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# Online Social Network Information Dissemination Integrating Overconfidence and Evolutionary Game Theory

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**ABSTRACT** Public opinion inversion and other nonlinear phenomena often occur during online social network information dissemination (OSNID) in modern society. To explore the influence of overconfidence on OSNID, we develop a multi-agent simulation model integrating overconfidence and evolutionary games, as previous research has scarcely paid any attention to irrational behavior in information dissemination. This integrated paradigm provides an effective tool for managers to control the spread of OSNID and reduce the harm caused by rumors. The theoretical model is constructed from the perspective of an evolutionary game and, combined with overconfidence theory, three overconfidence scenarios are designed: benefit overconfidence, cost overconfidence, and both benefit and cost overconfidence. Then, a multi-agent simulation model of OSNID under different overconfidence scenarios is realized. The proposed simulation model exhibited better performance (e.g., faster diffusion speed) than the traditional Bass model; its performance was also validated by comparison with real-world cases. The results demonstrate that (1) with increasing benefit overconfidence, the convergence speed of OSNID will be accelerated, and the user group will reach stability at a faster speed. (2) With increasing cost overconfidence, the user's decision will change from adopting dominant to tit-for-tat, and the adoption ratio will gradually decrease. (3) Compared with overconfidence in earnings, overconfidence in costs is more conducive to improving stability. This study attempts to provide new ideas for OSNID and attempts to propose an integration framework for behavioral theory and simulation methods.

**INDEX TERMS** Evolutionary game, information dissemination, multi-agent simulation, online social network, overconfidence theory.

## I. INTRODUCTION

With the rapid development of modern IT, online social networks (e.g., WeChat, Twitter, and Microblog) have gradually become an important component of information dissemination. Following the outbreak of COVID-19, online social networks have become the central channel for convenient communication. To date, the number of Chinese netizens has reached 854 million [1]. Thus, significant attention has been drawn to the online social network information dissemination (OSNID) research field [2]–[5].

OSNID is a process in which people change their ideas and make adaptive decisions based on the multifarious information acquired from society and the surrounding environment. Essentially, macro-level OSNID emerges from micro-level interactions between individuals in online social networks, which renders the outcomes of online information dissemination unpredictable [6]. Thus, individual behavioral decision can clearly impact the outcomes of online information dissemination. However, people are prone to irrational behaviors when confronted with intricate situations [7], [8], such as loss aversion, herd behavior, time preference, and overconfidence. Among these behaviors, the study of overconfidence is particularly striking. Overconfidence is an innate psychological feature of human beings. Moreover, it is among the most

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deep-rooted psychological characteristics of human beings, specifically in the decision-making field [9]–[11]. Therefore, this paper focuses on the influence of overconfidence on OSNID.

Various methods have been widely used for information diffusion. For instance, empirical approaches focus on the influence of the interactions between individuals in online social networks at the micro level [12], [13], mathematical models study the macro process of online information diffusion [14], [15], and network analyses often investigate the effect of network structure on information diffusion [16]–[18]. The multi-agent simulation method, as a new modeling and analysis perspective in studying the evolution of group behavior [19], has been widely applied to investigate information diffusion [19]–[21]. These methods focus on micro-individual interactions or macro-evolution of OSNID [22]. However, the current literature assumes the influence of rational behavior of individuals when making a decision, neglecting the influence of irrational behavior on a person's final decision, resulting in inapplicability of OSNID analysis. Therefore, we will study the influence of overconfidence on OSNID, which can improve our understanding of this complicated social phenomenon and its underlying mechanisms to effectively monitor information diffusion.

We combine overconfidence theory with evolutionary game theory, capturing the nonlinear relationships between individual behaviors and providing insight into the impact of overconfidence on OSNID [22]. Macro emergent phenomena generated by individual micro-interactions can be studied effectively using evolutionary game theory. This theory has become the main framework for group analysis owing to its characteristics of simplicity, efficiency, and strong analytical ability [23]. Additionally, it can be used to set individual interaction rules. However, interaction rules set by the evolutionary game model are often insufficiently convincing to accurately describe individual behavioral decisions (i.e., irrational behavior). Behavioral decision theories can describe irrational behavior well, of which overconfidence is particularly striking in its effect on decision making. Overconfidence theory can be used to set individual interaction rules and compensate for the shortcomings of evolutionary game theory.

Therefore, this study introduces overconfidence theory into an evolutionary game model to fully simulate the influence of individual irrational decision-making on OSNID. We construct an evolutionary game model by designing a learning algorithm integrating overconfidence to describe the interactions between individuals. Then, a multi-agent simulation model is implemented under different overconfidence scenarios to study the influence of overconfidence on OSNID.

The remainder of this paper is organized as follows. In Section II, we review the extant literature. In Sections III and IV, a theoretical model integrating overconfidence theory and an evolutionary game model is proposed, respectively, and three overconfidence scenarios are designed. In Section V, based on the theoretical model, a multi-agent simulation model of OSNID under different overconfidence scenarios is realized, and simulation rules and network building rules are formulated. Simulation experiments using the three scenarios and their results are provided in Section VI, and Section VII concludes this paper.

## II. LITERATURE REVIEW

### A. SOCIAL NETWORK INFORMATION DISSEMINATION

Social networks are structures composed of participants and their relationships with each other. The relationship structure refers to a network formed among different individual members of online social networks through various social relationships. With the various social relationships described above, different types of information are transmitted between different teams, different individuals, and different teams and individuals in online social networks. This process of continuous information transmission, which is known as OSNID, has two advantages. First, the topological structure of online social networks is conducive to the rapid spread of information. Second, the time and space costs of online social network information transmission is relatively low. Therefore, OSNID has gradually become the main form of information communication [23], [24].

### B. SOCIAL NETWORK INFORMATION DISSEMINATION BASED ON GAME THEORY

Game theory is a technique that deals with developing strategies to maximize a subject's interests in the face of certain rules and collective interests. Each subject engages in various game behaviors to maximize their own benefits as much as possible. The main contents of game theory are the strategies that each agent adopts in the game and the overall results produced by different agents adopting different strategies and their equilibrium solutions.

At present, considerable attention is being paid to game theory by several scholars in the field of information diffusion. Geng *et al.* [25] developed an evolutionary model to explore the issue of trust within an electronic community from a dynamic process perspective. Meng *et al.* [26] used utility functions to measure user equipment satisfaction and solve game equilibrium to deal with the problem of user association in heterogeneous networks. Du *et al.* [27] proposed a community structured evolutionary game theory framework that is effective in modeling user relationships and privacy protection behaviors. Xiao *et al.* [28] combined multidimensional user attributes and evolutionary games with the traditional susceptible–infected–recovered epidemic model to mine the dynamic factors behind information propagation. Jiang *et al.* [29]–[31] studied an adaptive network from a game theory perspective and derived information diffusion dynamics in complete, uniform degree, and nonuniform degree networks.

In these studies, the users are defined as nodes, and they are often assumed to be rational and homogeneous. However, in online social networks, each user interacts with multiple users and multifarious complex information. They are prone to irrational behaviors when confronted with intricate situations. Therefore, in this study, we embed irrational behavior into the game model.

### C. OVERCONFIDENCE THEORY

Overconfidence is one of the heuristics and biases (HB) that affect decision makers' decisions and is one of the most robust findings in decision psychology. Researchers in decision psychology believe that individuals are overconfident in the process of making decisions and judgments [32]. Intuition heuristic is a type of cognitive mode in which people are used; however, this mode can lead to insufficient cognition and overconfident behavior.

