

Study on the Evolution of Information Sharing Strategy for Users of Medical Cloud

Panpan Zhu

Tianjin University of Science and Technology

Jiang Shen

Nankai University

Man Xu (✉ td_xuman@nankai.edu.cn)

Nankai University

Research

Keywords: Evolutionary game, information sharing, online patient community, BA scale-free network

Posted Date: December 18th, 2019

DOI: <https://doi.org/10.21203/rs.2.19245/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

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.

Results: 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, 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.

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, the process of patient information sharing not only requires time and effort, but also risks such as privacy disclosure[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, promotes the information sharing and the community developments[7].Based on domestic and foreign theories, behavioral theorists guide the construction of community social network, promote the generation of participants' sense of belonging, trust and emotional support, and encourage participants to produce information contribution

behavior[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[14]. Instead, they will be issued from their own perspective, weighing benefits and risks and constantly adjusting the sharing strategy[15].Based on the evolutionary game theory, this paper constructs an evolutionary game model of information sharing among patients in online patient communities, and discusses the dynamic evolution process of information sharing behavior strategy when patients are faced with risk costs such as privacy disclosure and online resource demands,to study the influence of different behaviors on health information sharing results and explore the ways to improve the level of community information sharing.

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 [16], 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[17].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[18], 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:(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, 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[16].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, etc. 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, 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 is used to indicate the potential risks of information sharing.The revenue coefficient represents the revenue gained by the information sharer in the process of information transmission.Information conversion coefficient and information absorption coefficient are respectively used to represent the information externalization ability and information combination ability of community patients.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 specific benefits are shown in table 1 below.

Table 1. Patient information sharing benefit matrix of online patient community

| | | Patient <i>B</i> | |
|------------------|----------------|---|----------------------------------|
| | | Share | <u>Unshare</u> |
| Patient <i>A</i> | Share | $v_a r_a + v_b m_b n_a - v_a c_a,$ $v_b r_b + v_a m_a n_a - v_b c_b$ | $v_a r_a - v_a c_a, v_a m_a n_a$ |
| | <u>Unshare</u> | $v_b m_b n_a, v_b r_b - v_b c_b$ | 0, 0 |

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

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

Where, Ω_i represents the set of individuals playing the game with individual i in the t th 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[19]. 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[20]. Considering that Bounded rational game players may also make some mistakes in strategy adjustment, Femi updating rule is adopted to describe the adjustment process of information sharing strategy for online community patients, which reflects the uncertainty in the process of strategy selection and describes the strategy adjustment in the process of evolution[21]. 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[22]. This imitation probability is calculated according to Fermi function in statistical physics:

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

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 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 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 k value is to 0, the higher the individual's rationality is. When k value approaches infinity, it means that the individual is in a noisy environment, 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. Considering the difficulty of the study, the game study on the complex network is usually carried out by means of computer simulation[23]. 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 6 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 $x(t)$. $x(t) = nc(t)/N$, $nc(t)$ 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 initial collaborator ratio promotes the level of patient information sharing when the community is stable. The higher the proportion of initial collaborators, the higher the level of information sharing of patients when the community is stable, and the greater the benefits of users—as shown in figure 1. When there are no patients to share information at the beginning of the community, the community will not produce any value. Under the same conditions, the larger the proportion of initial collaborators and the network structure parameter ck , the higher the benefit of community patients.

The information sharing level are negatively related with the cost coefficient, namely with the increase of information sharing risk coefficient, information sharing level decrease, but the level of information sharing increases with the increase of network structure parameter ck , as shown in figure 2. It can be seen from figure 2 that when there is no cost for patients to share information, the sharing behavior is relatively stable and at a high level. When ck is 1, 2, 3 respectively, the corresponding information sharing

behavior of community patients is 400,800 and 1200. This situation is also true when the risk cost coefficient c is taken as 0.2, 0.4 and 0.6, and with the increase of the risk cost coefficient, the corresponding income level of different network structures is gradually declining. As shown in the figure, when ck is 3 and the cost coefficient is 0.2, the benefit of community patients is 1050. When the cost coefficient increases to 0.4, the benefit of patients decreases to 750. When the cost coefficient continues to increase to 0.6, the benefit of community patients fluctuates around 350. When c is 0.8, the benefit of community patients decrease to 40. This is also true when ck is 1 and 2. When the cost coefficient reaches 1, regardless of the network structure, the benefit of community patients directly drops to 0.

When the risk cost of information sharing is low (0-0.4), the proportion of partners choosing information sharing is high. When the cost factor increases to 60%, the level of information sharing drops significantly. When the degree ck of network nodes is 1, the patient information sharing level is only 20%, while when ck is 3, the patient information sharing level is floating around 75%. When the cost coefficient continues to increase to 0.8, some users in the community share information at the initial time. With the progress of interaction, all patients in the community do not share information soon, as shown in figure 3. At this point, all users exit from information sharing, corresponding to the above situation that the community revenue drops to zero.

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 figure 4 shows that the proportion of partners increases as the degree ck of network nodes increases.

