, this study develops an evolutionary game model of knowledge sharing in R&D teams in order to explore its system evolution path, the evolutionary stability strategy, and the influencing mechanism in knowledge sharing. Then using a simulation model, this study examines the dynamic evolution process of knowledge sharing within R&D teams. The results show that the effectiveness of knowledge sharing in the R&D teams can be promoted by R&D team members' cognitive ability, knowledge absorption ability, knowledge transformation ability, knowledge innovation ability, and the degree of knowledge complementarity within teams. The simulation results further show that reducing the environmental risk can also effectively improve R&D teams' innovation performance. The findings of this study thus provide evidence for knowledge sharing as an important route to sustainable development.

Keywords: evolutionary gaming theory; innovation performance; knowledge sharing; R&D team; simulation

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1. Introduction

Knowledge has become one of the most important driving forces of sustainable development in the era of the knowledge economy [1–4]. Firms have gradually recognized the importance of knowledge and innovation in obtaining sustainable competitive advantages [5–8]. Along with more multinational firms from newly industrialized economies joining the increasingly interconnected global market, the interfirm competition has become even more fierce and only those firms that can continuously create, transmit, and absorb new knowledge to innovate are able to succeed in the turbulent environment in the digital age [9–11]. It is thus essential for firms to improve knowledge sharing effectiveness in order to tackle the challenges brought by domestic and international competitors. In the process of obtaining heterogeneous knowledge, more firms have realized the importance of knowledge and knowledge management. The primary goal of knowledge management is to maximize the use of limited resources to achieve sustainable growth, and organizations need to guide employees to share individual knowledge and experience with each other, and then integrate and save them as collective knowledge resources, so that employees' cognition and insights can be effectively applied by others [12]. As the core element of knowledge management, knowledge sharing is the way by which firms apply and innovate knowledge, and ultimately form dynamic competitiveness [13]. For a firm to fully benefit from knowledge, individual knowledge needs to be continuously shared, learned, and transformed into team knowledge or organizational knowledge, so as to facilitate the ultimate realization of organizational goals [14,15]. Knowledge sharing between individual employees, teams, or organizations helps to develop and utilize resources, and helps reduce production costs and increase team performance.

Past research on knowledge sharing has largely focused on the characteristics of sharing parties, shared knowledge, environment, and the levels at which knowledge is shared (individuals, teams, organizations, etc.), and thus most knowledge-sharing research is limited to a static perspective. However, knowledge sharing is actually a dynamic process, and the strategic behaviors of sharing parties are interactive [16–21]. The realization of sharing behavior and the achievement of shared goals require sharing parties to work together. While obtaining benefits, the involved parties also pay costs and assume certain risks. This often leads to a sharing dilemma, i.e., sharing personal insights with coworkers may carry a cost for the sharing individuals which consequently leads, at the aggregate level, a co-operation dilemma, similar to a public-good dilemma [22]. As a result, knowledge sharing is by nature a gaming scenario, a calculated, dynamic, give-and-take process. The evolutionary game theory is the emerging theory developed from the traditional game theory that combines game theory analysis with a dynamic evolution process in order to develop a more holistic understanding of a dynamic interaction process. Therefore, the evolutionary game theory provides an appropriate perspective to understand the dynamic knowledge-sharing process within R&D teams.

In modern organizations, especially in knowledge-intensive firms, R&D teams are an important carrier for firms to carry out technological innovation. Their task is to integrate different pieces of internal knowledge and use them to achieve R&D goals. The research and development of new technologies, products, and processes all require a lot of knowledge, which makes knowledge sharing in R&D teams essential. Although the specialization of R&D personnel is conducive to the development of complex products, the decentralized distribution of knowledge among R&D team members also creates the need for effective knowledge sharing [16]. In addition, the complexity of the modern R&D process has also led to high task interdependence, but it is not possible for individuals to master all the knowledge required for these interdisciplinary tasks [17]. Therefore, knowledge sharing is again essential for all members of R&D teams, yet research on knowledge sharing specifically designed for R&D teams seems to be relatively fragmented. Although the pivotal role of knowledge and learning of new knowledge has been established by extant literature at both the organization and team level [23,24]), relatively little research has been conducted to examine the role of knowledge sharing on individuals that constitute the R&D teams, i.e., R&D team members [25]. Consequently, we know relatively little about the dynamic knowledge-sharing process and its effect on various aspects of R&D team members [25].

Based on knowledge-sharing research and the evolutionary game analysis, this study is intended to explore the evolution path of knowledge sharing among R&D team members at the individual level in order to help bridge the research gap as discussed in the last section. First of all, based on previous studies, this study examines the key factors that affect knowledge-sharing behaviors within R&D teams, and then refines and defines the factors that are essential to knowledge sharing, including potential income/benefits from knowledge sharing, cognitive ability, knowledge absorption capacity, knowledge transformation ability, knowledge complementarity, knowledge innovation ability, environmental risk, and team members' risk preference. Using the game profit matrix of knowledge sharing as the criterion variable, an evolutionary game model of knowledge-sharing behaviors in R&D teams is established. Based on the dynamic equation of the replicator, we then determine the evolution path of knowledge-sharing behaviors in R&D teams. Finally, the impact of different factors on the evolution path is simulated for their potential influences on knowledge sharing in R&D teams.

The remainder of this paper is organized as follows. Section 2 reviews related literature on knowledge sharing and its affecting factors. Section 3 constructs an evolutionary game model of knowledge-sharing behavior among R&D team members to analyze the stability of the model based on the Jacobian matrix, the replication dynamic phase diagram, and the sensitivity of the model parameters. Section 4 conducts a simulation study on the evolutionary game model to validate our predictions. Section 5 provides conclusions and management implications.

2. Literature Review

2.1. Knowledge Sharing

Knowledge sharing among R&D team members is a process to develop and utilize knowledge resources and promote team R&D performance. Members of R&D teams with heterogeneous characteristics in terms of knowledge, skills, professional experience, and work experience can stimulate creative solutions, thereby effectively increasing the depth and breadth of knowledge sharing [18]. Team rewards and profit sharing can also promote the exchange and creation of internal knowledge among team members [19]. However, there are certain risks associated with sharing knowledge. If team members share too much key knowledge, they may worry that their unique contribution to the organization will be reduced and thus lose their power position in the team. In addition, if some knowledge is improperly handled by other members, the losses suffered by them are immeasurable [20]. This is particularly true for R&D personnel because most of them have tacit knowledge, and its characteristics such as vagueness, stickiness, and implicitness will increase the hindrance to effective knowledge sharing [21].