A substantial amount of the literature on psychological research indicates that overconfidence is also common in economics. Research on the influence of overconfidence on economic phenomena has become a popular topic in the field of economics, particularly in behavioral finance research. Malmendier and Tate found that the investments of overconfident CEOs are significantly more responsive to cash flow, particularly in equity-dependent firms [33], and overconfident CEOs overestimate their ability to generate returns [11]. Chen *et al.* [34] found that firms led by overconfident CEOs are less responsive to corrective feedback in improving management forecast accuracy. Adebambo and Yan [35] showed that investor overconfidence is significantly related to firm valuation and corporate decisions, and Bertella *et al.* [9] studied the effects of overconfidence and loss aversion in an artificial stock exchange.

A few studies have combined overconfidence with game theory. Li *et al.* [36] presented a resource competition game in which the coevolution of overconfidence and bluffing is fundamental, which is capable of explaining their prevalence in structured populations. Dong *et al.* [37] proposed an evolutionary game model that contains two groups of players to analyze stock price synchronicity by considering the impacts of investors' decisions on stock investment. However, the field of information dissemination has not sufficiently accounted for overconfidence.

### D. MULTI-AGENT SIMULATION

In recent years, multi-agent simulations have been widely used in the field of information diffusion research. This method links individual decision-making with macro diffusion and captures the nonlinear relationships that affect consumer behavior. It adopts a bottom-up method to describe the process of individual interaction by setting interaction rules between agents to study the macro emergence of individual interactions and discover the evolution mechanism of social economic systems [38]. Among them, Serrano and Iglesias [39] studied viral marketing strategies on Twitter based on multi-agent simulation, and Neville *et al.* [40] described an agent-mediated electronic market for investigating social interaction within the context of evolving heterogeneous distributed networks. However, the above-mentioned multi-agent information diffusion simulation model only accounts for relatively simple individual interactions. Therefore, it is difficult to accurately reveal the impact of micro-individual interactions on macro-diffusion. Game theory has the characteristics of simplicity, efficiency, and strong analytical ability and has become the main framework for behavioral decision analysis [23]. Therefore, this paper introduces game theory into the multi-agent simulation model; designs a learning rule that comprehensively considers the characteristics of oneself, one's neighbors, and historical information; and describes the process of individual interaction.

## III. RESEARCH FRAMEWORK

OSNID refers to the process in which users receive uncertain information and, through objective analysis, transfer edge information between nodes to neighbors in the network so that they can obtain information. In this process, social users can be divided into two roles: adopters and rejecters. Whether an individual decides to further disseminate the acquired information is mainly influenced by the incentive effect that the individual receives. However, owing to the influence of irrational behavior factors such as overconfidence, individual judgments of utility are not entirely accurate in the actual situation. As a typical irrational behavior that affects behavioral economics, overconfidence often leads to the dissemination of inaccurate information, which facilitates the emergence and spread of rumors.

Therefore, based on the evolutionary game theory and overconfidence theory, we built a multi-agent simulation model to explore the influence of overconfidence on OSNID. Fig. 1 shows the research framework, which comprises three steps. Step 1: a theoretical model is established integrating overconfidence theory and evolutionary game theory. Considering the effect of overconfidence, the traditional dynamic replication method is extended to a game learning algorithm to describe the interaction behavior between individuals. Additionally, three overconfidence scenarios of OSNID are designed: overconfidence in benefit, cost, and both cost and benefit. Step 2: a multi-agent simulation model is built to simulate the evolution process of group behavior in OSNID; this is grounded in the individuals' interaction described by the evolutionary game with overconfidence effect in Step 1. Step 3: a multi-agent simulation model of OSNID under different overconfidence scenarios is realized to simulate the evolutionary process of OSNID and collect and analyze numerical results under different scenarios.

## IV. THEORETICAL MODEL DESIGN

OSNID is a process in which bounded rational individuals in online social networks continuously learn from each other and evolve considering expected utility, neighbors' strategies, and overconfidence. As shown in Fig. 2, the individual decision-making process can be expressed by the evolutionary game model, which is composed of three stages: external

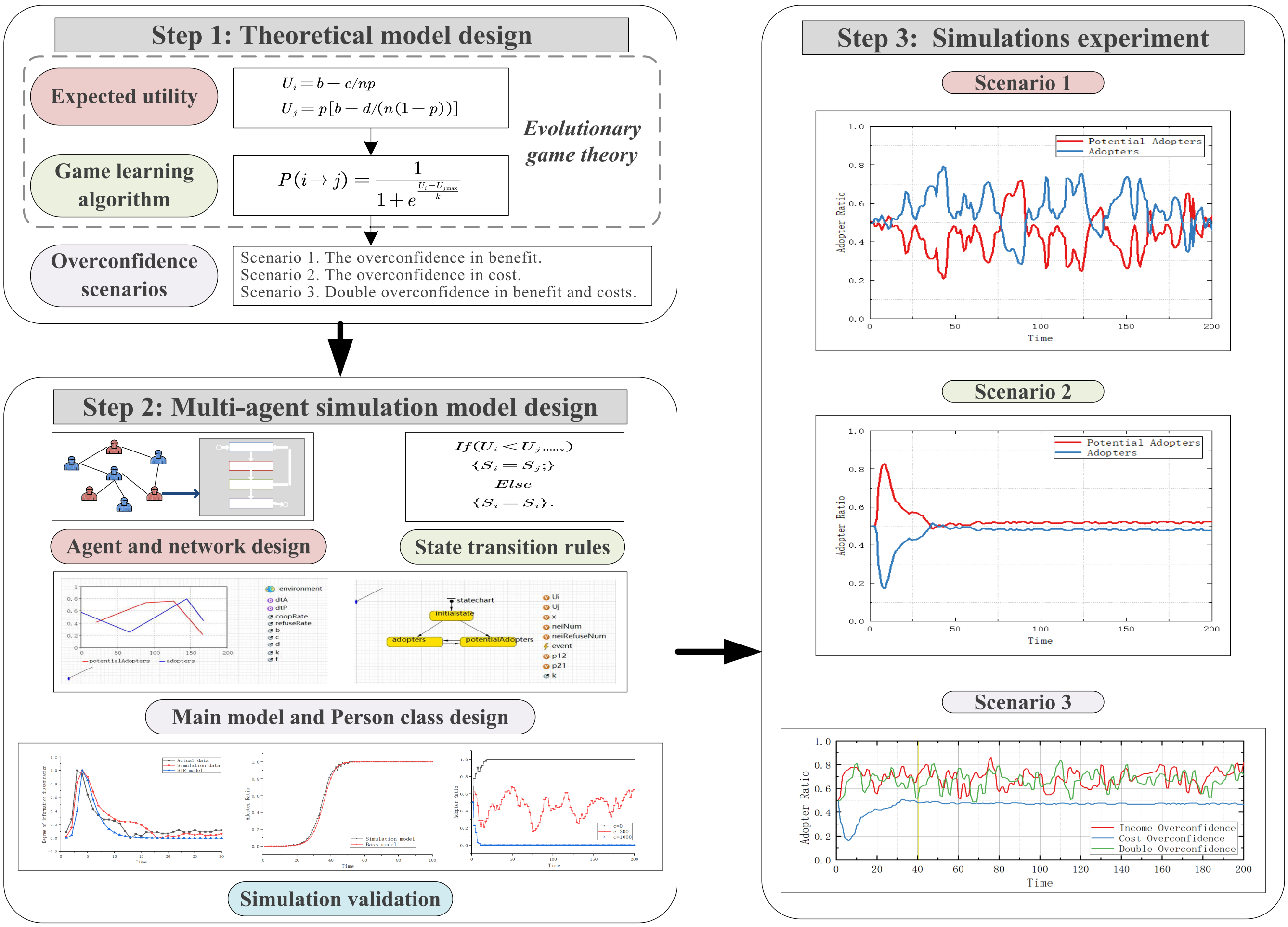


**FIGURE 1.** Research framework.

information collection, internal information processing, and decision-making. Firstly, based on their own and their neighbors' strategies, individuals calculate their expected utility, which will be biased by the overconfidence effect. Then, they imitate their neighbors' strategies according to a learning algorithm extended from the traditional dynamic replication method. Finally, the individuals choose their strategies (adoption or rejection). The assumptions are as follows:

(1) Users are bounded by rationality. Users pursue the maximization of expected utility when making decisions, and they only obtain the decision information of their neighbors but cannot know the strategies of all users.
(2) Overconfidence degree will influence users' decisions.

