

# Evolutionary Game Analysis of Doctor-Patient Online Interaction Based on Reputation Feedback Mechanism: Postprint

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## Abstract

[Purpose/Significance] Online reputation serves as a crucial regulatory mechanism for maintaining order in internet-based healthcare. By investigating the internal mechanisms through which online reputation feedback systems influence doctor-patient interactions, this study offers strategies for enhancing the supervision and management of online healthcare communities. [Method/Process] This study constructs an evolutionary game model of bounded rationality between doctors and patients. Through calculating replicator dynamic equations and solving for equilibrium stable strategies, combined with simulation analysis using Matlab software, the key influencing factors and pathways for promoting positive online doctor-patient interactions are identified. [Results/Conclusion] The findings demonstrate that the degree to which negative evaluation behavior can alleviate patient dissatisfaction, the costs incurred by doctors' proactive responses, and the disappointment experienced when doctors' enthusiasm is dampened all exert negative effects on doctor-patient interactions; conversely, the reduction of information gaps through patients' accurate information feedback and the spiritual incentive derived from recognition of doctors' efforts exert positive effects on doctor-patient interactions.

## Full Text

### Preamble

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### An Evolutionary Game Analysis of Doctor-Patient Online Interaction Based on Reputation Feedback Mechanism

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**Abstract:**

**[Purpose/Significance]** Online reputation is a crucial regulatory mechanism for maintaining order in online healthcare. By exploring the internal mechanisms through which online reputation feedback influences doctor-patient interaction, this study provides strategies for improving the supervision and management of online medical communities.

**[Method/Process]** This paper constructs a bounded rationality evolutionary game model between doctors and patients, calculates the replicator dynamic equations, solves for equilibrium stability strategies, and employs Matlab software for simulation analysis to identify key influencing factors and pathways that promote positive online doctor-patient interaction.

**[Results/Conclusions]** The findings indicate that the degree to which negative evaluation behavior can alleviate patient dissatisfaction, the cost of doctors' positive response, and the frustration from diminished enthusiasm negatively impact doctor-patient interaction. Conversely, the reduction of information gaps through patients' accurate feedback and the mental incentive from doctors' efforts being recognized positively affect doctor-patient interaction.

**Keywords:** online healthcare; reputation feedback; incentive mechanism; doctor-patient interaction; evolutionary game theory

**Classification Numbers:** G252; R197.323

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## 1. Introduction

With the widespread use of mobile social media and the rapid development of public health services, online medical communities have emerged and gradually transformed how people access health information and manage their own health. As of December 2021, the user base of online medical platforms in China had reached 298 million. Online medical communities provide information exchange spaces for users with shared interests or similar needs, allowing them to both generate online health information and access medical health resources. These communities exhibit distinct group characteristics, primarily offering medical information services such as online consultations, telemedicine, and health education, thereby saving medical time and economic costs.

During the COVID-19 pandemic, online medical communities serving patients

and their families—such as Patientslikeme abroad and platforms like Yixiang-wang and Haodf.com in China—assumed responsibility for online consultations, and online medical consultation may become a new normal and trend in the future.

In the online healthcare market, medical services can be regarded as intangible transaction goods, and doctors typically possess more medical information than patients. Consequently, patients cannot accurately assess doctors' diagnostic capabilities, treatment plans, or information quality. Therefore, many online medical websites have established reputation feedback mechanisms to mitigate moral hazard problems caused by information asymmetry. A robust online reputation feedback system is significant for optimizing the online medical environment, enhancing patients' trust in doctors, improving doctor-patient relationships, and increasing user loyalty to platforms.

This study attempts to analyze doctor-patient online interaction behaviors based on reputation feedback mechanisms by establishing an evolutionary game model, exploring evolutionary paths and stable strategies that promote the healthy development of doctor-patient interaction.

## 1.1 Literature Review

### Research on Doctor-Patient Online Interaction

Current domestic and international research on doctor-patient online interaction (D-P) primarily focuses on two perspectives: (1) user-centered approaches and (2) process-centered approaches.