Knowledge exists at different levels within an organization and is shared spontaneously in various environments [26]. Knowledge management requires companies to manage organizational knowledge as corporate assets and make full use of knowledge creation and knowledge sharing as key organizational capabilities [27]. Since Nonaka proposed the concept of knowledge sharing in 1991, academics and industry have paid increasing attention to the research and management of knowledge sharing among individuals, teams, organizations, and cross-organizations. Davenport and Prusak [28] defined knowledge sharing as a voluntary behavior. They defined knowledge sharing as the conscious exchange of knowledge by individuals, not involving routine or structured information exchange. Wang [13] believed that knowledge sharing refers to providing task information and skills, helping others and cooperating with others to solve problems, and developing new ideas and implementing policies or procedures. Bartol and Srivastava [9] defined knowledge sharing as the sharing of information, ideas, suggestions and expertise related to the organization between individuals. Ipe [15] argued that knowledge sharing between individuals refers to the process by which individuals transform their knowledge into a form that other individuals can understand, absorb, and use. Huang et al. [29] divided knowledge sharing into tacit knowledge sharing and explicit knowledge sharing. The process of tacit knowledge sharing includes the process of team members sharing personal experience, elaborating background knowledge and professional knowledge, and the characteristics of explicit knowledge sharing are that team members exchange ideas and knowledge in coded form. These studies show that while knowledge sharing has been examined from different perspectives and thus their definitions of knowledge sharing are different, but there are some key elements in common: the type of knowledge shared, the method or channel, and the level wherein the knowledge is shared (individual, team and organization) [30]. Individual knowledge needs to be transferred into team knowledge and then organization knowledge through various methods so as to promote the realization of organizational goals [15].

Knowledge sharing has a wide range of influencing factors. Many scholars have examined the behavior and process of knowledge sharing around social psychology, organizational and team characteristics, knowledge characteristics, motivation elements, and cultural characteristics [6,13]. A variety of studies have suggested improving organizational culture and atmosphere, management support, rewards and incentives, team diversity, social networks, knowledge of intellectual property, perceived benefits and costs, interpersonal trust and justice, individual attitudes, and others in order to help improve knowledge sharing effectiveness [3,6]. For example, Masa'deh [31] believed that creating an atmosphere of mutual trust, openness, and sharing is a key success factor in creating a knowledge-sharing environment. Transformational leadership and transactional leadership also have an important ability to promote the knowledge-sharing process within an organization [7]. Cabrera and Cabrera [22] proposed that the establishment of a good incentive system and the improvement of employees' self-efficacy are powerful measures to promote knowledge-sharing behaviors. Staples and Webster [32] found that for teams of different structures (local, mixed and distributed), there is a strong positive correlation between trust and knowledge sharing. However, when the degree of task interdependence is low, this relationship is stronger. That is, trust plays a stronger role in a weakly structured team. Liu and Liu [33] argued that individual self-efficacy perception can effectively promote knowledge sharing among R&D personnel. The research results of Akhavan and Mahdi [34] showed that social interaction relationships (structural capital factors), trust, reciprocity, and team identity (relationship capital factors) are significantly related to the willingness to share knowledge, and the willingness to share knowledge is further significantly related to knowledge-sharing behavior (collecting knowledge and donating knowledge). Wu [35] proposed that when employees are more satisfied with their knowledge-sharing environment, more knowledge-sharing behaviors will occur, and when the main driving force of knowledge sharing is economic (external motivation), employees may be more reluctant to share their knowledge.

2.2. Knowledge Sharing as an Evolutionary Game

Evolutionary game theory is a theory developed from the traditional game theory by combining game theory analysis with the dynamic evolution process. It is the application of traditional game theory to the dynamic process in evolving populations [36]. The traditional game theory emphasizes a static equilibrium or a comparatively static equilibrium of participants with an assumption that all participants are completely rational. In the process of decision-making, all participants can make rational judgments and decisions because they can obtain complete information. However, due to the complexity of an economic system or a society, no individual can be completely rational, let alone the assumption that every individual can remain completely rational and make perfect decisions at all times [37]. In other words, the traditional game theory has its own challenges in dealing with social interaction processes, the dynamic processes. During these processes, participants could change, and the purpose of their interactions could also change. These changes can affect the whole system, thereby changing the results and direction of the game. The evolutionary game perspective, however, combines the traditional game theory with the dynamic evolving process and thus can better explain the process of knowledge sharing among R&D team members thanks to its integration of traditional game theory with the evolution process.

Within the R&D teams and with common group performance goals, R&D personnel work together with each other to form a dynamic group. In the process of knowledge sharing, every team member has a dynamic cooperative and also competitive relationship with each other. Because of the limited rationality of participating individuals in such teams, the process of knowledge sharing tends to be a slow evolution process. In other words, knowledge sharing is a dynamic evolutionary game, and it should be analyzed with a dynamic evolutionary model, rather than a static approach. In this gaming process, the knowledge obtained by each participant is limited. Participants constantly adjust and improve their own future interests according to the obtained benefits, and constantly pursue a more satisfactory state in order to achieve a state of equilibrium. In this balanced state of equilibrium, if the opponents do not change their strategies, no individual will unilaterally adjust their strategy. The strategy at this time is called an evolutionarily stable strategy.

Literature on knowledge sharing has begun to adopt the game theory to explore the dynamic interaction process and influencing factors of knowledge sharing. For example, Chua [38] used the framework of multiplayer game theory to investigate the dynamic process of knowledge sharing. He found that the tendency of individual knowledge sharing is driven by a series of situational concerns and interests, and the choice of knowledge-sharing/retention strategy depends on the level of perceived rewards. Shih et al. [39] also studied the interactive behavior of knowledge sharing among high-tech employees in combination with the evolutionary game theory, and found that factors such as commitment, trust, reciprocity, and long-term relationships can drive employees to adopt sharing and cooperative behaviors. In addition, the introduction of agency competition and reward mechanisms can solve the "free-riding" phenomenon that is prone to collective cooperation. Bandyopadhyay and Pathak [40] used the evolutionary game analysis to analyze the interaction between the employees of the "host" company and the outsourcing company. Their results showed that when the degree of knowledge complementarity between employees is high, employees are more likely to engage in cooperative behaviors. Liu et al. [41] also applied the evolutionary game analysis to analyze the knowledge-sharing mechanism between firms in supply chain collaborative innovation, and they decomposed it into two stages of knowledge mining and knowledge transfer. Their results showed that mutual trust, property rights protection, and corporate culture integration can promote knowledge-sharing behaviors. In a similar study, Du et al. [42] pointed out that the factors that affect team knowledge sharing include knowledge stock, knowledge ratio, knowledge absorption coefficient, synergy coefficient, and knowledge-sharing cost.

However, while current research has adopted the game theory or even an evolutionary perspective to explore the process of knowledge sharing, it has largely focused on the macro level, i.e., firms or organizations and insufficient attention has been paid to the knowledge-sharing process at the individual level [43]. Research at the individual level within R&D teams is relatively rare. Given that the nature of the team environment and the level of analysis can affect the evolutionary results with different evolution paths and evolutionary stability strategies, it is essential to explore what affects knowledge-sharing behaviors within R&D teams when treating the knowledge-sharing process as a dynamic evolutionary game. Therefore, this study draws on contemporary research on the application of evolutionary game methods to knowledge sharing to develop an evolutionary model to explore knowledge sharing in R&D teams and then uses simulation to conduct an in-depth analysis of the knowledge-sharing process among R&D team members in order to better understand what facilitates knowledge sharing in R&D teams.

