International Journal of Innovative Computing, Information and Control
Volume **20**, Number **5**, October **2024** ISSN 1349-4198
pp. 1449–1461

EVOLUTIONARY GAME ANALYSIS OF MEDICAL SYSTEM INFORMATION COLLABORATION UNDER GOVERNMENT INCENTIVES

Sen Yang and Haiyan Wang*

School of Economics and Management
Southeast University
No. 2, Southeast University Road, Nanjing 211189, P. R. China
senyang@seu.edu.cn; *Corresponding author: hywang@seu.edu.cn

Received January 2024; revised April 2024

Abstract. *Information collaboration in the medical system is hindered by several factors, including the relatively high cost of implementing information technology solutions and the absence of adequate incentives. Consequently, there is often a lack of participation from medical institutions and patients in initiatives aimed at fostering information collaboration. We studied the impact of government intervention on information collaboration in the medical system. Due to the long-term nature of policies and information collaboration, we characterized and analyzed the issue through dynamic modeling. This paper constructs a three-party evolutionary game model of the medical system composed of the government, medical institutions and patient groups, and conducts stability analysis on the strategy combinations of information collaboration among various game players based on the Lyapunov's first method. We find that the government needs to adopt reasonable strategies to stimulate information collaboration, which should focus on the distribution of the benefits from network externalities and effective supervision methods so as to motivate other participants to choose cooperation strategies and improve the efficiency of information coordination in the medical system.*
Keywords: Information collaboration, Network externality, Free-riding behavior, Evolutionary game

1. **Introduction.** With the emergence of medical informatization and smart wearable devices, an increasing amount of health and medical information is being generated in people's daily lives [1]. The effective utilization of this information can improve the health status of the population, reduce medical costs, and enhance the precision of diagnosis and treatment, especially for those with chronic diseases [2]. Consequently, numerous governments, including the Chinese government, have encouraged to promote information collaboration through various policies within the medical system [3].

Information collaboration is a crucial mechanism for enhancing the efficient utilization of medical resources within the knowledge-intensive healthcare services sector. Some studies have analyzed the information collaboration among healthcare participants. On the one hand, inter-hospital information sharing can save medical expenses. Participation in health information exchange (HIE) by hospitals is influenced by factors such as the intensity of competition among medical institutions, the efficiency of service quality inputs, and the profit loss incurred from health check-ups [4]. On the other hand, the development of information systems enables patients to collaboratively store and manage health information with medical institutions [5], thereby facilitating the tracking of patients'

DOI: 10.24507/ijicic.20.05.1449

conditions [6]. Information collaboration requires cooperation between medical institutions and patients. When there is heterogeneity in patients' willingness to cooperate with information sharing, although information collaboration can improve the speed of each examination, the expected waiting time for patients in the healthcare system tends to increase instead [7]. Some other factors may also influence the equilibrium strategy of patients [8]. Additionally, information collaboration often lacks spontaneity. In public services, governments and insurance companies often act as payers to incentivize collaboration among participants, yet there is a lack of research on incentives for information collaboration between medical institutions and patients.

Some studies focus on the effects of government or payer incentives on the interactions among participants in public services, including medical services. Research indicates that patient readmission rates are jointly influenced by medical institutions and patients and require incentives through payment mechanisms [9]. Traditional fee-for-service payment methods fail to provide sufficient incentives to promote medical efforts, but risk- and cost-sharing mechanisms [10], outcome-based penalty contracts [11] and bundled payments [12] can. Moreover, subsidies and transfer payments are common means used to coordinate participants in public services. By using a portion of the revenue from comprehensive hospitals to expand the capacity of primary care, the issue of overcrowding in the healthcare system can be addressed [13]. At different budget levels, government subsidy incentives can improve social welfare and provide services to more patients [14]. Copayments and monetary incentives can mitigate chronic diseases [15]. However, benefit sharing also leads to free-riding behavior among information collaboration participants. Regulators, including the government, can address the issue of free-riding by implementing policies or organizing promotional campaigns [16]. Therefore, this study not only considers the information collaboration mechanisms among different participants but also analyzes when the government should incentivize information collaboration.

The implementation process of incentive policies is long-term and dynamic. The tripartite evolutionary game model can describe the influence of different factors on the behavioral decisions among the government, platform, and users [17]. Existing research shows that government interventions aimed at reducing risk costs and standardizing information quality are key to promoting information collaboration among hospitals [18]. Existing research tends to focus more on the impact of incentives on the quality of care and cost control. There is a lack of analysis on information collaboration within the healthcare system, with only a few studies emphasizing incentives for the informatization of medical institutions. There is a gap in research concerning incentives for information collaboration among multiple stakeholders, including medical institutions, patients, and government, under dynamic decision-making. This paper addresses this gap.

This paper makes two significant contributions. Firstly, we analyze the decision-making process regarding information collaboration within the medical system, which involves the government, medical institutions, and patient groups, from a dynamic perspective. Secondly, we conduct a quantitative analysis to examine the impact of network externality effects stemming from medical institutions and patients on the behavioral evolution of each participant. Additionally, we investigate the implications of free-riding behavior between medical institutions and patients on information collaboration.