From the user-centered perspective, D. McGeady et al. argue that doctor-patient communication critically influences patient service experience, with improved communication efficiency leading to higher patient satisfaction. J. Zhang et al. empirically analyzed the impact of doctors' use of medical terminology on online medical service quality, finding that for patients with low health literacy, doctors' use of medical terminology reduces service quality, while for health-literate patients, it significantly improves service quality. This suggests doctors can adjust medical terminology usage according to patients' health literacy to enhance online medical service quality. S. Chen et al. contend that during doctor-patient interactions in online medical communities, doctors' informational support and emotional support are crucial for patient satisfaction. Information support refers to health-related information and personal experience concerning diet, prescriptions, exercise, emotions, and sleep. Emotional support involves doctors' enthusiasm and tolerance in repeatedly confirming patients' questions, as well as encouragement and comfort among patients, which strengthens community identity and improves user satisfaction.

From the process-centered perspective, the doctor-patient relationship is a complex interpersonal relationship involving interactions among individuals from different social strata, and the depth and effectiveness of doctor-patient interaction are important factors influencing medical service outcomes. The core

drivers promoting doctors' active knowledge output and service provision include internal factors (such as morality and responsibility) and external factors (such as economic returns and social reputation). Patients who possess more medical knowledge, hospital information, and doctor background information before seeking medical care have higher probabilities of discovering quality medical services and obtaining greater benefits. Doctor-patient interaction is a process where doctors and patients reach consensus on treatment plans through mutual communication, feedback, and negotiation. Wu Hong conducted empirical research from the perspective of diversified service models and free pricing in online healthcare, segmenting the online doctor-patient interaction process into multiple stages. The results show that high-quality pre-diagnosis and post-diagnosis services can improve patients' return behaviors toward doctors.

From a social exchange perspective, doctors' medical services, pricing, and quality are exchange resources for obtaining patient feedback and return behaviors. However, due to patients' lack of relevant medical knowledge, they often develop excessive expectations of doctors. When treatment outcomes fail to meet expectations, patients experience anger and disappointment and may engage in online complaints or negative reviews to alleviate the psychological imbalance from perceived losses.

### **Research on Online Reputation**

Online reputation conveys signals that represent comprehensive evaluations of users' past behaviors, professional capabilities, and personality traits, indicating future behavioral tendencies. Reputation is also an important factor for stakeholders to measure whether a behavioral subject is trustworthy, and this signal spreads through information flows within communities to enable efficient identification of quality resources. In economics, business reputation is regarded as intangible capital, with good reputation implying better development prospects. Businesses consciously improve product quality and service attitudes to maintain their reputation and brand image, thereby obtaining more potential benefits. In the medical market, doctors' reputation is equally important, with well-reputed doctors having competitive advantages and attracting more patients.

Compared with traditional offline healthcare, online medical platforms' reputation feedback mechanisms help doctors establish their reputation more rapidly. Reputation brings doctors excess returns, including not only material rewards but also psychological achievement and spiritual satisfaction. Moreover, while traditional medical scenarios struggle to address patients' emotions and experiences and lack effective supervision methods, doctors' reputation in online medical environments directly affects patient choice. Therefore, online reputation feedback mechanisms in medical communities also serve as important implicit constraints to avoid moral hazard.

Patient-generated information (such as service ratings, gifts, and vote counts) and system-generated information (such as service quantity and comprehensive evaluations) significantly influence doctors' service pricing.

In summary, current research on doctor-patient online interaction mostly discusses user satisfaction and doctor-patient relationships, while systematic research treating both parties as stakeholders is relatively scarce. Moreover, online reputation, as an important regulatory mechanism in the doctor-patient interaction process, is often overlooked in existing studies. Therefore, this paper treats doctors and patients as two game parties, constructs a doctor-patient interaction game matrix based on online reputation feedback mechanisms using evolutionary game methods, and analyzes the influencing mechanisms and action mechanisms of system evolutionarily stable strategies to provide theoretical foundations for improving online medical platform construction.