3. Construction and Analysis of an Evolutionary Game Model

3.1. Variable Definition and Model Assumptions

Based on the existing research on knowledge sharing, this study focuses on the basic characteristics of R&D teams and selects a few key variables identified in the previous studies, including cognitive ability, absorptive ability, and transformation ability into the game model analysis. As in other studies, the following variables are defined:

$\pi_i(i = A, B)$ is selected as the symbol of the regular or normal income/benefits obtained when participants do not engage in knowledge sharing.

$\alpha_i(i = A, B)$ denotes cognitive ability, which refers to the knowledge level of participants. The higher the level of knowledge, the stronger the cognitive ability.

$\beta_i(i = A, B)$ represents knowledge absorption capacity, which refers to the ability of participants to recognize and digest the value of knowledge. The stronger the absorptive capacity, the higher the income/benefits generated.

$\lambda_i(i = A, B)$ denotes knowledge transformation ability, which refers to the ability of participants to transform knowledge. Participants acquire knowledge shared by different groups and transform it into their own knowledge.

$\gamma_{ij}(i, j = A, B)$ refers to the degree of knowledge complementarity. The complementary knowledge structure is the inherent attribute of knowledge. Different groups in the R&D team have different knowledge and skills. γ_{ij} indicates the extent to which the knowledge of a participant (i) complements the knowledge of another participant (j).

$\mu_i(i = A, B)$ is the variable to denote a participant's knowledge innovation ability to merge acquired knowledge with their own inherent knowledge and form new knowledge after obtaining shared knowledge.

$\omega_i(i = A, B)$ is the symbol of the risk coefficient, which refers to the risks that participants need to bear at the time of sharing knowledge. For example, after the member's own knowledge is shared, their own knowledge-power will be reduced accordingly.

$\varepsilon_i(i = A, B)$ represents the degree of risk preference, which refers to a participant's attitude towards risky situations.

In addition, in order to better reveal the knowledge-sharing behaviors and the process of knowledge sharing among R&D team members, this study has the following assumptions in model construction:

Assumption 1. *R&D team members are divided into two groups according to any proportion, group A and group B (hereinafter referred to as A and B). These two groups play a strategic game of knowledge sharing.*

Assumption 2. *A and B belong to the same R&D team and share the same R&D goals. Members have a certain degree of trust with each other, and the breadth and depth of their knowledge are higher than that of general teams in the organization. There is no opportunism and fraud in the R&D teams.*

Assumption 3. *Both A and B have bounded rationality. The strategy set of both parties when they play the game is {knowledge sharing, knowledge retention}. Simultaneously, the strategies of both parties affect each other, that is, each other will predict and then adjust their own strategies based on each other's strategic choices.*

Assumption 4. *A and B have to actively participate in knowledge sharing in order to complete R&D tasks, so that complementary knowledge can be transferred within the R&D team and can be effectively absorbed and used by the other party, thereby promoting knowledge creation and improving team R&D performance. The degree of knowledge creation and R&D performance improvement will be affected by factors such as R&D members' cognitive ability (α_i), knowledge absorption ability (β_i) and knowledge transformation ability (λ_i).*

Assumption 5. *When A and B engage in the knowledge-sharing game, the goal is to maximize their own incomes/benefits. The income is composed of four parts: normal income, direct income, synergistic income, and payment cost. The final income is equal to the normal income plus the direct income plus the synergetic income minus the cost of payment.*

In the process of knowledge sharing, one group will acquire and absorb the knowledge of another group, and bring direct income to itself, which can be expressed as $\lambda_i \alpha_j \beta_i (i, j = a, b)$. In addition, the knowledge complementarity and synergy between A and B will create new knowledge value, that is, the income generated by the innovation and synergy of knowledge. The synergy income of i generated by knowledge sharing can be expressed as $\mu_i \alpha_j \gamma_{ji} (i, j = a, b)$.

Due to the complexity of knowledge and the uncertainty existing in R&D tasks, R&D members may encounter certain risks in the process of knowledge sharing, which will directly translate into the costs paid by both parties in the game. The cost can be expressed as $\omega_i \varepsilon_i \alpha_i (i = a, b)$.

When all members of groups A and B adopt the knowledge-sharing strategy, the incomes of both parties will be $\pi_a + \lambda_a \alpha_b \beta_a + \mu_a \alpha_b \gamma_{ba} - \omega_a \varepsilon_a \alpha_a$ and $\pi_b + \lambda_b \alpha_a \beta_b + \mu_b \alpha_a \gamma_{ab} - \omega_b \varepsilon_b \alpha_b$. If all R&D members in group A and B take the knowledge-retention strategy, both parties will only obtain the normal income $\pi_i (i = a, b)$ for completing the R&D task. If one party chooses a knowledge-sharing strategy and the other chooses a knowledge-retention strategy, the incomes of the two parties will be $\pi_i - \omega_i \varepsilon_i \alpha_i$ and $\pi_j (i, j = a, b)$, respectively.

3.2. Model Establishment and Solution

Assuming that the proportion of members who take the strategy of knowledge sharing in group A is x, then the proportion of members who take the knowledge-retention strategy is 1–x. Similarly, y represents the proportion of the members who are willing to share knowledge in group B, while 1y represents the proportion of the members who choose to retain knowledge in group B. Combining the above assumptions and variable definitions, the income matrix of the two players is shown in Table 1.

Table 1. Income matrix.

A \ B	**Knowledge Sharing** y	**Knowledge Retention** $1-y$
Knowledge Sharing x	$\pi_a + \lambda_a\alpha_b\beta_a + \mu_a\alpha_b\gamma_{ba} - \omega_a\varepsilon_a\alpha_a$ $\pi_b + \lambda_b\alpha_a\beta_b + \mu_b\alpha_a\gamma_{ab} - \omega_b\varepsilon_b\alpha_b$	$\pi_a - \omega_a\varepsilon_a\alpha_a$ π_b
Knowledge retention $1-x$	π_a $\pi_b - \omega_b\varepsilon_b\alpha_b$	π_a π_b

For group A, let ${T_a}^1$ and ${T_a}^2$ be the incomes of group A when all members of Group A take the two different strategies (i.e., knowledge sharing or knowledge retention). According to Table 1, ${T_a}^1$ and ${T_a}^2$ are as follows.

$${T_a}^1 = \pi_a + y(\lambda_a\alpha_b\beta_a + \mu_a\alpha_b\gamma_{ba}) - \omega_a\varepsilon_a\alpha_a \tag{1}$$

$${T_a}^2 = y\pi_a + (1-y)\pi_a = \pi_a \tag{2}$$

The average income of group A (T_a) can be defined as follows.

$$\overline{T}_a = x{T_a}^1 + (1-x){T_a}^2 = \pi_a + x(y\lambda_a\alpha_b\beta_a + y\mu_a\alpha_b\gamma_{ba} - \omega_a\varepsilon_a\alpha_a) \tag{3}$$

