Received: 7 October 2023 | Revised: 15 November 2023 | Accepted: 27 November 2023 | Published online: 30 November 2023

RESEARCH ARTICLE

International Journal of Changes in Education
2024, Vol. 1(1) 32–40
DOI: 10.47852/bonviewIJCE32021834

BON VIEW PUBLISHING

Research on the Dynamic Evolution Law of Online Knowledge Sharing Under Trust

Dan Xia[1,*], **Yu Zhang**[1], **Ying Qiu**[2], **Si Zhang**[1], **Yuan Tian**[1] **and Xiaoxiong Zhao**[1]

[1]*Faculty of Artificial Intelligence in Education, Central China Normal University, China*

[2]*Songbai Middle School of Xiamen, China*

Abstract: In the context of the COVID-19 epidemic, it has become a new trend for people to use online learning communities for learning and communication. Previous studies had shown that trust was one of the important factors affecting knowledge sharing behavior in the online learning communities. However, related studies had not analyzed its mechanism from the micro level. Based on the knowledge sharing gain coefficient and multi-angle trust degree of the online learning communities, this paper constructed the corresponding public goods evolution game model and constructed the Holme–Kim theoretical network model according to the structural characteristics of the community user interaction network. The simulation experiment was carried out by using Matlab to analyze the influence of group trust value and individual trust value on group sharing behavior. From the micro level, this paper analyzed the evolution law of knowledge sharing behavior in the network under the influence of trust. The results showed that the degree of trust knowledge sharing played an important role in improving the behavior of group knowledge sharing. This study provided theoretical guidance for improving the level of knowledge sharing in the e-learning community and creating a good learning atmosphere.

Keywords: knowledge sharing, online learning, evolutionary game theory, Holme–Kim theoretical network model

1. Introduction

The degree of interaction among community users and the quality of community knowledge determine the development level of the online learning communities, and the knowledge sharing level and positivity of online learning communities users not only affect the knowledge quality of the online learning community but also stimulate the sharing enthusiasm of other users and attract more users.

With the rapid development of information technology, online learning communities provide people with a convenient learning environment. In the online learning community, people learn and communicate without restrictions on time, place, and number of participants. Knowledge sharing is considered to be one of the important processes in the development of the online learning community (Li & Li, 2010). Bartol and Srivastava (2002) defined knowledge sharing as the sharing of information, ideas, suggestions, and expertise related to certain fields among individuals. However, not all users in the communities choose to share knowledge. Szulanski (1996) held that some of the reasons why individuals are reluctant to share knowledge are (1) fear of losing ownership of knowledge, superiority; (2) knowledge sharing is not getting the rewards it deserves; and (3) individuals lack the time and resources needed to achieve this sharing. Therefore, how to promote knowledge sharing between members of the online learning communities has become the focus of relevant research.

*__Corresponding author__: Dan Xia, Faculty of Artificial Intelligence in Education, Central China Normal University, China. Email: danxia@ccnu.edu.cn

Openness, anonymity, dynamism, and other characteristics distinguish knowledge sharing in online learning settings from traditional systems and learning environments. In a system that is this open and dynamic, trust might play a major role in influencing how people share their knowledge. In fact, it was discovered that people were more likely to share knowledge in a learning environment where there was a higher degree of trust. This suggested that trust may play an even more important role in virtual environments (Alsharo et al., 2017). Therefore, exploring the impact of trust on knowledge sharing in online learning is of great significance to the development of online learning communities and the improvement of learners' online learning quality.

2. Literature Reviews

The process of knowledge sharing involves the self-transformation of knowledge within a specific community environment, facilitated by interactions between knowledge providers and recipients (Ouakouak et al., 2021). At present, most of the research on knowledge sharing focuses on professional virtual community, virtual community of practical, academic virtual community, etc. (Li et al., 2018). By combing the research of knowledge sharing at home and abroad, Ahmed et al. (2019) found that the research of knowledge sharing was mainly divided into empirical research and descriptive research, taking one or more theories as to the basic theory of the research, and establishing the corresponding research model, to determine the factors that affect the behavior of knowledge sharing; the commonly

© The Author(s) 2023. Published by BON VIEW PUBLISHING PTE. LTD. This is an open access article under the CC BY License (https://creativecommons.org/licenses/by/4.0/).

used basic theories are social cognitive theory, social capital theory, organizational citizenship behavior, etc. By summarizing relevant literature, it is found that trust is one of the important factors that affect users' knowledge sharing in the community. Drawing on social cognition theory, Chen and Hung (2010) investigated the influencing factors of knowledge-sharing behavior from both situational and individual perspectives through a questionnaire survey. The results showed that trust had a significant positive impact on knowledge sharing behavior. Hsu et al. (2007) divided trust into economy-based trust, information-based trust, and identity-based trust and proved through empirical research that trust was very important and played a significant positive role in knowledge sharing of virtual community members. Based on the relational dimension of social capital theory, Hau and Kang (2016) collected 140 data from the online community, which were used for empirical analysis. The results showed that trust had a significant impact on knowledge sharing. In addition, based on organizational citizenship behavior, Mutahar et al. (2022) found a significant positive relationship between trust and knowledge sharing in organizations. In addition, trust significantly predicted organizational citizenship behavior, which in turn significantly influenced knowledge sharing.

Although trust is the key factor to encourage community members to share knowledge, there are some differences in the mechanism of trust under different theoretical bases. In social cognitive theory, trust is an environmental factor that influences users' knowledge sharing behavior. In the theory of social capital, trust belongs to the relationship dimension, which positively affects the knowledge sharing behavior of community members. In the theory of organizational citizenship behavior, trust could directly or indirectly affect the virtual community sense of community members and then promote knowledge sharing among members (Ahmed et al., 2019).

