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ORIGINAL ARTICLE

Study on the evolution of information sharing strategy for users of online patient community

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Abstract
Technological advances are driving the growth of online health communities. However, there are some problems such as low user participation and insignificant social benefits in online health communities. This paper discusses the evolution law of information sharing behavior of members of online health community to study the influence of different behaviors on health information sharing results and explore the ways to improve the level of community information sharing. Based on BA scale-free network (Albert-László Barabás and Réka Albert scale-free network), this paper established an information sharing behavior model for members of online health community with the evolutionary game theory method, and discussed the influence of different game parameters and initial conditions on the evolution results of information sharing behavior of community patients with the method of numerical experiment. It is found that the key to improve the level of community information sharing is to improve the benefit of patients' information sharing, the proportion of patients sharing information at the initial moment, and the degree of network nodes, and reduce the sharing cost. Community managers should improve the information conversion ability and information absorption ability of community patients through offline activities, professional guidance, and other forms. At the same time, it can reduce the difficulty and risk of information sharing and strengthen the connection among members, thus comprehensively enhancing the value of the community.

Keywords Evolutionary game · Information sharing · Online patient community · BA scale-free network

1 Introduction

As an important support for extending medical and health services, online health communities make the communication between community members independent of time, space, and social status, and provide effective support for the information exchange between patients [1]. By participating in community discussions, users of the online patient community can get support and help from other users of the community. Therefore, more and more patients collect and obtain medical information through the online community [2]. Community patient autonomy information sharing is an important basis for community sustainable development [3]. However, there are various risks and costs in online patient community members' information sharing behavior, which can inhibit their enthusiasm for information sharing [4].

Research on information sharing behavior of virtual community members can be divided into three categories: motivation theory, management technology, and behavior theory. Motivation theorists study the relationship between the motivation, goal, and behavior of knowledge sharing [5], pointing out that the motivation of users' information sharing is the "usefulness" of the network [6]. The management technical school solves the knowledge transfer obstacle from the system, the idea, the operation, the technology, and so on aspect, and promotes the information sharing and the community

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developments [7]. Behavior theory encourages community members to participate in information sharing activities by promoting their sense of belonging and trust [8]. The particularity of online health community information sharing subject and information object is very different from the general virtual community [9]. Patients in online health communities have urgent emotional needs and information needs, and their ability of information expression and absorption is uneven [10]. Moreover, because of the particularity of medical information, the information shared by community patients is highly sensitive [11, 12]. Once the patient's medical information is leaked, serious adverse consequences may be caused [13]. Therefore, in most cases, information sharing decisions of patients will not be made from the perspective of the collective interests of the community and share their own information without reservation [1]. Instead, they will be issued from their own perspective, weighing benefits and risks and constantly adjusting the sharing strategy [14]. At present, the research on health information behavior of online community members is mostly based on questionnaire data and network data crawling. Due to the limitations of research methods, it is impossible to analyze the impact of community members' network structure on the level of information sharing. Based on this, this paper abstracts the topological structure of online health community members into BA scale-free network model, constructs the evolutionary game model of community information sharing, and discusses the influence mechanism of network structure and game parameters on the evolutionary stable equilibrium level of community information sharing behavior.

2 Proposed method

2.1 Network evolution

Connections between members of the online patient community are not fully coupled or completely random, but have a specific network structure. Online health communities have a very obvious scale-free feature [15]; that is, the degree of the network is power-law distribution: most nodes have only a few connections, and a few nodes have a lot of connections. Therefore, BA scale-free network proposed by Albert-László Barabás and Réka Albert was selected in this study to describe the network structure between community patients. The network structure between community members provides access to information resources for members. The information sharing process of community members is influenced by many factors such as network structure and individual attributes. The information sharing subject of online patient community is patients, the shared object is health-related information, and the situation is online community. Influenced by the above three factors, the information sharing behavior of online patient community shows the following characteristics: (1) The information sharing behavior of community patients is a voluntary behavior, and other individuals cannot force it [16]. In the process of information sharing, there are many uncertain factors and information asymmetry among community members, which belong to incomplete information game. (2) According to the theory of rational behavior, community members seek to obtain the maximum benefit with the least input. However, because the process of community information sharing is a process of incomplete information game, the information sharing decision is uncertain, and community members can only make bounded rational behavior. (3) The information sharing behavior of online community members is not a one-time behavior. They constantly adjust their decisions according to the sharing strategies of other community members [17], which is a dynamic multi-game process. Therefore, this paper combined complex network evolution game theory to study the dynamic evolution mechanism of information sharing among patients in online patient community.