The rest of this paper is organized as follows. In Section 2, we outline the research problem regarding information collaboration. In Section 3, we delve into the evolutionary equilibrium of each participant under various conditions. In Section 4, we present a numerical study to analyze network externalities and free-riding behavior. Finally, in Section 5, we provide concluding remarks.

2. **Problem Description.** In this section, we outline the model framework of our research and make some assumptions. In the information collaboration of the medical system, there are three types of participants, namely the government (G), medical institutions (H), and patient groups (P). The government mainly provides different incentives and supervision for the medical institutions and patient groups to facilitate their information collaboration. In this process, we assume that all participants exhibit bounded rationality. Due to the differences among individual participants and the complexity and uncertainty of the environment they face, incomplete information renders the behavioral decisions of the participants to exhibit bounded rationality. Participants cannot find the optimal strategy and equilibrium point from the beginning. Instead, they are more likely to seek a satisfactory one. Therefore, participants need to continuously learn during the game, gradually correcting strategic mistakes, and constantly imitating and improving the most favorable strategies for themselves and others [17,19]. The information collaboration strategy among relevant participants is determined through multiple games, which is constructed by the tripartite evolutionary game theory. All the notations for the parameters and variables in the model are listed in Table 1.

Table 1. Notations of parameters and variables

Notations	Descriptions
x	Probability of the government taking an active attitude
y	Proportions of the medical institutions choosing to be cooperative
z	Proportions of the patients groups choosing to be cooperative
C_G, C_H, C_P	Cost of the government, medical institutions and patients groups when they choose active attitude or to be cooperative respectively
F_H, F_P	Additional expenses of the government when medical institutions or patient groups are non-cooperative with information coordination
T_H, T_P	Additional medical expenses of medical institutions or patient groups when they are non-cooperative with information coordination
R_G, R_H, R_P	Basic benefits of the government, medical institutions and patient groups in the operation of the medical system
I_H, I_P	Social benefits of medical institutions and patient groups generated by information collaboration
α, β	Proportions of social benefits reserved by the government from medical institutions and patient groups
U_H, U_P	Free-rider benefits of medical institutions and patient groups

2.1. **Behavior of participants.** In the process of information collaboration, the government can take a neutral attitude and pay for the medical services via fee for service, or it can take a positive attitude to stimulate information collaboration. On the one hand, it may implement payment schemes like bundled payments to incentivize medical institutions and patient groups to decrease costs through information collaboration [8]. On the other hand, the government can redistribute the social benefits of network externalities to other participants to foster motivation for information collaboration [3].

Medical institutions have the option to cooperate with information collaboration or not. When they take a negative stance, they solely provide medical services to patients. Conversely, when they adopt a positive approach, medical institutions enhance their level of informatization and engage in information sharing among hospitals. This practice not only enhances the accuracy of diagnosis and reduces unnecessary expenses [4] but also facilitates the implementation of preventive measures by primary hospitals.

Patient groups can also decide whether to cooperate with information collaboration. They can enhance the level of collaboration by registering with family doctors and undergoing timely health checks, among other actions. If patients actively cooperate with information collaboration, the likelihood of misdiagnosis during diagnosis and treatment will be reduced due to a more comprehensive patient health profile [19]. This also means that the costs of diagnosis and treatment due to readmission, as well as travel expenses, will decrease. Additionally, patients who actively update their health information can save doctors' consultation time during diagnosis and treatment, resulting in patient groups facing shorter waiting times in the healthcare system. However, due to variations in patient compliance, when patient compliance is low, their efforts required to cooperate with information collaboration are high, thus affecting their collaborative decision-making.

2.2. **Cost of participants.** The government can promote information collaboration within the medical system by formulating policies and implementing corresponding supervision to enhance the efficient allocation of medical resources. When the government takes an active attitude the cost is C_G. If medical institutions or patient groups fail to cooperate with information coordination, the government, as the payer, will incur additional medical expenses, respectively F_H, F_P.

When medical institutions actively cooperate with information collaboration, they incur cost C_H to improve their information level and establish and maintain inter-hospital information systems. When the government adopting a positive attitude, hospitals failing to cooperate with information coordination will share the additional expenses of patient diagnosis and readmission fees due to the government's payment method, which is T_H.

Likewise, when patient groups actively participate in information collaboration, their costs increase C_P. Conversely, if they fail to cooperate, they will bear a portion of the medical expenses T_P, assuming the government takes a positive attitude.

2.3. **Benefit of participants.** In the operation of the medical system, the government, medical institutions and patient groups derive basic benefits R_G, R_H, R_P, respectively. When medical institutions or patient groups cooperate with information collaboration, social benefits I_H and I_P will be generated, such as reducing medical expenses and improving government reputation. The government redistributes part of these benefits to medical institutions or patient groups to motivate them to continue information collaboration, with proportions of $1-\alpha$ and $1-\beta$. In addition, when the government adopts positive attitude, it receives transfer payments T_H, T_P from the other two participants when they do not cooperate with information coordination.

