

Research Article

A Tripartite Evolutionary Game Analysis of Online Knowledge Sharing Community

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Received 2 June 2022; Revised 6 August 2022; Accepted 10 September 2022; Published 20 September 2022

Academic Editor: Xu Zheng

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With the rapid development of information technology, online knowledge monetization has emerged as a potential business model for several social Q&A platforms, which brings more complex benefits and cost tradeoffs for users. However, most of the previous studies were based on free Q&A platforms, which made it difficult to explain the influencing factors of various stakeholders in the decision-making process of knowledge sharing and failed to comprehensively analyze the behavior of knowledge sharing subjects using dynamic system theory. This study establishes a tripartite evolutionary game model of knowledge consumers, knowledge providers, and knowledge payment platforms and discusses evolutionary stability strategies, evolutionary trends, and factors affecting the evolutionary path of tripartite behavior. The extensive experimental results show that knowledge payment is an important way to promote knowledge sharing. Meanwhile, the implementation of a rewards and punishment system on payment platforms will encourage knowledge providers to provide high-quality knowledge content and increase the willingness of knowledge consumers to pay, thereby facilitating the knowledge-sharing process. This paper provides the decision-making basis for the operation of the online knowledge community and proposes a new proposition to solve the conflict of interest in the process of knowledge sharing from the perspective of evolutionary theory.

1. Introduction

With the rise of mobile internet and information-flow browsing modes, online knowledge communities have become an important platform for knowledge acquisition, sharing, communication, and learning, which gradually changed the traditional mode of people creating and acquiring knowledge, such as Quora, Zhihu, and “Baidu Knows” [1]. Such platforms are mainly based on users asking questions, answering questions, and discussing questions. In addition, it also emphasizes interpersonal communication, attracting professionals in related fields to participate in question and answer with a good community atmosphere, so as to achieve the purpose of sharing knowledge [2]. However, due to the explosive growth of user traffic, the traditional online knowledge community is increasingly exposed, such as uneven Q&A quality, low question response rate, poor persistence, and intellectual property infringement. In recent years, with the rise of new business

models of online knowledge monetization, knowledge payment has become a good way to solve the problem of knowledge sharing in virtual communities, which solves the dilemma of users’ passive participation and sharing [3]. According to relevant reports, the market size of China’s knowledge payment industry has maintained a growth of more than 40% in recent years and will reach 180 billion in 2023, which further demonstrates that knowledge sharing will release unprecedented power and is crucial to promoting the healthy development of knowledge sharing market.

To investigate the subject behaviors of various stakeholders in the knowledge sharing decision-making process under the knowledge payment model, this paper establishes an evolutionary game model involving knowledge consumers, knowledge providers, and knowledge payment platforms; analyzes the game relationship, strategies, and interest; and derives the Nash equilibrium [4]. Game theory analysis is combined with dynamic evolutionary processes in evolutionary games, which emphasize dynamic processes of

strategic change rather than specific equilibrium results [5]. The three aspects of the questions investigated in this research are as follows: (1) How do the three stakeholders make strategic choices? (2) What factors influence the formation of stable points? (3) What is the strategy when the three stakeholders are stable? Therefore, this study focuses on model construction and simulation experiments to explore the equilibrium strategies of the three stakeholders under different conditions, as well as the impact of each parameter on participants' strategy choices. In addition, we verify the importance of reward and punishment measures in the model. Finally, some management inspirations and suggestions are put forward according to the simulation results. The innovation of this paper is to use the evolutionary game system to analyze the interaction and evolution patterns of consumers, providers, and knowledge platforms on knowledge payment, as well as the behaviors of stakeholders that affect the game process.

The remainder of this paper is structured as follows. In Section 2, we review the relevant literature from two aspects, i.e., the knowledge sharing and evolutionary game theory. Section 3 describes the problem and lists the relevant parameters and basic assumptions. In Section 4, we discuss the ESS in two scenarios. The numerical simulation of the evolutionary game experiment is explained in Section 5. Section 6 summarizes the paper and puts forward relevant suggestions and deficiencies.

2. Related Work

2.1. Knowledge Sharing. The evolution from knowledge sharing to knowledge payment is actually a process of knowledge monetization [6, 7]. Many scholars have done related research on the motivation of sharing knowledge. From an economic perspective, financial incentives can improve users' social participation and are the main motivation for users to actively share knowledge [8]. At a noneconomic level, Al-Husseini [9] argues that the main factors that affect the motivation for information sharing are attitudes and subjective norms which are followed by social relationships, trust, and positive attitudes toward helping others. Brédif et al. [10] conducted research on the motivation of stakeholders based on the perspective of biodiversity and believed that collective rules are related to taking a proactive approach to territorial quality. Meanwhile, shared motivation is related to each person's personality attributes and involves social relations.

In addition, some scholars have further studied the key factors that affect users' continued willingness to use. According to Zhao et al. [11], the primary aspects that knowledge searchers consider before paying are benefits and costs; thus, knowledge payment platforms should attempt to enhance service quality. Huo and Li [12] believe that perceived value, subjective norms, platform quality, trust, satisfaction, and habits are the main factors affecting users' continued use of knowledge-based payment platforms. Jo [13] believes that the level of supporting technology, usage level, perceived usefulness, and user satisfaction significantly affect users' willingness to use.

Due to the establishment of a trust relationship between the two parties, knowledge production is developing towards refinement, and some scholars are also studying the influencing factors of users' willingness to pay. Jin [14] analyzed from social exchange theory and capital theory and believed that functional risk and emotional risk significantly had a substantial impact on users' willingness to pay for information. Yu et al. [15] take UTAUT theory as the core and emphasize that perceived cost, peer influence, and content quality will greatly affect users' willingness to pay for knowledge products. Zhang et al. [16] started with the pricing of knowledge products and improved users' willingness to pay by comparing how factors such as the quality level and price of knowledge products affect the decision-making of each game subject.

