

## *Retraction*

# **Retracted: Modeling and Simulation of Cultural Communication Based on Evolutionary Game Theory**

### **Complexity**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] W. Chen and B. Jin, "Modeling and Simulation of Cultural Communication Based on Evolutionary Game Theory," *Complexity*, vol. 2021, Article ID 6115606, 12 pages, 2021.

## Research Article

# Modeling and Simulation of Cultural Communication Based on Evolutionary Game Theory

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In the process of cultural dissemination, the dissemination of false information will have a negative impact on the entire environment. In this case, it is an effective method to regulate the behavior of cultural dissemination participants. Based on the community network structure and the improved classic network communication model, this paper constructs the susceptible-infected-recovered (SIR) model for the grassroots communication of engineering safety culture and discusses the law of grassroots transmission of engineering safety culture. The communication process is simulated, and it is concluded that a good engineering safety culture will be the first to be covered by low-level engineering safety culture in the process of dissemination. With a modularity coefficient of 0.5 as the boundary, it will affect the scale of good safety culture in different directions; the dissemination infection rate of low-level engineering safety culture changes in the same direction with the speed and scale of transmission; the maximum transmission scale of low-level engineering safety culture does not decrease with the increase of the initial value of the susceptible state. When the initial value of the immune state is 15%, the low-level safety culture scale is the lowest value of 0.135, which is the low initial value of employees with low-level engineering safety culture and is more conducive to control its maximum spread. It also puts forward management recommendations for the subjects and objects of the grassroots dissemination of engineering safety culture. This paper transforms cultural communication into an evolutionary game model, uses a game tree to describe it, and analyzes that the model has a Nash equilibrium point by adding a penalty function to the income matrix. This model can encourage cultural communication participants to take honest behaviors, effectively restrain the transmission of false information, and promote a virtuous circle of cultural communication.

## 1. Introduction

The vigorous development of the Internet and the huge number of netizens have transformed cultural promotion from traditional media promotion into an interactive, open, shared, and diverse network of cultural communication [1]. The diversity of its communication channels, the efficiency of communication, and the richness of the dissemination content have profoundly changed people's work, study, and lifestyle. At the same time, the rapid spread of some false information and bad culture on the Internet has caused social panic, which has become the fuse for some violent incidents. Such issues are highly concerned by people [2]. However, because these information promotion media only

inform the people of social and political conditions through "public announcements" and have not changed people's social networks and communication methods, it is therefore easy for the government and researchers to capture culture. In addition, at this time, as the social network structure has not changed compared with the before item, it is easier to control the spread of culture [3]. Therefore, how to ensure the authenticity of the content and the honesty of network participants' behaviors in the spread of online culture has become a hot topic for scholars [4].

Coevolutionary algorithms (CoEA) have the same origin as traditional evolutionary algorithms. They both simulate Darwinian genetics and survival of the fittest to solve problems. It is a hot spot in computational intelligence

research in recent years [5]. Coevolution refers to the evolution of the population considering both the strategy and the structure. When one species evolves, the selection pressure between species changes, and other species will adapt to this change. Sexual response, resulting in highly adaptive evolution among species, is divided into cooperative coevolutionary algorithms and competitive coevolutionary algorithms [6]. At present, game theory is widely used in the fields of ecology, military, sociology, and finance to study the evolution process and results of group behavior. From the point of view of game theory, biological evolution is an optimization process. Whether the biological evolution process reaches a stable state depends on whether the evolution has reached a state of relative advantage, until the next evolution mode occurs, that is, the next optimization is initiated [7]. The central issue of game theory is the interaction of participants and the strategies adopted. A mixed strategy means a strategy that requires participants to randomly choose different actions with a certain probability distribution under a given information situation [8]. Coevolution search involves one or two populations. In the coevolution of a population, the fitness of an individual is based on the competition between individuals in the population. In the coevolution of two populations, the fitness of an individual is based on the behavior of individuals in other populations. In order to adapt to the complex and dynamic evolutionary system environment, individuals or populations establish competition or cooperation relationships to evolve the optimal population [8].