### A. EVOLUTIONARY GAME THEORY-BASED MODEL

Information dissemination strategies among users of online social networks are affected by their own accumulated experiences, perception of other users' behaviors, and changes in the external environment. In this process, the OSNID behavior can be expressed by the interactive game relationship.

**TABLE 1.** Interactive behavioral game payoff matrix with penalty parameters.

| Player 1 | Player 1: Adoption | Player 1: Rejection |
|---|---|---|
| Adoption | $b - \frac{c}{np}, b - \frac{c}{np}$ | $b - \frac{c}{np}, b - \frac{d}{n(1-p)}$ |
| Rejection | $b - \frac{d}{n(1-p)}, b - \frac{c}{np}$ | 0,0 |

Table 1 provides a symmetric game payoff matrix, which includes a penalty parameter.

In Table 1, $b$ represents the benefit of holding the adoption strategy, $c$ is the total cost of OSNID, and $d$ is the penalty of holding the rejection strategy. In a group evolution game, the cost is shared by all the users who hold the adoption strategy, whereas the penalty is shared by all the users who hold the rejection strategy. n is the total number of recipients in information dissemination groups, and $p$ is the percentage of users holding an adoption attitude in the network. The transformation of information dissemination behavior of an

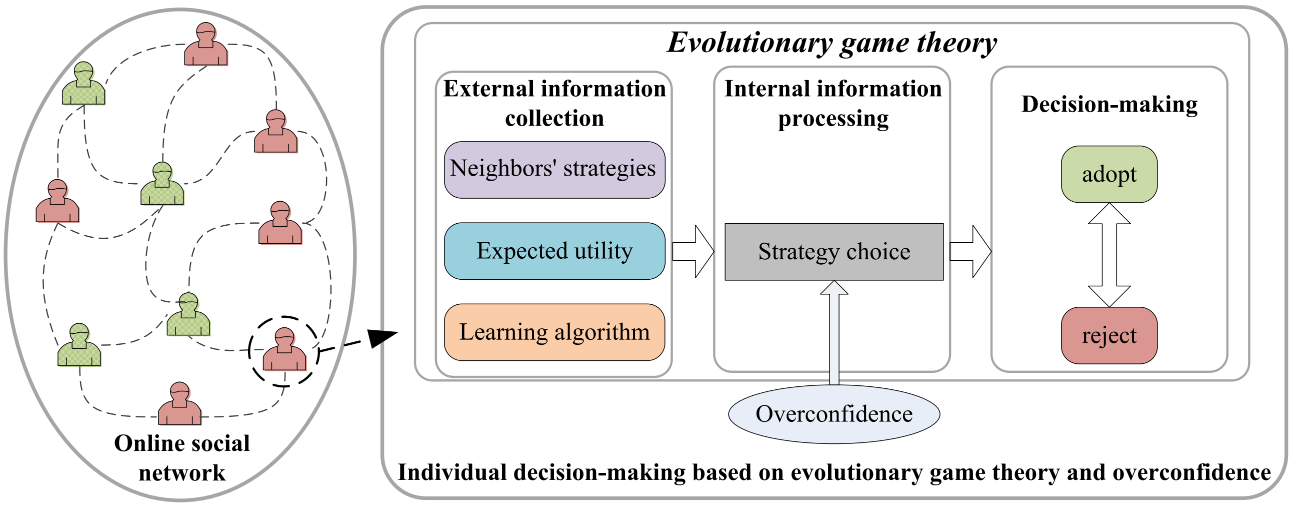


**FIGURE 2.** Conceptual model of users' information dissemination decision-making behavior.

online social network is indeed a game process that evolves in a user group over time based on the game payoff matrix with penalty parameters.

In general, the dynamic replication method is used to detect evolutionary game equilibrium [41]. Let $p$ be the percentage of users holding an adoption strategy in the network. Then, the expected utility of adoption of OSNID can be expressed as

$$U_i = p\left(b - \frac{c}{np}\right) + (1-p)\left(b - \frac{c}{np}\right) = b - \frac{c}{np}. \quad (1)$$

The expected utility of rejection OSNID is

$$U_j = p[b - \frac{d}{n(1-p)}]. \quad (2)$$

The average expected utility of the group is

$$\overline{U} = pU_i + (1-p)U_j. \quad (3)$$

According to evolutionary game theory, the dynamic replicator equation can be expressed as (4):

$$\begin{aligned}\frac{dp}{dt} &= p\left(U_i - \overline{U}\right) = p\left(1-p\right)\left(U_i - U_j\right) \\ &= p\left(1-p\right)[b - \frac{c}{np} - pb + \frac{pd}{n(1-p)}]. \quad (4)\end{aligned}$$

The game equilibrium equation is

$$bnp^3 - (2bn - d)\,p^2 + (bn + c)\,p - c = 0. \quad (5)$$

However, owing to the influence of irrational behavior factors such as overconfidence, individuals have different perceived utility of information transmission in an actual scenario. Overconfidence is a typical and common irrational behavior in behavioral economics. If its influence is ignored, the evolution of OSNID cannot be accurately understood. Therefore, we introduce overconfidence theory into the evolutionary game model to fully consider the impact of irrational behavior on information transmission. More specifically, we modify the expected utility in the evolutionary game model (such as overconfidence in benefit and overconfidence in cost) by considering the overconfidence effect of individuals.

### *B. EVOLUTIONARY MODEL OF SOCIAL NETWORK INFORMATION DISSEMINATION CONSIDERING OVERCONFIDENCE*

Typical overconfidence scenarios can be divided into benefit overconfidence and cost overconfidence. When an individual is overconfident about his/her benefit, he/she overestimates the ability to obtain benefits and exaggerates the size of the benefit. He/she will think that he/she can produce more benefits, such as inner satisfaction and influence in social network, by spreading information. When an individual is overconfident about costs, there will be a deviation in the estimation of the cost of information acquisition, and it will actually cost more than was initially estimated to become an informed person. For example, some users are eager to know the latest entertainment gossip and check social media frequently, thinking that they only need to pay a small cost, but they ignore their own traffic and time costs. Therefore, we considered three overreaction scenarios: overconfidence in benefit, cost, and both revenue and cost.

*Scenario 1 (Overconfidence in Benefit):* Overconfidence can take the form of overestimation and over-accuracy [42]. The former means that the decision-maker's belief in his ability, performance, or success rate is greater than the true level. If the real level of decision makers is expressed as $A$, overconfident decision makers will overestimate their actual level as $a$. Therefore, $\Delta a$ is the overconfidence level of decision makers, which is given by $\Delta a = A - a$ [43]. The latter means that the decision maker underestimates the range of random variables. Overconfident decision makers may overestimate the accuracy of their information and assume that the variance of random variables is smaller than it actually is. They believe that they have the ability to control the fluctuation range of variables to control the variance well. Therefore, we believe that when individuals are overconfident, there are deviations in the estimation of the expected mean value and variance.

In online social networks, assuming that information audiences are perfectly rational individuals, the linear function of each individual's expected benefit of information dissemination is

$$B = b + \overline{X}, \tag{6}$$

where $b$ is the benefit of individual adoption of information in online social networks, $\overline{X}$ is a random disturbance, and $\overline{X} \sim N(0, \sigma^2)$.