In addition, many scholars had realized that trust had multiple dimensions and classified trust according to different standards. According to the object of trust, Rotter (1967) divided trust into interpersonal trust, which refers to the trust between community members, and system trust, which refers to the trust of community members to the community. McAllister (1995) classified trust as cognitive-based trust, which is perceived as reliable and capable of getting things done, and emotional trust, which is based on friendly relationships. According to the different stages of the relationship, Lewicki and Bunker (1996) divided trust into calculus-based trust, knowledge-based trust, and identification-based trust. Calculus-based trust is the hope to obtain return through the process of establishing and maintaining a relationship and the fear of being punished for violating trust; knowledge-based trust is based on the knowledge gained by other users through long-term interaction; and identification-based trust is based on trusting other members without worrying about their own interests (Panteli & Sockalingam, 2005). Trust, as one of the key influencing factors in the online learning community, had a direct or indirect impact on the knowledge sharing behavior in the community in many aspects. Many scholars had proved it through empirical research. Sun and Du (2010) measured the level of knowledge sharing in real-name virtual community from the two aspects of Q & A frequency and Q & A quality, and the empirical results show that trust is positively correlated with Q & A frequency and Q & A quality. Through empirical research, Tamjidyamcholo et al. (2013) found that trust was closely related to community knowledge sharing intention and attitude. According to Platt et al.'s (2018) analysis of knowledge sharing in the healthcare industry, trust could boost the incentive for healthcare professionals and associated organizations to exchange medical knowledge. Overall, recent research indicated that people were hesitant to share sensitive and personal information with people they did not trust (Butt, 2021) and that trust between users in a community had a significant positive effect on knowledge sharing (Gubbins & Dooley, 2021; Lee et al., 2020; Rutten et al., 2016). Therefore, interpersonal collaboration was predicated on trust (Vasin et al., 2020), and it was a key factor in enabling knowledge sharing behaviors (Curado & Vieira, 2019).

Although a large number of scholars had proved the influence of trust on knowledge sharing behavior in online learning communities through theoretical and empirical studies, most of the studies were to establish theoretical models, adopted social investigation methods, or examined the influence of influencing factors on knowledge sharing willingness or knowledge sharing behavior from the perspective of game theory, without further analyzing the process of its influence from the micro level (Zhang et al., 2016). Game theory is a field of study that uses suitable mathematical models and techniques to evaluate, forecast, and influence autonomous individuals' decision-making behaviors in stakeholder situations. In contrast, the theoretical instrument of evolutionary dynamics was employed to illustrate the process of group evolution (Nowak, 2006). Evolutionary game theory, which combines traditional game theory with evolutionary dynamics, is a fundamental paradigm for explaining how group decisions arise and change. It offered a useful theoretical framework for researching cooperative behavior in online learning communities (Gintis, 2000). Currently, most of the researches based on evolutionary game theory use the prisoner's dilemma game model, which is a typical two-person game model and emphasizes the game between two and two. Zhang et al. (2016) analyzed the game process of knowledge sharing in virtual academic communities based on the prisoner's dilemma, constructed a game payoff matrix, and found that the trust relationships between members could effectively alleviate the prisoner's dilemma, improved the possibility of community members to choose sharing strategies, and made the game results more inclined to collective rationality.

For online learning community, all users can share knowledge in the community, the shared knowledge is stored on the platform, and other users can browse and learn; for the characteristics of the online community, this study extends the prisoner's dilemma game with two-person participation to a public goods game (PGG) with multi-player participation. The PGG model is a typical multi-player game model in game theory, which can better describe the knowledge sharing behaviors in an online learning community: consider that there are N participants, who can choose to put c into the public goods box or choose not to do so. After all the people perform the decision-making behavior, suppose the number of people who choose to put in is x, then the total input (public resources) cx will be doubled by r and then evenly distributed to all the people, so that the betrayer who chooses not to put in has a gain of $P_D = rcx/N$, and the collaborator has a gain of $p_c = P_D - c$ due to the input of c. Obviously, the cooperator in the PGG has the risk of loss (when the number of inputs $x < N/r$), while the free-rider betrayer is always strictly higher than the cooperator because he or she does not put in but shares the public resources, and the cooperation strategy is strictly dominated strategy. Without the restriction of effective mechanism, the result of the game is that rational people will choose to "hitchhike" and not to invest, thus giving up the construction of public resources and falling into the tragedy of the commons. However, in this study, we added the mechanism of trust to investigate whether trust has a positive effect on the evolution of knowledge behavior in e-learning communities.

The evolutionary game of knowledge-sharing strategies needs to take place within the user's interaction network. Due to factors such as the large number of nodes in the actual interaction network, limited computational capabilities, and the time-consuming nature of experiments, conducting the experimental part of the game in a real-world setting is not feasible. Therefore, we aim to simulate the knowledge-sharing behavior of community users through a computer. We have chosen the Holme-Kim (HK) scale-free network model to construct the interaction network, with the goal of establishing a network model that accurately reflects real-world conditions and characterizes the interaction relationships among users in the online learning community. Holme and Kim (2002) proposed the HK scale-free network model with tunable clustering coefficients and improved the network generation algorithm by introducing the triad formation (TF) step, which used an adjustable parameter pt to construct the network by continuously constructing the network. By improving the network generation algorithm and introducing the TF step with an adjustable parameter pt, the final network inherited the original power law distribution and had high clustering characteristics, which was more in line with the actual situation and could portray the interaction relationship between the users of the e-learning platform in a more suitable way.