Since medical institutions and patient groups are directly involved in medical services, they may exhibit free-riding behavior. When one participant actively participates in information coordination, the other participants benefit additionally. For instance, when medical institutions actively cooperate, patient groups can receive more accurate treatment and avoid the cost of repeated examination during transfers. Similarly, when patients actively cooperate, medical institutions can save on the cost of diagnosis and treatment due to reduced patient readmission rates, and shorten consultation times for outpatient clinics. The free-rider benefits of medical institutions and patients are respectively U_H and U_P.

2.4. **Profit matrix.** Suppose the probabilities of government taking an active attitude and a neutral attitude are x and $1-x$, respectively; the probabilities of medical institutions being cooperative and non-cooperative with information collaboration are y and $1-y$; and the probabilities of patient groups to be cooperative and non-cooperative are z and $1-z$.

When the government takes an active attitude, it incurs a cost of supervision. In this scenario, if medical institutions or patients choose to cooperate, the government can acquire social benefits, and distribute them to medical institutions or patients in specific proportion. However, if medical institutions or patients choose not to cooperate, the government will face additional expenses. When medical institutions or patients choose not to cooperate, the government will incur additional expenses. This expenditure includes extra medical costs, such as medication errors and other expenses resulting from a lack of information support [6], as well as the cost equivalent to the damage to the government's reputation in public health [18]. As a penalty for non-cooperation, the government imposes transfer payments on the non-cooperating participants. For medical institutions, this penalty is reflected in the government's payment for medical services, while for patients, it is reflected in the reimbursement ratio. In cases where only one of the participants, either medical institutions or patient groups, chooses to cooperate, the non-cooperating one can gain additional benefits by free-riding without incurring costs. The profit matrix of the government, medical institutions, and patient groups, considering these costs and benefits, is shown in Table 2.

Table 2. Profit matrix of participants

Medical institutions	Patient groups	Government	
		Active x	Neutral $1-x$
Cooperative y	Cooperative z	$R_G+\alpha I_H+\beta I_P-C_G$	R_G
		$R_H+(1-\alpha)I_H-C_H$	R_H-C_H
		$R_P+(1-\beta)I_P-C_P$	R_P-C_P
	Non-cooperative $1-z$	$R_G+\alpha I_H+T_P-F_P-C_G$	R_G-F_P
		$R_H+(1-\alpha)I_H-C_H$	R_H-C_H
		$R_P+U_P-T_P$	R_P+U_P
Non-cooperative $1-y$	Cooperative z	$R_G+\beta I_P+T_H-F_H-C_G$	R_G-F_H
		$R_H+U_H-T_H$	R_H+U_H
		$R_P+(1-\beta)I_P-C_P$	R_P-C_P
	Non-cooperative $1-z$	$R_G+T_H+T_P-F_H-F_P-C_G$	$R_G-F_H-F_P$
		R_H-T_H	R_H
		R_P-T_P	R_P

Based on the profit matrix and the probability of different strategies adopted by the participants, the expected profit of the government can be calculated for both positive and neutral attitudes. Additionally, the average expected profit can be determined as follows:

$$\begin{aligned}
E_{Gy} &= yz(R_G+\alpha I_H+\beta I_P-C_G)+(1-y)z(R_G+\beta I_P+T_H-F_H-C_G)\\
&\quad +y(1-z)(R_G+\alpha I_H+T_P-F_P-C_G)\\
&\quad +(1-y)(1-z)(R_G+T_H+T_P-F_H-F_P-C_G)\\
E_{Gn} &= yzR_G+(1-y)z(R_G-F_H)+y(1-z)(R_G-F_P)\\
&\quad +(1-y)(1-z)(R_G-F_H-F_P)\\
\overline{E_G} &= xE_{Gy}+(1-x)E_{Gn}
\end{aligned}$$

The expected profit of medical institutions is as follows:

$$\begin{aligned}
E_{Hy} &= xz(R_H+(1-\alpha)I_H-C_H)+(1-x)z(R_H-C_H)\\
&\quad +x(1-z)(R_H+(1-\alpha)I_H-C_H)+(1-x)(1-z)(R_H-C_H)\\
E_{Hn} &= xz(R_H+U_H-T_H)+(1-x)z(R_H+U_H)+x(1-z)(R_H-T_H)
\end{aligned}$$

$$
\begin{aligned}
&\quad + (1-x)(1-z)R_H \\
\overline{E_H} &= yE_{Hy} + (1-y)E_{Hn}
\end{aligned}
$$

The expected profit of patient groups is as follows:

$$
\begin{aligned}
E_{Py} &= xy(R_P + (1-\beta)I_P - C_P) + (1-x)y(R_P - C_P) \\
&\quad + x(1-y)(R_P + (1-\beta)I_P - C_P) + (1-x)(1-y)(R_P - C_P) \\
E_{Pn} &= xy(R_P + U_P - T_P) + (1-x)y(R_P + U_P) + x(1-y)(R_P - T_P) \\
&\quad + (1-x)(1-y)R_P \\
\overline{E_P} &= zE_{Py} + (1-z)E_{Pn}
\end{aligned}
$$

The behaviors of the three participants in the information collaboration will mutually influence each other, and they will dynamically adjust their strategies by imitating individuals in the group who achieve higher outcomes, aiming to maximize their profits and achieve Pareto optimality.