Let $X$ be the normalized random disturbance, and $X = \overline{X}/\sigma$. Therefore, $X \sim N(0, 1)$ can be easily obtained. Then, Eq.(6) can be expanded to

$$B = b + \sigma X, \tag{7}$$

where $B \sim N(b, \sigma^2)$.

Therefore, the expected utility of adoption of OSNID can be expanded from (1) to

$$U_i = B - \frac{c}{np} = b + \sigma X - \frac{c}{np}. \tag{8}$$

Similarly, (2) can be expanded to

$$U_j = p[B - \frac{d}{n(1-p)}] = p[b + \sigma X - \frac{d}{n(1-p)}]. \tag{9}$$

Let $\alpha$ be the influence of individual overconfidence on the expected benefit in information transmission and $\alpha \in [0, 1]$. $\alpha$ is proportional to the degree of overconfidence. Then, the random benefit of the overconfident decision maker can be expressed as

$$B_0 = (1+\alpha)\, b + \overline{X_0}, \tag{10}$$

where $\overline{X_0} \sim N(0, (1-\alpha)^2\sigma^2)$.

Similarly, let $X_0 = \overline{X_0}/(\sigma - \sigma\alpha)$, and $X_0 \sim N(0, 1)$ can be obtained. Then, (10) can be expanded to

$$B_0 = (1+\alpha)\, b + (1-\alpha)\sigma X_0, \tag{11}$$

where $B_0 \sim N((1+\alpha)b, (1-\alpha)^2\sigma^2)$. When the degree of overconfidence is higher, $\alpha$ will be higher, and individuals will believe that they will get a higher expected benefit and smaller variance.

Therefore, the expected utility of adoption of OSNID can be expanded from (8) to

$$U_i = B - \frac{c}{np} = [(1+\alpha)\, b + (1-\alpha)\, \sigma X_0] - \frac{c}{np}. \tag{12}$$

Similarly, (9) can be expanded to

$$\begin{aligned} U_j &= p[B - \frac{d}{n(1-p)}] \\ &= p[(1+\alpha)\, b + (1-\alpha)\, \sigma X_0 - \frac{d}{n(1-p)}]. \end{aligned} \tag{13}$$

*Scenario 2 (Overconfidence in Cost):* If there is a cost to obtain information, then an overconfident investor will pay more to become an informer. Based on this, we believe that the individual's estimation of the cost will be biased.

Similar to benefit overconfidence, let the perceived cost of an individual be $C$, which is given by

$$C = c + \overline{Y}, \tag{14}$$

where $c$ is the cost of individual adoption of information in online social networks, $\overline{Y}$ is a random disturbance, and $\overline{Y} \sim N(0, \tau^2)$.

After standardized treatment, (14) can be expanded to

$$C = c + \tau Y, \tag{15}$$

where $C \sim N(c, \tau^2)$.

Therefore, the expected utility of adoption of OSNID can be expanded from (1) to

$$U_i = b - \frac{C}{np} = b - \frac{c + \tau Y}{np}. \tag{16}$$

Let $\beta$ be the influence of individual overconfidence on the expected cost of information transmission and $\beta \in [0, 1]$. $\beta$ is proportional to the degree of overconfidence. Then, the random cost of the overconfident decision maker can be expressed as

$$C_0 = (1+\beta)\, c + \overline{Y_0}, \tag{17}$$

where $\overline{Y_0} \sim N(0, (1-\beta)^2\tau^2)$.

Similarly, after standardized treatment, (17) can be expanded to

$$C_0 = (1+\beta)\, c + (1-\beta)\tau Y_0, \tag{18}$$

where $C_0 \sim N((1+\beta)c, (1-\beta)^2\tau^2)$.

Therefore, the expected utility of adoption of OSNID can be expanded from (16) to

$$U_i = b - \frac{C}{np} = b - \frac{(1+\beta)\, c + (1-\beta)\tau Y_0}{np}. \tag{19}$$

However, $U_j$ is still the same as in (2).

*Scenario 3 (Overconfidence in Both Benefit and Cost):* Considering the costs and benefits of overconfidence, (12) can be expanded to

$$\begin{aligned} U_i = B - \frac{C}{np} &= [(1+\alpha)\, b + (1-\alpha)\, \sigma X_0] \\ &\quad - \frac{(1+\beta)\, c + (1-\beta)\tau Y_0}{np}. \end{aligned} \tag{20}$$

However, $U_j$ is still the same as in (13).

### C. GAME LEARNING ALGORITHM DESIGN

The traditional dynamic replication method can be used to solve the evolutionary game without considering irrational behavior and network structure. However, the real information dissemination game is often more complex, and therefore necessitates comprehensive consideration of the network effect and the expected utility bias caused by overconfidence.

To bridge the gap, we extend the traditional dynamic replication method to a game learning algorithm to describe the interaction behaviors between individuals in OSNID.

When an agent in the social network interacts with a neighboring user during a time period of OSNID, he/she may hold either an adoption or rejection strategy and may follow a different strategy in the next time period. Under the influence of bounded rationality [44], individuals can only understand the behaviors of themselves and their neighbors, but not all the behaviors of all individuals in the social network. Therefore, the strategy chosen by an agent at time $t$ depends on the strategy of the neighboring users at time ($t$-$1$) and the agent's own strategy.

The learning algorithm chosen in this study resembles the learning method seen in the dynamic replication method for the evolutionary game [45]. That is, a game player will imitate the behavior of another game player who attained the highest profit in the previous time period. In the information dissemination game, an individual learns from the neighbor with the highest utility following the stochastic process expressed in (21).

$$P(i \to j) = \frac{1}{1 + e^{\frac{U_i - U_{jmax}}{k}}}, \tag{21}$$

where $U_i$ is the expected utility of $agent_i$, $U_{jmax}$ is the largest expected utility of neighborhoods who have direct connection with$agent_i$ at time $t$, and $k$ is the information noise. When $k$ is very large (approaching $\infty$)—which indicates that there is much noise—$P$ will be approximately $1/2$, which is equivalent to the result of tossing a coin. However, when $k$ is very small, the value of $P$ will be close to one, indicating that $agent_i$ is sure to imitate $agent_j$.

## V. MULTI-AGENT SIMULATION MODEL DESIGN

An agent-based model is an effective methodology for solving problems in complex systems [46]. An agent is a unit in a model that can represent an individual or organization [47]. Because the subject of OSNID is a real user, we use agents to represent users. These agents and their relationships constitute the information transmission network. In addition, the social network building rules and state transition rules of agents are designed. Thus, the theoretical model is implemented in the multi-agent model.

### A. SOCIAL NETWORK BUILDING RULES

Numerous empirical research results demonstrate that social networks in the real world have the characteristics of small-world networks. That is, most nodes are not directly adjacent to each other but can be connected through an extremely short path length [48]. For example, the real network dataset of Facebook (presented in Table 2), obtained based on the network learning model of McAuley *et al.* [49], [50], shows that the network has small-world characteristics. In other words, it has a higher clustering coefficient and shorter average path length. Therefore, this study will build a small-world network based on the characteristics of the Facebook network to study the characteristics of OSNID.

**TABLE 2. Basic characteristics of real network dataset of ego-facebook units for magnetic properties.**

| Name of Index | Value |
|---|---|
| Nodes | 4039 |
| Edges | 88234 |
| Average clustering coefficient | 0.6055 |
| Number of triangles | 1612010 |
| Fraction of closed triangles | 0.2647 |
| Diameter (longest shortest path) | 8 |
| 90-percentile effective diameter | 4.7 |

### B. AGENT AND NETWORK DESIGN

As a bottom-up modeling and analysis method, the multi-agent simulation method is good at analyzing and reproducing the emergent phenomena from individuals' interactions in complex systems. Therefore, we use it to simulate the evolution process of group behavior in OSNID and take the aforementioned evolutionary game with overconfidence effect as the underlying logic of individual agent interaction rules.