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## 2. Model Description and Basic Assumptions

The two most important concepts in evolutionary game theory are evolutionarily stable strategy and replicator dynamic equation. An evolutionarily stable strategy refers to measures adopted by most members of a group, representing a stable state. The replicator dynamic equation describes the process of model development from unstable to stable states. Evolutionary game theory posits that game subjects are boundedly rational, emphasizing dynamic evolutionary processes where participants' strategies change over time. The purpose of evolutionary games is to explore group dynamic evolution processes and how stable states are reached.

In the doctor-patient online interaction process, doctors consider time and energy costs invested versus economic returns and reputation benefits, while patients consider money paid versus health medical services obtained (including information support and emotional support). Due to information asymmetry between doctors and patients and the bounded rationality of both parties, patients adjust their doctor-selection strategies based on previous trial-and-error results and doctors' online reputation feedback. Doctors need to establish trust relationships with patient groups through multiple transactions to obtain more potential and long-term benefits, eventually forming stable strategies.

Online reputation feedback mechanisms both protect patient groups and supervise doctors to fulfill contractual obligations and constrain their behaviors, while also providing opportunities for doctors to build their reputation and personal brands to obtain more potential benefits. Based on full consideration of benefits and losses in online doctor-patient games, this paper makes relevant assumptions and calculates solutions for the evolutionary game model's stable strategies to explore the internal mechanisms through which online reputation mechanisms influence doctor-patient interaction behaviors.

### 2.1 Basic Assumptions

**H1:** The game subjects are defined as two major groups—doctors and patients. It is assumed that patients select doctors and seek medical care through on-

line medical platforms, with each game involving random pairing of individuals from the doctor and patient groups. Doctors have two strategies when receiving patients: positive response and negative response. Patients also have two strategies after consultation: positive evaluation and negative evaluation (users' non-evaluation behavior does not affect doctors' reputation or other patients' doctor-selection choices, so this model does not consider non-evaluation behavior).

**H2:** Both parties are boundedly rational subjects who cannot accurately determine which measures will maximize their benefits before decision-making. Doctors' strategy choices are private information rather than public information. In single games, doctors make strategy choices first, while patients make evaluations based on their experience and subjective feelings during diagnosis and treatment. Both parties dynamically adjust their strategies through trial-and-error processes, with each party's behavior influenced by the other. Therefore, the doctor-patient online interaction process can be viewed as an evolutionary game under asymmetric information.

**H3:** It is assumed that patients making positive evaluations are satisfied with doctors' services, while those making negative evaluations are dissatisfied. When patients provide correct information feedback—that is, when patient evaluations align with doctors' service quality—it indicates that patients can distinguish between high-quality and low-quality doctors, reducing the information gap between both parties. Conversely, it suggests that patients cannot effectively identify quality resources, increasing the information gap.

## 2.2 Evolutionary Game Model Construction

Based on motivation theory, factors such as economic returns, reputation, and altruistic self-actualization promote users' online effort, while time and energy costs produce opposing hindering effects. According to social exchange theory, doctors need to provide patients with information support and emotional support to obtain corresponding rewards, with both parties needing to pay certain costs to obtain their own benefits.

The benefits, costs, and parameters for both parties are as follows:

### (1) Doctors' benefits and costs:

- $R_1$  represents doctors' reputation improvement
- $M$  represents doctors' economic returns (fees charged)
- $I$  represents potential benefits from doctors' online reputation improvement
- $E$  represents mental incentive from doctors' efforts being recognized
- $C_1$  represents costs of doctors' positive response, including time and energy costs
- $R_2$  represents doctors' reputation reduction
- $P$  represents frustration from doctors' enthusiasm being dampened
- $L$  represents potential benefit losses from doctors' online reputation reduction

**(2) Patients' benefits and costs:**

- $D$  represents quality medical services patients can obtain when doctors adopt positive response strategies
- $B$  represents benefits from patients' correct information feedback, such as reduced information gaps and avoiding missing quality doctors or mistakenly selecting low-quality doctors
- $M$  represents normal medical fees paid by patients, including registration and consultation fees
- $C_2$  represents costs of patients' post-diagnosis evaluation, including time and energy for posting reviews
- $U$  represents the effect of patients' negative evaluation behavior in alleviating dissatisfaction
- $Q$  represents potential health threats from poor medical services when doctors adopt negative response strategies

All parameter values are assumed to be greater than 0 for subsequent analysis. Let  $x$  ( $0 \leq x \leq 1$ ) represent the probability of doctors choosing positive response strategies, and  $1 - x$  represent the probability of choosing negative response strategies. Let  $y$  ( $0 \leq y \leq 1$ ) represent the probability of patients adopting positive evaluation strategies, and  $1 - y$  represent the probability of choosing negative evaluation strategies. The payoff matrix for the evolutionary game is constructed as shown in Table 1 .