Similarly, the average income of group B (T_b) can be defined as follows.

$$\overline{T}_b = y{T_b}^1 + (1-y){T_b}^2 = \pi_b + y(x\lambda_b\alpha_a\beta_b + x\mu_b\alpha_a\gamma_{ab} - \omega_b\varepsilon_b\alpha_b) \tag{4}$$

Then we construct replicator dynamic equations for group A and group B:

$$\frac{dx}{dt} = x\left({T_a}^1 - T_a\right) = x(1-x)(y\lambda_a\alpha_b\beta_a + y\mu_a\alpha_b\gamma_{ba} - \omega_a\varepsilon_a\alpha_a) \tag{5}$$

$$\frac{dy}{dt} = y\left({T_b}^1 - T_b\right) = y(1-y)(x\lambda_b\alpha_a\beta_b + x\mu_b\alpha_a\gamma_{ab} - \omega_b\varepsilon_b\alpha_b) \tag{6}$$

This study first analyzes the dynamic equation of group A. When $x^* = 0, x^* = 1$ or $y^* = \frac{\omega_a\varepsilon_a\alpha_a}{\lambda_a\alpha_b\beta_a + \mu_a\alpha_b\gamma_{ba}}$, the percentage of R&D team members who take the knowledge-sharing strategy in group A is stable. Similarly, when $y^* = 0, y^* = 1$ or $x^* = \frac{\omega_b\varepsilon_b\alpha_b}{\lambda_b\alpha_a\beta_b + \mu_b\alpha_a\gamma_{ab}}$, the proportion of R&D team members who take the knowledge-sharing strategy in group B is stable.

Therefore, we can get the local equilibrium points of the dynamic system:

$$(0,0), (0,1), (1,0), (1,1), \left(\frac{\omega_b\varepsilon_b\alpha_b}{\lambda_b\alpha_a\beta_b + \mu_b\alpha_a\gamma_{ab}}, \frac{\omega_a\varepsilon_a\alpha_a}{\lambda_a\alpha_b\beta_a + \mu_a\alpha_b\gamma_{ba}}\right) \tag{7}$$

The Jacobian matrix J is calculated by copying dynamic equations of A and B:

$$\begin{bmatrix} (1-2x)(y\lambda_a\alpha_b\beta_a + y\mu_a\alpha_b\gamma_{ba} - \omega_a\varepsilon_a\alpha_a) & x(1-x)(\lambda_a\alpha_b\beta_a + \mu_a\alpha_b\gamma_{ba}) \\ y(1-y)(\lambda_b\alpha_a\beta_b + \mu_b\alpha_a\gamma_{ab}) & (1-2y)(x\lambda_b\alpha_a\beta_b + x\mu_b\alpha_a\gamma_{ab} - \omega_b\varepsilon_b\alpha_b) \end{bmatrix} \tag{8}$$

As described above, the system has 5 local stable points. The stability analysis is performed according to the local stability analysis method of the Jacobian matrix [44]. The results are shown in Table 2.

Table 2. Local stability analysis of evolutionary game systems.

Equilibrium Point	detJ	trJ	Stability
(0,0)	+	−	ESS
(0,1)	+	+	Unstable
(1,0)	+	+	Unstable
(1,1)	+	−	ESS
(x*, y*)	−	0	Saddle point

Note: (x*,y*) = $\left(\frac{\omega_b\varepsilon_b\alpha_b}{\lambda_b\alpha_a\beta_b+\mu_b\alpha_a\gamma_{ab}}, \frac{\omega_a\varepsilon_a\alpha_a}{\lambda_a\alpha_b\beta_a+\mu_a\alpha_b\gamma_{ba}}\right)$.

When $\lambda_b\alpha_a\beta_b + \mu_b\alpha_a\gamma_{ab} - \omega_b\varepsilon_b\alpha_b > 0$, $\lambda_a\alpha_b\beta_a + \mu_a\alpha_b\gamma_{ba} - \omega_a\varepsilon_a\alpha_a > 0$, and $\omega_b\varepsilon_b\alpha_b > 0$, $\omega_a\varepsilon_a\alpha_a > 0$, only two of the five local equilibrium points have local stability, which are (0,0) and (1,1). The corresponding strategies respectively are that all R&D members take the knowledge-retention strategy and the knowledge-sharing strategy. The system also has two unstable equilibrium points: (0,1) and (1,0), and a saddle point. The replication dynamic phase diagram of the dynamic game system describes the dynamic evolution process of the two-party game [45], as shown in Figure 1.

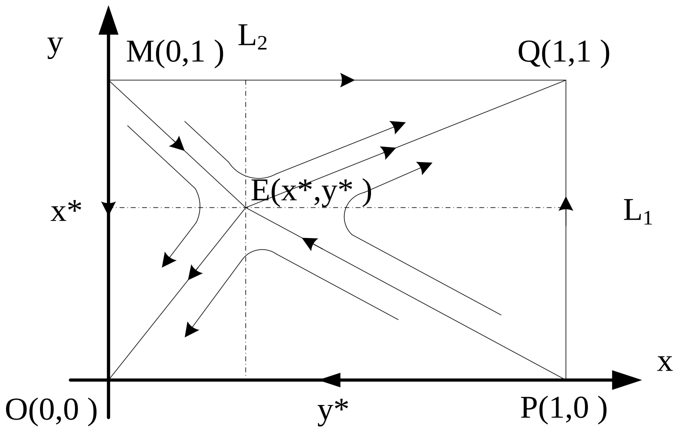


Figure 1. Replicated dynamic phase diagram.

As depicted in Figure 1, the system converges to point O and point Q of the evolutionary game stability strategy. The two dotted lines L1 and L2 passing through the saddle point E divide a plane region consisting of X[0,1] and Y[0,1] into four quadrants. Different starting positions of the game will lead to different final results. The specific analysis is as follows:

(1) When the initial state of the game is in the first quadrant, where the proportion of the members of group A and group B taking the knowledge-sharing strategy is greater than x* and y*, the evolutionary game system will converge to the evolutionarily stable strategy point Q (1,1). All members of A and B tend to adopt the knowledge-sharing strategy, which thus promotes the occurrence of knowledge-sharing behaviors.

(2) When the initial state of the game is in the second quadrant, two results may occur. The system may converge to O (0,0) or Q (1,1). The final equilibrium will be affected by the rate at which A and B adjust their strategies If the evolution goes into the first quadrant passing through L2, it will converge to the evolution-stable strategy point Q (1,1). All members in A and B are willing to share knowledge to promote the occurrence of knowledge-sharing behaviors. If the evolution passes into the third quadrant through L1, it will converge to the evolutionary stability strategy point O (0,0). All R&D members adopt the knowledge-retention strategy, and thus knowledge-sharing behaviors will not occur.

(3) When the initial state of the game is in the third quadrant, the proportion of the members taking the knowledge-sharing strategy of A is less than x* and that of B is less than y*. The system will converge to the evolution-stable strategy point O (0, 0). All R&D

members adopt the knowledge-retention strategy, and knowledge-sharing behaviors will not occur.