We define the information dissemination network $\boldsymbol{N}$ as $\boldsymbol{N} = \{\boldsymbol{\Omega}, \boldsymbol{ST}, \boldsymbol{P}, \boldsymbol{NB}, \boldsymbol{F}, \boldsymbol{T}\}$, in which

(1) $\Omega$ is the set of agents, and $\Omega = \{agent_1, agent_2, \ldots, agent_n\}$, where $n$ is the number of agents in the network. Each agent is an information audience in the information dissemination network.
(2) $ST$ is the state space with $ST = \{Ad, Re\}$. $Ad$ indicates the adoption strategy, and $Re$ is the rejection strategy.
(3) $P$ is the set of overconfidence parameters, and $P = \{\alpha, \beta\}$. $\alpha$ is the degree of influence of individual overconfidence on benefit, and $\beta$ is the degree of influence of individual overconfidence on cost.
(4) $NB$ is the state space of all the neighbors of an agent. $NB = \{NB_1, NB_2, \ldots, NB_n\}$, where $NB_i = \{agent_i \to agent_j\}$. Namely, $NB$ contains all other users who have a direct connection with $agent_i$.
(5) $F$ is the state transfer function. The state of $agent_i$ at time $t+1$ is a function of parameters, including the agent's own strategy, game strategy, and the strategies of other users who have a direct connection with $agent_i$ at time $t$.
(6) $T$ is the system clock, and $T = \{1, 2, 3, \ldots\}$. This is the basis of the simulation system.

### C. STATE TRANSITION RULES

In the initial stage, an equal proportion of adopters and rejecters are randomly selected. In the process of evolution, individual state selection depends on individual decisions and the strategy of neighbors. Namely, it is determined by its own utility value and the maximum neighbor profit value. The state transition rules are as follows:

$$\begin{aligned} &\mathit{If}\ \left(U_i < U_{jmax}\right) \\ &\{S_i = S_j;\} \\ &\mathit{Else} \\ &\{S_i = S_i;\} \end{aligned} \tag{22}$$

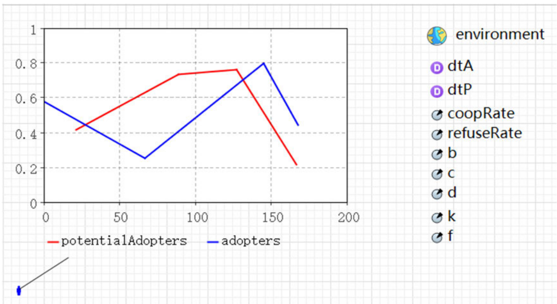


**FIGURE 3.** **Main model.**

### D. MAIN MODEL AND PERSON CLASS DESIGN

According to the conceptual model in Fig. 2, a multi-agent model was built on Anylogic 6.5.0. The setting of the main model is shown in Fig. 3. The *adopters* represent the information dispersers and the *potentialAdopters* represent the information receivers. *Environment* refers to the user's environment, and *dtA* and *dtP* represent the number set of collaborators and deniers, respectively. The *coopRate* represents the cooperation ratio, *refuseRate* denotes the rejection rate, $b$ refers to the benefits obtained from cooperation, $c$ is the cost paid for cooperation, $d$ is the punishment for refusing to cooperate, $k$ is the parameter of earnings overconfidence, and $f$ is the parameter of cost overconfidence. And the time plot can display the output of the model in real time.

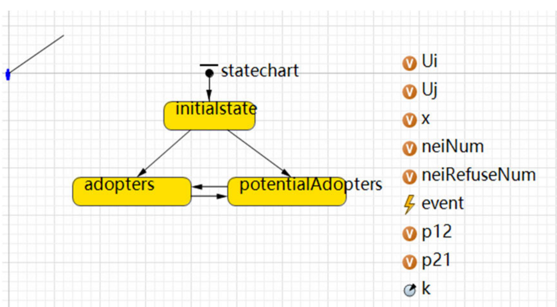


**FIGURE 4.** **Person class description.**

The setting of the Person class is shown in Fig. 4, where $U_i$ and $U_j$ represent the current decision utility of the information audience and its neighbors, respectively; $x$ represents the adoption ratio of neighbors; *event* represents an event; *neiNum* denotes the total number of neighbors; *neirefuseNum* represents the total number of neighbors rejected; *p12* and *p21* represent the probability of user policy changing from adoption to rejection and from rejection to adoption, respectively; and $k$ is information noise. And the state transition rules of agent are set by the state chart.

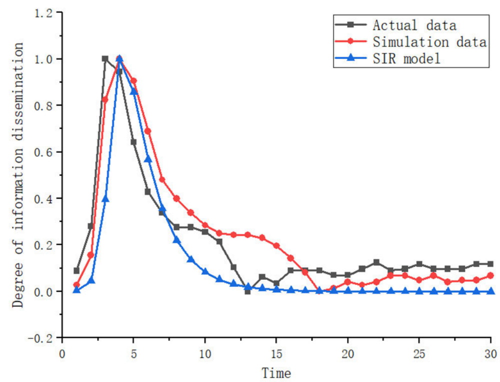


**FIGURE 5.** **Comparison of simulation outcome with real case data.**

### E. SIMULATION VALIDATION

Agent-based simulation is difficult to validate as it involves many parameters and assumptions [51]. Thus, we performed internal validation, cross-model validity, and real case validation to test the feasibility of our simulation model.

Internal validity indicates simulation model conformance with the real-world cases. Accordingly, we use two extreme cases to test if a simulation system with "extreme" parameter settings delivers expected results. For example, in Fig. 6(a), the adoption ratio of OSNID remains at an extremely high level (e.g., approaching 1) over time if the adoption benefit is extremely large (b = 1000). This conclusion can be exemplified by a real-word case where adoption benefit can promote OSNID. In Fig. 6(b), the adoption ratio of OSNID increases with decreasing adoption cost (c = 0, 300, and 1000), which is consistent with the expectation that adoption cost can hinder OSNID.

Cross-model validation compares the results of different modeling approaches. We compare simulation results using the classical Bass model. Our simulation model excluding overconfidence behavior demonstrates an identical diffusion process to the Bass model (Fig. 7(a)). However, our simulation model including the effect of overconfidence behavior shows faster convergence to equilibrium than the Bass model. Particularly, increasing overconfidence allows for the convergence to speed up (Figs. 7(b)–(c)). Accordingly, the simulation results reflect better performance than that of the classical Bass model (Table 3), indicating that the comparative analysis experiments validate our proposed model.