This article starts from the main participants of the network culture communication, transforms the network culture communication process into a game process equivalently, establishes an appropriate model, effectively prevents the occurrence of adverse events caused by the dissemination of false information, and promotes the benignity of the network culture communication cycle. This article expands the construction mechanism of coevolutionary algorithms, combines evolutionary algorithms and game theory, designs new coevolutionary algorithms based on the hybrid strategy idea of game theory, improves the original hybrid strategy framework, and combines hybrid mutation strategies. Extending to hybrid crossover strategies, new collaborative strategies are proposed for genetic operators, selection operators, and search mechanisms of evolutionary algorithms. Inspired by the mixed strategy idea of game theory, a new mixed strategy is designed, new mutation operators are added to the mixed strategy framework, the mixed strategy is extended to the mixed cross strategy, and the strategy based on the mixed cross and mixed mutation is proposed by the new coevolutionary algorithm. The proposed algorithm can automatically select operators and dynamically use the most effective operators in different stages of evolution. The algorithm adopts multiple evolution modes at the same time, which has the implicit feature of multiple subpopulations. The new generation population is produced under the synergistic effect of multiple evolution modes. At the same time, efficient coevolution models and algorithms are established, and new coevolution algorithms are used to solve optimization

problems such as function optimization, evolutionary clustering, multi-issue cultural communication, and combinatorial auction bid determination. Using game theory and social network analysis methods, a cultural communication model based on the game of bounded rationality is established, and then the social network is abstracted into a network model that is convenient for research through complex network theory. On this basis, this paper conducts further theoretical analysis and simulation analysis of the model, separately studies the propagation of the model under different network structures, communication strengths, social deterrence, and trust thresholds, and broadens the scope of application of the research conclusions. It is of great significance to the study of social networks and the critical value of the communication model. This model can encourage cultural communication to participate in honest behavior, effectively suppress the transmission of false information, and promote a good cycle of cultural communication.

## 2. Related Work

In recent years, scholars have conducted in-depth and extensive research on the dissemination of network information and the carrier of network culture. Adami et al. [9] constructed the SIR model H1 to study the spreading mechanism of infectious diseases. Because it has many similarities with network information dissemination, it was applied to the study of the law of network information dissemination. Jäger [10] introduced it into the SIR model concepts such as leadership opinions and herd behavior and established the evolutionary model of conflict information dissemination. Wang et al. [11] added a “contacted” state to the SIR and proposed a mechanism to forward network information in social media. Tang et al. [12] studied the network information which is classified, and an E-C model is established to improve the probability of favorable information dissemination. The above research results have established appropriate models from the aspects of network information dissemination rules, dissemination channels, connections between information dissemination participants, and so on and solved some of the problems of information conflicts and high probability of harmful information dissemination in the process of network information dissemination. No research has been conducted on the behavior of participants in network information dissemination.

In terms of cultural communication models, the first and most important model is the communication model based on the infectious disease model. Epidemics are clearly related to the spread of public opinion in social networks, and they also show very similar structural mechanisms. Epidemic research not only has a significant impact on human health but also provides new ideas for analyzing the process of information dissemination. Cultural dissemination activities meet the SIR dissemination model used in epidemiology. This problem was originally given by Wilson et al. [13]. He proposed the random network SIR model, who believed that culture can only be known to 80% of the