(4) When the initial state of the game is in the fourth quadrant, two kinds of results may also appear. The system may converge to O (0,0) or Q (1,1). The final equilibrium will be affected by A and B's strategy adjustment speed. If the evolution passes L1 into the first quadrant, it will converge to the evolution-stable strategy point Q (1,1). All members adopt the knowledge-sharing strategy to promote the occurrence of knowledge sharing. If the evolution passes L2, and then enters the third quadrant, it will converge to the stable strategy point O (0,0). All R&D members adopt the knowledge-retention strategy, and knowledge-sharing behaviors will not occur.

From these analyses, we can see that the evolutionary knowledge-sharing game of group A and group B in R&D teams has two possible results. One is that it may be stable in strategy (knowledge sharing, knowledge sharing), and the other is that it may be stable in strategy (Knowledge retention, knowledge retention). Which strategy of the evolutionary knowledge-sharing game becomes stable and thus reaches a balanced equilibrium, in the end, is closely related to the income function of participating parties in the knowledge-sharing process.

3.3. Sensitivity of the Model Parameters

According to the previous definitions of the parameters in the evolutionary game model of the knowledge sharing in R&D teams, this section will analyze the effects of some parameters in the income function on the result of the evolutionary game system. From the replicated dynamic phase diagrams (Figure 1) of A and B, we can see that the system in the upper right of the polyline (EPQM) is stable at point Q (1,1). It converges to a strategy mode in which all members are willing to share knowledge. Suppose $\frac{\alpha_a}{\alpha_b} = \rho$ and $0 < \lambda_i, \mu_i, \gamma_{ij}, \omega_i, \varepsilon_i < 1$, then the acreage of area EPQM is $S_{EPQM} = 1 - \frac{1}{2}\left(\frac{\omega_b \varepsilon_b}{\lambda_b \beta_b + \mu_b \gamma_{ab}} \frac{1}{\rho} + \frac{\omega_a \varepsilon_a}{\lambda_a \beta_a + \mu_a \gamma_{ba}} \rho\right)$.

(1) Cognitive ability α_i. It can be seen from the above formula that S_{EPQM} is a function of ρ that increases first and then decreases. The parameter ρ is the ratio of the cognitive ability of group A to group B, i.e., α_a / α_b. The probability of the system converging to Q first increases and then decreases along the changes of ρ. When $\rho \epsilon \left(0, \sqrt{\frac{\omega_b \varepsilon_b (\lambda_a \beta_a + \mu_a \gamma_{ba})}{\omega_a \varepsilon_a (\lambda_b \beta_b + \mu_b \gamma_{ab})}}\right)$, the probability increases; when $\rho \epsilon \left(\sqrt{\frac{\omega_b \varepsilon_b (\lambda_a \beta_a + \mu_a \gamma_{ba})}{\omega_a \varepsilon_a (\lambda_b \beta_b + \mu_b \gamma_{ab})}}, \infty\right)$, the probability decreases. That is, to promote the knowledge-sharing behavior among R&D team members, it is necessary to increase the value of ρ, but ρ must be controlled within a reasonable range.

(2) Knowledge absorption capacity β_i. Because $\frac{dS}{d\beta_a}$ and $\frac{dS}{d\beta_b}$ are both greater than zero, S_{EPQM} will increase as the members' knowledge absorbing ability increases. As a result, the probability of the evolutionary game system converging to Q will increase, that is, it is more likely for all R&D members to share knowledge.

(3) Knowledge transformation ability λ_i. $\frac{dS}{d\lambda_a}$ and $\frac{dS}{d\lambda_b}$ are both greater than zero. As the members' knowledge transformation ability increases, S_{EPQM} will increase, and the system will have a greater probability of converging to Q. Consequently, a larger proportion of team members tend to adopt knowledge-sharing strategies.

(4) Risk coefficient ω_i. $\frac{dS}{d\omega_a}$ and $\frac{dS}{d\omega_b}$ are both less than zero. As the sharing risk decreases, S_{EPQM} will increase, and the possibility of the system converging to Q will be greater. It is thus more likely that all members of the team will adopt knowledge-sharing strategies when sharing risk decreases.

(5) The degree of risk preference ε_i. $\frac{dS}{d\varepsilon_a}$ and $\frac{dS}{d\varepsilon_b}$ are both less than zero. As members' risk preference decreases, S_{EPQM} will gradually increase, and the system will be more likely to converge to Q. R&D team members are more likely to adopt knowledge-sharing strategies for low-risk preference.

(6) The degree of knowledge complementarity γ_{ij}. $\frac{dS}{d\gamma_{ba}}$ and $\frac{dS}{d\gamma_{ab}}$ are equal to greater than zero. As the degree of knowledge complementarity between groups continues to increase, S_{EPQM} will increase, and the system will be more likely to converge to point Q.

As a result, A and B will be more likely to adopt knowledge-sharing strategies when the degree of knowledge complementarity increases.

(7) Knowledge innovation ability μ_i. $\frac{dS}{d\mu_a}$ and $\frac{dS}{d\mu_b}$ are both greater than zero. With the enhancement of the innovation ability of R&D team members, S_{EPQM} will increase, and the evolutionary game system is more likely to converge to point Q. Consequently, a larger proportion of R&D members choose to adopt knowledge-sharing strategies when knowledge innovation ability increases.

4. Simulation Analysis of Evolutionary Game Model

Our model shows that different model parameters have different influences on the result of the evolutionary game of knowledge sharing. In order to better analyze and visualize the result, a numerical simulation was adopted to further verify the conclusions with the help of MATLAB software.

In order to facilitate the research without losing generality, this paper sets the initial value of each parameter as $\alpha_a = 0.6$, $\alpha_b = 0.2$; $\beta_a = 0.2, \beta_b = 0.3$; $\lambda_a = 0.2, \lambda_b = 0.4$; $\mu_a = 0.4$, $\mu_b = 0.5$; $\gamma_{ab} = 0.2$, $\gamma_{ba} = 0.4$; $\omega_a = 0.3$, $\omega_b = 0.5$; $\varepsilon_a = 0.1$, $\varepsilon_b = 0.2$. The evolution time is assigned as [0,400], and the horizontal axis and the vertical axis represent x and y, respectively. We will simulate the influence of different initial values and parameter changes on the dynamic knowledge-sharing evolution process within the space range of $[0,1] \times [0,1]$.

4.1. Impact of Initial Values

Figure 2 shows the evolution process of knowledge sharing when the initial proportion of members in group A who choose the knowledge-sharing strategy is 0.1 (i.e., $x_0 = 0.1$), and the initial member ratios in group B are 0.3, 0.5, 0.7, 0.9 (i.e., $y_0 = 0.3, 0.5, 0.7, 0.9$). Figure 3 shows the evolution process of strategy selection for different groups when $x_0 = 0.6$ and y_0 is the same value as in Figure 2. Through comparison, it can be found that the larger the proportion of initial members who choose knowledge-sharing strategies in each group, the greater the probability that they will eventually be balanced in the (knowledge sharing, knowledge sharing) strategy set, and the speed of evolution will also increase.