In the network evolution game perspective, the interaction network described who online users play with, while the strategy learning network portrayed who online users learn from to obtain information about gains and strategy behavior. Trust acted on users' gains during the game, and game gains influence users to change their game strategies by selecting learning objects from the best, thus affecting the evolution of knowledge sharing strategies.

In summary, this study portrayed the interaction structure among individuals with HK network and the knowledge sharing decision-making paradigm of individuals under the influence of trust with evolutionary game, which provided a new research framework for analyzing and predicting the knowledge sharing behaviors of groups under the trust environment in online learning communities, and a systematic study of which could quantitatively understand the impact of trust on the evolution of knowledge sharing cluster behaviors.

3. Research Methodology

Under the background of "Internet+Education," trust was regarded as a crucial motivation for knowledge sharing in e-learning platforms. This paper cross-fertilized multidisciplinary knowledge such as complex network theory and evolutionary game method and introduced natural science research paradigm into the study of educational issues. We constructed a corresponding evolutionary game model to investigate the mechanism of group trust and individual trust on knowledge sharing behavior in open, dynamic, and complex networks, with a view to providing a reference for online learning platform administrators on how to effectively improve the enthusiasm of group knowledge sharing. Since the time and the network scale required for evolutionary game were difficult to be realized in the real world, and software simulation could be based on reasonable values for evolutionary game and intuitively showed the final trend of the development of things over time; therefore, this study referred to the existing literature to give values to the variables in the model constructed in this paper one by one in a scientific way, and used MATLAB 2017a software to simulate the evolutionary game model to analyze the impact of the changes in the value of the group trust parameter and the value of the individual trust parameter on the decision-making of the user's knowledge sharing behaviors.

3.1. Evolutionary game model variables

The traditional game theory mainly studies the interactive behaviors and results between rational individuals, while the evolutionary game theory focuses on the repeated game of limited rational individuals and continuous adaptive learning to optimize their own income. Based on the public goods model, this paper constructed an evolutionary game model. The PGG model is a classical multi-player game model: the number of rational participants in the group is N, according to their ideas, each participant decides whether to invest in the public box if the choice of investment is a cooperative strategy; otherwise, it is a betrayal strategy. At the end of the investment session, the total investment in the public box will be multiplied by r and divided equally among all participants (including those who did not invest).

Suppose the size of the community is N. According to the characteristics of knowledge sharing among users of the online learning community, the following variables are constructed in this paper:

(1) Knowledge: K

People's knowledge reserve has some differences, so the amount of knowledge each user has also has some differences. $K = \{K1, K2, K3, \ldots, Kn\}$ represents the knowledge capacity of each user in the community.

(2) The cost of knowledge sharing: C

The time, energy, and other costs that users need to spend when sharing knowledge. $C = \{C1, C2, C3, \ldots, CN\}$ represents the cost of knowledge sharing for each user in the community, and when the user chooses not to share knowledge, $c = 0$.

(3) Knowledge sharing income factor: r

Users internalize the acquired knowledge to improve their knowledge capacity. Because users have different internalization abilities, knowledge gain coefficients are also different. For convenience of research, this paper does not consider this difference. In the game model, the gain coefficient of knowledge sharing is as follows: the total investment in the public goods box is multiplied by r times and is distributed equally to the members of the community.

(4) Community incentive factor: R

The community receives rewards for users who do knowledge sharing.

(5) Trust: T

The degree to which community users trust other users. Depending on the degree of trust, the amount of capital invested in the game will vary accordingly. Its value range is [0,1], where 0 means complete distrust and 1 means complete trust.

(6) Number of neighbors for the user: Ω

Due to the difference of users' knowledge, the users are divided into multiple groups centering on themselves, and the members of the groups are the neighbors of the central users to interact within the group. $\Omega = \{\Omega_1, \Omega_2, \ldots, \Omega_n\}$ represents the number of neighbors for each user in the community.

3.2. How the game payoffs are calculated

In the PGG, users participate in the self-centered and their neighbor-centered group games. Due to the difference of trust degree, the corresponding investment will be different. If user i chooses the sharing strategy, the amount of knowledge invested is "$T * K_i$", otherwise 0. The amount of knowledge obtained for each group is $(T*K_i)/(\Omega_i+1)$. Finally, the total amount of knowledge gained by the group is multiplied by r times and divided equally among each participant in the group (including those who do not share). The income obtained by user i participating in the group game centered on neighbor j is calculated as follows:

$$U_{i,j} = \frac{r}{|\Omega_j| + 1} * \sum\nolimits_{l \in \Omega_j \cup j} \left(\frac{K_l * T * s_l}{|\Omega_l| + 1} \right) - \frac{K_i * T * s_i}{|\Omega_i| + 1} \tag{1}$$

Where S_i represents the strategy of user i, $S_i = 1$ when the user adopts the sharing strategy, otherwise 0; Ω_i represents the number of neighbors for user i. When users choose to share knowledge, they will lose the advantage of occupying knowledge alone and need to spend a certain cost, but the community will reward users based on how much they share. The cumulative benefits to user i are therefore as follows:

$$U_i = R * T * K_i * s_i - C + \sum\nolimits_{j \in \Omega_i \cup i} U_{i,j} \tag{2}$$

3.3. Strategy update rule

At present, the most common updating methods in the research are to imitate the strategy of the neighbors with the highest returns, Fermi dynamics, etc., From a biological and social perspective, individuals want to improve their incomes by imitating the behavior of successful people, so users choosing learning objects are not completely random, and learning objects will have an impact on strategy choice. The literature by Shi et al. (2009) proposes a method of prioritizing user income as a learning object, and the probability that user i selects user j as a learning object is

$$Q_{i \to j} = \frac{e^{P_j * A}}{\sum_{l \in \Omega_i} e^{P_l * A}} \tag{3}$$

Where A is a tunable parameter and Ω_i is the set of i's neighbors, when $A > 0$, high income neighbors are more probability to be used as learning objects; when $A = 0$, it is equivalent to randomly selecting a neighbor as the learning object. This paper assumes that $A = 1$.