The main research ideas and hypotheses in this paper include the following: (1) The BA network is used to depict the interaction between patients in the online health community; that is, the nodes in the network represent the patients in the community, and the edges represent the game relations between patients. (2) The game model describes the information sharing process among community patients and describes the behavioral strategy selection and value benefits of users, and the repeated game represents the continuous interaction between users. (3) According to Femi process, the strategy adjustment rules of information sharing evolutionary game are determined, and the evolution process of continuous user interaction is explained. (4) By simulating the evolution of patient information sharing in online health community, this paper discusses the difference between dynamic equilibrium of bounded rational individuals under different behavior patterns.

2.2 Information sharing game model

The online patient community has very obvious scale-free characteristics [15]. In this study, BA scale-free network was selected to describe the relationship structure between users of the online patient community. On the one hand, community patients hope to get information support from other users, such as personalized health assessment. On the other hand, due to the high sensitivity of medical information, online users will be more cautious in the process of relevant information communication. In the process of information sharing, $S = \{0, 1\}$ represents the patient's strategy set. 0 represents the non-cooperation strategy, i.e., not participating in information sharing. 1 represents cooperation strategy and participation in information sharing. The risk factor c is used to indicate the potential risks of information sharing. The benefit coefficient r represents the revenue gained by the information sharer in the process of information transmission. The benefit coefficient of information sharing should be greater than the cost coefficient of information sharing; otherwise, community members will not participate in information sharing. Information conversion coefficient m and information absorption coefficient n are respectively used to represent the information externalization ability and information combination ability of community patients. v represents the information reserve of community patients. The benefits of users are determined by themselves and their game objects. The information storage level of information sharers is multiplied by its information externalization capability coefficient times the information absorption capability coefficient of information receivers, which is the amount of information that information receivers can receive in each information sharing process. The above parameters are mutually independent and uniformly distributed [0,1].

The benefits of information sharing of community members are determined by themselves and the other side of their game. There are two kinds of information sharing strategies for each member of the community: sharing and not sharing. Therefore, there are three kinds of benefits for both sides of the game in the process of game.

(1) Both sides adopt sharing strategy

In the process of information sharing, the information sharer can first obtain the benefit VR from the process of self-information sharing; at the same time, in the process of information sharing, the various costs invested by the information sharer are VC. If the other side of the game also chooses to share information, in addition to the benefits brought by information sharing for itself, it can also obtain information support from the sharing party. The amount of information support obtained is determined by the information reserve level of the other party, the information transformation ability of the other party and the information absorption ability of the information absorption party. Therefore, when both sides of the game share information, the revenue of both sides is determined by their own sharing revenue VR, the revenue VMN brought by the sharing strategy of the other side, and the sharing cost VC. The specific calculation is VR + VMN − VC.

(2) One side of the game adopts the sharing strategy and the other side does not

If there is only one party sharing information and the other party does not share information, the information sharer can only obtain the benefit VR from his own information sharing behavior and bear the sharing cost VC. The party who does not share information does not generate cost and can obtain information revenue VMN provided by the sharing party.

(3) No sharing strategy adopted by both sides of the game

If both sides of the game do not conduct information sharing, there will be no revenue and no cost. At this time, the revenue of both sides of the game is zero.

The specific benefit matrixes are shown in Table 1.

According to the above game payoff matrix, patients participating in the information sharing game get the following benefits in the tth game:

$$U_i(t) = \sum_{j\in\Omega_i} s_i A s_j^T \tag{1}$$

where Ω_i represents the set of individuals playing the game with individual i in the tth game; s_i is the strategy vector of individual i at moment t; and s_j^T is the strategy vector transpose of individual j at moment t who is playing game with individual i. A is the income matrix shown in Table 1.