Although patients' information conversion ability has no significant effect on their information sharing level. But compare the differences between the sub-graph in figure 5, it can be found that the income level of community patients increases with the increase of information conversion coefficient. Each sub-graph shows that under the condition of a certain information transformation coefficient (m value from 0.2 to 1), the benefits of community patients increase with the increase of network structure parameter ck . When the information conversion ability of community patients is very low, for example, when the value of m is 0, the network structure has little impact on the benefits of patients. When ck is 1, 2 and 3, the benefits of community patients all fluctuate around 40. With the increase of information conversion coefficient to 0.2, the influence of network structure on its revenue has been preliminarily shown. When compared with ck value 2 and 3, community patients with ck value of 1 had the lowest benefit, but at this time, patients with ck value of 2 and 3 showed little difference in benefits. In the range of patients' information conversion coefficient of 0.4 to 1, patients' benefits increase with the increase of conversion coefficient.

Take ck value of 0.3 as an example. When the patient's information conversion ability coefficient is 0.4, the profit keeps fluctuating around 225. With the patient's information conversion capacity increased to 0.6, the available benefits increased to 350. On the other hand, although network structure has a promoting effect on community patients' earnings, but when ck is not particularly low, the promotion

effect of ck on the benefit of community patients is limited. such as when the information conversion coefficient of patients is between 0.6 and 1 and ck is 1, the benefits of patients are all 100. The increase of patients' benefit when ck increased from 1 to 2 was higher than that when ck increased from 2 to 3.

The patient's information absorption ability has no significant impact on the community information sharing level. In the process of information absorption coefficient increasing from zero to 1, the proportion of information sharers under different ck basically remains unchanged, the proportion of partners with node degree 1 is about 40%, and the proportion of information sharers with node degree 2 and 3 is about 70%. That is, network node degree c plays a phased role in promoting the level of community information sharing, as shown in figure 6.

Similar to the information conversion coefficient, although it has no significant influence on the information sharing level of community patients, the information absorption capacity of patients and the network node degree ck have significant promotion effects on their benefits, as shown in figure 7. As can be seen from the figure, with the increase of patients' information absorption capacity, patients' benefits increase. When the information absorption coefficient is 0.2 and the network node degree ck is 3, the community patient benefit is only 150. When the information absorption coefficient increased to 0.8, the benefit of community patients with network node degree ck of 3 reached 500. At the same time, patients' benefits increase with the increase of network structure, and with the increase of information absorption capacity, the increase of network structure ck has more obvious promotion effect on patients' benefits. When the information absorption coefficient is relatively low ($n = 0.2$), the network node degree increases from 2 to 3, the benefit of information sharers increases from 100 to about 120. When the information absorption coefficient is relatively high ($n = 0.8$), the network node degree ck increases from 2 to 3, and the information sharer's profit increases from 300 to about 550. It can be seen that, under the dual function of information absorption capacity and network node degree, it is more beneficial to improve the benefits of information sharing.

When the benefit coefficient increased from zero to 0.2, it had little effect on promoting the information sharing behavior of community patients. The proportion of patients in the community who choose to share information is still zero. When patients' benefit coefficient of information sharing was increased to 0.4, the benefit coefficient gradually promoted information sharing behavior. When the profit coefficient increased from 0.4 to 0.6, the proportion of users participating in information sharing increased substantially, from the original unshared information to about 80% of users choosing to share information, as shown in figure 8.

The benefit coefficient of patient information sharing can promote the benefit of community patients. The patient benefit coefficient in this study represents the benefits brought by the user's information sharing behavior, regardless of whether other patients share information or not. At the same time, with the increase of network structure coefficient ck , the overall benefit of community patients gradually increased. Moreover, the larger the benefit coefficient of patient information sharing, the more obvious the promotion effect of network structure on the total benefit of community patients, as shown in figure 9.

The influence of community patients' information reserve on their information sharing behavior is promoted in stages, as shown in figure 10. It can be seen from the figure that when the information reserve level of patients is relatively low (below 0.4), 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, the promotion effect of community patient user information reserve level on information sharing behavior is staged. When the information storage level of users increased from 0.6 to 1, the number of users who chose to share information barely changed.

The information reserve level of community patients has a limited role in promoting the information sharing behavior, and it increases with the increase of network structure parameter ck . When community patients do not have any information reserves, the community cannot create value for users, as shown in figure 11. Therefore, the community platform manager should provide some information as well as communication space for users in the initial stage. A large amount of information is generated during the interaction between community members, which is usually in a scattered and disordered state. Community managers should collect, sort and store such information and establish a community information warehouse. Once the information demanders have information needs, the community can act as the information provider to conduct initial interaction with the information demanders, so that other patients in the community can have more time and energy to provide more advanced information and patients can obtain more benefits.