people. Liu et al. [16] analyzed the diffusion of culture in ordinary networks and pointed out that random networks are easier to carry out cultural transmission. In recent years, scholars have given another propagation model called the threshold model. This model assumes that the probability of an individual getting information is satisfied with the sigmoid function of the proportion of people who already know the information around the individual to the overall population. Kong et al. [14] elaborated on the contagion function and the connection strength function (CSF) to explore the effect of the degree of deviation from the transmission speed and the nonlinear contagion on cultural diffusion in a complex social system. The sociological theory believes that there are often important figures in cultural communication, that is, opinion leaders of important nodes have a key value in the cultural diffusion stage. Some experts regard opinion leaders as special agents to implement model construction and analyze their nature in the cultural transmission stage. Liao et al. [15] gave a new model. This model assumes that the probability of hearing public opinion is related to the number of communicators contacted, that is, "0-1-2" influence. In addition, some scholars have studied the process of cultural communication through game theory. Liu et al. [16] analyzed the herd situation in cultural diffusion based on the evolutionary game, pointed out that the memory of the agent and the type of the agent can all have an effect on the cycle of the herd effect, divided the people into Type A (those who know the situation of the event) and Type B (people who do not know the situation), and studied the evolutionary game of cultural development between A and B. There are also researchers who believe that many people are not familiar with the specific situation. Based on this, a two-person symmetric evolutionary game model based on asymmetric information conditions, that is, the game between A and B, was established and simulated. The results show that here herding behavior is easy to produce in the environment. Individuals in the group choose to follow blindly and maintain the same viewpoints. The agglomeration of herd behavior is affected by various factors such as the interaction benefits of the analysis strategy, the cost coefficient, and the length of memory [17]. Of course, there are also other knowledge systems to analyze cultural transmission activities through analyzing the spread of SARS and using differential equations as the theoretical basis to describe the transmission behavior.

In terms of the network model of cultural communication, researchers analyze the situation of cultural communication in complex networks. The selected complex network models are NW small-world and BA scale-free models [18]. The main contribution of the model is to find that individual opinions in the social system are vulnerable to the influence of the external social people. If the number of people is large, the effect will be stronger, that is, if you want to make the individual obey, the opinions of other people are compared with the individual itself who plays a stronger role. However, because individual opinions are not absolutely right or wrong, people's opinions often exist in both, and each gives a differentiated and continuous opinion model [19]. The above model has a precise definition for the

single mutual influence between individuals and analyzes the more macrocomplex activities in the system with the help of several iterations of the microinfluence between individuals. The above model adopts the material dispersion and heat transfer model in the physics system in the construction phase and then implements a large-scale Monte Carlo simulation, aiming at the power of the irreversible public opinion transmission model in the BA scale-free system analysis of learning activities and critical activities [20–23].

### 3. Construction of Cultural Communication Model Based on Evolutionary Game Theory

*3.1. The Basic Theory of Evolutionary Game Theory.* Game theory is a branch of mathematical theory that studies and helps rational people make decisions in interactive situations [24, 25]. It is a theoretical study of optimal decision-making problems under conflicting conditions using rigorous mathematical models [26]. From the perspective of the strategy adopted by the players, it can be divided into noncooperative game theory and cooperative game theory. The noncooperative game mainly refers to how the participants in the game choose strategies to maximize their gains when they have conflicts of interest. The emphasis is on the individual's rationality. According to Nash's theory, each player has its own strategy set and objective function. In the game process, each player chooses his own best strategy under the condition that the game strategy of other players is determined. Inspired by the game theory mixed strategy, a new coevolution algorithm is designed. The genetic operator, selection operator, and search mechanism of the company proposed new collaborative strategies and established efficient coevolution models and algorithms. A node  $x$  (corresponding to the player's hypothesis is P1) randomly selects one of its neighboring nodes (corresponding to the player's hypothesis P2) and becomes the opponent's strategy with a certain probability, which is often used. The evolution criteria are as follows:

$$w(p1 - p2) = \frac{1}{(1 + e^{(u1 - u2) * k})}, \quad (1)$$

where  $u$  represents the cumulative income of  $p_i$ , and  $k=0$  represents noise, which indicates the possibility of an individual's irrational behavior that is often taken as 0.1. If  $k > 0$ , it means that all information has been covered by noise, and then different individuals will undergo arbitrary changes; if  $k < 0$ , it means that the imitation rule has been determined; and when  $u=0$ , individual  $x$  will definitely adopt the P2 strategy.