2.3 Policy update rule

Community patients often show limited rationality when making shared decisions [18]. The initial strategy selection of users is not optimal, but continuous learning and evolution in the process of continuous interaction and benefit balance, and finally determining a better strategy [19]. The policy adjustment rules of the Femi process can better reflect the uncertainty in the process of community members' information interaction [20]. Game individuals gain benefits by playing games with all their neighbors. When an individual wants to update his or her game strategy, a neighbor is randomly selected for comparison. If the neighbor's benefit is higher than his or her own, the patient will imitate the neighbor's strategy in the next round of game with a certain probability [21]. This imitation probability is calculated according to Fermi function in statistical physics:

$$W_{Si\leftarrow Sj} = \frac{1}{1 + exp\left[\left(U_i - U_j\right)/k\right]} \tag{2}$$

S_i represents the strategy adopted by individual i in this round, U_i represents the benefits of individual i in this round, and S_j represents the benefits of individual j in this round. This

Table 1 Patient information sharing benefit matrix of online patient community

		Patient B	
		Share	Unshare
Patient A	Share	$v_a r_a + v_b m_b n_a - v_a c_a$, $v_b r_b + v_a m_a n_b - v_b c_b$	$v_a r_a - v_a c_a$, $v_a m_a n_b$
	Unshare	$v_b m_b n_a$, $v_b r_b - v_a c_a$	0, 0

function indicates that, when the return of individual i in this round is lower than that of individual j, it is easy for i to accept j's strategy in this round. If the return of i is higher than that of j, i will still adopt the strategy of j with a small probability. This irrational choice of the individual is characterized by $k(k \geq 0)$. The closer the k value is to 0, the higher the individual's rationality. When k value approaches infinity, it means that the individual is in a noisy environment and unable to make rational decisions and update his strategy randomly.

3 Experiments

The evolutionary game on the complex network, the network structure between individuals, the game model, and the strategy adjustment rules all have different degrees of influence on the evolution of individual behavior in the network. Evolutionary game research on network is usually carried out by means of computer simulation [22]. This study used Matlab to simulate the evolution of information sharing in the online patient community.

The first step is to generate a scale-free network of $N = 500$. The second step is to determine whether there is a connection between the two patients. If there is a connection, the game will be played according to Table 1 game payoff matrix. The third step is to calculate the game benefits of each patient and the proportion of information sharers in the game. Fourth, after the end of each game, each patient updated the strategy according to the strategy updating rules. The fifth step is to determine whether the system is stable (the proportion of patients in the system who choose to share information remains the same). When the proportion of partners selected for information sharing remains unchanged, the system is stable. The cooperation frequency of patients at this time is calculated and simulation results are output. Otherwise, go to step 2. The sixth step is to adjust the input and compare the evolution results of community information sharing under different values of parameters.

At the initial moment, each individual chooses C (information sharing) according to probability $x(0 < x < 1)$ as his initial game strategy. The proportion of collaborators in the community at time t is called the collaborator density $x(t)$. $x(t) = nc(t)/N$, where $nc(t)$ represents the number of collaborators in the community at time t and N represents the total number of people in the community. With the development of repeated game, the cooperative density changes dynamically.

4 Results and discussion

The information sharing level is negatively related with the cost coefficient; with the increase of information sharing cost coefficient, the level of information sharing decrease, but the level of information sharing increases with the increase of network structure parameter ck, as shown in Fig. 1 (the horizontal axis is the game time and the vertical axis is the level of information sharing).

Figure 2 (the horizontal axis is the game time and the vertical axis is the level of information sharing) shows that the patient information conversion coefficient has no significant impact on the community information sharing level. That is, with the improvement of patient information conversion coefficient, the number of information sharing users in the community basically remains unchanged. Meanwhile, the network structure ck can promote the information sharing behavior of community patients. Each sub-graph in Fig. 4 shows that the