After determining the learning object, the strategy is updated. Fermi dynamics is a strategy update rule. Fermi dynamics, as one of the classical strategy update methods, is based on calculating a learning probability, according to which user i determines whether to imitate learning object j to update the strategy. The formula for learning probability is as follows:

$$W(s_j - s_i) = \frac{1}{1 + e^{\frac{P_i - P_j}{k}}} \tag{4}$$

Where P_i and P_j, respectively, represent the income of user i and user j in this round of game. According to the formula, the probability of users learning a neighbor strategy largely depends on the income difference between the two. Parameter k describes the noise factors of the environment and describes the irrational degree of individuals. When $k \to 0$, it means that the individual has complete rationality, which will only learn the strategy of neighbors higher than its own income, while as k increases, individual rationality decreases and the likelihood of learning low-income neighbor strategy increases. In reality, users are all limited rational individuals, and k is usually 0.1.

4. Process and Results

4.1. The simulation steps

This paper used Matlab to simulate the evolution of knowledge sharing behavior in the online learning community, to explore the impact of trust on users in the online learning community, and to analyze the simulation results.

The simulation was performed on a HK network of size $N = 300$ (generated by the tunable clustering parameter $pt = 0.6$). Nodes in the network were randomly assigned with the same probability to share or not to share strategy, which were 1 and 0, respectively. The various discrepancies between users were not considered for the time being, and the initial parameter value is $k = 1$, $C = 0.01$, $r = 1.56$, $R = 0.11$. The simulation steps were as follows:

Step 1: Initialize the HK network model, in order to facilitate the simulation, the size of the network model is set to $N = 300$;
Step 2: Initialize the strategy of the network node;
Step 3: Play games between nodes and calculate their respective benefits;
Step 4: The node in the network selects a neighbor as the learning object according to the priority selection method, and then updates the strategy through the Fermi rule;
Step 5: Turn to step 3, until the end of the set time step.

To improve the reliability of the data and reduce the error of the probability, on the basis that the initial network and initial strategy distribution remain unchanged, all relevant data points were taken from the average result after 30 independent operations. When the network evolved to the set time step, the proportion of shared nodes in the network was used to evaluate the group sharing level.

4.2. Analysis of simulation results

4.2.1. Simulation analysis of the influence of network scale on the evolution of group knowledge sharing

Network size may have some influence on the evolution of knowledge sharing, so this paper simulated the network of 100 and 1000 nodes under the same parameters, as shown in Figure 1.

From these two pictures, it could be found that the end result of evolution to steady state was the same, both tending to 0. Users hoped to improve their income by imitating the behavior of high-income users, so users were updated, and they are more likely to learn from them and updated their own strategy. However, in the absence of intervention, most of the high-income users adopted a non-sharing strategy. With the evolution process, users in the group gradually tended to choose non-sharing strategy, resulting in low sharing level of the group, so the proportion of shared nodes was reduced, this proved that online platforms should explore ways to build trusting relationships between users, as people were reluctant and unaccepting of sharing knowledge with others in an environment where there was a lack of trust (Gagné et al., 2019).

In addition, the HK network of scale 100 reached the steady state before the 10th time step, while the HK network of scale 1000 reached the steady state before the 100th time step. Thus, it could be seen that with the growth of the size of the online learning community network, the evolution time of knowledge sharing behavior would also increase. Why did this happen? Mainly because the number of neighbors corresponding to nodes in the network would also change according to the change of network scale, and the interaction between

Figure 1
Level of sharing at different network sizes. (a) HK network with a scale of 100 and (b) HK network with a scale of 1000