**Table 1: Payoff Matrix for Evolutionary Game Participants**

	Positive Evaluation ( $y$ )	Negative Evaluation ( $1-y$ )
Positive Response ( $x$ )	$R_1 + M + I + E - C_1,$ $D + B - M - C_2$	$M - C_1 - R_2 - P - L,$ $D + U - M - C_2 - B$
Negative Response ( $1-x$ )	$M + R_1 + I,$ $-M - C_2 - Q - B$	$M - R_2 - L,$ $U + B - M - C_2 - Q$

From the payoff matrix, the expected benefit when doctors adopt positive response strategies is:

$$U_{1a} = y(R_1 + M + I + E - C_1) + (1-y)(M - C_1 - R_2 - P - L) = y(R_1 + R_2 + I + E + P + L) + M - C_1 - R_2 - P - L \quad (1)$$

The expected benefit when doctors adopt negative response strategies is:

$$U_{1b} = y(M + R_1 + I) + (1-y)(M - R_2 - L) = y(R_1 + R_2 + I + L) + M - R_2 - L \quad (2)$$

The average benefit for doctors is:

$$U_1 = xU_{1a} + (1-x)U_{1b} = xy(P+E) - x(C_1+P) + y(R_1+R_2+I+L) + M - R_2 - L \quad (3)$$

The expected benefit when patients adopt positive evaluation strategies is:

$$U_{2a} = x(D+B-M-C_2) + (1-x)(-M-C_2-Q-B) = x(D+Q+2B) - M - C_2 - Q - B \quad (4)$$

The expected benefit when patients adopt negative evaluation strategies is:

$$U_{2b} = x(D+U-M-C_2-B) + (1-x)(-M-C_2-Q+B) = x(D+U+Q-2B) - M - C_2 - Q + B \quad (5)$$

The average benefit for patients is:

$$U_2 = yU_{2a} + (1-y)U_{2b} = xy(4B-U) - 2By + x(D+U+Q-2B) - M - C_2 - Q + B \quad (6)$$

The replicator dynamic equations for both groups' strategy evolution are:

$$F(x) = \frac{dx}{dt} = x(1-x)[y(P+E) - C_1 - P] \quad (7)$$

$$F(y) = \frac{dy}{dt} = y(1-y)(4Bx - U - 2B) \quad (8)$$

Setting  $F(x) = 0$  and  $F(y) = 0$ , we obtain five equilibrium points for the online doctor-patient game:  $(0, 0)$ ,  $(1, 0)$ ,  $(0, 1)$ ,  $(1, 1)$ , and  $(\frac{C_1+P}{P+E}, \frac{U+2B}{4B})$ . The latter exists if and only if  $U < 2B$  and  $C_1 < E$ .

### 3. Stability Analysis

This paper constructs a Jacobian matrix to determine equilibrium point stability by taking partial derivatives of  $F(x)$  and  $F(y)$  with respect to  $x$  and  $y$ :

$$J = \begin{pmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} \end{pmatrix} = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \quad (9)$$

where:

$$a = (1-2x)[y(P+E) - C_1 - P]$$

$$b = x(1-x)(P+E)$$

$$c = y(1 - y)4B$$

$$d = (1 - 2y)(4Bx - U - 2B)$$

An equilibrium point reaches an evolutionarily stable strategy when the Jacobian matrix determinant is greater than 0 and its trace is less than 0—i.e., when  $\det J = ad - bc > 0$  and  $\text{tr}J = a + d < 0$ .