2.2. Evolutionary Game Theory. Originating from the study of biological evolution, evolutionary game theory (EGT) defines the structure of competition and strategies and is very useful for explaining many complex and difficult problems [17]. Babu and Mohan [18] constructed a game theoretical framework to study the sustainability of supply chains from multiple dimensions. Liu et al. [19] used an evolutionary game theory model to discuss the discriminatory pricing behavior of big data in the service supply chain and proposed a governance method to prevent service platforms from using price discrimination. The stakeholder game model in the cloud environment designed by Sun [20] is aimed at encouraging cooperation between the two parties, thereby promoting mutual trust between users and cloud service providers. Li et al. [21] paid attention to the utilization rate of construction waste and compared the two situations with and without recycling capacity, which provided management enlightenment for recycling units and the government. Xie et al. [22] selected stakeholders in mobile learning data sharing from the perspective of privacy protection and constructed a mixed-policy game model including users and platforms, which achieved the best balance between privacy protection and data sharing. Zomorodi and Segrè [23] applied evolutionary game theory to a genome-scale metabolic model, regarded interacting micro-life as a subject, and simulated invasion experiments, which have significant implications for artificial ecosystem and microbial studies.

3. Model Formulation

3.1. Problem Description. Knowledge sharing has three stakeholders, namely, knowledge consumers, knowledge providers, and knowledge payment platform, and its workflow is shown in Figure 1. Knowledge consumers usually ask questions on knowledge payment platforms and determine what they are willing to pay, and their main goal is to get the maximum knowledge benefit with the least cost. The knowledge provider chooses whether to share the knowledge or not and gets paid for answering the question. As an intermediary agency connecting supply and demand, the knowledge payment platform can enjoy the economic flow brought about by the increase in the user base. With the establishment of the trust relationship

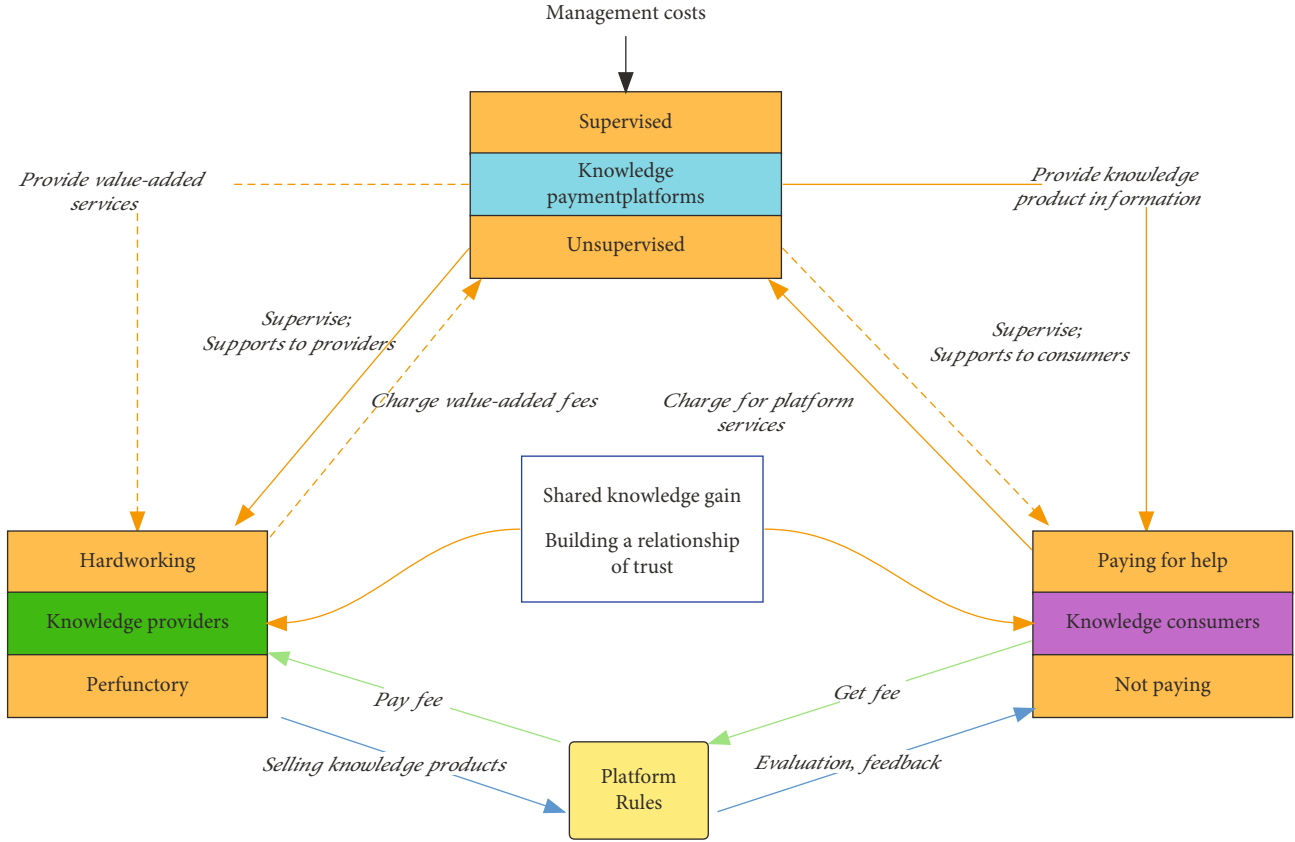


FIGURE 1: Knowledge sharing workflow.

between knowledge consumers and knowledge providers, platforms will show a significant preference for strict supervision, and at the same time, they will provide additional value-added services for knowledge consumers to promote greater profits. This paper intends to describe the training mechanism and strategy evolution of the game parties by constructing a stakeholder evolutionary game model, and then analyze the influence of knowledge sharing environment, sharing willingness, reward and punishment mechanism, and other factors on the game parties.

3.2. *Model Assumptions.* To facilitate modeling, this study abstracts the following assumptions from reality.

Assumption 1. In the evolutionary game model proposed in this paper, “Paying for help” and “Not paying” are the alternative strategies of knowledge consumers. “Hardworking” and “Perfunctory” are the alternative strategies of knowledge providers; “Supervised” and “Unsupervised” are optional strategies for knowledge payment platforms. The strategy selection probabilities of knowledge consumers choosing “Paying for help,” knowledge payment platform “Supervised,” and knowledge providers “Hardworking” are x , y , and z , respectively, and $x, y, z \in [0, 1]$.