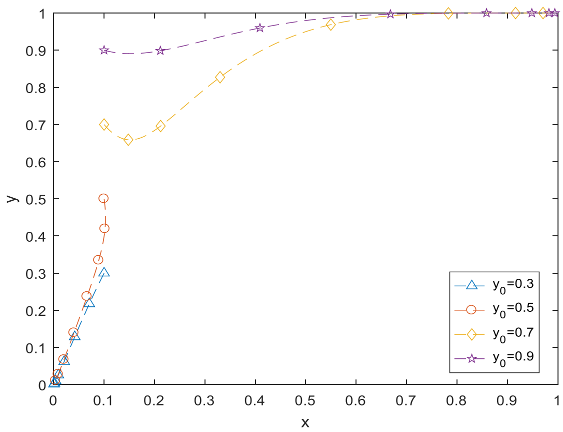


Figure 2. The dynamic evolution with $x_0 = 0.1$.

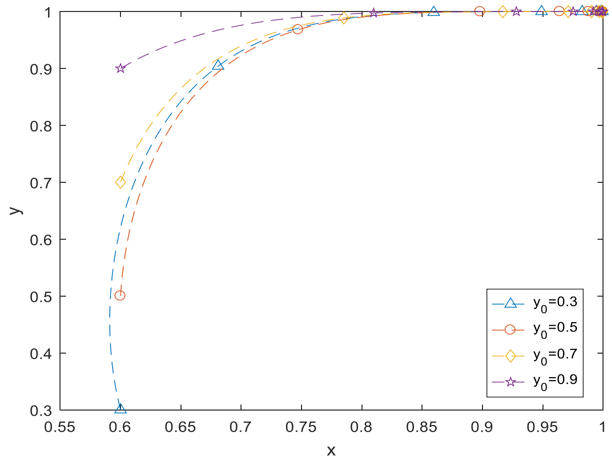


Figure 3. The dynamic evolution with $x_0 = 0.6$.

4.2. Impact of β_i, λ_i, γ_{ij} and μ_i

Keeping other parameters consistent with those in Figure 2, the knowledge absorption capacity β_b of group B is increased from 0.3 to 0.7. The evolution process of x and y is shown in Figure 4. Comparing Figures 2 and 4 shows that when the knowledge absorption capacity increases, the probability of eventually reaching the (1,1) equilibrium point will increase, and the evolution process will also accelerate.

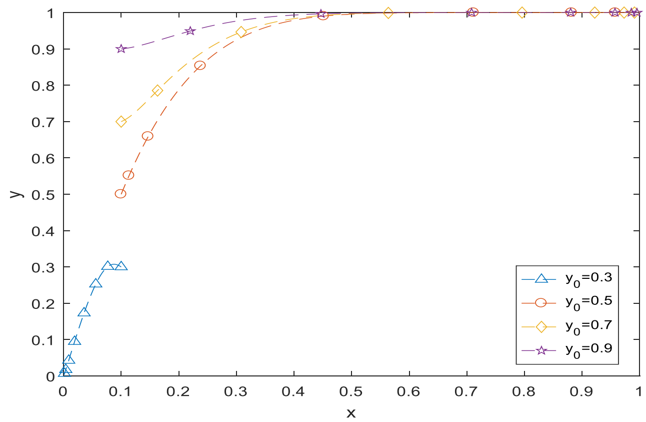


Figure 4. Impact of knowledge absorptive capacity (β_i).

In the same way, keeping other parameters consistent with those in Figure 2, the knowledge transformation ability of group A (i.e., λ_a) is increased from 0.2 to 0.5, the knowledge complementarity of group B to group A (i.e., γ_{ba}) is increased from 0.4 to 0.6, and the knowledge innovation of group A (i.e., μ_a) is increased from 0.4 to 0.6, respectively. The evolution processes after each change are shown in Figures 5–7 one by one. Comparing them with Figure 2 shows that the probabilities of the evolution result reaching (1,1) point all increases. Therefore, it can be concluded that the enhancement of knowledge absorptive capacity (β_i), knowledge transformation capacity (λ_i), the degree of knowledge complementarity (γ_{ij}), and the knowledge innovation capacity (μ_i) will all promote the occurrence of knowledge-sharing behaviors.

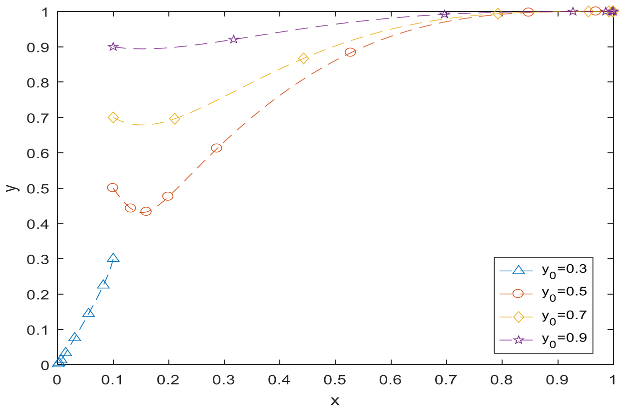


Figure 5. Impact of knowledge transformation ability (λ_i).

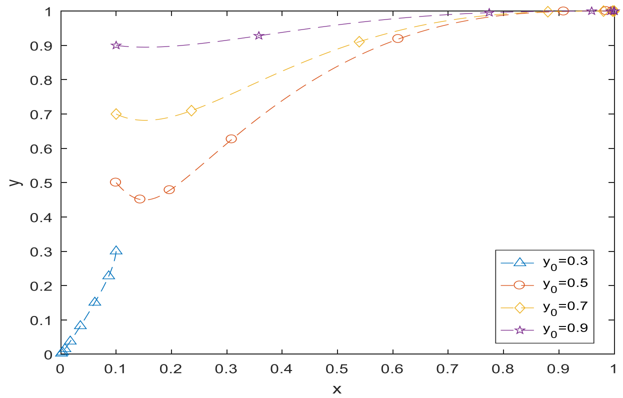


Figure 6. Impact of knowledge complementarity (γ_{ij}).

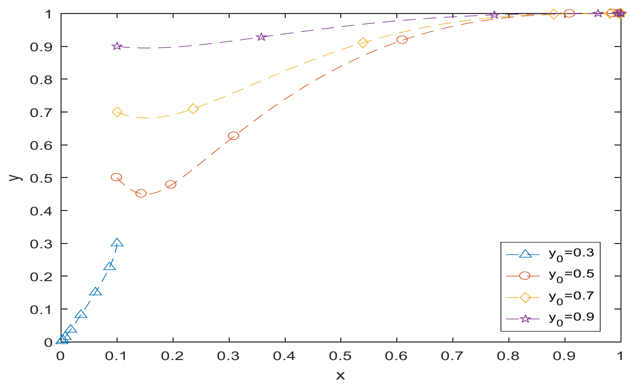


Figure 7. Impact of knowledge innovation ability (μ_i).