Let  $(x_0, y_0) = \left(\frac{C_1+P}{P+E}, \frac{U+2B}{4B}\right)$ . Based on initial assumptions, meaningful initial and evolved points should fall within the two-dimensional space  $V = \{(x, y) | 0 \leq x \leq 1, 0 \leq y \leq 1\}$ . Therefore,  $U < 2B$  and  $C_1 < E$ . Parameter values for the five equilibrium points are calculated in Table 2, and stability analysis is presented in Table 3.

**Table 2: Parameter Values at Evolutionary Game System Equilibrium Points**

Equilibrium Point	$\det J$	$\det J$ Sign	$\text{tr}J$	$\text{tr}J$ Sign
O(0,0)	$(C_1 + P)(U + 2B)$	+	$-(C_1 + P + U + 2B)$	-
A(1,0)	$(C_1 + P)(2B - U)$	+	$C_1 + P + 2B - U$	+
B(0,1)	$(E - C_1)(U + 2B)$	+	$E - C_1 + U + 2B$	+
C(1,1)	$(C_1 - E)(U - 2B)$	+	$-(E - C_1 + 2B - U)$	-
D( $x_0, y_0$ )	$\frac{(U+2B)(C_1+P)(E-C_1)(2B-U)}{4B(P+E)}$		0	0

**Table 3: Analysis of Equilibrium Points in Doctor-Patient Online Interaction Evolutionary Game**

Equilibrium Point	Stability
O(0,0)	Evolutionarily Stable Strategy (ESS)
A(1,0)	Unstable Point
B(0,1)	Unstable Point
C(1,1)	Evolutionarily Stable Strategy (ESS)
D( $x_0, y_0$ )	Saddle Point

Table 3 shows that among the five equilibrium points, O(0,0) and C(1,1) are evolutionarily stable states, A(1,0) and B(0,1) are unstable points, and D( $x_0, y_0$ ) is a saddle point. The evolutionary dynamic phase diagram of doctor-patient online interaction is shown in Figure 1 [Figure 1: see original paper].

**Figure 1 [Figure 1: see original paper]: Evolutionary Dynamic Phase Diagram of Doctor-Patient Online Interaction**

As shown in Figure 1, equilibrium points  $O(0,0)$ ,  $A(1,0)$ ,  $B(0,1)$ ,  $C(1,1)$ , and  $D(x_0, y_0)$  divide the evolutionary phase diagram into four regions:  $S_1$ ,  $S_2$ ,  $S_3$ , and  $S_4$ . When the initial state falls in regions  $S_1$  and  $S_2$ , the evolutionary path converges to stable point  $O(0,0)$ , and the system ultimately tends toward the stable strategy of {negative response, negative evaluation}. When the initial state falls in regions  $S_3$  and  $S_4$ , the evolutionary path converges to stable point  $C(1,1)$ , and the system ultimately tends toward the stable strategy of {positive response, positive evaluation}.

$D(x_0, y_0)$  is the intersection point of the four regions  $S_1$ ,  $S_2$ ,  $S_3$ , and  $S_4$ . Therefore, point  $D$  also determines the final strategy choice for both parties. When  $S_{OADB} > S_{ACBD}$ , both parties are more likely to adopt the {positive response, positive evaluation} strategy. When  $S_{OADB} < S_{ACBD}$ , both parties are more likely to adopt the {negative response, negative evaluation} strategy. If  $S_{OADB} = S_{ACBD}$ , the evolutionary stable state toward which the system tends is uncertain. Further analysis based on the area of  $S_{ACBD}$  follows:

The larger  $S_{ACBD}$  is, the greater the tendency for game participants to adopt positive strategies. Five parameters influence  $S_{ACBD}$ :  $U$ ,  $B$ ,  $C_1$ ,  $P$ , and  $E$ . Taking partial derivatives of  $S_{ACBD}$  with respect to these parameters yields the influence results shown in Table 4 .