Assumption 2 (knowledge consumers). When choosing “Paying for help” and “Not paying” strategies, knowledge

consumers usually consider two factors, namely, the time cost of searching for relevant information and the benefits of adopting this strategy. If knowledge providers adopt the “Hardworking” strategy, knowledge consumers can obtain knowledge benefits B_1 , perceived benefits $(1-r)P$, and knowledge platform value-added services and exclusive service benefits G_1 . If the knowledge provider adopts the “Perfunctory” strategy, the knowledge consumer can only get the knowledge benefits B_2 ($B_2 < B_1$) and the perceived loss L due to the low quality of the content. When knowledge consumers choose the “Not paying” strategy, they will spend a certain amount of time T in the process of knowledge search and can only obtain the low-quality knowledge benefit B_3 ($B_3 < B_2$) provided by the platform.

Assumption 3 (knowledge providers). When providing knowledge services, knowledge providers can receive direct benefits F . If they adopt a “Hardworking” strategy, they will get additional perceived benefits G_2 from the knowledge platform such as priority promotion, quality certification, and credit rating. At the same time, the knowledge provider pays the communication cost W_1 . If the “Perfunctory” strategy is adopted, knowledge providers will reduce costs and maximize their own interests in the process of providing services, then knowledge providers will generate W_2 ($W_1 > W_2$) the speculative cost. In this case, the knowledge provider loses trust and pays a certain fine H_1 to the knowledge consumer for this

TABLE 1: Benefit matrix under different portfolio strategies.

	Knowledge consumer	Knowledge payment platform	Knowledge provider
(H_1, L_1, S_1)	$G_1 - F + B_1 + (1 - r)P$	$R_1 + M - C$	$F - W_1 + rP + G_2$
(H_1, L_1, S_2)	$G_1 - F + B_2 - L + H_1$	$R_1 - C$	$F - W_2 - H_1 - H_2$
(H_1, L_2, S_1)	$G_1 - F + B_1 + (1 - r)P$	$R_2 + \alpha M - C - D$	$F - W_1 + rP + G_2$
(H_1, L_2, S_2)	$G_1 - F + B_2 - L + H_1$	$R_2 - C - D$	$F - W_2 - H_1 - H_2$
(H_2, L_1, S_1)	$B_3 - T$	$-C$	$F - W_1 + G_2$
(H_2, L_1, S_2)	$B_3 - T$	$-C$	0
(H_2, L_2, S_1)	$B_3 - T$	0	$F - W_1 + G_2$
(H_2, L_2, S_2)	$B_3 - T$	0	0

behavior. In addition, the knowledge platform will impose additional perceptual penalties H_2 , such as downgrades and noncertification. If the knowledge demander chooses to pay for help and the knowledge provider adopts a ‘‘Hardworking’’ strategy, the mutual trust between the two parties will increase, further bringing additional perceived benefits to the knowledge provider.

Assumption 4 (knowledge payment platform). The knowledge payment platform provides users with a space to share knowledge and formulates corresponding reward and punishment systems for knowledge providers and knowledge consumers, with a total operating cost of C . When the knowledge payment platform adopts the ‘‘Supervised’’ strategy, the quality of the platform’s content improves, which leads to an increase in user traffic, and the platform obtains benefit R_1 . When the knowledge payment platform adopts the ‘‘Unsupervised’’ strategy, the knowledge sharing atmosphere is low, and the knowledge payment platform only gets a small amount of user traffic benefit R_2 and direct benefit αM ($0 < M < 1$). Furthermore, knowledge consumers’ trust in the platform is reduced and perception loss D is caused.

Based on the above assumptions, this paper obtains 8 combinations, i.e., $(H_1$ Paying for help, L_1 Supervised, S_1 Hardworking), $(H_1$ Paying for help, L_1 Supervised, S_2 Perfunctory), $(H_1$ Paying for help, L_2 Unsupervised, S_1 Hardworking), $(H_1$ Paying for help, L_2 Unsupervised, S_2 Perfunctory), $(H_2$ Not paying, L_1 Supervised, S_1 Hardworking), $(H_2$ Not paying, L_1 Supervised, S_2 Perfunctory), and $(H_2$ Not paying, L_2 Unsupervised, S_1 Hardworking), $(H_2$ Not paying, L_2 Unsupervised, S_2 Perfunctory). The benefit matrix under different strategies are shown in Table 1.

In summary, the symbols used in this paper are shown in Table 2.

3.3. Model Structuring. The behaviors of knowledge platforms, knowledge providers, and knowledge consumers interact and impact each other and constantly adjust strategic choices to maximize benefits. Based on the previously proposed assumptions, this paper solves the formation conditions of evolutionary stable strategies by establishing a tripartite evolutionary game replication dynamic equations.

3.3.1. The Replication Dynamic Equation of Knowledge Consumers. The main purpose of knowledge consumers is to obtain the highest knowledge gain. When the expected benefits are met, they choose a ‘‘Paying for help’’ strategy to facilitate transactions. Assuming that the expected benefit of knowledge consumers choosing the ‘‘Paying for help’’ strategy is E_{d1} , the expected benefit of choosing the ‘‘Not paying’’ strategy is E_{d2} , and the average expected benefit is \tilde{E}_d .

$$E_{d1} = (B_1 - B_2 + (1 - r)P + L - H_1)z + G_1 - F + B_2 - L + H_1, \quad (1)$$

$$E_{d2} = B_3 - T. \quad (2)$$

According to (1) and (2), the average expected benefit \tilde{E}_d of knowledge consumers can be obtained as follows:

$$\tilde{E}_d = xE_{d1} + (1 - x)E_{d2}. \quad (3)$$

Furthermore, the replication dynamic equation of knowledge consumers selection strategy is expressed as

$$\begin{aligned} F(x) &= x(E_{d1} - \tilde{E}_d) = x(1 - x)(E_{d1} - E_{d2}) \\ &= x(1 - x)\{[B_1 - B_2 + (1 - r)P + L - H_1]z + G_1 \\ &\quad - F + B_2 - L + H_1 - B_3 + T\}. \end{aligned} \quad (4)$$

3.3.2. The Replication Dynamic Equation of Knowledge Payment Platform. The main purpose of the knowledge payment platform is to obtain greater profits. When there is a sufficient number of users, they will choose to actively ‘‘Supervised’’ to obtain greater profits. Assuming that the expected benefit of the knowledge payment platform choosing the ‘‘Supervised’’ strategy is E_{s1} , the expected benefit of choosing the ‘‘Unsupervised’’ strategy is E_{s2} , and the average expected benefit is \tilde{E}_s .

$$E_{s1} = xzM + xR_1 - C, \quad (5)$$

$$E_{s2} = \alpha xzM + (R_2 - C - D)x. \quad (6)$$

TABLE 2: Symbols and descriptions.