4.3. Impact of ω_i and ε_i

Keeping other parameters consistent with those in Figure 2, this study increases the risk coefficient of group A (i.e., ω_a) from 0.3 to 0.5, and the evolution process is shown in Figure 8. Compared with Figure 2, it can be found that as the risk coefficient increases, the probability of group members choosing a knowledge-sharing strategy will decrease, and the probability that the evolution result reaching the (0,0) point increases. In the same way, increasing the degree of risk preference of group A (i.e., ε_a) from 0.1 to 0.2, the probability of reaching the (0,0) equilibrium point increases, as shown in Figure 9. It can be seen that the environment risk coefficient (ω_i) and the degree of risk preference (ε_i) both have a negative impact on the choice of knowledge-sharing behavior.

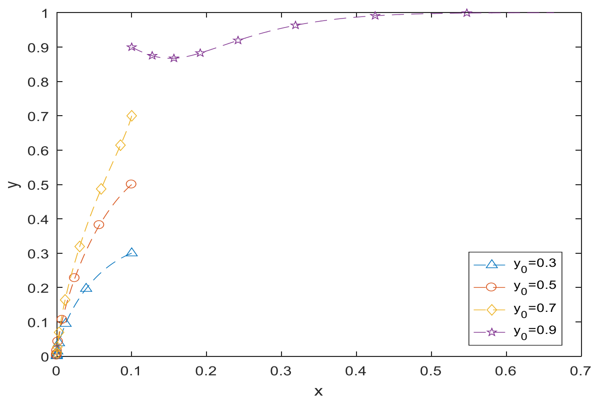


Figure 8. Impact of the risk coefficient (ω_i).

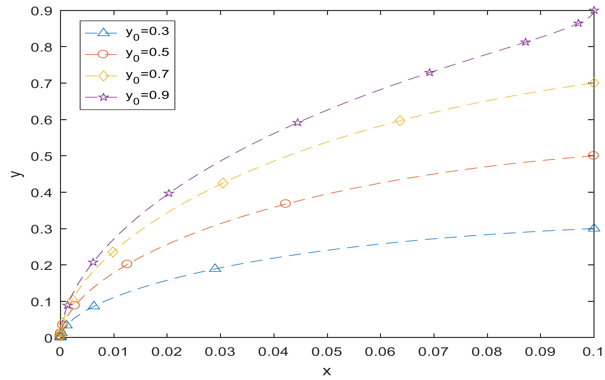
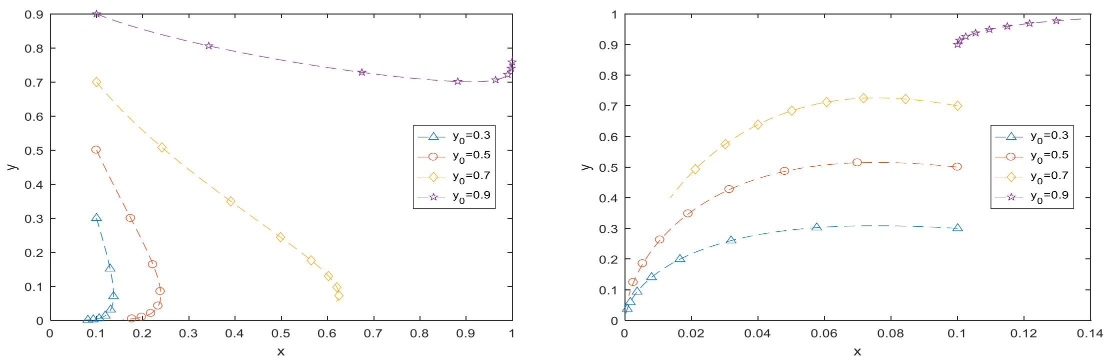


Figure 9. Impact of the risk preference coefficient (ε_i).

4.4. Impact of ρ

From the above sensitivity analysis on the parameter ρ (the ratio of the cognitive ability of group A to group B, α_a/α_b), it can be seen that the probability that the evolutionary game of knowledge sharing eventually reach the point of (knowledge sharing, knowledge sharing) (i.e., S_{EPQM}) is not a monotonic function of ρ: it increases first and then decreases. So, the parameter ρ is changed in two directions. Keeping other parameters consistent with those in Figure 2, we reduce the cognitive ability of group A (i.e., α_a) from 0.6 to 0.1. At this time, ρ changes from 3 to 0.5, and the ratio becomes smaller. The evolution curve is shown in Figure 10a.



(**a**) (**b**)

Figure 10. Impact of cognitive ability ratio (ρ): (**a**) Decrease in cognitive ability ratio and (**b**) Increase in cognitive ability ratio.

Then, keeping other parameters consistent with those in Figure 2, we reduce the cognitive ability of group B (i.e., α_b) from 0.2 to 0.1. At this time, ρ changes from 3 to

6, the ratio becomes larger, and the evolution curve is shown in Figure 10b. Comparing Figure 10a,b with Figure 2, it can be found that if the parameter ρ changes in two directions (increasing or decreasing), the probability that the evolution result tends to (0,0) will both increase. Therefore, with the improvement of the cognitive ability ratio in both groups, the promotion of knowledge-sharing behavior first becomes larger and then smaller.

5. Discussions and Conclusions

Knowledge sharing in R&D teams is a dynamic interactive process. Team members learn from each other and adjust their own strategies based on their prediction of what the other parties would do to reach a stable and balanced equilibrium. In modern organizations, especially in knowledge-intensive firms, R&D teams are an important carrier for firms to carry out technological innovation. Although the pivotal role of knowledge and learning of new knowledge has been established by extant studies at both the organization and team level, relatively little research has been conducted to examine knowledge sharing in R&D team members. Consequently, we know relatively little about the dynamic knowledge-sharing process and its effect on various aspects of R&D team members [25]. Based on previous research on knowledge sharing, this study constructs an evolutionary game model of the dynamic knowledge-sharing process within R&D teams to examine the mechanism of system evolution in order to better understand the stability strategies and influencing factors in knowledge sharing in R&D teams. The findings can help fill the research gap in how knowledge sharing could reach a stable equilibrium within R&D teams. A simulation analysis of this model shows that a variety of key factors have a positive effect on the knowledge sharing in the R&D team and these factors are knowledge absorption ability, transformation ability, knowledge innovation ability, and the degree of knowledge complementarity. These factors can help R&D team members absorb new information, create new knowledge, and promote knowledge sharing. In addition, when the cognitive gap is maintained within a reasonable range, team members' cognitive ability will have a positive effect on knowledge sharing. As expected, the estimated risk of knowledge sharing, and the team members' risk preference both have a negative effect on knowledge-sharing behaviors.