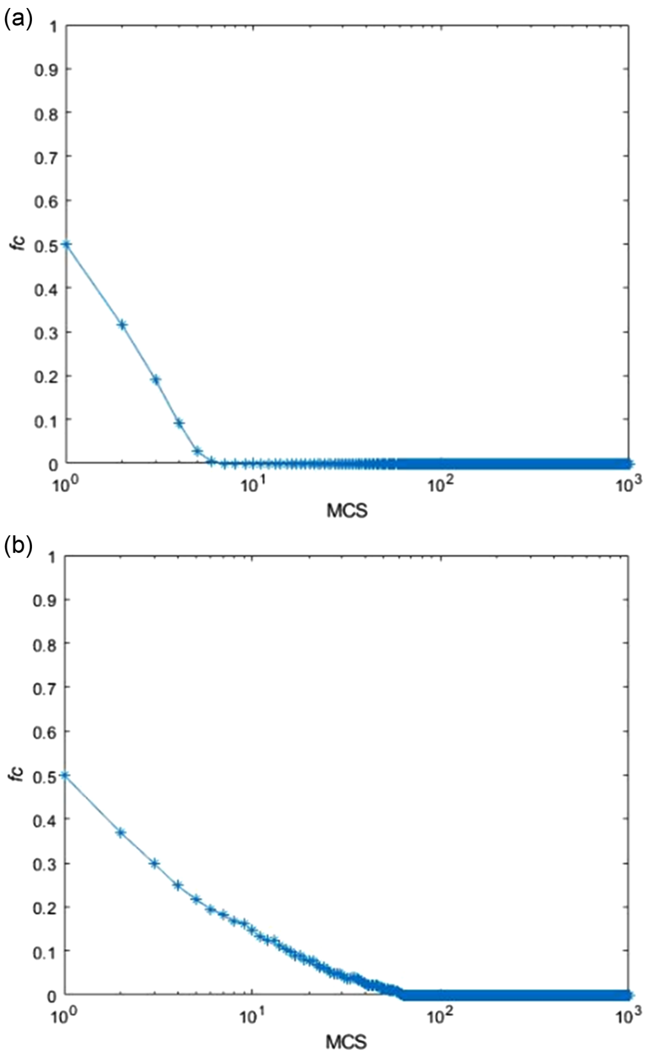
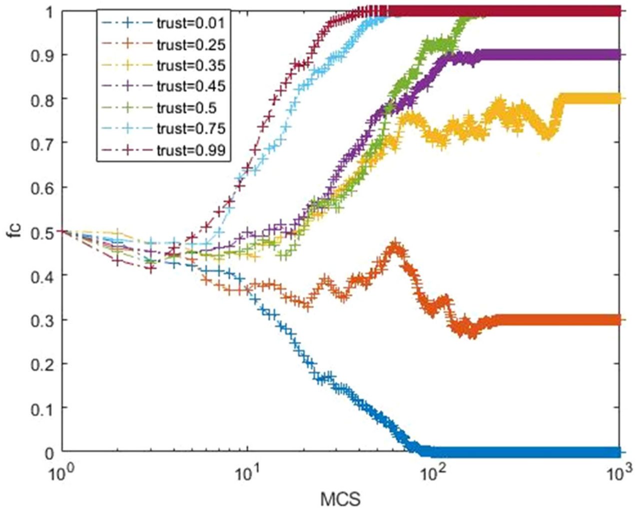


Figure 2
The change of knowledge sharing level with time under different trust levels



neighbors was richer, so it took longer to evolve to a stable state. Similarly, in a real-world online learning community, interactions increased as the community grows. It would take some time for the community to reach a stable state.

Based on the above analysis, it could be concluded that the network of different scale would affect the rate of population evolution to stable state, but not the final stable state. That is, in the community, the scale of the community would affect the time for community users to find the optimal strategy, but would not affect the final strategy selection result of users. In order to facilitate the simulation study, the following simulation would be carried out in the size of 300 HK network.

4.2.2. Simulation analysis of the influence of group trust on the evolution of group knowledge sharing

The sharing amount of community users varied with the degree of trust. Figure 2 shows the change of knowledge sharing level with time under different trust levels, and the values of trust were 0.01, 0.25, 0.35, 0.45, 0.50, 0.75, and 0.99, respectively. As shown in the simulation result diagram, when $T = 0.01$, the proportion of users who choose sharing strategy in the group gradually tended to 0; when $T = 0.25$, $T = 0.35$, and $T = 0.45$, the proportion of users who chose sharing strategy in the group was between 0 and 1, but when $T = 0.25$, the sharing level of the group was low, while $T = 0.35$ and $T = 0.45$ were at a high level; when $T = 0.5$, $T = 0.75$, and $T = 0.99$, the proportion of users who chose sharing strategy tended to 1. This showed that trust had a forward impact on the knowledge sharing behavior of online learning communities and could promote the emergence of shared behavior in groups.

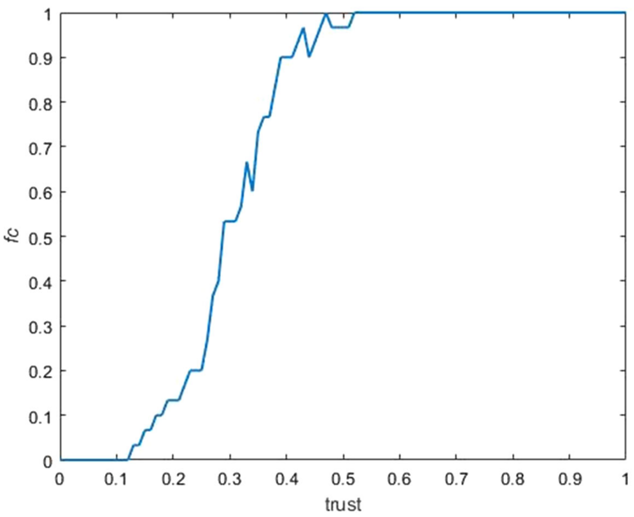
When the group trust level was low, even if users chose the sharing strategy in the process of game, they would chose to share less knowledge because of the low degree of trust. Due to the small amount of shared knowledge, they would obtain less community sharing rewards and the cost of sharing. This made the users who chose the sharing strategy obtain less benefits or even losses. However, users who chose not to share become a more profitable part of the group. Due to users' propensity to emulate the actions of successful individuals with higher incomes in order to enhance their own earnings, a predominant trend emerged where the majority opted to mimic the behavior of non-sharers. Specifically, as group evolution stabilized, most users adopted a non-sharing strategy. This discovery underscored, at a micro level, the positive impact of the group's average trust on knowledge sharing. It crystallized the significance of trust in facilitating knowledge sharing, aligning with insights from prior research findings.

When the group trust level was high, the users who choose the sharing strategy would share more knowledge because of the high trust level. At this time, due to the amount of knowledge shared in the public box was more, the benefits of members and community sharing rewards were more, the cost of sharing was lower and could be ignored, and the benefits of users who chose to share in the group are higher. In this case, most users would choose to imitate the behavior of sharers, that is, when the group evolution reached a steady state, most users chose the sharing strategy.