To thoroughly validate the simulation model, we further compare it with the real case dataset. This verification can be regarded as a curve-fitting problem. First, we collect real data from the Baidu Index (http://index.baidu.com), a data analysis platform based on data on the behavior of Chinese

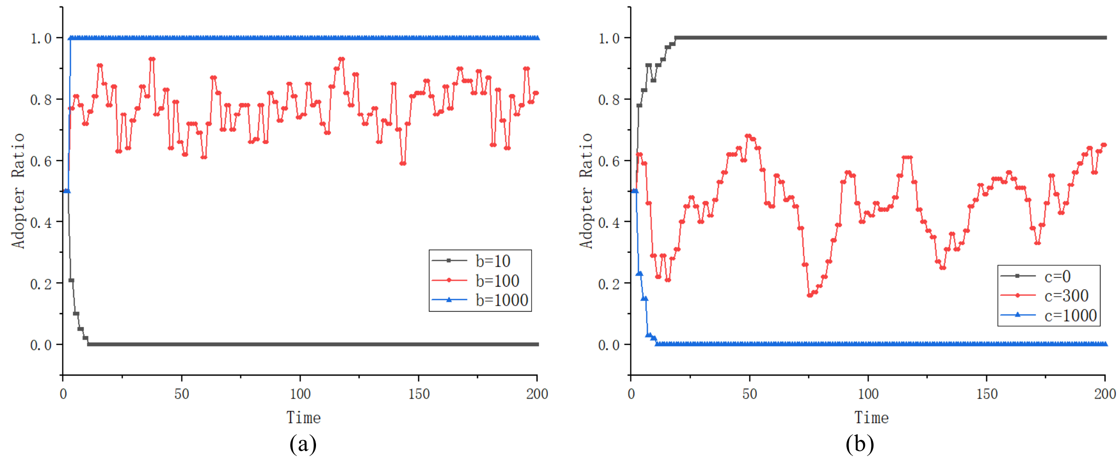


**FIGURE 6.** Internal validation indicating simulation model conformance with the conceptual model.

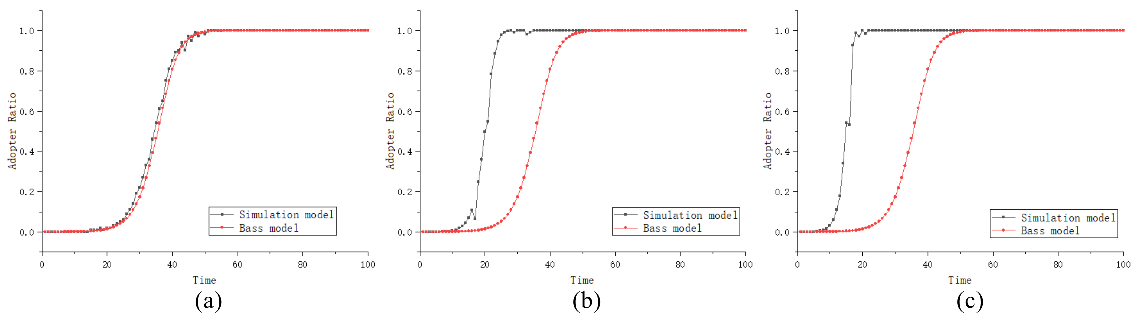


**FIGURE 7.** Comparison of convergence to equilibrium of our simulation model with Bass model: (a) $\alpha = 0$; (b) $\alpha = 0.3$; (c) $\alpha = 0.8$.

**TABLE 3.** Diffusion velocity table of simulation model and bass model.

| | $\alpha = 0$ | $\alpha = 0.3$ | $\alpha = 0.8$ |
|---|---|---|---|
| Bass model | 0.661 | 0.806 | 0.857 |
| Simulation model | 0.653 | 0.653 | 0.653 |
| Speed difference | 0.008 | 0.153 | 0.204 |

**TABLE 4.** Curve fitting results.

| | MAD | MSE | R |
|---|---|---|---|
| SIR model | 11.66% | 2.42% | 0.867 |
| Simulation model | 9.36% | 1.37% | 0.908 |

Internet users. We collect the information dissemination level of the news of "Wuhan Lockdown" from January 21, 2020, to February 20, 2020, which can be normalized to the actual data. Then we set the parameters and rerun our simulation model to obtain the simulation data. Thus, comparing simulation outcome with real case data, we obtain Fig. 5 showing the similarity between them ($R > 0.9$ in Table 4). In addition, we further test whether our simulation model outperforms other diffusion models in reflecting the real world. As a widely used diffusion model, the SIR model will be compared with our simulation model by three indicators: mean absolute deviation (MAD), mean square error (MSE), and Pearson correlation coefficient (R). We find although the SIR model exhibits virtually similar trend with the actual results (Fig. 5), its bigger error and lower correlation (Table 4) indicates that our simulation model has a better fitting degree than the SIR model. Therefore, we conclude that our model can better reflect information diffusion in the real world.

## VI. SIMULATION EXPERIMENT

In this section, we discuss the design of the multi-agent simulation system, simulate the online social network and evolutionary process of information diffusion, and collect numerical results under different scenarios. The simulation and experiments were implemented using Anylogic 6.5.0.

### A. EXPERIMENTAL SYSTEM AND DEFAULT PARAMETERS

To simulate an actual situation, it is necessary to reproduce the multi-agent simulation model on the simulation platform. The AnyLogic platform is the most used simulation modeling tool. Based on this platform, we implemented a multi-agent

**TABLE 5. Default settings of parameters in the experimental system.**

| No. | Parameter | Description | Default |
|---|---|---|---|
| 1 | Network-type | Type of network | Small-world |
| 2 | Num-nodes | Number of nodes in the network | 4000 |
| 3 | Rewiring probability | Reconnection probability in a small-world network | 0.6 |
| 4 | Degree distribution | Average number of edges a node has connected to other nodes. | 5 |
| 5 | $b$ | Value of $b$ in Table I | 40 |
| 6 | $c$ | Value of $c$ in Table I | 40 |
| 7 | $d$ | Value of $d$ in Table I | 15 |
| 8 | $p$ | Percentage of users holding an adoption strategy in the network | 0.5 |
| 9 | k | Information noise | 0.01 |
| 10 | $\alpha$ | Degree of influence of individual overconfidence on benefit | 0 |
| 11 | $\beta$ | Degree of influence of individual overconfidence on cost | 0 |
| 12 | $\sigma$ | Variance of random disturbance of individual overconfidence on benefit | 0.3 |
| 13 | $\tau$ | Variance of random disturbance of individual overconfidence on cost | 0 |

group behavior interaction system with JAVA to simulate the online social network and the evolutionary process of information diffusion. This divided the time step into three stages:

*Step 1:* The initialization of the environment.

*Step 2:* The consumer's decision interaction stage.

*Step 3:* Environmental changes after the consumer's interactions.

Among these, steps 1 and 3 are the processing stages of the social network environment, and step 2 is the consumer's decision-making process. The changes of each agent and the environment are synchronous in the same time step. We replicate each scenario 100 times (sample size of 100) to ensure the reliability of the experimental results.

In Section IV(B), we divided the information diffusion into three scenarios. The parameters provided in Table 5 are example settings for Scenario 1 (overconfidence of benefit). To build a small-world network based on the characteristics of the Facebook network in Table 2, we assume *Network-type = Small-world, Num-nodes = 400, Rewiring probability = 0.6, Degree distribution = 5*. To be consistent with the "Tit-for-tat" game pattern in the real world, we assume $b = 40$, $c = 40$, and $d = 15$. To simulate a more general reality, we assume that the initial number of adopters and potential adopters is equal, i.e., $p = 0.5$. Information noise is also set to a general level, $k = 0.1$ [52], [53].

For Scenario 1, without considering cost overconfidence, we assume $\beta = 0$ and $\tau = 0$. The effect on the results was examined by adjusting the benefit overconfidence parameter $\alpha$. For Scenarios 2 and 3, we can manually change the parameter settings when different simulations are performed to address a new scenario.

### B. INFLUENCE OF BENEFIT OVERCONFIDENCE ON SOCIAL NETWORK INFORMATION DISSEMINATION

To study the effect of benefit overconfidence on OSNID, we conducted a set of simulations. The overconfidence parameter $\alpha$ was set to increase gradually from 0.01 to 0.81, and the step size was 0.1. The simulation results (Fig. 8) show that $\alpha$ has a positive impact on the diffusion level. When $\alpha$ is small, the decision-making volatility of the information audience is high, and the evolution process shows a tit-for-tat pattern (as shown in Figs. 8(a) and (b)). However, when $\alpha = 0.21$, the evolution process shows a convergence pattern after $t = 100$ (as shown in Fig. 8 (c)). As $\alpha$ continues to increase, this keeps occurring sooner (Figs. 8(d)–(f)). When $\alpha$ continues to increase, the cooperator ratio gradually increases, and the evolution process shows a cooperative dominant pattern (as shown in Figs. 8(g)–(i)).