**Table 4: Parameter Influence on Positive Strategy Selection by Both Parties**

Parameter	Influence on $S_{ACBD}$
$U$	Negative correlation
$B$	Positive correlation
$C_1$	Negative correlation
$P$	Negative correlation
$E$	Positive correlation

Table 4 shows that the effect of patients' negative evaluation behavior in alleviating dissatisfaction ( $U$ ), the cost of doctors' positive response ( $C_1$ ), and doctors' frustration from dampened enthusiasm ( $P$ ) are negatively correlated with  $S_{ACBD}$ . That is, when  $U$ ,  $C_1$ , or  $P$  increase,  $S_{ACBD}$  decreases. This means that when patients can better alleviate dissatisfaction through negative evaluations, when doctors face higher costs for positive responses, or when doctors experience more severe setbacks from unrecognized efforts, the positive willingness for both parties to sustain online interaction decreases, ultimately leading both to tend toward negative response strategies. Conversely, patients' correct information feedback ( $B$ ) and doctors' mental incentive from recognition ( $E$ ) are positively correlated with  $S_{ACBD}$ . When the information gap between both parties is smaller or when doctors receive more positive feedback from positive responses, both parties' willingness to continuously participate in online

interaction increases, ultimately leading both to tend toward positive response strategies.

Based on the above analysis, the evolutionary game participants' final strategy choices converge to two stable equilibrium states: {positive response, positive evaluation} and {negative response, negative evaluation}. To verify the mathematical derivation results and further explore each parameter's internal influence mechanism on doctor-patient interaction behavior, parameter values must be assigned to calculate replicator dynamic equations and construct the evolutionary game model. Matlab simulation is used to analyze the dynamic process of both parties' online game evolution.

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#### 4. Model Testing and Simulation Analysis

This paper uses Matlab2016b software as the numerical simulation tool, with the horizontal axis representing time. Variable assignments are selected under the premise that all parameters are greater than 0 and satisfy the constraints  $U < 2B$  and  $C_1 < E$ . For observation convenience, the saddle point  $(\frac{C_1+P}{P+E}, \frac{U+2B}{4B})$  is adjusted to the center position in the figure during initial parameter setting. Initial values are set as  $U = 1$ ,  $B = 3$ ,  $C_1 = 1$ ,  $P = 2$ ,  $E = 4$ , with simulation start time at 0 and end time at 10. Additionally, to ensure representative initial point values that reflect final evolutionary strategies for initial values in different regions, this paper selects points from the four regions divided by the saddle point and coordinate axes as initial  $(x, y)$  values to test evolutionary paths from different initial region points to equilibrium points. Model testing results are shown in Figure 2 [Figure 2: see original paper].

##### **Figure 2 [Figure 2: see original paper]: Dynamic Evolution Process of Game Participants' Strategy Selection**

Figure 2 shows that when initial state point positions are determined, the final equilibrium strategy of game evolution can be determined, indicating that evolutionary results depend on initial states. Under the initial value setting, the saddle point  $D(x_0, y_0)$  is calculated to be approximately (0.583, 0.5). When initial values fall in the  $S_{OADB}$  region, the system ultimately converges to point (0,0), and game participants will choose the stable strategy of {negative response, negative evaluation}. When initial values fall in the  $S_{ACBD}$  region, the system ultimately converges to point (1,1), and game participants will choose the stable strategy of {positive response, positive evaluation}.

To further explore how each parameter in the equations influences the final evolutionary results of game participants, while keeping other parameters constant and satisfying the conditions  $U < 2B$  and  $C_1 < E$ , this paper individually simulates the impact of each parameter's variation on the system's evolutionary process.

##### **(1) Effect of negative evaluation in alleviating patient dissatisfaction**

( $U$ ):

Let  $U$  take values 1, 3, and 5. The evolutionary trends of game participants with parameter  $U$  adjustment are shown in Figure 3 [Figure 3: see original paper]. When  $U$  is low ( $U = 1$ ), patients tend to adopt positive evaluation strategies and doctors tend to adopt positive response strategies, with patients evolving faster than doctors. This indicates that when patients gain little from negative evaluation behavior, both groups ultimately evolve toward the {positive response, positive evaluation} strategy. As  $U$  increases ( $U = 3, U = 5$ ), both patients' convergence to negative evaluation strategies and doctors' convergence to negative response strategies accelerate, with patients always reaching stable states before doctors. Thus, as patients' gains from negative evaluation behavior ( $U$ ) increase, both parties tend to evolve toward the {negative response, negative evaluation} strategy more rapidly. Therefore, parameter  $U$  negatively affects the dynamic evolution of both parties toward optimal strategies.