5. Conclusions

In this paper, we found the following factors such as the benefit coefficient of information sharing, the patient's information reserve level, the patient density of information sharing at the initial time, the patient's information transformation ability and information absorption ability have a positive influence on the level of patient information sharing in the online patient community. 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. In the process of information sharing and communication with other users, community users internalize the information provided by others into their own knowledge through their own understanding and application, so as to realize their own knowledge growth. Information owners share their information with other users in the

community for others to learn and use, so as to realize the circulation of information and improve the efficiency of information utilization. To establish a long-term incentive mechanism, such as the points system, reward system and upgrade system, so that information sharers can obtain a sense of satisfaction and achievement in the process of information sharing, and become the backbone of community information sharing;By building a good community environment, reduce costs and risks of information sharing, expand information sources, rich form of information exchange, sustain a continuous, effective information sharing activities, make the community members get more benefits from information sharing activities, raise the enthusiasm of user participation, improve community members information sharing level.

Abbreviations

Albert-László Barabás and Réka Albert scale-free network(BA scale-free network)

Declarations

Availability of supporting data: We can provide the data.

Competing interests

These no potential competing interests in our paper.

Funding

This study was partially funded by the National Natural Science Foundation of China (numbers 71971123,71571105).

Authors' contributions

All authors contribute to the work.

Acknowledgements

Thanks for the potential reviewers.

Author details

Panpan Zhu: College of Management and Economics, Tianjin University, China

Jiang Shen: College of Management and Economics, Tianjin University, China

Man Xu: School of Business, NanKai University, China

References

1. Yan Z, Wang T, Chen Y, et al. Knowledge sharing in online health communities: A social exchange theory perspective[J]. *Information & Management*, 2016, 53(5): 643-653.
2. Fox S. *The Social Life of Health Information 2011* [M]. Pew Internet & American Life Project Washington, Dc, 2011.
3. Zhang X , Liu S , Deng Z , et al. Knowledge sharing motivations in online health communities: A comparative study of health professionals and normal users[J]. *Computers in Human Behavior*, 2017:S0747563217303989.
4. Tao A-J. *To Discuss the Privacy Protection of Personal Medical Information*[D]. Southwest University of Political Science and Law, 2010.
5. Nonaka I. *The knowledge-creating company*[M], *The knowledge-creating company*. Harvard Business Press, 2015:175–187.
6. Smith J M, Price G R. *The Logic of Animal Conflict*[J]. *Nature*, 1973, 246(11):5-5.
7. Meng F, Guo X, Peng Z, et al. The routine use of mobile health services in the presence of health consciousness[J]. *Electronic Commerce Research and Applications*, 2019, 35: 100847.
8. Wicks P, Keininger D L, Massagli M P, et al. Perceived benefits of sharing health data between people with epilepsy on an online platform[J]. *Epilepsy & Behavior*, 2012, 23(1): 16-23.
9. Oh S . The characteristics and motivations of health answerers for sharing information, knowledge, and experiences in online environments[J]. *Journal of the Association for Information Science & Technology*, 2014, 63(3):543-557.
10. Krasnova H, Spiekermann S, Koroleva K, et al. Online social networks: why we disclose[J]. *Journal of Information Technology*, 2010, 25(2):109-125.
11. Perse E M, Ferguson D A. The benefits and costs of web surfing[J]. *Communication Quarterly*, 2000, 48(4):343-359.
12. Matthews P, Simon J. *Evaluating and Enriching Online Knowledge Exchange: A Socio-epistemological Perspective*[M]// *Virtual Communities, Social Networks and Collaboration*. 2012.
13. Zhang X, Chen X, Hou D-L, et al. An Analysis of Online Health Information Disclosure Willingness Influencing Factors: An Integrated Model of TPB and Privacy Calculus [J]. *Information and Documentation Services* 2016, 37(1):48-53
14. Yan Z, Wang T, Chen Y, et al. Knowledge sharing in online health communities: A social exchange theory perspective[J]. *Information & Management*, 2016, 53(5):643-653.
15. Escoffery C, Diiorio C, Yeager K A, et al. Use of Computers and the Internet for Health Information by Patients with Epilepsy [J]. *Epilepsy & Behavior*, 2008, 12 (1): 109-114.
16. Barabasi AL, Albert R. Emergence of Scaling in Random Networks[J]. *Science*, 1999, 286(5439):509-512.
17. Zhang J-Q. Empirical Research on Information Acquiring and Information Sharing Intention and Behavior in Virtual Communities [J]. *Information Science*, 2015(8):59-64.

18. Vaala S E, Lee J M, Hood K K, et al. Sharing and helping: predictors of adolescents' willingness to share diabetes personal health information with peers[J]. Journal of the American Medical Informatics Association, 2017, 25(2): 135-141
19. Kreps D. Notes on the Theory of Choice[M]. Routledge, 2018.
20. Weibull J W. Evolutionary game theory[M]. MIT press, 1997.
21. Hauert C, Szabó G. Game theory and physics[J]. Am.j.phys, 2005, 73(5):405-414.
22. Simon S R, Evans J S, Benjamin A, et al. Patients' Attitudes Toward Electronic Health Information Exchange: Qualitative Study[J]. Journal of Medical Internet Research, 2009, 11(3):e30.
23. Huberman BA, Glance NS. Evolutionary games and computer simulations.[J]. Proceedings of the National Academy of Sciences of the United States of America, 1993, 90(16):7716-7718.