The basic concepts of the game theory include players (participants), sequence of actions, strategies, return function (payment), information, and equilibrium. (1) Participants in the game are individuals who make decisions. Their goal is to maximize their effectiveness by choosing actions. After the rules of the game are determined, all participants are equal. (2) Actions are choices made by participants at a certain point in time (stage).  $A = \{i, a\}$  represents the set of all actions available for selection, and  $\{i, a\}$  represents a specific

action of  $i$  participant. In the  $n$ -person game, the vector  $a = (a_1, \dots, a_n)$  of the actions of  $n$  participants is called a combination of actions.

$$f(u1, u2) = \frac{(u2 - u1)}{(\max(s, t) - \min(u1, u2))}. \quad (2)$$

(3) The strategy is the rules of action of the participants in each link of the game, that is, what rules to choose actions according to the action concentration.  $S_i$  represents the set of all the strategies that can be selected by  $i$  participant. If each of  $n$  participants chooses a strategy, the  $n$ -dimensional vector  $s = (s_1, \dots, s_n)$  is called a strategy combination. (4) Benefits correspond to each group of possible decision-making choices of each participant, and there should be a result that represents the gains and losses of each participant under the strategy combination. Profit is the fundamental goal pursued by all players, and it is also the main basis for their behavior and judgment. The  $u_n$  represents the income combination of  $n$  participants.

$$F = \{n, \{s(i), i = 1, \dots, n\}, \{f(i), i = 1, \dots, n\}\}. \quad (3)$$

One of the basic characteristics of the game is that the profit of  $i$  participant is a function of the strategy choices of all participants, that is, the profit of any participant depends on its own strategy choices and the strategy choices of all the other players. (5) Action sequence means that when there are multiple independent decision-making parties making decisions, sometimes, the decision-making of these game parties is required to be prioritized. Different sequences are generally different games, even if the game parties and the set of actions are the same. From the perspective of the order of action, games can be divided into static games and dynamic games. A static game is a game in which all players choose strategies at the same time or can be regarded as simultaneous; a dynamic game is a game where each player chooses and acts in sequence, and in turn, and the players who choose later and act generally can see others before they choose their actions. The sequence of actions has an important influence on the outcome of the game.

$$u(i)(x1, x2, \dots, xi, \dots, xn) > = f(i)(x1, \dots, xn)^{-1}. \quad (4)$$

The division of the game can be carried out from two perspectives. According to the sequence of participants' actions, the game can be divided into static game and dynamic game. According to participants' knowledge of the characteristics, strategy space, and benefits of other parties, the game can be divided into complete information game and incomplete information game. According to the combination of the above two division methods, four types of games can be obtained, namely, static games with complete information, dynamic games with complete information, static games with incomplete information, and dynamic games with incomplete information. Therefore, the strategy

that each player should adopt must be his best response to the strategy predictions of other players.

$$T(x) = \frac{x(x+1)}{(x-1) \cdot (\ln(x+1)/x)}. \quad (5)$$

(6) What embodies the basic principle of the game is the idea of Nash equilibrium, which is named after the mathematician Nash. Nash equilibrium strategy refers to a combination of strategies. In order to maximize their own profit or utility, each participant must adopt the strategy that is the best response to other participants, namely, each participant must maximize the benefits, so they will not easily deviate from this strategy combination. The four equilibriums corresponding to the four games are Nash equilibrium, subgame refined Nash equilibrium, Bayesian Nash equilibrium, and refined Bayesian Nash equilibrium.