3. **Replication Dynamics and Evolutionary Stability Analysis.**

3.1. **Replication dynamics analysis.**

The replication dynamic equations can effectively describe the information collaboration problem. By characterizing a group composed of game participants with bounded rationality, strategies yielding outcomes better than the average level will gradually be adopted by more participants. As a result, the proportions of participants adopting various strategies in the group will change.

The replication dynamic equations are as follows:

$$
\begin{aligned}
F(x) &= \frac{dx}{dt} = \left(E_{Gy} - \overline{E_G}\right) = x(1-x)((y-1)T_H + (z-1)T_P - \alpha I_H y - \beta I_P z + C_G) \\
F(y) &= \frac{dy}{dt} = \left(E_{Hy} - \overline{E_H}\right) = y(1-y)(((\alpha-1)I_H - T_H)x + U_H z + C_H) \\
F(z) &= \frac{dz}{dt} = \left(E_{Py} - \overline{E_P}\right) = z(1-z)(((\beta-1)I_P - T_P)x + U_P y + C_P)
\end{aligned}
$$

3.2. **Evolutionary stability analysis.**

Let $F(x) = 0$, $F(y) = 0$, $F(z) = 0$, the equilibrium points of this model can be computed. Judging the stability of the equilibrium point by constructing the Jacobian matrix and solving the determinants. The Jacobian matrix J is as follows:

$$
J = \begin{bmatrix}
\dfrac{\partial^2 F(x)}{\partial x^2} & \dfrac{\partial^2 F(x)}{\partial x \partial y} & \dfrac{\partial^2 F(x)}{\partial x \partial z} \\[2ex]
\dfrac{\partial^2 F(y)}{\partial y \partial x} & \dfrac{\partial^2 F(y)}{\partial y^2} & \dfrac{\partial^2 F(y)}{\partial y \partial z} \\[2ex]
\dfrac{\partial^2 F(z)}{\partial z \partial x} & \dfrac{\partial^2 F(z)}{\partial z \partial y} & \dfrac{\partial^2 F(z)}{\partial z^2}
\end{bmatrix}
$$

The stability of strategy combinations in the three-party game can be determined according to the Lyapunov's first method. The stable solutions in multi-population evolutionary games are strict Nash equilibria, which are necessarily pure strategies. Therefore, this paper will analyze the stability of the 8 equilibrium points in the three-party evolutionary game. We substitute the equilibrium point of the pure strategy into the Jacobian matrix to find the determinants. The determinants and stability analysis of each point are shown in Table 3.

According to the Lyapunov's first method, when all determinants λ of the Jacobian matrix are less than 0, the equilibrium point is an asymptotically stable point; when there

TABLE 3. Determinants and stability analysis of equilibrium points

Stable point	Determinant	Stability condition
$E_1(0,0,0)$	$\lambda_1 = -C_H$ $\lambda_2 = -C_P$ $\lambda_3 = T_H + T_P - C_G$	$T_H + T_P < C_G$
$E_2(1,0,0)$	$\lambda_1 = C_G - T_H - T_P$ $\lambda_2 = (1-\alpha)I_H + T_H - C_H$ $\lambda_3 = (1-\beta)I_P + T_P - C_P$	$C_G < T_H + T_P$ $(1-\alpha)I_H + T_H < C_H$ $(1-\beta)I_P + T_P < C_P$
$E_3(0,1,0)$	$\lambda_1 = C_H$ $\lambda_2 = -U_P - C_P$ $\lambda_3 = \alpha I_H + T_P - C_G$	
$E_4(0,0,1)$	$\lambda_1 = C_P$ $\lambda_2 = -U_H - C_H$ $\lambda_3 = \beta I_P + T_H - C_G$	
$E_5(1,1,0)$	$\lambda_1 = C_G - T_P - \alpha I_H$ $\lambda_2 = C_H - (1-\alpha)I_H - T_H$ $\lambda_3 = (1-\beta)I_P + T_P - U_P - C_P$	$C_G < T_P + \alpha I_H$ $C_H < (1-\alpha)I_H + T_H$ $(1-\beta)I_P + T_P < U_P + C_P$
$E_6(1,0,1)$	$\lambda_1 = C_G - T_H - \beta I_P$ $\lambda_2 = C_P - (1-\beta)I_P - T_P$ $\lambda_3 = (1-\alpha)I_H + T_H - U_H - C_H$	$C_G < T_H + \beta I_P$ $C_P < (1-\beta)I_P + T_P$ $(1-\alpha)I_H + T_H < U_H + C_H$
$E_7(0,1,1)$	$\lambda_1 = C_H + U_H$ $\lambda_2 = C_P + U_P$ $\lambda_3 = \alpha I_H + \beta I_P - C_G$	
$E_8(1,1,1)$	$\lambda_1 = C_G - \alpha I_H - \beta I_P$ $\lambda_2 = C_H + U_H - (1-\alpha)I_H - T_H$ $\lambda_3 = C_P + U_P - (1-\beta)I_P - T_P$	$C_G < \alpha I_H + \beta I_P$ $C_H + U_H < (1-\alpha)I_H + T_H$ $C_P + U_P < (1-\beta)I_P + T_P$