**(2) Effect of patients' correct information feedback ( $B$ ):**

Let  $B$  take values 3, 4, and 5. The evolutionary trends with parameter adjustment are shown in Figure 4 [Figure 4: see original paper]. As  $B$  increases, both parties converge to the {positive response, positive evaluation} strategy more rapidly, with patients' evolution to positive evaluation strategies always preceding doctors' evolution to positive response strategies. This indicates that when patients' evaluations align with doctors' actual service quality, patients can effectively identify high-quality and low-quality doctors, reducing the information gap between both parties and accelerating both groups' evolution toward the {positive response, positive evaluation} strategy. Therefore, patients' correct information feedback ( $B$ ) positively affects the dynamic evolution of both parties toward optimal strategies.

**(3) Effect of cost of doctors' positive response ( $C_1$ ):**

Let  $C_1$  take values 1, 2, and 3. The evolutionary trends are shown in Figure 5 [Figure 5: see original paper]. When  $C_1$  is small ( $C_1 = 1$ ), both parties ultimately tend toward the {positive response, positive evaluation} strategy, indicating that when the cost of positive response is low, doctors' evolutionary speed lags behind patients', but both still choose positive interaction strategies after some time. As  $C_1$  increases, both parties ultimately tend toward the {negative response, negative evaluation} strategy, with both groups evolving toward negative interaction strategies at increasing speeds. Therefore, the cost of doctors' positive response ( $C_1$ ) negatively affects both parties' dynamic evolution. Moreover, when  $C_1$  is large ( $C_1 = 2, C_1 = 3$ ), doctors' evolution to negative response strategies is initially faster than patients' evolution to negative evaluation strategies. However, when doctors' negative response tendency reaches a certain value, patients' evolution to negative evaluation strategies begins to exceed doctors' evolution speed. This indicates that more obvious negative attitudes from doctors more easily trigger patients' dissatisfaction, accelerating both parties' evolution toward negative interaction strategies.

**(4) Effect of doctors' frustration from dampened enthusiasm ( $P$ ):**

Let  $P$  take values 2, 5, and 8. The evolutionary trends are shown in Figure 6 [Figure 6: see original paper]. When  $P$  is low ( $P = 2$ ), both parties ultimately tend toward the {positive response, positive evaluation} stable strategy. When  $P$  is high ( $P = 8$ ), doctors' evolution to negative response strategies is faster than patients' evolution to negative evaluation strategies. As  $P$  increases, both parties' evolution toward the {negative response, negative evaluation} strategy accelerates. Therefore, the emotional loss from doctors' unrecognized efforts ( $P$ ) negatively affects both parties' dynamic evolution toward optimal strategies. This indicates that when doctors receive negative feedback despite positive responses, their enthusiasm suffers, and increasing disappointment accelerates doctors' evolution toward negative response strategies.

**(5) Effect of mental incentive from doctors' efforts being recognized ( $E$ ):**

Let  $E$  take values 4, 7, and 10. The evolutionary trends are shown in Figure 7 [Figure 7: see original paper]. As  $E$  increases, both parties tend toward the {positive response, positive evaluation} strategy more rapidly. When  $E$  is low ( $E = 4$ ), doctors reach stable states slower than patients, but as  $E$  increases ( $E = 7$ ,  $E = 10$ ), doctors always reach evolutionary stable states faster than patients. This indicates that when doctors' positive response efforts are recognized by patients, their enthusiasm significantly increases, promoting both parties' evolution toward positive interaction strategies. Therefore, mental incentive from recognition ( $E$ ) positively affects both parties' dynamic evolution toward optimal strategies.