Symbol	Description
F	The cost of a creative commons
B_1	Benefits of knowledge providers using a “Hardworking” strategy
B_2	Benefits of knowledge providers using a “Perfunctory” strategy
B_3	Low-quality knowledge gains from the platform
G_1	Additional benefits from the platform when knowledge consumers choose a “Paying for help” strategy
G_2	Additional benefits from the platform when knowledge providers choose a “Hard-working” strategy
P	Knowledge providers provide additional perceived benefits for both parties
r	Share scale factor
W_1	Costs for knowledge providers choosing a “Hardworking” strategy
W_2	Costs for knowledge providers choosing a “Perfunctory” strategy
L	The perceived loss suffered by knowledge consumers
H_1	Fines for knowledge providers who choose dishonesty due to perfunctory behavior
H_2	Perceptual penalties imposed by platforms on knowledge providers’ perfunctory behavior
C	The supervision cost of knowledge payment platform
M	The benefits of knowledge payment platform
R_1	The economic benefits of user traffic brought about by the platform’s active supervision
R_2	The economic benefits of user traffic brought about by negative platform supervision
D	The loss of trust to the platform is reduced
T	The time cost of knowledge consumers in the process of seeking knowledge

According to (5) and (6), the average expected benefit \tilde{E}_s of the knowledge payment platform can be obtained as follows:

$$\tilde{E}_s = yE_{s1} + (1 - y)E_{s2}. \quad (7)$$

From this, the replication dynamic equation of knowledge payment platform selection strategy is expressed as follows:

$$\begin{aligned} F(y) &= y(E_{s1} - \tilde{E}_s) = y(1 - y)(E_{s1} - E_{s2}) \\ &= y(1 - y)[(1 - a)xzM + (R_1 - R_2 + C + D)x - C]. \end{aligned} \quad (8)$$

3.3.3. The Replication Dynamic Equation for Knowledge Providers. The main purpose of knowledge providers is to get more compensation. When the reward is greater than the time cost, they will choose the “Hardworking” strategy to complete the sharing behavior. Assuming that the expected benefit of the knowledge provider choosing the “Hardworking” strategy is E_{p1} , the expected benefit of choosing the “Perfunctory” strategy is E_{p2} , and the average expected benefit is \tilde{E}_p .

$$E_{p1} = rPy + F - W_1 + G_2, \quad (9)$$

$$E_{p2} = (F - W_2 - H_1 - H_2)y. \quad (10)$$

According to (9) and (10), the average expected benefit \tilde{E}_p of knowledge providers can be obtained as follows:

$$\tilde{E}_p = zE_{p1} + (1 - z)E_{p2}. \quad (11)$$

Furthermore, the replication dynamic equation of knowledge provider selection strategy is expressed as

$$\begin{aligned} F(z) &= z(E_{p1} - \tilde{E}_p) = z(1 - z)(E_{p1} - E_{p2}) \\ &= z(1 - z)[(rP - F + W_2 + H_1 + H_2)y + F - W_1 + G_2]. \end{aligned} \quad (12)$$

4. Evolutionary Equilibrium Analysis

4.1. Jacobian Matrix. The evolutionary stable equilibrium solution of a replicated dynamical system can be found by solving the local stability of the Jacobian matrix of the replicated dynamical system.

The replication dynamic system of knowledge consumers, knowledge providers, and knowledge payment platforms is as follows:

$$\begin{cases} F(x) = x(1-x)[(B_1 - B_2 + (1-r)P + L - H_1)z + G_1 - F + B_2 - L + H_1 - B_3 + T], \\ F(y) = y(1-y)[(1-a)Mxz + (R_1 - R_2 + C + D)x - C], \\ F(z) = z(1-z)[rP - F + W_2 + H_1 + H_2)y + F - W_1 + G_2]. \end{cases} \quad (13)$$

By calculating the partial derivatives of x , y , and z for $F(x)$, $F(y)$, and $F(z)$, respectively, the Jacobian matrix of the knowledge-sharing replication dynamic system is as follows:

$$J = \begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} & \frac{\partial F(y)}{\partial z} \\ \frac{\partial F(z)}{\partial x} & \frac{\partial F(z)}{\partial y} & \frac{\partial F(z)}{\partial z} \end{bmatrix} = \begin{bmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{bmatrix}. \quad (14)$$

Among them,

$$\begin{aligned} F_{11} = & -(x-1)(B_2 - B_3 - F + G_1 + H_1 - L + T \\ & - z(B_2 - B_1 + H_1 - L + P(r-1))) \\ & - x(B_2 - B_3 - F + G_1 + H_1 - L + T \\ & - z(B_2 - B_1 + H_1 - L + P(r-1))), \end{aligned} \quad (15)$$

$$F_{12} = 0, \quad (16)$$

$$F_{13} = x(x-1)(B_2 - B_1 + H_1 - L + (r-1)P), \quad (17)$$

$$F_{21} = -y(y-1)(C + D + R_1 - R_2 - z(a-1)M), \quad (18)$$

$$\begin{aligned} F_{22} = & y(C - x(C + D + R_1 - R_2) + xz(a-1)M) \\ & + (y-1)(C - x(C + D + R_1 - R_2) + xz(a-1)M), \end{aligned} \quad (19)$$

$$F_{23} = xy(y-1)(a-1)M, \quad (20)$$

$$F_{31} = 0, \quad (21)$$

$$F_{32} = -z(z-1)(H_1 - F + H_2 + W_2 + rP), \quad (22)$$

$$F_{33} = 0, \quad (23)$$

$$F_{34} = 0, \quad (24)$$

$$\begin{aligned} F_{33} = & -z(F + G_2 - W_1 + y(H_1 - F + H_2 + W_2 + rP)) \\ & - (z-1)(F + G_2 - W_1 + y(H_1 - F + H_2 + W_2 + rP)). \end{aligned} \quad (25)$$