$$S(k) = \sum_{i=1}^{\min(k, c-k)} f(k) \cdot p\left(\frac{k}{2}\right) \cdot (1-p)^i, \quad (6)$$

$$p(k) = \frac{2f(k)}{(ki-1) \cdot k(i)}.$$

The mathematical definition of Nash equilibrium can be expressed as follows: consider a game of  $n$  players, where the serial number of any player is  $i$ ;  $S_i$  represents the set of strategies that player  $i$  can choose, and any particular strategy is represented by  $S_i$ ; let  $S = S_n, \dots, 1$ , which means that each participant chooses a strategy combination in the form of a strategy;  $u_i$  means  $i$  participant's income function; and  $S_n$  is the participant's choice of strategy  $S = S_n, \dots, 1$  for the benefit of  $i$  participant. We use  $G = S_1, \dots, S_n$  and use  $u_1, \dots, u_n$  to represent this game. The variables used in the equation are described in Table 1.

**3.2. Hybrid Strategy Evolutionary Algorithm under Game Theory.** The basic evolutionary multiobjective optimization algorithm has weak local search capabilities in complex spaces. By introducing appropriate local searches, the balance between search space exploration and development can be maintained. In this paper, the decomposition-based multiobjective evolutionary algorithm framework is used, and the hybrid strategy evolutionary algorithm is used to solve several single-objective optimization subproblems after decomposition; a decomposition-based multiobjective hybrid strategy with local search is proposed by Zhang, Yan, and Mohsen Guizani. The algorithm uses the uniform design method to generate the aggregate weight vectors of the subproblems. The hybrid crossover strategy can make full use of the advantages of different crossover operators. At the same time, the algorithm is based on the convergence characteristics of the evolutionary process, combined with the local search strategy, to obtain the optimal solution set that is close to the Pareto frontier.

As the calculation of the membership degree of data points in FCM is the main factor affecting the efficiency of algorithm execution, a new accelerated FCM algorithm (accelerated fuzzy *c*-means, AFCM) is proposed to accelerate FCM and an evolutionary clustering algorithm is proposed based on FCM. The AFCM algorithm uses a sampling initialization operation to generate better initial cluster centers. For data points with larger membership degrees, the fuzzy cluster centers are updated through a one-step *k*-means operation, while only small membership degrees are updated to accelerate the FCM algorithm. The most prominent model is the ER model proposed by Erdős and Rényi, which is defined as follows: in a graph composed of  $N$  nodes and  $N/2$  possible edges, randomly connected, a random network  $G$  is formed. The average degree of a random network is proportional to  $N$ . The node degree distribution obeys the Poisson distribution. In the ER diagram, whether different nodes have the same neighbors or not, the probability of their interconnection is  $p$ . The propagation matrix of the evolutionary game is shown in Table 2.

Inspired by game theory, individuals in EP are regarded as players in the game. Each individual chooses a mutation strategy from their strategy set according to the selection probability and produces a descendant according to this strategy. If the random variable satisfies the probability distribution function  $F_s$ , the mutation operator is called the mutation strategy. The set of mutation strategies is composed of probability distributions such as Cauchy, Gaussian, and Levy. The hybrid strategy is described as follows: in each generation, an individual chooses a mutation strategy from their strategy set according to the selection probability  $p(s)$ . This probability distribution is called the mixed strategy distribution in game theory. The key issue is to find a good or optimal mixed probability  $p(s)$  for each individual. Evolutionary computing has been successfully applied to various numerical optimization and combinatorial optimization problems. The experimental results show that the performance is significantly improved when dealing with high-dimensional single-mode functions based on the hybrid strategy of classical evolutionary algorithms and single-point mutation algorithms. This mixed probability distribution changes with evolutionary algebra.

As shown in Figure 1, the algorithm has also been improved rapidly. Differential evolution is a simple and effective global optimization algorithm. The main driving force of the differential evolution algorithm is mutation operation, mainly by adding the weighted difference vector of two individuals to the third individual who came up to realize it. Differential evolution has been combined with other algorithms to produce various hybrid algorithms. The differential mutation strategy is introduced as follows, one of the pure strategies used in this article. The individual  $x_i$  in the algorithm can be expressed as an  $n$ -dimensional vector.