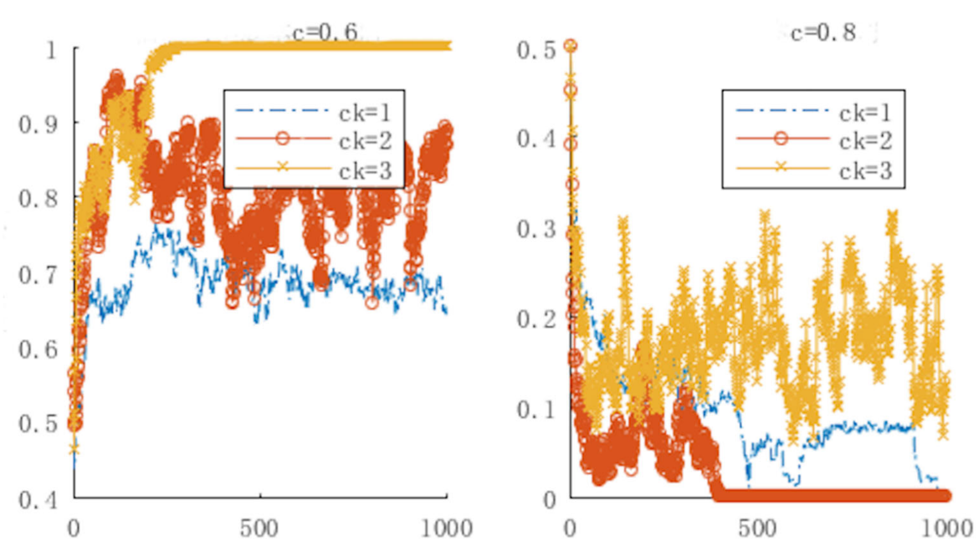

Fig. 1 Influence of cost coefficient on information sharing level

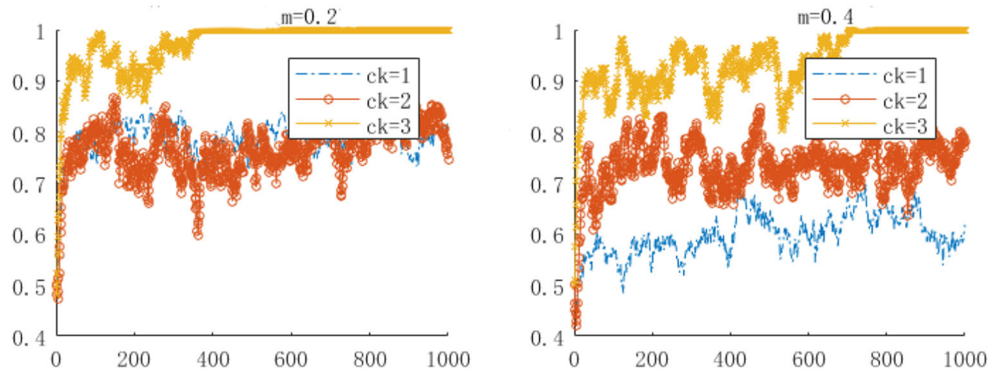

Fig. 2 Influence of information conversion coefficient on information sharing level

proportion of partners increases as the degree *ck* of network nodes increases.

The patient's information absorption ability has no significant impact on the community information sharing level, as shown in Fig. 3 (the horizontal axis is the game time and the vertical axis is the level of information sharing). And the network structure *ck* can promote the information sharing behavior of community patients.

Income coefficient promotes the evolution level of information sharing behavior, as shown in Fig. 4 (the horizontal axis is the game time and the vertical axis is the level of information sharing).

The influence of community patients' information reserve on their information sharing behavior is promoted in stages, as shown in Fig. 5. It can be seen from the figure that, when the information reserve level of patients is relatively low (0.2), patients who choose information sharing in the community will eventually give up information sharing with the progress of interaction time. With the increase of information reserve level of patients, their sharing behavior gradually improved. However, when the level of information reserve reaches 0.4, the level of information sharing increases when the community information is stable, as shown in Fig. 5 (the horizontal axis is the game time and the vertical axis is the level of information sharing).

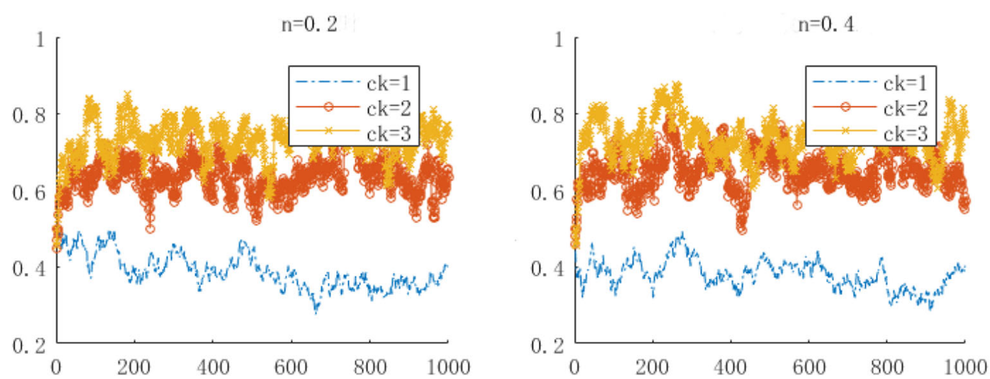

Fig. 3 Influence of information absorption coefficient on information sharing level