The simulation results were further analyzed. When the trust degree made the group steady state reach a high (low) sharing level, the higher (lower) the trust degree, the group would evolve to steady state faster. This is mainly because with the evolution process, the income gap between users who chose different strategies was gradually widened. When the income gap is large enough, the group can quickly reach a steady state.

In addition, through the simulation result diagram given in Figure 2, it could be found that when the trust value was greater than 0.5, the proportion of users who chose to share tended to 1, but when it was less than 0.5, the proportion was less than 1. Therefore, this paper considered whether there was a trust threshold. When the trust value is greater than the threshold, the group sharing level would eventually tend to 1. On the basis of the above, the simulation was carried out again to observe the sharing level of groups in steady state with the same parameters and different trust values. The data points were the last 100 data after 1500 Monte Carlo time steps. These data were obtained by averaging after 30 independent operations. The simulation results are shown in Figure 3.

Figure 3
With the change of trust value, the level of knowledge sharing of the group

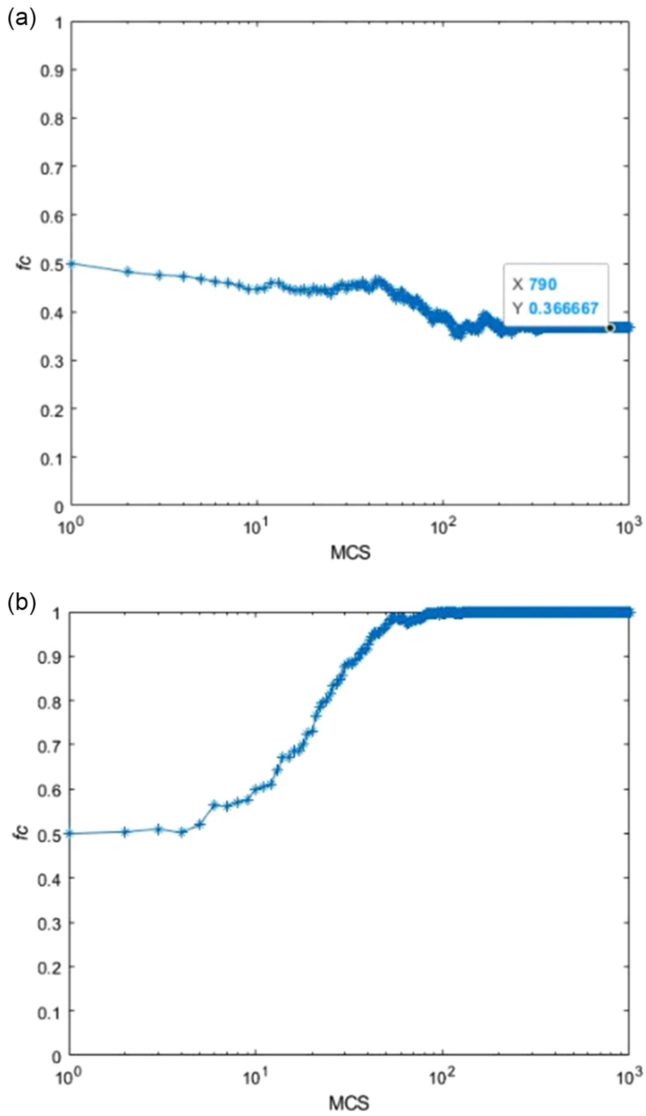


With the increase in trust levels, more and more nodes within the group gradually chose to share. However, despite occasional sporadic mutations, the trend remained unchanged. These mutations primarily stemmed from users retaining some uncertainty when selecting random objects. In summary, when the trust level reached around 0.4, the group often displayed a moderate to high level of sharing.

4.2.3. Simulation analysis of the influence of individual trust value difference on the evolution of group knowledge sharing

In practice, there were some differences in the degree of trust between people. In view of this situation, a group knowledge sharing evolution based on individual trust value difference was proposed and simulated. In order to simulate the difference of individual trust in reality, the trust value of each user was initialized randomly. The results are shown in Figure 4. The average trust value of the group in Figure 4(a) was 0.2506, and the average trust value of the group in Figure 4(b) was 0.5073. The simulation was mainly to verify the impact of trust differences among individuals

Figure 4
The change of group sharing level under different individual trust values. (a) The average trust value of the group was 0.2506 and (b) The average trust value of the group was 0.5073



on the results of group knowledge sharing level, so the individual trust value was not changed. Through the analysis in Figure 4, it could be found that when the group evolves to a steady state, the sharing level of the group was lower when the average trust level was low. When the average trust level was 0.5073, the sharing level of the group also reached a high level. Therefore, the difference of trust degree between individuals had little effect on the sharing level of the group, and the average trust degree of the group was the key to the evolution of the group.

5. Conclusions and Suggestions

Firstly, this paper constructed a public goods evolutionary game model of knowledge sharing among users in online learning community. Then, Matlab was used to carry out simulation experiments from the perspective of group trust value and individual trust value. Finally, it explored and analyzed the impact of trust on knowledge sharing behavior from the micro level.

5.1. Characteristics of the research

5.1.1. Choice of game model

Compared with the traditional prisoner's dilemma game model, the PGG model would be more fit with the interactive characteristics of the community in the real situation. Prisoner's dilemma game is a two-person game, which is a point-to-point interaction form, while PGG is a multi-person group game, which is a form of group interaction. The interaction modes of the two are completely different. The interaction form in online learning community is obviously multi-person interaction, so it is more appropriate to adopt multi-person game model – PGG model. In reality, users with the same knowledge demand are more likely to interact and become neighbors to form a group. The community platform plays the role of a public goods box. Publishing the shared knowledge on the platform is equivalent to investing in the public goods box. Each user determines the amount of shared knowledge according to his own strategy and trust, and then plays a game. The model can well describe the evolution process of users' knowledge sharing behavior in the community.