5.1. Theoretical Implication

Based on previous research, this study identifies key factors that affect knowledge sharing in R&D teams, and then establishes an evolutionary game model, an integrated model that combines the traditional game theory with the dynamic evolution process, in order to develop a more holistic understanding of a dynamic knowledge-sharing process within R&D teams. Then using simulation analysis, this study provides strong reasoning for the important role of team members' cognitive ability, knowledge absorption ability, knowledge transformation ability, knowledge innovation ability, and the degree of knowledge complementarity in facilitating knowledge sharing among team members. From a theoretical perspective, the evolutionary game theory provides an appropriate perspective to explore the dynamic knowledge-sharing process within R&D teams, which has often been treated as a static outcome in previous research, and thus this study can enhance our understanding of knowledge sharing by adopting a dynamic gaming perspective. The mathematical model developed in this study, together with simulation analyses, can also provide a cost-effective method to validate the effects of various variables on knowledge-sharing behaviors in R&D teams. The evolutionary game model on knowledge sharing thus can add value to the knowledge literature and shed light on how to build a more robust knowledge-sharing theory that is more consistent with the dynamic nature of knowledge sharing, as well as the dyadic exchange of knowledge assets—a gaming model.

5.2. Practical Implications

This study examines different parameters in a knowledge-sharing process in R&D teams using the evolutionary game model. The parameter analysis and simulation results using the evolutionary game model show that R&D team members' cognitive ability, knowledge absorption ability, knowledge transformation ability, environmental risk, risk preference, knowledge complementarity, and knowledge innovation ability all have important and dynamic influences on knowledge-sharing behavior. Based on this verified game model on knowledge sharing in R&D teams, the findings of this study can provide important insights on how to promote knowledge sharing in R&D teams in order to help achieve sustainable growth in the age of the knowledge economy. Some of the practical implications should be based on the impact of examined factors on the equilibrium of the evolutionary game to develop organizational practices in order to promote knowledge sharing among R&D team members, and these implications focus on designing effective selection, learning, and training, risk reduction, and knowledge complementary strategies.

5.2.1. Formulate an Effective Team Selection Strategy

R&D teams deal with complex tasks and a rich set of information, and the cognitive ability of team members is thus particularly important. In order to improve R&D team performance, it is necessary to formulate an effective selection strategy to pick team members. R&D team members will be better off in knowledge sharing within teams when there are different cognitive abilities within the teams in order to facilitate knowledge sharing. As found in this study, a gap between different cognitive abilities can inspire different views and unique suggestions, which can have a direct impact on the effective research and development process as well as on research and development efficiency [46]. However, the cognitive gap also needs to be controlled within a certain range, as indicated in our simulation results. If the cognitive gap between groups is too large, it could hinder team members from communicating and sharing knowledge and skills and thus have a negative impact on the achievement of R&D team goals.

5.2.2. Create a Conducive Learning and Training System

Knowledge absorption is team members' abilities to learn and internalize acquired information and knowledge. The findings of this study show that organizations should develop conducive training and learning systems to provide opportunities for R&D personnel to increase their knowledge stock, improve the depth and breadth of knowledge assets, enhance their learning abilities, and explore new fields and skills in order to develop new knowledge and innovation based on prior knowledge. The accumulation of enrichment and learning experiences can help R&D team members better absorb new knowledge from each other [47]. At the same time, an effective incentive mechanism also needs to be established to increase the motivation of team members to absorb and learn new knowledge, to accelerate the integration and application of knowledge in the R&D process, and to facilitate the generation of new knowledge within R&D teams.

5.2.3. Build a Knowledge-Sharing Platform

Our study has shown that R&D team members' knowledge transformation ability is also important. Organizations need to build a knowledge-sharing platform to help team members to transform tacit knowledge, promote tacit knowledge, and crystalize and internalize explicit knowledge in order to strengthen the interaction process of knowledge within R&D teams [9]. This is relatively easy to implement in the age of digitalization and organizations can create different online platforms accessible to all team members and conducive to various forms of knowledge sharing. It is recommended that R&D teams design different knowledge-sharing channels to suit the different nature of various knowledge, to make tacit knowledge explicit so that it is easier to share, and to effectively integrate newly acquired knowledge and generated knowledge with existing knowledge. R&D teams can make full use of the diversification of data platforms and social media to help connect team members with each other, and to build a knowledge database and knowledge map suitable for team members to input, analyze, and transform knowledge within a knowledge-sharing network platform [5].

5.2.4. Reduce Knowledge-Sharing Associated Risks

Knowledge sharing sometimes comes with risks and thus R&D team members are faced with a dilemma [22]: sharing personal knowledge with coworkers may carry a personal cost for the sharing individuals even if it may be better for the team. Organizations should promote the establishment of a knowledge-sharing rewarding mechanism to avoid potential loss in knowledge value. At the same time, organizations should design effective intellectual rights protection policies to reduce the role of a particular member's knowledge status and knowledge rights that often hinder the willingness of knowledge sharing in order to improve overall performance in R&D teams [48,49]. Organizations need to strengthen intellectual property protection to ensure sharing members have justified knowledge benefits. In addition, organizations need to create a working environment that promotes knowledge sharing and form a corporate culture of trust and mutual assistance. Such an organizational atmosphere is especially important in R&D teams.

5.2.5. Construct a Complementary Knowledge Structure

Our study has shown that in an R&D team with a common goal, the degree of knowledge complementarity also determines the degree of knowledge sharing among team members: The greater the knowledge complementarity, the higher the necessity for knowledge sharing and also the degree of knowledge sharing. Different team members come with different knowledge bases, and the heterogeneity of knowledge will produce synergistic effects. Simultaneously, knowledge complementation can also help mobilize efficient knowledge absorption among members and promote knowledge sharing [50]. Therefore, organizations are urged to create a complementary knowledge structure in considering building R&D teams so as to enhance knowledge complementarity among team members, and thus to ensure the diversity of relevant knowledge background in team members to promote more effective knowledge sharing.

5.3. Limitation and Further Research

While this study has shed light on how to manage the knowledge-sharing process within R&D teams in order to achieve sustainable growth, some cautions need to be considered in applying the findings of this study. To begin with, the evolutionary game model is built on the premise of a set of assumptions, and its scope of application will be subject to these assumptions. That being said, these assumptions are reasonably realistic in that they do not impose unreasonable requirements on R&D team members in this study, such as the assumptions of treating R&D team members as individuals with bounded rationality and seeking for their own interests yet trying to achieve the R&D team goals by willingly participating in knowledge sharing, which, to a certain extent, helps improve the generalizability of this study. Second, in view of the characteristics of R&D teams, only those important key factors as identified in previous studies are selected to build the evolutionary model, which may limit the generalizability of this study. Future research can incorporate more factors based on a reasoned logic to make the model more robust, and of course also with the consideration of parsimony and comprehensiveness. Finally, the evolutionary game model is validated with a simulation method, not with empirical data from organizations. Follow-up research can collect knowledge-sharing data from R&D teams in industries for empirical analysis, which would be more able to reveal the behavioral characteristics and process mechanism of knowledge sharing among R&D teams.

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