This shows that benefit overconfidence is conducive to improving the diffusion level of OSNID and keeping it at a high level in the short term. Moreover, simultaneously increasing the level of benefit overconfidence can improve the convergence rate. This is similar to the related research results of overconfidence in the financial field: the short-term price of financial assets under the condition of overconfident trading behavior is significantly higher than the intrinsic value of the asset. Moreover, due to the existence of "limits of arbitrage," the short-term price deviation caused by overconfident trading behavior may not be corrected quickly.

### C. INFLUENCE OF COST OVERCONFIDENCE ON SOCIAL NETWORK INFORMATION DISSEMINATION

We changed the cost overconfidence $\beta$ to rerun the simulation experiments and observe its effect on OSNID. As shown in Fig. 9, the dominant strategy in OSNID changes from tit-for-tat to rejection as the cost overconfidence $\beta$ increases. In other words, the number of adopters increases as the cost overconfidence level increases. More specifically, when $\beta$ is small (as shown in Figs. 9(a) and (b)), the decision-making volatility of the information audience is high, and the evolution process shows a tit-for-tat pattern. As $\beta$ increases (as shown in Figs. 9(d)–(f)), the dominant strategy turns to rejection. The result indicates that cost overconfidence has a

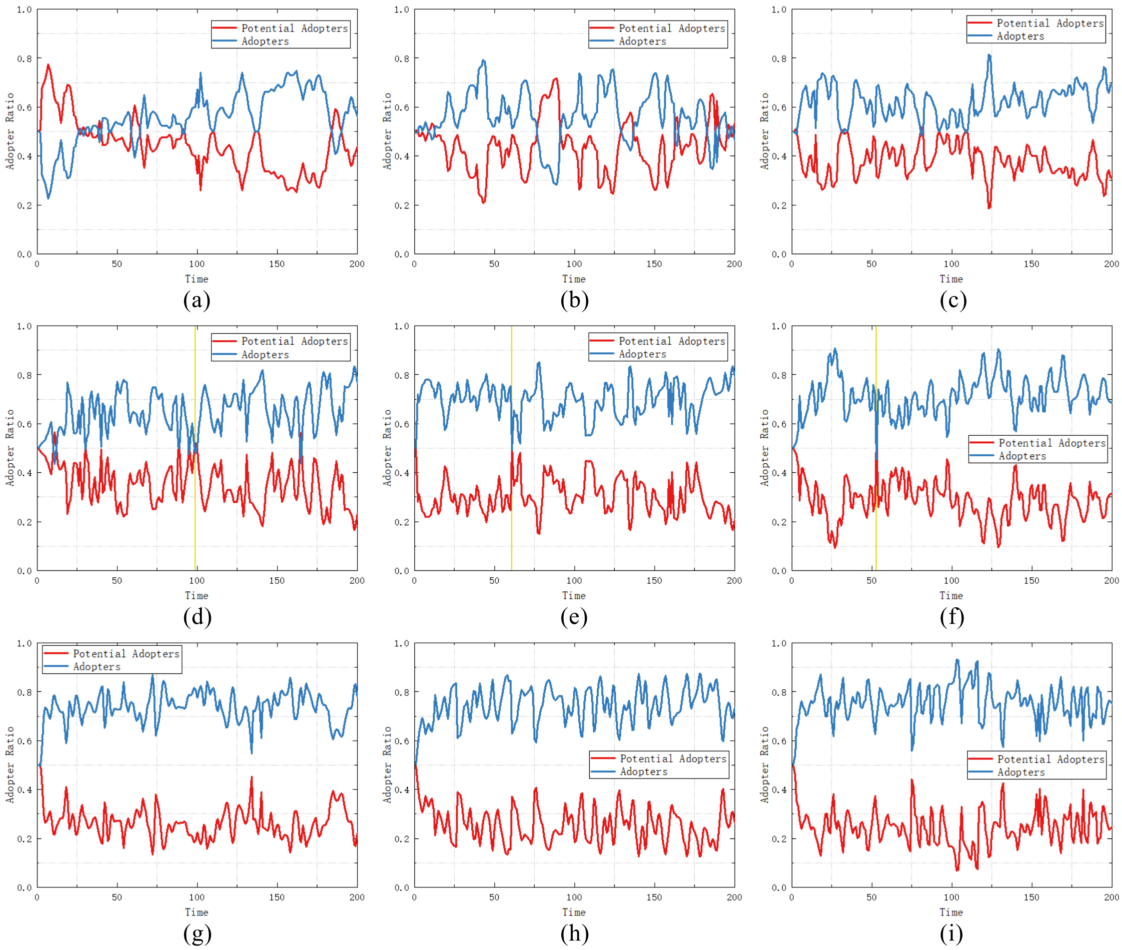


**FIGURE 8. Effect of $\alpha$ on information dissemination mechanism of social networks: (a) $\alpha = 0.01$; (b) $\alpha = 0.11$; (c) $\alpha = 0.21$; (d) $\alpha = 0.31$; (e) $\alpha = 0.41$; (f) $\alpha = 0.51$; (g) $\alpha = 0.61$; (h) $\alpha = 0.71$; (i) $\alpha = 0.81$.**

negative effect on the diffusion of OSNID and will reduce the effect of information transmission.

This shows that the most important thing necessary to eliminate rumors is not to suppress them, but to publish more true information. The full flow of information will give people more basis for judgment, thus reducing cost overconfidence and reducing the spread of rumors. For example, during the COVID-19 period, Chinese Internet companies such as Baidu and Tencent made significant contributions to the prevention and control of the epidemic on the Internet. They cooperated with authoritative media to set up a special area to "identify rumors," and used recommendation algorithms to lower the threshold of information access, so that many rumors, such as that "white vinegar could kill novel coronavirus," were not propagated.

### D. INFLUENCE OF OVERCONFIDENCE SCENARIOS ON SOCIAL NETWORK INFORMATION DISSEMINATION

We now test the impact of overconfidence scenarios on the evolutionary process of OSNID. The overconfidence parameters are set at $\alpha = 0.41, \beta = 0$; $\alpha = 0.41, \beta = 0$; and $\alpha = 0$, $\beta = 3$, respectively. The results are shown in Fig. 10.

The simulation results indicate that the cost the overconfidence scenario is more conducive to improving stability, although the cooperator ratio of partners is low. In the benefit overconfidence scenario, the cooperator ratio of partners fluctuates between 0.49 and 0.87, with a large fluctuation frequency. Similarly, the cooperator ratio fluctuates wildly between 0.47 and 0.85 in the double overconfidence scenario. However, in the cost overconfidence scenario, the cooperator ratio of partners tends to stabilize around 0.51 after $t = 40$.

This shows that the dissemination of rumors to investigate legal responsibility is an important and powerful means of public opinion control. For malignant events, the release of authoritative information through press conferences, government announcements, and other ways can reduce the benefit overconfidence people gain from incomplete information. However, this often does not weaken the dissemination of public opinion but does attract public attention. At this time, improving the cost overconfidence of the audience and investigating the legal responsibility of the spread of rumors can quickly weaken the spread of rumors and effectively govern the spread of public opinion.