exist determinants λ greater than 0 in the Jacobian matrix, the equilibrium point is an unstable point. Based on Table 3, it is determined that the equilibrium points $E_3(0,1,0)$, $E_4(0,0,1)$ and $E_7(0,1,1)$ have determinants greater than 0; thus, these three points can only be unstable points. Regarding the remaining five equilibrium points $E_1(0,0,0)$, $E_2(1,0,0)$, $E_5(1,1,0)$, $E_6(1,0,1)$, $E_8(1,1,1)$, they are stable points when meeting the stability conditions. The analysis is as follows.

Case 1 is characterized by the determinant of the stable point E_1. The three-party evolutionary stability strategy is {Neutral, Non-cooperative, Non-cooperative}, with the size of the transfer payment being pivotal in the government's decision-making process. If the costs incurred by the government's positive stance cannot be balanced, a neutral approach will be adopted. Consequently, the losses incurred by medical institutions and patient groups from non-cooperation decrease, leading the entire system towards information isolation.

Case 2 is expressed by the determinant of point E_2. The restrictive conditions affecting the government are opposite to those in situation 1. When the expected benefits of the government adopting a positive attitude exceed the associated costs, the government tends to take a positive attitude. In this scenario, medical institutions and patient groups must weigh the transfer payment when they choose not to cooperate with information coordination. If the benefits derived from network externality fail to cover the transfer payment, the evolutionary stable strategy becomes {Active, Non-cooperative, Non-cooperative}.

Case 3 is expressed by the determinant of point E_5. In this case, the benefit of medical institutions to cooperate with information collaboration exceeds the transfer payment when they choose a non-cooperative strategy, while the situation is reversed for patients. Consequently, the government implements benefit distribution to medical institutions and collects transfer payments from patients. The evolutionary stable strategy of the system is {Active, Cooperative, Non-cooperative}.

Case 4 is expressed by the determinant of point E_6. The variables affecting medical institutions and patient groups are the same as case 3, but the critical conditions are opposite. At this time, the evolutionary stable strategy of the system is {Active, Non-cooperative, Cooperative}. However, whether medical institutions or patient groups do not cooperate with information collaboration, it will undermine the overall optimization of the system.

Case 5 is expressed by the determinant of point E_8. When the government adopts positive attitude, its cost is less than the benefits brought by network externalities. Simultaneously, the benefits allocated to medical institutions and patient groups for information coordination exceed the transfer payment when they do not cooperate. The evolutionary stable strategy of the system is {Active, Cooperative, Cooperative}. All three parties actively engage in information coordination, leading to rational resource utilization. With medical resources becoming increasingly scarce, the government is increasingly inclined to utilize payment methods that allow medical institutions and patients to share the losses resulting from declining health levels, thereby promoting active information sharing and collaboration among all participants. The distribution of benefit and the formulation of transfer payments in payment methods are the key to achieving ESS.

4. **Numerical Study.**

4.1. **Simulation analysis of network externality benefits.**

Since there are no direct equations or dependencies among the model parameters in this paper, setting the parameters to reflect their basic relative magnitudes is sufficient. Additionally, adjustments to the parameters can be made based on real-world scenarios and specific analytical contexts. Therefore, after consulting opinions from several experts in relevant fields and referencing literature on collaboration between medical systems and patients, as well as incentives for collaboration in public services, the specific values of the basic model parameters are set as follows: $I_H = 10$, $I_P = 6$, $C_G = 6$, $C_H = 5$, $C_P = 2$, $U_H = 4$, $U_P = 2$, $T_H = 6$, $T_P = 2$. $I_H + I_P > C_G + C_H + C_P$ ensures an overall improvement in system performance, when all participants actively cooperate with information collaboration. The transfer payment for non-cooperative participants T_H, T_P is respectively greater than or equal to the benefits U_H, U_P they could gain from free-riding behavior, ensuring the effectiveness of regulation. Due to the specialized nature of healthcare services, medical institutions, as the provider and primary user of healthcare information, have higher costs C_H and benefits I_H, U_H compared to patient. Therefore, their behavior becomes the primary target of government regulation and the penalties T_H they faced are significant.