Let $F(x) = 0$, $F(y) = 0$, $F(z) = 0$, that is, the rate of change of the system strategy selection is zero, the 10 equilibrium points of the dynamic system can be obtained (E_9 and E_{10} are meaningless), which are $E_1(0, 0, 0)$, $E_2(0, 0, 1)$,

$E_3(0, 1, 0)$, $E_4(1, 0, 0)$, $E_5(0, 1, 1)$, $E_6(1, 1, 0)$, $E_7(1, 0, 1)$, and $E_8(1, 1, 1)$. The boundaries of the evolutionary game are E_1 to E_8 , and the region enclosed by the boundary is called the equilibrium solution region of the tripartite evolutionary game, $E = (x, y, z | 0 \leq x \leq 1, 0 \leq y \leq 1, 0 \leq z \leq 1)$.

4.2. Stability Analysis. According to the evolutionary game theory and the Jacobian matrix of the knowledge-sharing replication dynamic system, the Jacobian matrix at the equilibrium point $E_1(0, 0, 0)$ is as follows:

$$J = \begin{bmatrix} -C & 0 & 0 \\ 0 & F + G_2 - W_1 & 0 \\ 0 & 0 & B_2 - B_3 - F + G_1 + H_1 - L + T \end{bmatrix}. \quad (26)$$

By formula (26), we find that the eigenvalue of the Jacobian J of the replicating dynamic system at the equilibrium point $E_1(0, 0, 0)$ are $\lambda_1 = -C$, $\lambda_2 = F + G_2 - W_1$, and $\lambda_3 = B_2 - B_3 - F + G_1 + H_1 - L + T$. Similarly, the corresponding eigenvalues are obtained by substituting each equilibrium point into the Jacobian matrix, as shown in Table 3.

If the eigenvalues of the Jacobian matrix are all less than 0, the equilibrium point is proved to be a stable point of evolutionary game. The knowledge sharing model proposed in this paper has many parameters, and the variation of single parameter will have a great influence on the stability of the replication dynamic system. Without loss of generality, we discuss two cases, and the stability analysis is shown in Table 4.

Scenario 1. $F - W_1 + rP + G_2 < 0$, the benefit obtained by the knowledge provider is less than the cost paid, and the equilibrium point corresponding to the Jacobian matrix of the replication dynamic system is $E_5(1, 1, 0)$. In this case, knowledge consumers adopt a "Paying for help" strategy, knowledge providers adopt a "Perfunctory" strategy, and knowledge platforms adopt a "Unsupervised" strategy, which is the evolutionary stability point of the replication dynamic system.

Scenario 2. $F - W_1 + rP + G_2 > 0$, the benefit obtained by the knowledge provider is greater than the sum total of the transmission cost, communication cost, and opportunity cost; there is only one equilibrium point $E_8(1, 1, 1)$ in the Jacobian matrix of the replication dynamic system of knowledge sharing. In this case, knowledge consumers adopt "Paying for help," knowledge providers adopt "Hardworking" strategy, and knowledge platforms adopt "Supervised" strategy as the stable point of the replication dynamic system.

TABLE 3: System equilibrium points and eigenvalues.

	λ_1	λ_2	λ_3
$E_1(0,0,0)$	$-C$	$F + G_2 - W_1$	$B_2 - B_3 - F + G_1 + H_1 - L + T$
$E_2(1,0,0)$	$F + G_2 - W_1$	$D + R_1 - R_2$	$B_3 - B_2 + F - G_1 - H_1 + L - T$
$E_3(0,1,0)$	C	$G_2 + H_1 + H_2 - W_1 + W_2 + P * r$	$B_2 - B_3 - F + G_1 + H_1 - L + T$
$E_4(0,0,1)$	$-C$	$W_1 - G_2 - F$	$B_1 - B_3 - F + G_1 + P + T - P * r$
$E_5(1,1,0)$	$R_2 - R_1 - D$	$G_2 + H_1 + H_2 - W_1 + W_2 + P * r$	$B_3 - B_2 + F - G_1 - H_1 + L - T$
$E_6(1,0,1)$	$W_1 - G_2 - F$	$D + M + R_1 - R_2 - M\alpha$	$B_3 - B_1 + F - G_1 - P - T + P * r$
$E_7(0,1,1)$	C	$W_1 - H_1 - H_2 - G_2 - W_2 - P * r$	$B_1 - B_3 - F + G_1 + P + T - P * r$
$E_8(1,1,1)$	$R_2 - M - R_1 - D + M\alpha$	$W_1 - H_1 - H_2 - G_2 - W_2 - P * r$	$B_3 - B_1 + F - G_1 - P - T + P * r$

TABLE 4: Stability analysis.

Equilibrium points	Scenario 1: $F - W_1 + rP + G_2 < 0$				Scenario 2: $F - W_1 + rP + G_2 > 0$			
	λ_1	λ_2	λ_3	Stability	λ_1	λ_2	λ_3	Stability
$E_1(0, 0, 0)$	—		+	Unstable point	—			Uncertain
$E_2(1, 0, 0)$		+	—	Unstable point		+		Unstable point
$E_3(0, 1, 0)$	+	—	+	Unstable point	+	+		Unstable point
$E_4(0, 0, 1)$	+	+	+	Unstable point	—		+	Unstable point
$E_5(1, 1, 0)$	—	—	—	ESS	—	+		Unstable point
$E_6(1, 0, 1)$	+	+	—	Unstable point		+	—	Unstable point
$E_7(0, 1, 1)$	+	+	+	Unstable point	+	—	+	Unstable point
$E_8(1, 1, 1)$	—	+	—	Unstable point	—	—	—	ESS