5.1.2. Strategy update rule

Compared with the traditional strategy update method, the priority update strategy is more suitable with the policy update method of community users. In the traditional strategy updating mode, users randomly select a neighbor and update the strategy according to Fermi rule. This method has strong randomness. From the perspective of biology and society, in reality, most users want to obtain greater benefits. Therefore, it is more likely to learn from users with high benefits, but it does not rule out that some users may learn strategies from users with low benefits. Therefore, this paper introduced the priority update strategy, took the income as the standard to select the learning object, calculated the relevant probability value, and then updated the strategy. This method better reflects the learning behavior of users in the online learning community, reduces the error caused by randomness, and further depicts the evolution process of knowledge sharing behavior in the community.

5.2. Research conclusion

5.2.1. Simulation analysis of the influence of network scale on the evolution of group knowledge sharing

Network scale was the number of users in online learning community, which would affect the time for community users to find the optimal strategy, but would not affect the final strategy selected by users.

5.2.2. Simulation analysis of the influence of group trust on the evolution of group knowledge sharing

Group trust played a positive role in promoting knowledge sharing in online learning community, and there was a trust threshold. When the trust degree reached this threshold, the community could be at a high sharing level. Firstly, this paper analyzed the knowledge sharing behavior of users in the community by setting the group trust and proved that the group trust played a positive role in promoting the knowledge sharing behavior of users. Secondly, by simulating the evolution of knowledge sharing under different trust, it was proved that when the trust reached a certain degree, the community could be at a high sharing level. Finally, due to the differences in the degree of trust between people, the simulation analysis of individual trust was further carried out. The results showed that its impact was similar to that of group trust, which better explained the promoting effect of trust on users' knowledge sharing behavior and could improve the level of group sharing.

5.3. Recommendations

According to the experimental simulation results, this paper put forward corresponding suggestions on the management of online learning community, so as to promote the knowledge sharing behavior of community users and maintain the long-term and stable development of the community.

5.3.1. Enhance the trust of community users to other members and the community

Higher trust could effectively promote community knowledge sharing behavior. The community makes it easier for learners to acquire new knowledge by optimizing platform resources, which is a way to enhance users' trust in the community. In addition, the community can hold some relevant activities that can promote community user interaction and set up a reasonable interaction mechanism to provide users with a good communication environment, so as to promote users' trust in the community and other users in the community, so as to better improve the knowledge sharing degree of the group.

5.3.2. Set up a reasonable reward mechanism

The community should give some rewards to users according to their knowledge sharing behavior, both materially and spiritually. For example, set the score ranking list, give certain score rewards according to different degrees of user knowledge sharing, arrange according to the number of points, and update the score ranking list every other cycle. In addition, scores can also be used to exchange material rewards to encourage users to actively participate in knowledge sharing.

5.4. Implications and further research

The long-term and stable development of online learning community needs to rely on community managers and community users. This paper analyzed the impact of trust on user knowledge sharing in online learning community from the micro level and put forward corresponding suggestions according to the research results. This had certain theoretical and practical significance for promoting the knowledge sharing behavior of online learning community. However, there are still some deficiencies. For example, this paper mainly studied the influencing factor of trust value in detail, but in the actual online learning community, the factors affecting knowledge sharing are very complex, and even there may be cross effects, so it needs to be further studied.

Funding

This work was sponsored by the National Natural Science Foundation of China, under Grant Number 61907021, 62077016.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

References

Ahmed, Y. A., Ahmad, M. N., Ahmad, N., & Zakaria, N. H. (2019). Social media for knowledge-sharing: A systematic literature review. *Telematics and Informatics*, *37*, 72–112. https://doi.org/10.1016/j.tele.2018.01.015

Alsharo, M., Gregg, D., & Ramirez, R. (2017). Virtual team effectiveness: The role of knowledge sharing and trust. *Information & Management*, *54*(4), 479–490. https://doi.org/10.1016/j.im.2016.10.005

Bartol, K. M., & Srivastava, A. (2002). Encouraging knowledge sharing: The role of organizational reward systems. *Journal of Leadership & Organizational Studies*, *9*(1), 64–76. https://doi.org/10.1177/107179190200900105

Butt, A. S. (2021). Termination of personal relationship and their effects on knowledge sharing in supply chains. *Knowledge and Process Management*, *28*, 18–28. https://doi.org/10.1002/kpm.1643

Chen, C., & Hung, S. (2010). To give or to receive? Factors influencing members' knowledge sharing and community promotion in professional virtual communities. *Information & Management*, *47*(4), 226–236. https://doi.org/10.1016/j.im.2010.03.001

Curado, C., & Vieira, S. (2019). Trust, knowledge sharing and organizational commitment in SMEs. *Personnel Review*, *48*(6), 1449–1468. https://doi.org/10.1108/PR-03-2018-0094

Gagné, M., Tian, A., Soo, C., Zhang, B., Ho, K. S. B., & Hosszu, K. (2019). *Why employees don't share knowledge with each other*. Retrieved from: https://hbr.org/2019/07/why-employees-dont-share-knowledge-with-each-other

Gintis, H. (2000). *Game theory evolving: A problem-centered introduction to modeling strategic behavior*. USA: Princeton University Press.