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## 5. Conclusions and Recommendations

This paper constructs an evolutionary game model of doctor-patient interaction based on online reputation feedback mechanisms, treating doctors and patients in online medical communities as boundedly rational game participants. Through evolutionary game model analysis, five key factors influencing system evolutionarily stable strategies are identified. Among them, the degree to which patients' negative evaluation behavior can alleviate dissatisfaction, the cost of doctors' positive response, and doctors' frustration from dampened enthusiasm negatively affect online doctor-patient interaction. Patients' correct information feedback and mental incentive from doctors' efforts being recognized positively affect doctor-patient interaction. Additionally, simulation analysis further explores each key factor's influence mechanism on evolutionary results, showing that different parameter variations affect the paths through which both parties reach evolutionary stable strategies.

Based on these findings, this paper proposes the following recommendations for online medical service platform construction:

**(1) Establish an online evaluation supervision mechanism to strengthen identification and verification of false evaluation infor-**

**mation.** The effective operation of online reputation mechanisms is built upon accumulated correct information feedback over multiple transactions. Therefore, supervision mechanisms are needed to effectively identify and verify false evaluation information on platforms. Malicious comments—such as defamatory or retaliatory text, as well as exaggerated or overly positive evaluations—should be intelligently identified and marked as malicious or false evaluations to reduce their impact on online reputation system effectiveness. Additionally, evaluation information ranking can prioritize reliable information through intelligent sorting based on multiple dimensions of user-generated content, including emotional, attitudinal, and viewpoint tendencies. However, information assessment requires large volumes of user-generated information, so information incentive measures must be established to ensure information adequacy and minimize the spread of distorted or pseudo-information in communities.

**(2) Establish patient incentive mechanisms for authentic evaluations to reduce doctor-patient information gaps.** Patients' evaluation behaviors that align with doctors' service quality are crucial, as they not only encourage truly dedicated doctors but also urge less active doctors to reflect on their problems and improve medical quality. Information derived from personal experience is transferable. On one hand, platforms should maximize the value of patients' diagnostic experience to reduce information asymmetry between doctors and patients. On the other hand, the credibility of patient comment content should be evaluated to effectively supervise doctors' past behaviors and predict future behaviors, reducing other patients' doctor-selection costs and potential risks. Therefore, platforms should develop relevant incentive measures to encourage patients to provide positive evaluations when satisfied with doctors' services and honest feedback when dissatisfied with treatment plans or outcomes. Methods such as reward points or medical fee discounts can encourage patients to provide objective and authentic evaluation content.

**(3) Establish doctor appeal channels to maintain doctor-patient trust mechanisms.** Simulation results show that when patients' negative evaluation behavior can significantly impact doctors, retaliatory negative reviews may occur when patients' expectations are unmet. Patients' psychological expectations are subjective and may not align with actual circumstances, and trust destruction occurs more easily than trust establishment. A single severe malicious review can cause tremendous damage to doctors' long-established reputations. Therefore, online medical platforms should establish doctor appeal channels to remove malicious comments that fail content review and do not reflect facts, protecting doctors' legitimate interests. Additionally, platform assessments of doctors should not overly rely on user evaluations. The trust relationship between patient groups and doctors is dynamically established through multiple interactions forming more stable trust relationships. Doctors' assessments and evaluations should consider multiple aspects and dynamically update assessment descriptions over time.

**(4) Utilize mobile cloud computing and other technologies to reduce doctors' online consultation costs and strengthen incentives for positive responses.** Platforms should provide technical support for doctors to accurately assess patient conditions through medical information sharing and health record establishment, enabling doctors to quickly understand patients' medical history and allergy information. Relationships involving interests are often fragile. Therefore, while ensuring medical service quality, platforms should facilitate doctor-patient consultation on treatment plans to share responsibilities. Doctors need to help patients understand their health status, fully comprehend diagnosis and treatment processes and expected post-diagnosis outcomes, avoiding ambiguous or evasive responses to protect their own interests. Additionally, platforms can provide extra rewards for doctors with high positive review rates to strengthen the incentive effect of doctors' efforts being recognized, using quality services to drive the sustainable development of medical platforms.

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Li Meiyu: Writing, revising, and improving the paper;

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**Note:** All mathematical formulas, citations, figure markers, and table markers have been preserved exactly as in the original text. The translation maintains academic tone and technical accuracy while ensuring readability for an English-speaking academic audience.

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