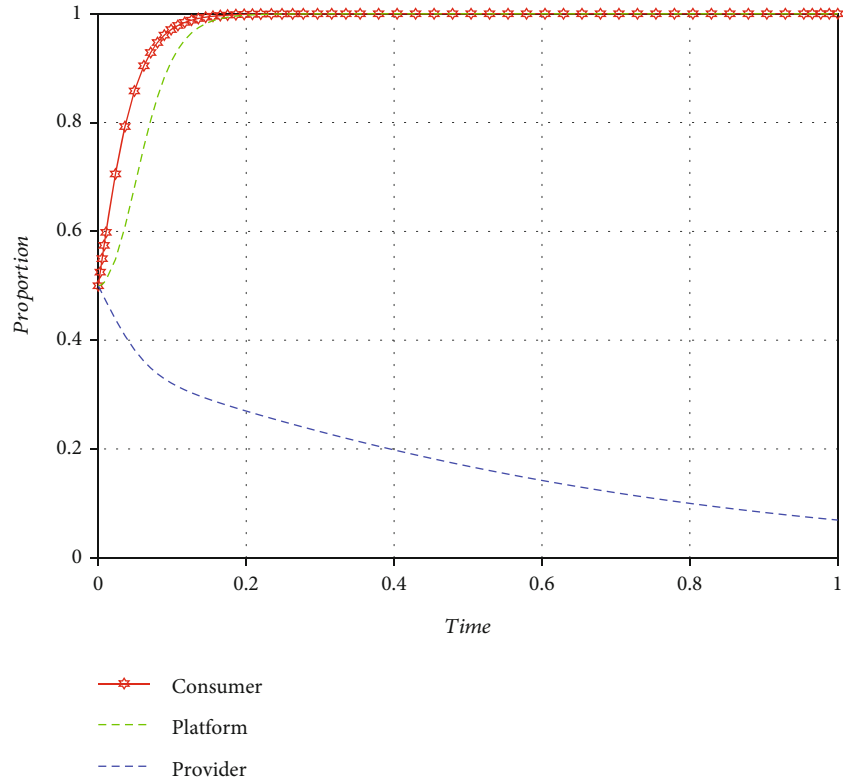
5. Simulated Analysis

To verify the rationality of the tripartite evolutionary game model proposed in this paper, three groups of simulation experiments are designed as follows: (1) the influence of reward and punishment mechanisms on the decision-making of three parties of knowledge sharing, (2) The influence of different factors on the results of rewards and punishments, and (3) the effectiveness of the evolutionary game model under different initial strategies.

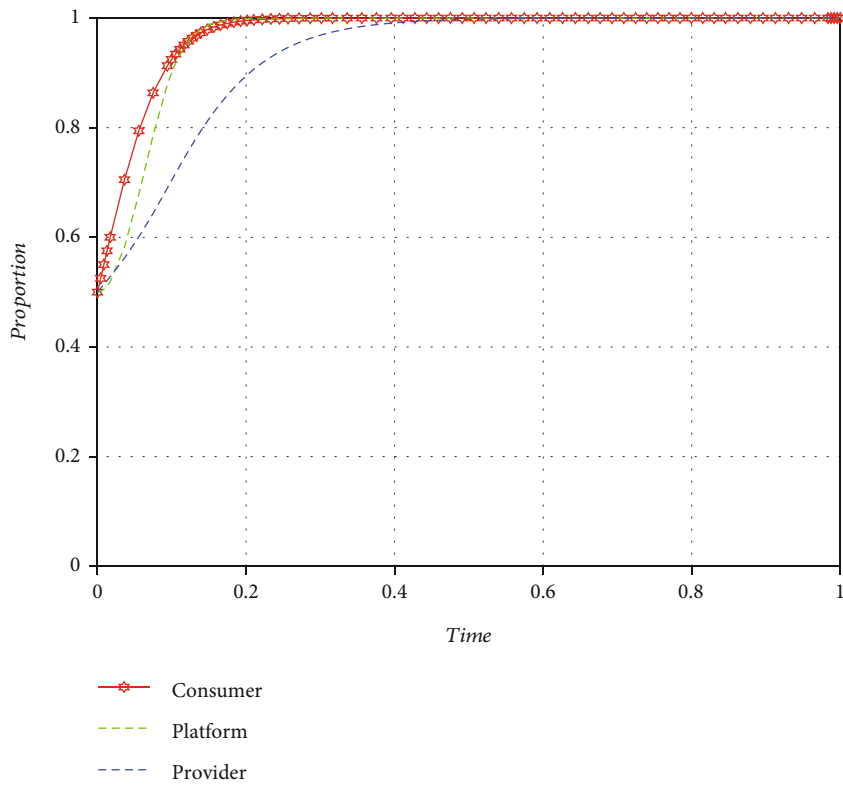
5.1. The Effect of Rewards and Punishments on Evolutionary Outcomes. To verify the effect of the reward and punishment mechanism on the tripartite decision-making of consumers, providers, and knowledge platforms. We designed two comparative experiments. A set of parameters satisfying Scenario 1 is $B_1 = 25, B_2 = 15, r = 0.3, P = 10, L = 10, H_1 = 0, G_1 = 10, F = 0, B_3 = 10, T = 20, a = 0.3, M = 30, R_1 = 30, R_2 = 20, C = 40, D = 20, W_2 = 15, W_1 = 25, H_2 = 0,$ and $G_2 = 5$, representing the strategy choice of the three parties in the state of no rewards and punishments. The other set of parameters satisfies Scenario 2: $B_1 = 25, B_2 = 15, r = 0.3, P = 10, L = 10, H_1 = 10, G_1 = 10, F = 20, B_3 = 10, T = 20, a = 0.3, M = 30, R_1 = 30, R_2 = 20, C = 40, D = 20, W_2 = 15, W_1 = 25, H_2 = 5,$ and $G_2 = 5$, representing the strategic choice of the three parties under the condition of reasonable rewards and punishments.

As shown in Figure 2(a), when the knowledge platform does not implement reward and punishment mechanisms, knowledge providers will lose motivation to share knowledge and adopt a “Perfunctory” strategy. In this case, the knowledge provided by the platform is of low quality, which is not conducive to the sustainable growth of the knowledge sharing environment. In the case of knowledge platform implementation of reward and punishment mechanism, as shown in Figure 2(b). The strategy set of three parties is (H_1 “Paying for help,” L_1 “Supervised,” and S_1 “Hardworking”). Therefore, the interests of the three parties are more closely related, which is in line with the characteristics of bounded rational people, and they all hope to maximize their own interests, which is beneficial to the long-term construction of a knowledge-sharing environment.