Network externality benefit is the increasing social benefits that occur when medical institutions or patient groups cooperate with information collaboration and the government adopts a positive attitude. The government can allocate it to participants who adopt the cooperation strategy through payment mechanisms and other incentives. In this simulation, the other parameters are fixed, and the values of α and β are changed for analysis. They are respectively set to $\alpha = 0.2$, $\alpha = 0.5$, $\alpha = 0.8$, and $\beta = 0.2$, $\beta = 0.5$, $\beta = 0.8$. For medical institutions, the government can influence the value of α by establishing an assessment index system for information collaboration or implementing differentiated payment mechanisms for medical expenses. This allows the return of network externality benefits, such as savings in medical expenses, to medical institutions, and even rewards them to incentivize their information collaboration. For patients, the government can collaborate with medical institutions to establish corresponding incentives to influence the value of β. For example, in some cities in China, patients with chronic diseases who actively cooperate with post-treatment care, undergo regular check-ups, and update their health information in a timely manner can earn points to redeem certain health services for free. The changes of α and β ranged in $[0, 1]$ signify the intensity of the government's incentives for the two participants in information collaboration. As the distribution ratio decreases, the government gradually shifts from benefiting from information collaboration behavior to incurring expenditures. As shown in Figure 1, the abscissa represents the evolution time, and the ordinate represents the probability value of the behavior strategy.

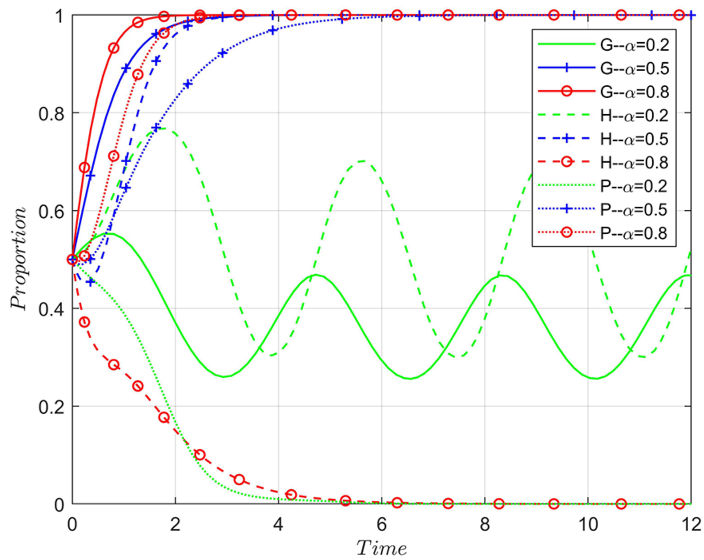

FIGURE 1. Impact of network externality on medical institutions

In Figure 1, α represents the distribution ratio between the government and the medical institutions. When the government accounts for a large proportion ($\alpha = 0.8$), the benefits that medical institutions can obtain from network externality are relatively low, insufficient to offset the costs required for information collaboration, leading them to lean towards non-cooperative strategies. As α decreases ($\alpha = 0.5$), the benefits of medical institutions gradually increase and will exceed the cost they need to pay. At this point, medical institutions are more willing to adopt a cooperative strategy leading to the overall optimization of the system and the achievement of an evolutionary stable ESS. However, when the benefits of medical institutions further increase, the stable state is broken. The behavior strategies of the government and medical institutions will fluctuate over time. Insufficient government benefits can cause its strategy to fluctuate with changes in reputation or profit targets, thereby affecting the strategic choices of medical institutions. Therefore, an appropriate and moderate distribution ratio α will contribute to achieving the optimal evolutionary stability of the system.

According to Figure 2, as β decreases ($\beta = 0.5$ and 0.2), the benefit that patients can obtain from the network externality increases gradually. Its strategy shifts from non-cooperative to cooperative. Compared with medical institutions, the externality benefit of patient information collaboration is relatively small, and transferring a large proportion of this benefit will not significantly impact government revenue. Therefore, reducing β can help patient groups achieve the evolutionary stable policy of system optimization.

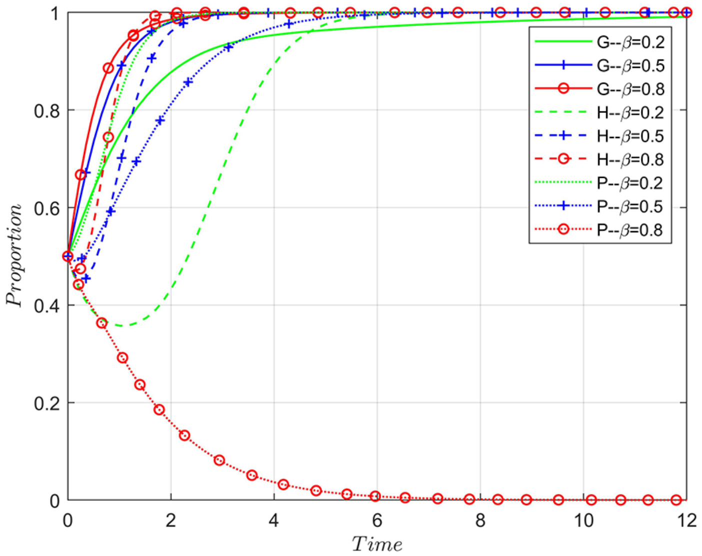

FIGURE 2. Impact of network externality on patients

While ensuring its own benefits, the government needs to fairly distribute the benefits of network externalities to motivate other participants to choose cooperative strategies. Insufficient benefit distribution by the government may fail to provide effective incentives, while excessive distribution can dampen its enthusiasm for regulation. The government should carefully explore viable approaches, which may involve considering performance-based payment methods like bundled payment and pay for performance, as well as exploring different reimbursement models for patients' medical expenses.