Figures

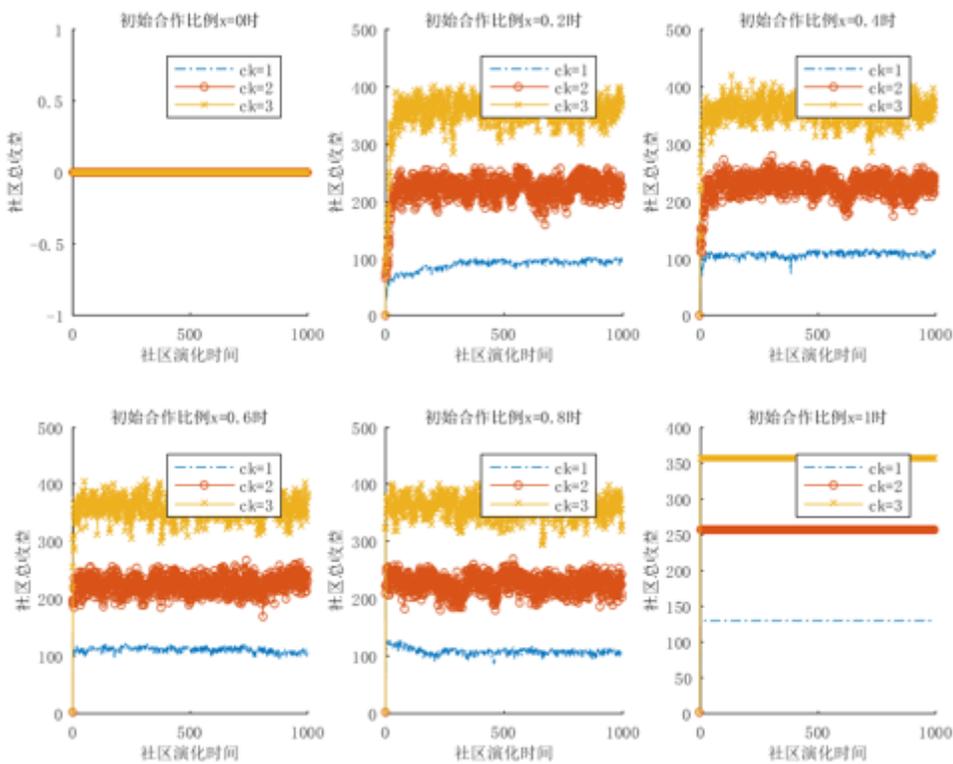


Figure 1

Influence of initial collaborator ratio on patient information sharing benefits

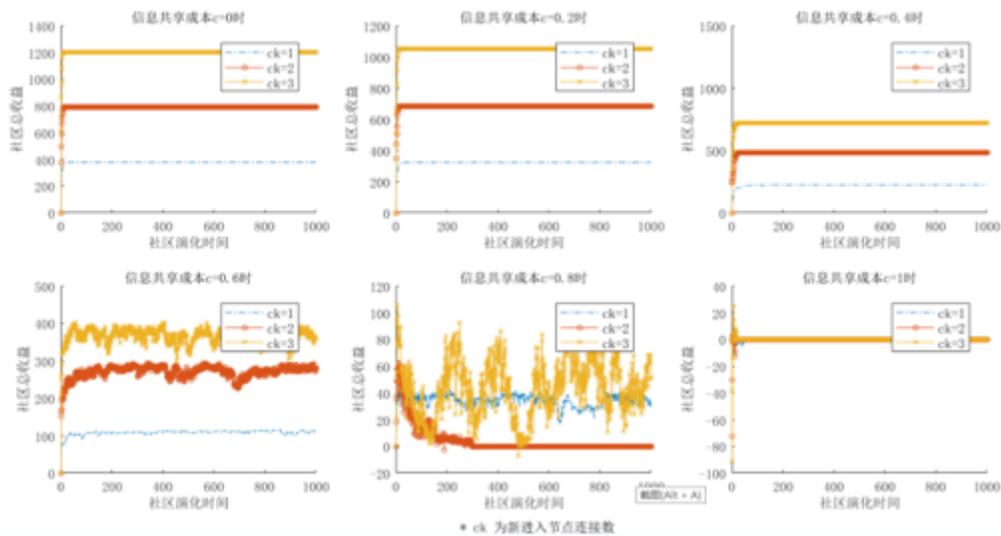


Figure 2

The impact of cost on the benefits of community patients