An individual dynamically updates the probability distribution of each strategy to be used to select the operator used by the next generation. If a certain generation of an operator produces a better solution, then this operator will be selected with a higher probability.

**3.3. Optimization of Model Weight Parameters.** The crossover and mutation operators used in genetic algorithms vary depending on the problem. They can be standard genetic operators or operators designed by users to solve specific problems more effectively. When the problems of GA applications increase, more and more crossover and genetic operators are constructed by users. As a result, choosing or designing a suitable operator to solve a specific problem becomes more important and requires trial and error. There are many difficulties in deciding which crossover and mutation operators to use. In order to overcome this difficulty, this paper proposes an automatic operator selection technology based on a hybrid strategy. According to the probability of an individual hybrid strategy, a suitable crossover mutation operator is automatically selected from a given set. At the same time, the most effective operator can be dynamically used in different stages of evolution. This paper uses the method of ecological evolution simulation experiment to find that the strategy has stronger antinoise performance, while the original strategy is easier to win in a low-noise environment; in addition, the higher the frequency of interaction between individuals, the more beneficial the strategy of cooperation. In the process of reducing the frequency of interaction, cooperation was carried out. The strategy gradually loses its advantage, the game is equivalent to a single game, and the betrayal strategy becomes the optimal strategy.

(1) Initialization: include the so-called coupled network with  $N$  different nodes around it, where the nodes are evenly distributed around a circle, and all nodes are mutually related to the  $k/2$  nodes adjacent to it. There are  $N$  nodes in the network. (2) Randomized reconnection: use probability  $P$  to randomly reconnect different edges in the network, that is, open the originally connected node, establish a connection relationship with other unconnected nodes, and specify what is at most one edge between any two points, and there cannot be repeated connections or self-connections. In the small-world network form, if the formula  $p > 0$  is satisfied, we can say that the network is a complete regular network, and if the formula  $P = 1$  is satisfied, we can say that the network is an incomplete random network.

The Nash equilibrium is a general concept of the solution of a static game with complete information. On this basis, the solution of other types of games can also be found. Table 3 lists the distribution of various weights. Under the assumption of "completely rational", each player in the game takes the maximization of his own return as the ultimate goal, but the return of the game is determined not only by the strategy chosen by the player himself but also by other strategies in the game. When the participant's strategy combination is  $S$ , if neither party in the game can change their decisions to increase their benefits, we can call it a Nash balance. In a game involving  $n$  individuals, among the strategies selected by all participants in the game, the vector composed of strategies of all participants except  $i$  is given, if there is a combination of strategies, so that the inequality holds for all strategies  $i$ -s that are optional for a certain participant  $i$ .

As shown in Figure 2, the framework steps of the co-evolution algorithm based on hybrid strategy are as follows: (1) Initialization: include the initialization of individual vectors in the population and the initialization of the probability distribution vectors of individual hybrid strategies. The mixed mutation strategy also includes the initialization of the standard deviation vector of the mutation. Each pure strategy in the mixed strategy set is initialized to an equal probability distribution. (2) Crossover or mutation operation: for each individual  $i$  who wants to perform a crossover operation, randomly select another body  $j$ , select a crossover strategy according to the probability in the mixed crossover strategy vector, perform the crossover operation, and produce two offspring individuals. For each individual  $i$  who wants to perform mutation operation, select a mutation strategy according to the probability in the mixed mutation strategy vector, perform mutation operation, and produce a progeny individual. (3) Fitness evaluation: calculate the objective function value as the individual's fitness value. (4) Perform q-tournament selection. (5) Update the probability distribution of the mixed strategy: update the individual's mixed strategy probability according to the update rule of the mixed strategy probability.