4.2. **Simulation analysis of free riding behavior.** Figure 3 and Figure 4 reflect the impact of the free-riding behavior among medical institutions and patients on the process of information collaboration. The benefits U_H, U_P obtained by medical institutions and patients through free-riding behavior vary depending on their types. For instance,

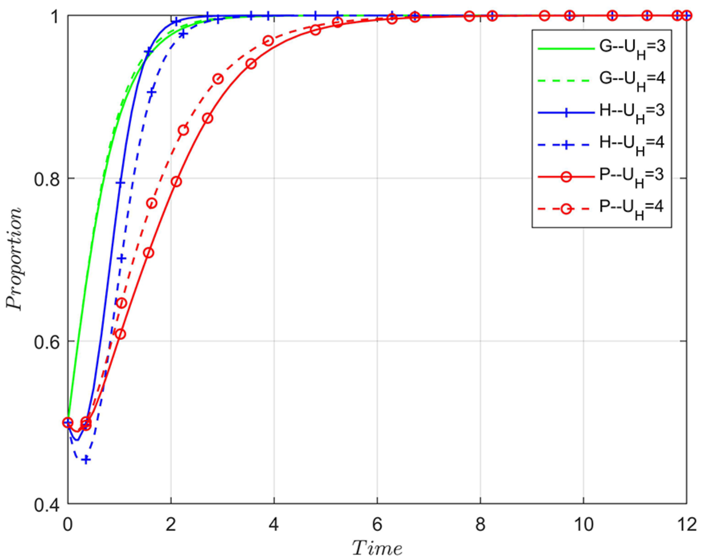

FIGURE 3. Free-riding behavior of medical institutions

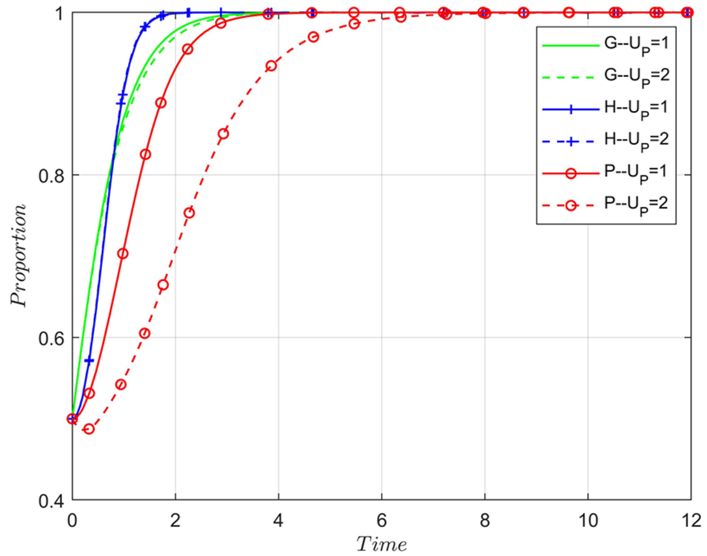

FIGURE 4. Free-riding behavior of patients

suburban or primary hospitals, due to their relatively poor infrastructure and information technology level, may derive smaller benefits from information updates. Similarly, patient benefits may differ based on the type of illness they suffer from; for instance, patients with chronic diseases requiring long-term care may derive higher benefits from information updates compared to those with acute illnesses.

It can be observed that free-riding behavior hinders the adoption of cooperative strategies by participants. The higher benefits the behavior can make, the less likely non-cooperative participants are to change their strategies, and the later ESS can be achieved. Additionally, free-riding behavior appears to have little impact on the government's strategic choices, potentially allowing medical institutions and patients to engage in unrestricted free-riding. Therefore, the government needs to formulate effective supervision methods to avoid free-riding behavior in the medical system. One approach involves enhancing incentives for collaborative behavior by organizing promotional campaigns and providing technical support. Simultaneously, another strategy entails designing mechanisms that effectively increase the costs associated with free-riding behavior, thereby regulating the conduct of participants.

5. **Conclusions.** This paper constructs a three-party evolutionary game model of information collaboration in the medical system, and finds that due to the externalities associated with information collaboration, the distribution of benefits and free-riding behaviors affect the decision-making of each participant, which in turn affects the overall level of information collaboration in the healthcare system. The following suggestions about information collaboration in the medical system are given: the government needs to adopt reasonable strategies to stimulate information collaboration, such as an effective payment mechanism. This is mainly reflected in two aspects. 1) As medical resources become scarce, the government's benefits from information collaboration increase. Consequently, it tends to penalize non-cooperative behaviors that lead to a decline in health levels by increasing transfer payments for the non-cooperative participant, encouraging active information sharing and collaboration among all participants. 2) While ensuring its own benefits, the government must also judiciously distribute the benefits derived from network externalities to incentivize other participants to adopt cooperative strategies.