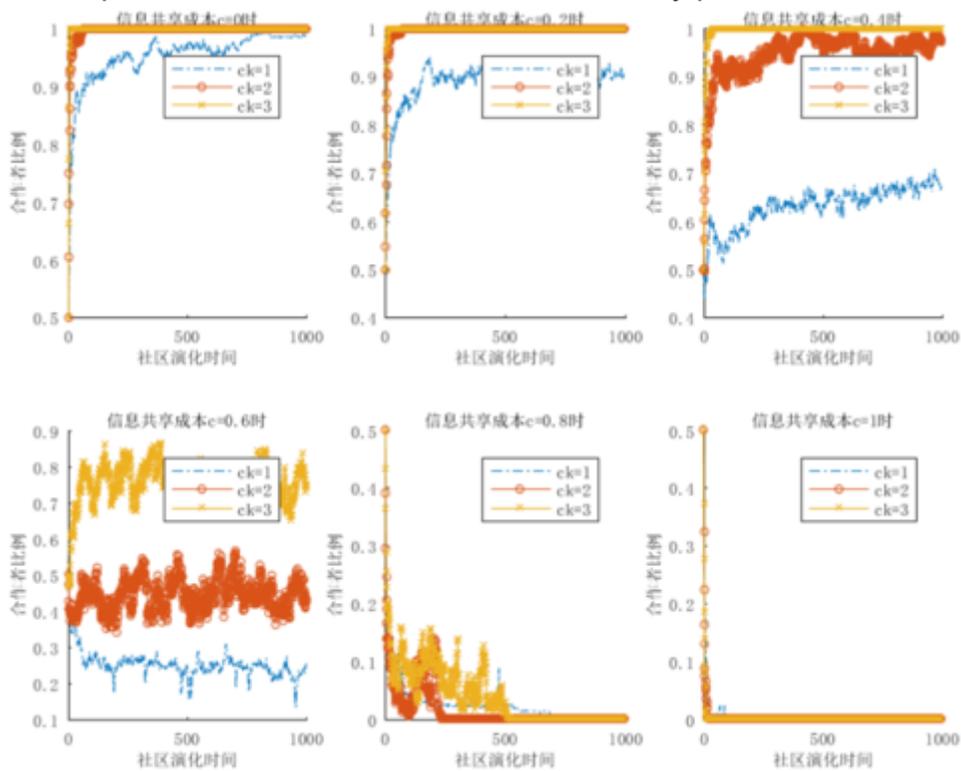


Figure 3

Impact of cost on information sharing level

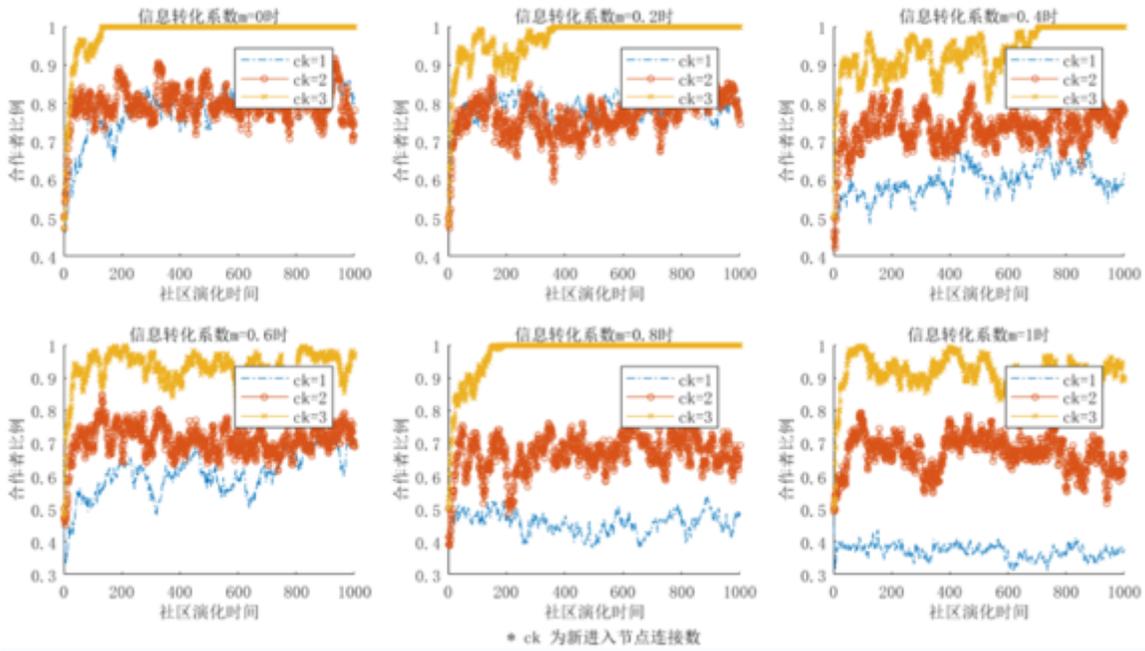


Figure 4

Influence of patient information conversion ability on information sharing level

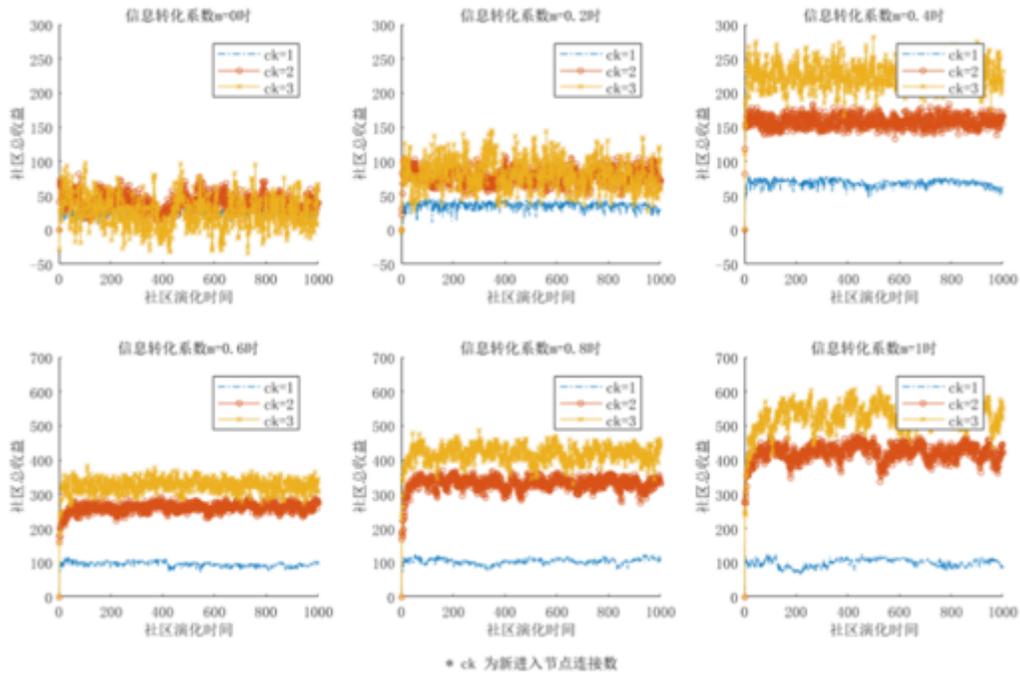