#### 4. Application and Analysis of Cultural Communication Model Based on Evolutionary Game Theory

*4.1. Application Simulation of Cultural Communication Model.* This article first examines the influence of trust between individuals on the effect of cultural communication. We randomly select the statistical results of a hot topic on Sina Weibo as a sample for research. By sorting out the original data, the functional relationship between user comments and forwarding is extracted. Then, simulation and visualization tools are used to construct social network topologies under different individual trust levels. The most famous properties of complex networks in the real world are the small-world effect and scale-free characteristics. The small-world network also has a smaller average shortest path and a larger aggregation coefficient. The degree of nodes in a scale-free network obeys a power-law distribution, such as the Internet. In the process of cultural dissemination, social networks are constantly changing due to new users joining, old users logging off, and changes in friend relationships.

Considering that the time for dissemination of hot information and ordinary events will not be too long, this section will not consider it. Network changes in the process of cultural dissemination. This article grabs the Sina Weibo dataset of about 8,200 Sina Weibo users (including Sina Weibo information, Sina Weibo forwarding relationship, user information, user-friend relationship, and other data), analyzes the relationship between active users' comments and forwarding, and constructs a relational network structure with visual tools. In order to observe the influence of network density on the effect of cultural communication, this paper sets the number of nearest neighbors of each network to 2, 4, and 6, respectively. Based on the other initial

conditions, we examine the two networks of scale-free network and small-world network. For the cultural communication effect under this simulation, 50 simulations were performed for each case with a time step of  $T=500$  to take the average value to reduce errors. The specific results are shown in Figure 3.

Data verification is obtained by analyzing the probability of node degree in the network graph. By reading the data captured from Sina Weibo and using visualization tools, the probability distribution diagram of the node degree generated by the actual data of part of Sina Weibo was drawn. This research involves three important concepts: participant  $N$ , strategy  $S$ , and revenue  $U$ . General users usually play two roles in the group. One is to post information to relatives and friends, and the other is to receive information from relatives and friends.

In the process of receiving information, users have two decisions: spread (forward) and nontransmit (do not forward). Therefore, for cultural communication, the formula for constructing strategic alternatives for participants is  $ST = S - N$  (transmission, does not spread). If  $j$  chooses not to spread the strategy, it means that both parties give up spreading public opinion, then the spread cost and benefit in the whole group are zero, and the payment function of both is zero. Conversely, the same is true for  $j$ . The goal pursued by both parties is to obtain the greatest benefit at a lower cost. *Parameter Setting.* (1) Game model: in the cultural communication game, let the values of  $i-j$  and  $C$  be 0.48 and 2, respectively. This value method is consistent with the parameter setting in the "prisoner's dilemma". (2) Network model: set the network scale  $N=500$ , when the connection direction is not considered,  $k=4$ , according to BA scale-free network, random network, WS small-world network, and regular grid network construction algorithm, in order to establish the above four types of networks. When constructing a scale-free network, set the number of edges added each time to  $m$ -links; when constructing a random network, set the average degree and set the total number of edges to  $N$ -links  $= k*N/2 = 1,000$ ; when constructing a small-world network, set the probability of randomized reconnection  $p=0.1$ ; when constructing a regular network, set the degree of each node to 4, that is,  $K=4$ . First, simulate the game process under the above four network models (scale-free network, small-world network, random network, and regular network) and examine the proportion of the number of people participating in the network in each case.

The nodes in Figure 4 represent users in the social network. The blue node in the middle of the figure represents the initial disseminator of the culture. The connection between the nodes indicates that the culture is spread between the two nodes. The length of the connection is shown in this paper. For the degree of trust between users, the shorter the distance is, the higher the degree of trust is, and the culture has been spread once. The simulation found that the culture spreads outward from the center of the graph. As the distance increases, the degree of trust decreases. When it reaches a certain value, the information dissemination stops. The results show that when the trust among users in a group is higher, the culture can be spread more quickly; the lower

TABLE 1: Variables used in equation (6).

$s$	Choices in sequence
$u$	Combination of the division
$f$	Nash equilibrium
$k$	Strategic layer

TABLE 2: The propagation matrix of the evolutionary game.