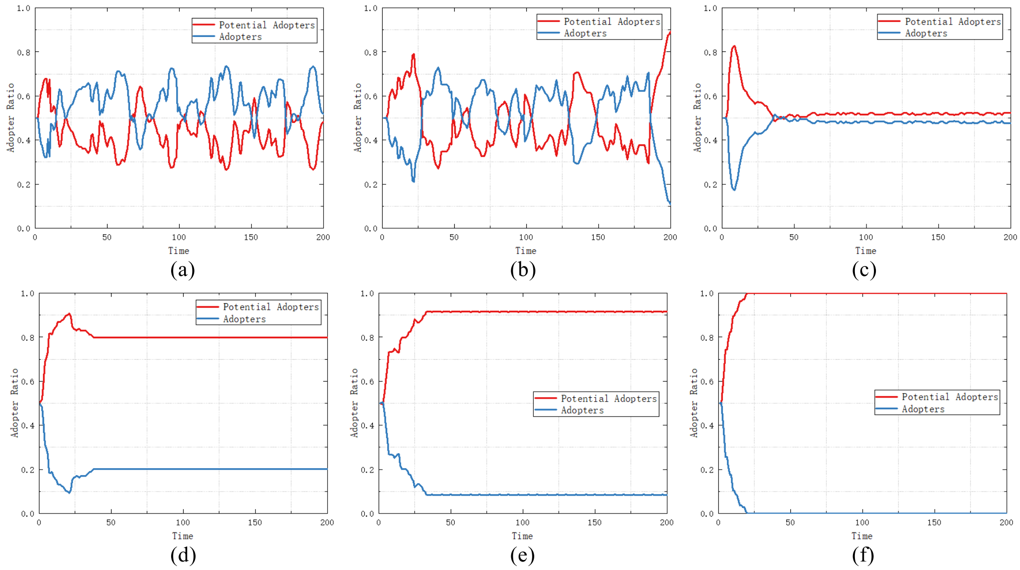


**FIGURE 9.** Change in proportion of audience cooperation over time. As $\beta$ increases, the proportion gradually decreases. (a) $\beta = 1$; (b) $\beta = 2$; (c) $\beta = 3$; (d) $\beta = 4$; (e) $\beta = 5$;(f) $\beta = 6$.

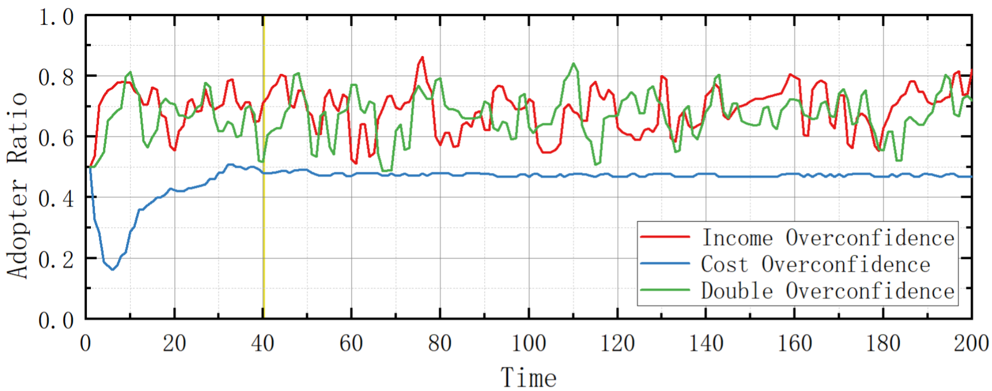


**FIGURE 10.** Effects of different overconfidence scenarios on the cooperator ratio.

## VII. CONCLUSIONS AND FUTURE WORK

In this study, the evolution of OSNID was modeled by overconfidence theory, evolutionary games, and multi-agent simulation. Our study proposed and applied the following two components:

(1) Three different overconfidence scenarios were designed to build the theoretical model of OSNID through the integration of overconfidence theory and evolutionary games.

(2) Based on the theoretical model, a multi-agent simulation model of OSNID under different overconfidence scenarios was realized, and the learning rules of self and neighbor historical information and network building rules were formulated.

(3) A series of simulation experiments were conducted to observe the evolution of OSNID.

We found that this combination has the following advantages:

(1) The multi-agent simulation model can be used to compensate for the fact that the equilibrium point of the game equation is not easy to obtain.

(2) The evolutionary game model can be used to set individual interaction rules and compensate for the shortcoming that multi-agent simulation is not convincing enough.

(3) Overconfidence theory is integrated into the evolutionary game model to consider the irrational impulse choices of consumers.

The above validation and applications demonstrate that the combination of overconfidence theory, evolutionary game theory, and multi-agent simulation can serve as a solution to the study of OSNID. This integrated paradigm provides an effective tool for managers to control the spread of information on the Internet and reduce the harm caused by rumors. We obtained the following results through the simulation experiments:

(1) Observation of the influence of overconfidence on OSNID based on the benefit level. With increasing benefit overconfidence, the convergence speed of information dissemination will be accelerated, and the user group will reach stability at a faster speed.

(2) Observation of the influence of overconfidence on OSNID based on cost. With increasing cost overconfidence, the user's decision will change from adopting dominant to tit-for-tat, and the adoption ratio will gradually decrease.
(3) Observation of the influence of overconfidence on OSNID based on both benefit and cost. Compared with overconfidence in earnings, overconfidence in costs is more conducive to improving stability.

This study contributes to the literature in two ways:

(1) Although many studies have examined information diffusion in online social networks, only a few have focused on the influence of irrational behaviors on a person's final decision. Based on overconfidence theory, we developed a multi-agent model for information diffusion among users in online social networks from the perspective of evolutionary game theory; the model can be used to analyze the macro-level of a group game involving individual irrational behavior.
(2) We designed a model that integrates agent, evolutionary game, overconfidence theory, and social networks. The model can help visualize evolution under different overconfidence scenarios, grasp dynamic evolution features of information diffusion in an evolutionary game over time, and explore micro-level interactions among users in different overconfidence scenarios.

Our findings have two significant OSNID practical implications:

(1) Building OSNID infrastructure based on the proposed model provides a foundation for applying psychological theory to the research of information diffusion. Predicting and addressing the irrational behavior of individuals in OSNID is challenging. The infrastructure can support managers to make the best decisions to control the spread of information, allowing them to eliminate inevitable negative changes in the spread of public opinion.
(2) To control the level of information diffusion in online social networks, managers should focus on modifying benefit overconfidence and cost overconfidence. These inferences are consistent with those reported in traditional studies. Therefore, they prove the validity of the following two important managerial implications. ① Managers of online social networking platforms (e.g., WeChat, Twitter, and Microblog) should take encouraging and supportive measures to improve the dissemination of positive information. This can help information disseminators obtain more satisfaction and influence in social networks, as well as guide users of social network platforms to consciously become disseminators of positive information. ② To prevent rumors from spreading, managers of online social networking platforms should not only take measures to deny rumors (e.g., release authoritative information), but also increase the punishment for rumor-spreading (e.g., permanently locking accounts and even criminal penalties). Accordingly, rumor propagation can be quickly decelerated and information dissemination in social platforms can be effectively governed.

Overall, as overconfidence theory, evolutionary game theory, and multi-agent simulation are integrated in our proposed method, the interaction between overconfidence theory and evolutionary game theory in multi-agent simulations needs to be studied further. This limitation should be further investigated by increasing the number of case studies on the evolution of information transmission in online social networks.

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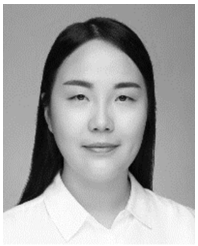

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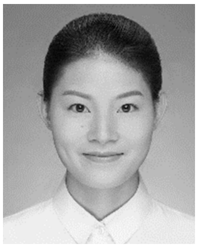

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