Additionally, effective supervision methods need to be formulated by the government to prevent free-riding behavior and enhance the efficiency of information coordination within the medical system.

There is a limitation in our study, which provides a possible direction for the next research work. We did not consider the reflection of government incentives by different tiers of medical institutions and its impact on information collaboration.

Acknowledgment. This work is supported by the National Natural Science Foundation of China under Grant No. 72071042. The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers.

REFERENCES

[1] E. Fichera, E. Gray and M. Sutton, How do individuals' health behaviours respond to an increase in the supply of health care? Evidence from a natural experiment, *Social Science & Medicine*, vol.159, pp.170-179, 2016.

[2] H. K. Bhargava and A. N. Mishra, Electronic medical records and physician productivity: Evidence from panel data analysis, *Management Science*, vol.60, pp.2543-2562, 2014.

[3] M. Zhang and Z. Kong, A tripartite evolutionary game model of emergency supplies joint reserve among the government, enterprise and society, *Computers & Industrial Engineering*, vol.169, 2022.

[4] B. Niu, H. Xu and Z. Dai, Check only once? Health information exchange between competing private hospitals, *Omega*, vol.107, 2022.

[5] J. Moon and D. Kim, Design and implementation of distributed ledger-based health data management system, *International Journal of Innovative Computing, Information and Control*, vol.16, no.3, pp.1117-1124, 2020.

[6] M. Z. Hydari, R. Telang and W. M. Marella, Saving patient ryan – Can advanced electronic medical records make patient care safer?, *Management Science*, vol.65, no.5, pp.2041-2059, 2019.

[7] M. Y. Sun, Q. F. Chai and C. T. Ng, Managing the quality-speed tradeoff in blockchain-supported healthcare diagnostic services, *Omega*, vol.120, 2023.

[8] Z. G. Zhang and X. Yin, Information and pricing effects in two-tier public service systems, *International Journal of Production Economics*, vol.231, 2021.

[9] D. A. Andritsos and C. S. Tang, Incentive programs for reducing readmissions when patient care is co-produced, *Production and Operations Management*, vol.27, pp.999-1020, 2018.

[10] F. Bravo, R. Levi, G. Perakis and G. Romero, Care coordination for healthcare referrals under a shared-savings program, *Production and Operations Management*, vol.32, pp.189-206, 2022.

[11] E. Adida and F. Bravo, Contracts for healthcare referral services: Coordination via outcome-based penalty contracts, *Management Science*, vol.65, pp.1322-1341, 2019.

[12] K. Arifoğlu, H. Ren and T. Tezcan, Hospital readmissions reduction program does not provide the right incentives: Issues and remedies, *Management Science*, vol.67, pp.2191-2210, 2021.

[13] Z. G. Zhang and X. Yin, Designing a sustainable two-tier service system with customer's asymmetric preference for servers, *Production and Operations Management*, vol.30, no.11, pp.3856-3880, 2021.

[14] W. Zhou, Q. Wan and R.-Q. Zhang, Choosing among hospitals in the subsidized health insurance system of China: A sequential game approach, *European Journal of Operational Research*, vol.257, pp.568-585, 2017.

[15] H. Zhang, C. Wernz and D. R. Hughes, A stochastic game analysis of incentives and behavioral barriers in chronic disease management, *Service Science*, vol.10, pp.302-319, 2018.

[16] K. Kang and B. Q. Tan, Carbon emission reduction investment in sustainable supply chains under cap-and-trade regulation: An evolutionary game-theoretical perspective, *Expert Systems with Applications*, vol.227, 2023.

[17] Q. Zhang, Y. Yang and B. Liu, Research on operation strategy of online trading platform based on stochastic evolutionary game, *International Journal of Innovative Computing, Information and Control*, vol.18, no.2, pp.551-560, 2022.

[18] Q. Zhang, L. Wang, N. Geng and Z. Jiang, Evolutionary game analysis of medical information sharing based on the government regulation, *Operations Research and Management Science*, vol.29, pp.23-31, 2020.

[19] H. Gintis, *Game Theory Evolving: A Problem-Centered Introduction to Modeling Strategic Behavior*, Princeton University Press, 2000.

Author Biography

Sen Yang received the B.S. degree in Logistics Management from Southeast University, Nanjing, China, in 2017.

He is currently pursuing a Ph.D. degree in Management Science and Engineering at Southeast University, Nanjing, China. His research interests focus on operations management and information collaboration in healthcare system.

Haiyan Wang received the Ph.D. degree in System Engineering from Southeast University, China, 2001.

Prof. Wang is currently a professor with the School of Economics and Management, Southeast University. His research interests include supply chain management, logistics management, mechanism design, and health information service management. His publications have appeared in EJOR, IJPE, IJPR, Omega, Service Science and other journals.