Figure 5

Influence of patients' information conversion ability on information sharing benefits

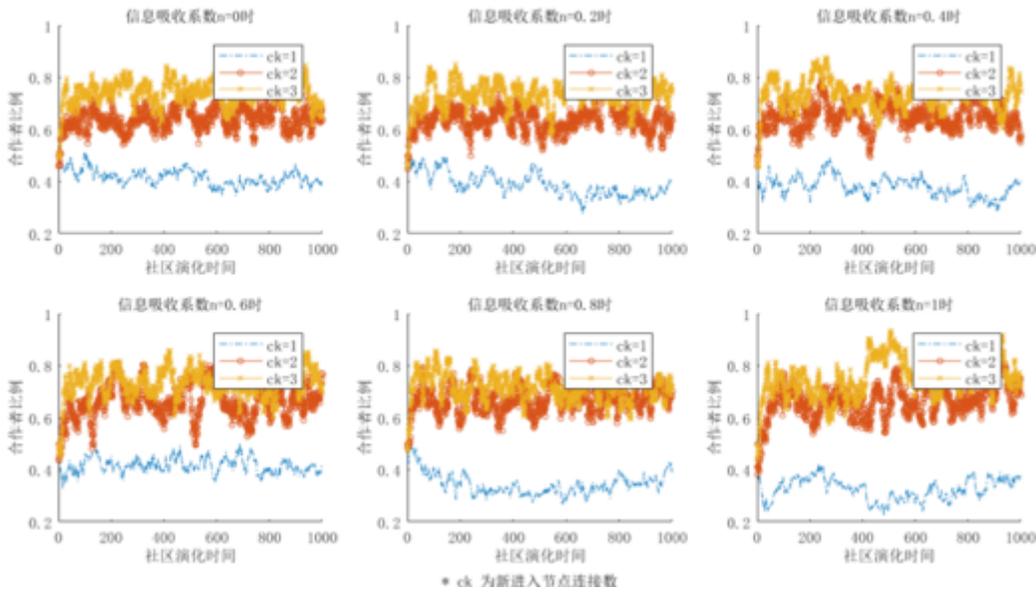


Figure 6

Influence of patient information absorption capacity on information sharing level