5.2. The Influence of Different Factors on Reward and Punishment Results. To explore the influence of different factors on three-party decision-making, we conducted numerical simulation, and the initial parameters were set as follows: $B_1 = 15, B_2 = 15, r = 0.5, P = 20, L = 10, H_1 = 15, G_1 = 10, F = 20, B_3 = 10, T = 20, a = 0.5, M = 30, R_1 = 30, R_2 = 20, C = 40, D = 20, W_2 = 15, W_1 = 25, H_2 = 5,$ and $G_2 = 10$. On the premise of satisfying Scenario 2, we fine-tune the values of $F, B_1, T, M,$ and H_1 to analyze the influence of different factors on the process and results of the evolutionary game. In addition, we also



(a) Three parties' strategy choice without reward or punishment



(b) Three parties' strategy choice with reward or punishment

FIGURE 2: Tripartite strategy comparison of implementing or not implementing reward and punishment mechanisms.

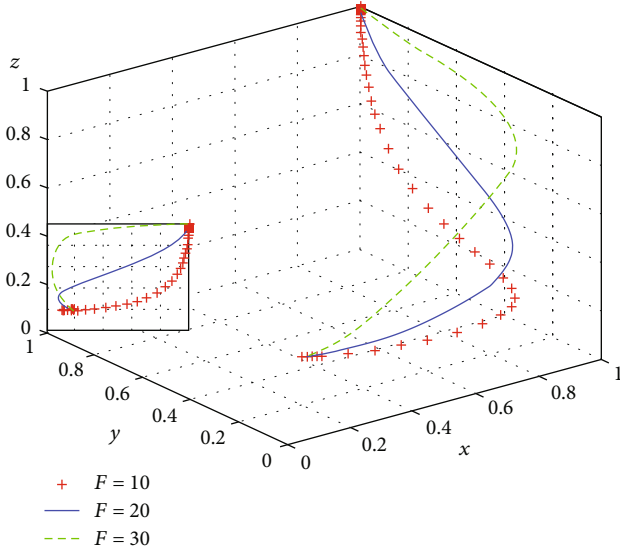


FIGURE 3: The impact of compensation paid by knowledge consumers.

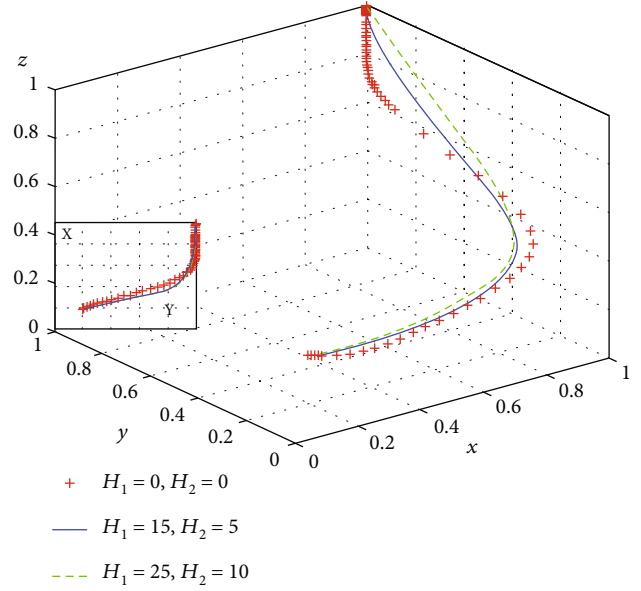


FIGURE 5: The impact of the level of punishment.

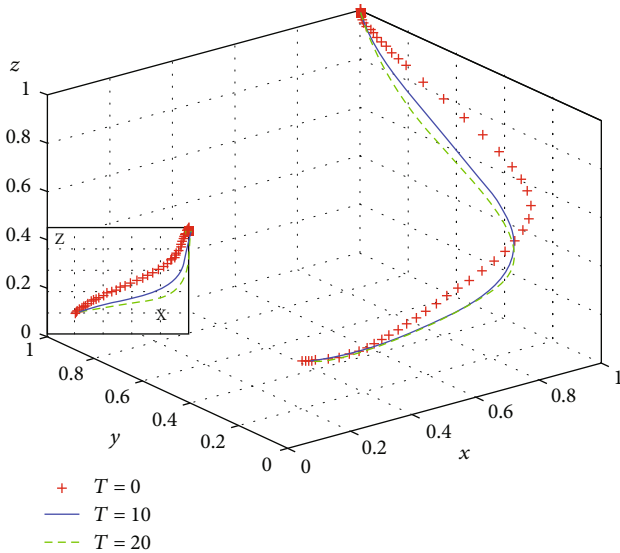


FIGURE 4: The impact of search time cost.

put forward suggestions to promote a better knowledge atmosphere according to the experimental analysis results.

When F is set to 10, 20, and 30, respectively, according to the results of Figure 3, we can draw the following conclusion: As the system evolves to a stable point, with the increase of knowledge consumers' willingness to pay, the probability of knowledge providers adopting the "Hardworking" strategy and the probability of knowledge platform actively "Supervised" gradually increase, which is in line with the current situation, and the higher the bonus paid by consumers, the more attractive knowledge providers are to share their knowledge. At the same time, the active participation of consumers can also bring traffic to the platform, which in turn promotes the platform to more actively motivate and guide users.

When T is set to 0, 10, and 20, respectively, according to the results of Figure 4, we can draw the following conclusion: As the system develops to a stable point, the time cost for consumers to search for knowledge increases and they are more likely to adopt a "Pay for help" strategy, which is also in line with the reality. If the cost to the user exceeds the benefit, it is not worth spending a lot of time searching for knowledge. As a rational economic man, if the cost exceeds the benefit, the "Paying for help" strategy will be chosen more frequently.