Gubbins, C., & Dooley, L. (2021). Delineating the tacit knowledge-seeking phase of knowledge sharing: The influence of relational social capital components. *Human Resource Development Quarterly*, *32*(3), 319–348. https://doi.org/10.1002/hrdq.21423

Hau, Y. S., & Kang, M. (2016). Extending lead user theory to users' innovation-related knowledge sharing in the online user community: The mediating roles of social capital and perceived behavioral control. *International Journal of Information Management*, *36*(4), 520–530. https://doi.org/10.1016/j.ijinfomgt.2016.02.008

Holme, P., & Kim, B. J. (2002). Growing scale-free networks with tunable clustering. *Physical Review E*, *65*(2), 026107. https://doi.org/10.1103/PhysRevE.65.026107

Hsu, M. H., Ju, T. L., Yen, C., & Chang, C. (2007). Knowledge sharing behavior in virtual communities: The relationship between trust, self-efficacy, and outcome expectations. *International Journal of Human-Computer Studies*, *65*(2), 153–169. https://doi.org/10.1016/j.ijhcs.2006.09.003

Lee, Y. L. A., Malik, A., Rosenberger III, P. J., & Sharma, P. (2020). Demystifying the differences in the impact of training and incentives on employee performance: Mediating roles of trust and knowledge sharing. *Journal of Knowledge Management*, *24*(8), 1987–2006. https://doi.org/10.1108/JKM-04-2020-0309

Lewicki, R. J., & Bunker, B. B. (1996). Developing and maintaining trust in work relationships. In R. M. Kramer & T. R. Tyler (Eds.), *Trust in organizations: Frontiers of theory and research* (pp. 114–139). SAGE Publications.

Li, G. X., & Li, Y. J. (2010). Knowledge sharing behavior in learning online communities: A social capital perspective. In *IEEE International Conference on Management of Innovation & Technology*, 910–915. https://doi.org/10.1109/ICMIT.2010.5492821

Li, J., Li, H., Yang, F., Shen, X. L., & Wang, Y. F. (2018). Review of knowledge sharing in virtual communities: A theoretical perspective. *Information Sciences*, *36*, 171–176.

McAllister, D. J. (1995). Affect-and cognition-based trust as foundations for interpersonal cooperation in organizations. *Academy of Management Journal*, *38*(1), 24–59. https://journals.aom.org/doi/abs/10.5465/256727

Mutahar, Y., Farea, M. M., Abdulrab, M., Al-Mamary, Y. H., Alfalah, A. A., & Grada, M. (2022). The contribution of trust to academic knowledge sharing among academics in the Malaysian research institutions. *Cogent Business & Management*, *9*(1), 2038762. https://doi.org/10.1080/23311975.2022.2038762

Nowak, M. A. (2006). *Evolutionary dynamics: Exploring the equations of life*. USA: Harvard University Press.

Ouakouak, M. L., AlBuloushi, N., Ouedraogo, N., & Sawalha, N. (2021). Knowledge sharing as a give-and-take practice: The role of the knowledge receiver in the knowledge-sharing process. *Journal of Knowledge Management*, *25*(8), 2043–2066. https://doi.org/10.1108/JKM-04-2020-0323

Panteli, N., & Sockalingam, S. (2005). Trust and conflict within virtual inter-organizational alliances: A framework for facilitating knowledge sharing. *Decision Support Systems*, *39*(4), 599–617. https://doi.org/10.1016/j.dss.2004.03.003

Platt, J. E., Jacobson, P. D., & Kardia, S. L. R. (2018). Public trust in health information sharing: A measure of system trust. *Health Services Research*, *53*(2), 824–845. https://doi.org/10.1111/1475-6773.12654

Rotter, J. B. (1967). A new scale for the measurement of interpersonal trust. *Journal of Personality*, *35*(4), 651–665. https://psycnet.apa.org/doi/10.1111/j.1467-6494.1967.tb01454.x

Rutten, W., Blaas-Franken, J., & Martin, H. (2016). The impact of (low) trust on knowledge sharing. *Journal of Knowledge Management*, *20*(2), 199–214. https://doi.org/10.1108/JKM-10-2015-0391

Shi, D. M., Yang, H. X., Hu, M. B., Du, W. B., Wang, B. H., & Cao, X. B. (2009). Preferential selection promotes cooperation in a spatial public goods game. *Physica A: Statistical Mechanics and Its Applications*, *388*(21), 4646–4650. https://doi.org/10.1016/j.physa.2009.07.031

Sun, K., & Du, R. (2010). Influential factors of knowledge sharing in virtual communities with real-name system: An empirical research. *Journal of Intelligence (in Chinese)*, *29*(4), 83–87.

Szulanski, G. (1996). Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strategic Management Journal*, *17*(S2), 27–43. https://doi.org/10.1002/smj.4250171105

Tamjidyamcholo, A., Baba, M. S. B., Tamjid, H., & Gholipour, R. (2013). Information security-professional perceptions of knowledge-sharing intention under self-efficacy, trust, reciprocity, and shared-language. *Computers & Education*, *68*, 223–232. https://doi.org/10.1016/j.compedu.2013.05.010

Vasin, S. M., Gamidullaeva, L. A., Wise, N., & Korolev, K. Y. (2020). Knowledge exchange and the trust institution: A new look at the problem. *Journal of the Knowledge Economy*, *11*(3), 1026–1042. https://doi.org/10.1007/s13132-019-00588-2

Zhang, M., Zheng W. W., & Shi, G. L. (2016). Game analysis of knowledge sharing in academic virtual community-based on the perspective of trust. *Information Science*, *34*(2), 55–58.

How to Cite: Xia, D., Zhang, Y., Qiu, Y., Zhang, S., Tian, Y., & Zhao, X. (2024). Research on the Dynamic Evolution Law of Online Knowledge Sharing Under Trust. *International Journal of Changes in Education*, *1*(1), 32–40. https://doi.org/10.47852/bonviewIJCE32021834