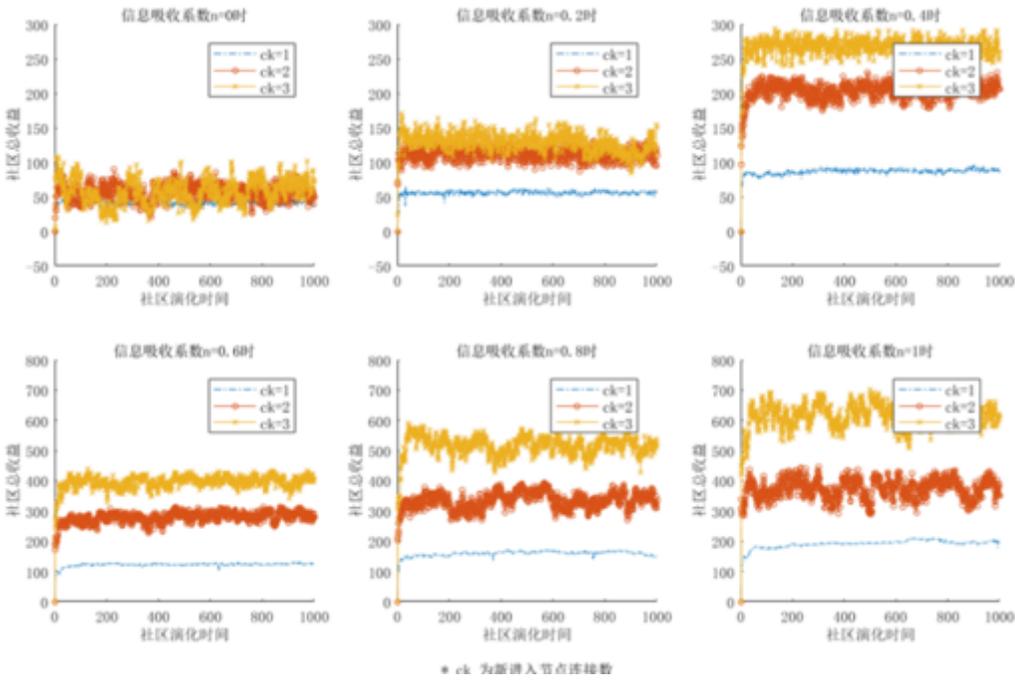


Figure 7

Influence of information absorption capacity on the benefits of information sharing

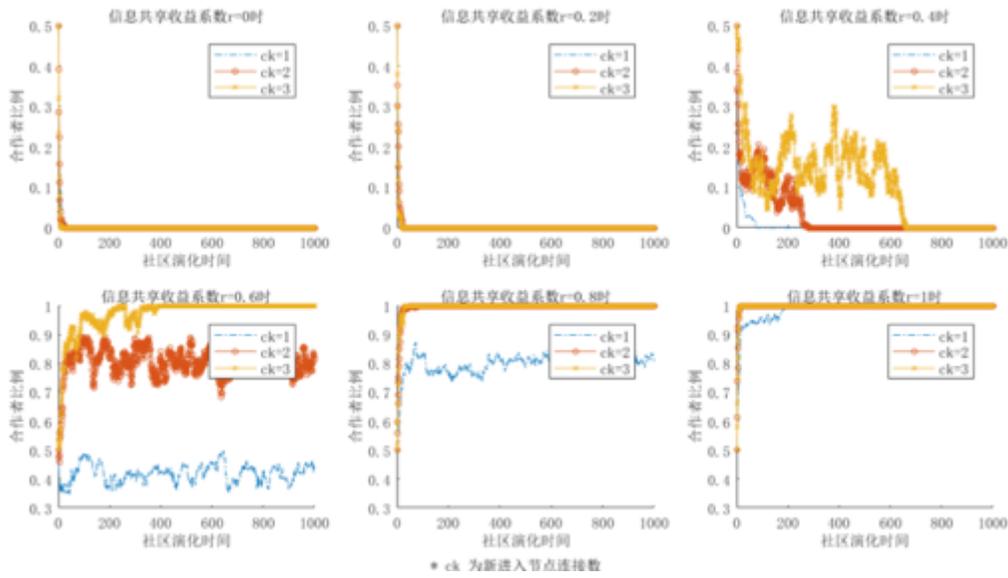


Figure 8

Influence of benefit coefficient on information sharing level of community patients