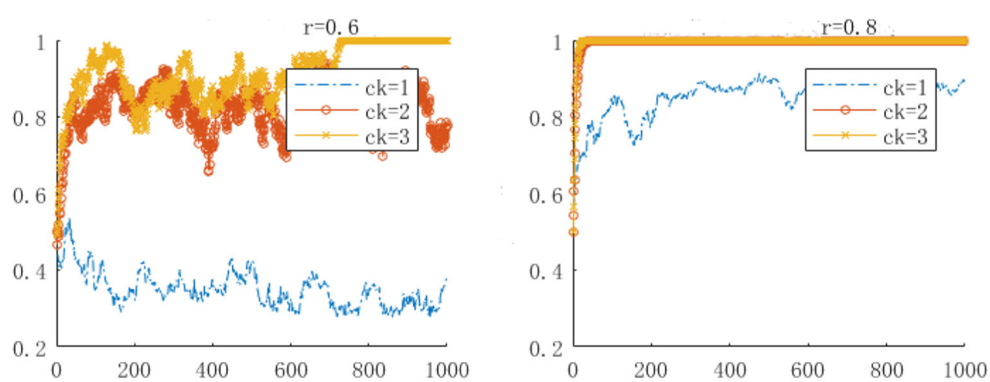

Fig. 4 Influence of benefit coefficient on information sharing level

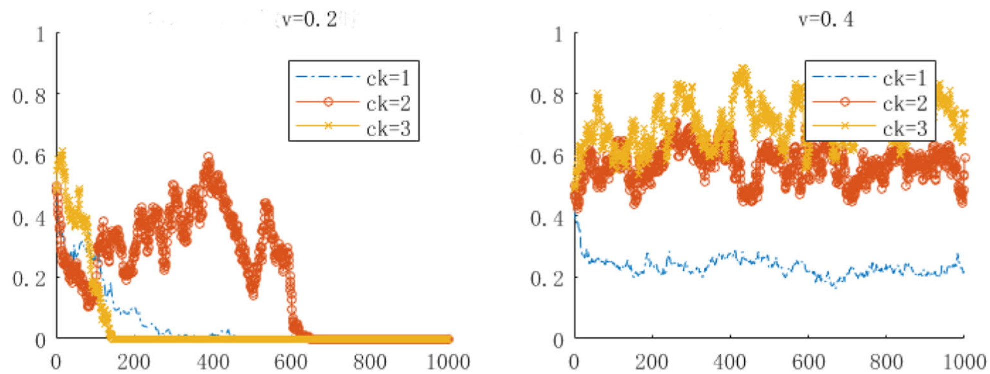

Fig. 5 Influence of patient information reserve on information sharing level

5 Conclusions

The experimental results show that the benefit coefficient, information reserve, initial sharing ratio, information transformation ability, and absorption ability all play an active role in promoting the level of information sharing. There is a positive correlation between the node degree of community patients and the information sharing level of community users. The network structure with high node degree can promote the interaction between community members and facilitate the information sharing among them. However, the risk cost coefficient of information sharing has a negative regulating effect on the level of sharing cooperation. Based on this, the community manager can combine the user characteristics and information characteristics of the online patient community to promote the information sharing level from multiple dimensions. Community managers can improve the information conversion ability and information absorption ability of community patients through offline activities, professional guidance, and other forms.

For the invisible information, the organization information system should be constructed, and the information should be combed and integrated to reduce the difficulty of its transmission. Community members absorb information provided by others to help them manage their health. Information owners share their information with other users in the community for others, so as to realize the circulation of information and improve the efficiency of information utilization. Community managers should strive to create a good community atmosphere, increase the connectivity of community members, improve the benefits of community members' information sharing, and promote the enthusiasm of information sharing.

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Data availability We can provide the data.

Compliance with ethical standards

Competing interests The authors declare that they have no conflict of interest.

Ethical approval and consent to participate Approved.

Consent for publication Approved.

Abbreviations BA scale-free network, Albert-László Barabás and Réka Albert scale-free network; ICR, initial collaborator ratio

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