When H_1 is set to 0, 15, or 25, and H_2 is set to 0, 5, or 10, according to the results of Figure 5, we can draw the following conclusion: As the system evolves to a stable point, the platform penalizes the knowledge provider for untrustworthy behavior. The greater the punishment, the greater the probability of knowledge providers adopting a "Hardworking" strategy and the probability that the knowledge payment platform will actively motivate and guide users. This is because the greater the punishment for the untrustworthy behavior of the knowledge provider, the greater the trust of knowledge consumers in the platform and the stronger the willingness to consume; and the knowledge provider also avoids adopting a "Perfunctory" strategy as much as possible because of the greater punishment.

5.3. The Validity of Game Models under Different Initial Strategies. Figure 6(a) corresponds to Scenario 1. The final equilibrium point of the system without the punishment mechanism is $E_5(1, 1, 0)$. In this case, the knowledge provider gets the same reward regardless of whether the answer is good or bad. However, in order to maximize their own interests, knowledge providers will cut costs and adopt a "Perfunctory" strategy to produce low-quality content. Figure 6(b) corresponds to Scenario 2; the final equilibrium point is $E_8(1, 1, 1)$ when the system implements the punishment mechanism. In other words, knowledge providers provide high-quality knowledge under the supervision of the platform; The platform is

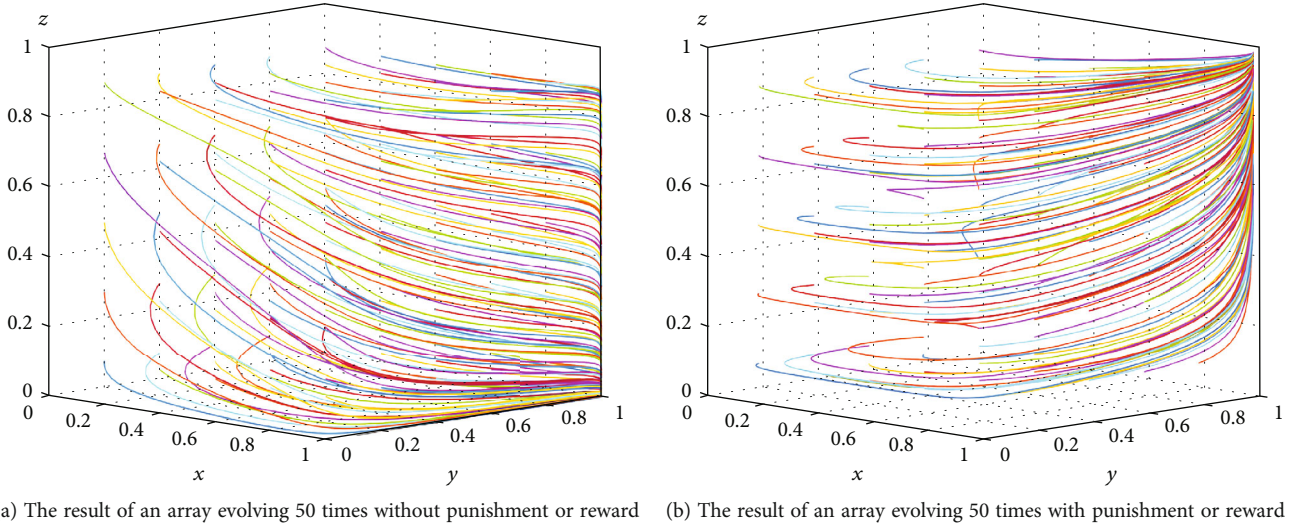


FIGURE 6: The result after 50 times of array evolution in different states.

responsible for actively motivating and guiding users. Consumers respect others' intellectual copyright and pay for acquired knowledge, which maximizes the interests of all participants and promotes knowledge sharing.

In summary, the simulation results are consistent with the stability analysis results, and the conclusion has guiding significance for promoting knowledge sharing.

6. Conclusion

This paper establishes a tripartite evolutionary game model among knowledge consumers, knowledge providers, and knowledge payment platforms and analyzes the evolutionary stability strategies and evolutionary trends of stakeholders. The simulation results show that knowledge payment is an effective way to promote knowledge sharing, and consumers' willingness to pay, reward and punishment mechanism, and platform income are the important factors affecting the decision-making of the three parties. Therefore, we draw the following conclusions through comparative analysis:

- (1) Knowledge payment can be promoted by the creation of a knowledge-sharing chain. Knowledge, as the distillation and sublimation of data, has a value-added trend in the digital economy. People need to keep learning new things and finding new ways. However, with the rapid development of information technology, it is easy for people to feel tired when they have easy access to massive information. Knowledge payment is a perfect solution for users to acquire, process, share, and trade knowledge. Everyone can directly or indirectly participate in the whole process of knowledge sharing chain according to their own professional field, which also provides more possibilities for building a learning society
- (2) The reward and punishment mechanism can boost the quality of knowledge content. On the one hand,

the implementation of a reward mechanism will promote knowledge providers to continuously improve knowledge content; on the other hand, punishment measures will guide knowledge providers to avoid using "perfunctory" strategies to reduce service quality. Therefore, high-quality service content can not only improve user experience and satisfaction but also have positive significance for forming a complete knowledge-sharing chain and building a knowledge-sharing ecosystem

- (3) The supervisory role of the knowledge platform. Knowledge is the core of the knowledge payment platform, and the usefulness of information is what users care about most. If the platform does not supervise and constrain the behavior of participants, the reliability and accuracy of knowledge will be difficult to guarantee, thus affecting the willingness of potential consumers to pay. Therefore, strict supervision of the knowledge sharing process can not only protect the interests of participants from losses and promote knowledge sharing transactions but also enhance the reputation of the platform and promote a virtuous circle of knowledge sharing ecology

In the future, we will introduce a knowledge-based pricing strategy [24, 25] to comprehensively consider how price competition dynamically affects the strategy choices of different agents by dynamically adjusting price parameters. At the same time, we will further consider integrating advanced technologies such as blockchain and federated learning into the knowledge sharing system to fully realize the trade-off between knowledge sharing and property rights protection.

Data Availability

The data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This article is supported in part by the Humanities and Social Science Fund of Ministry of Education of China (Grant No. 21YJCZH197) and the Scientific and Technological Innovation Programs of Higher Education Institutions in Shanxi (Grant No. 2020L0252).

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