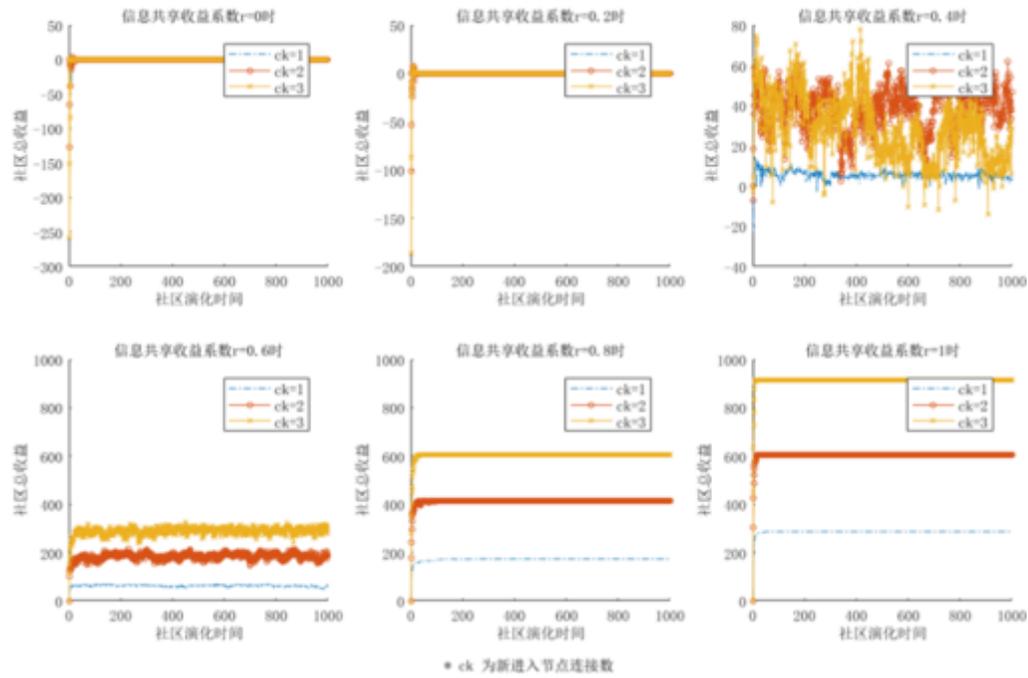


Figure 9

Influence of revenue coefficient on information sharing revenue

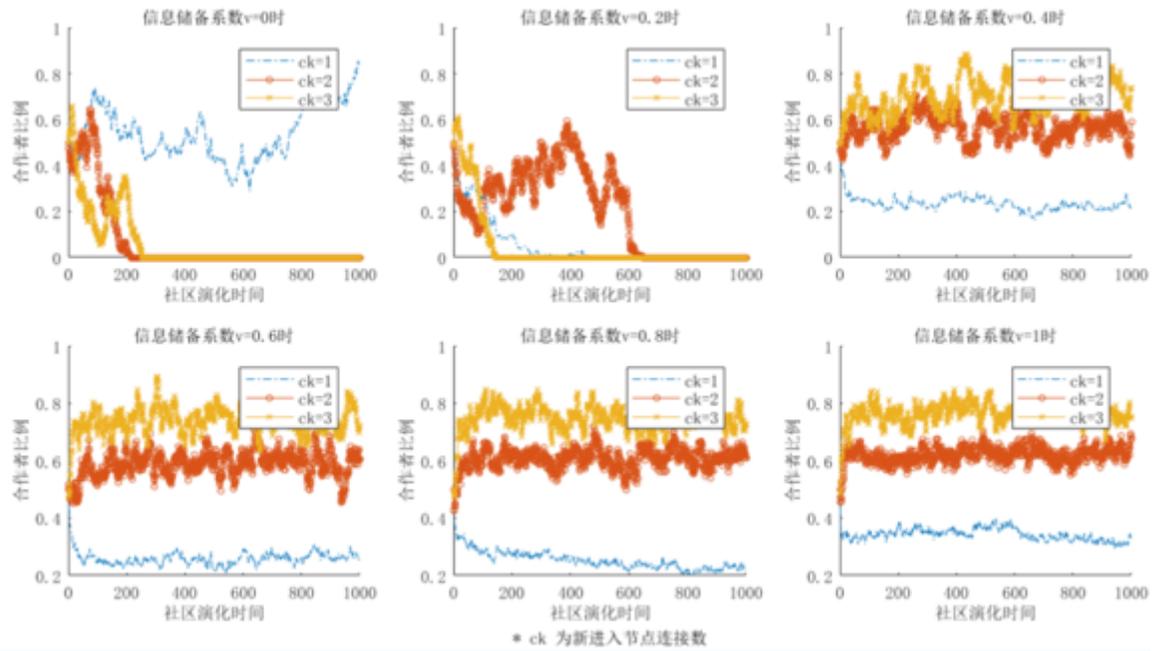


Figure 10

Influence of patient information reserve on information sharing level

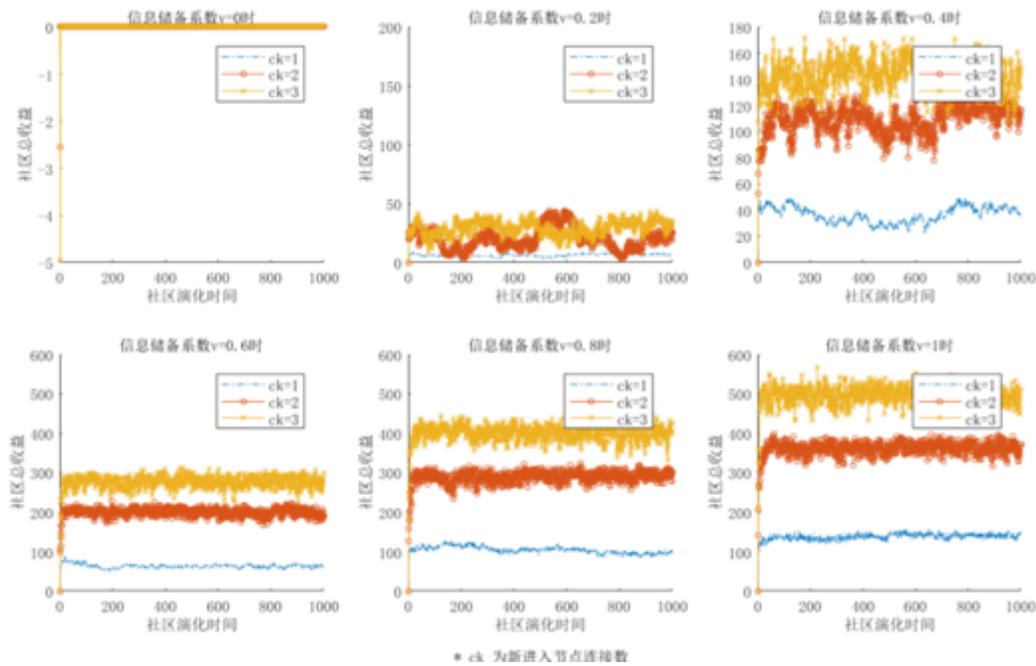


Figure 11

Influence of information reserve level of patients on community benefits