Object	Spread factor 1	Spread factor 2	Ratio
A1	0.8	0.2	0.61
A2	0.1	0.6	0.22
A3	0.1	0.2	0.17

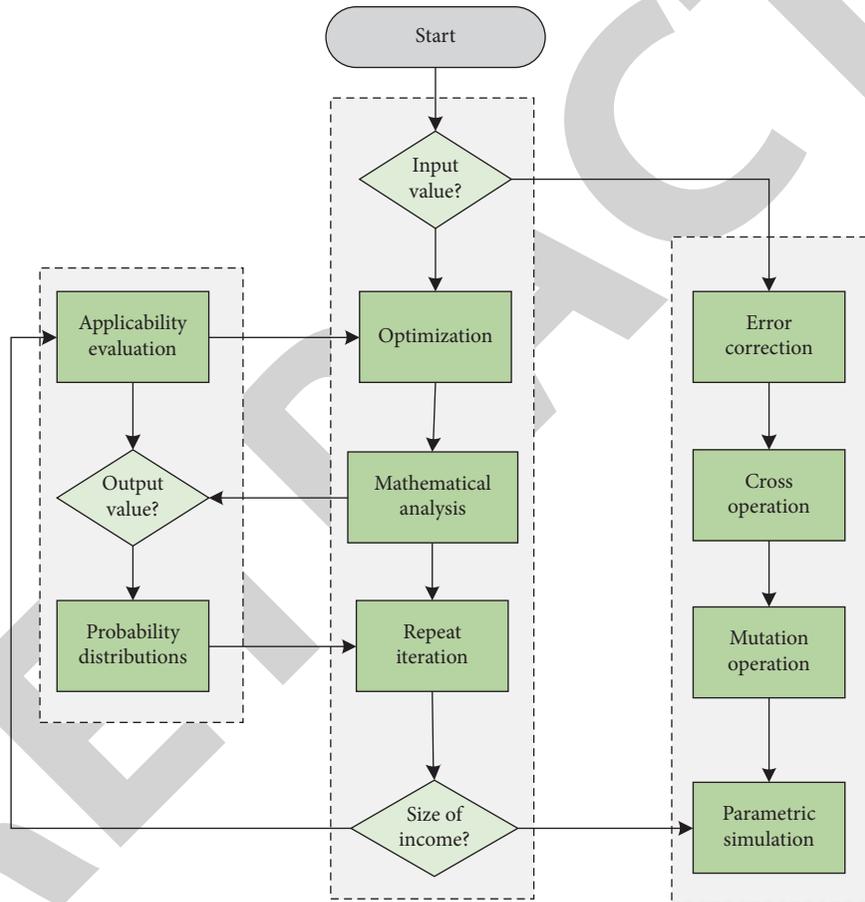


FIGURE 1: Hybrid strategy evolutionary algorithm.

the trust is, the lower the expected benefits of users, and the coverage of cultural dissemination can only be expanded to a limited range.

**4.2. Example Results and Analysis.** In the real complex cultural communication environment, much information about opponents is unknown, which is not conducive to satisfying the interests of all parties, and it is even difficult to reach an agreement on cultural communication. The actual cultural communication system should have an effective

learning and decision-making mechanism in order to obtain dynamic domain knowledge from the cultural communication environment that may change. Adjusting the concession strategy adaptively benefits both parties of cultural communication and improves the efficiency and success rate of cultural communication. All participants in the network play games with their neighbors, and the reward of the game is the sum of the rewards obtained from the game with all the neighbors. Participants use the improved pairing comparison update rule to randomly select a neighbor to compare the average returns of both parties and transform it into the

TABLE 3: List of model weight parameters.

Crossover operator weight	Mutation operator weight	Percentage of nodes
0.19	0.81	0.26
0.78	0.22	0.34
0.24	0.76	0.51
0.31	0.69	0.49

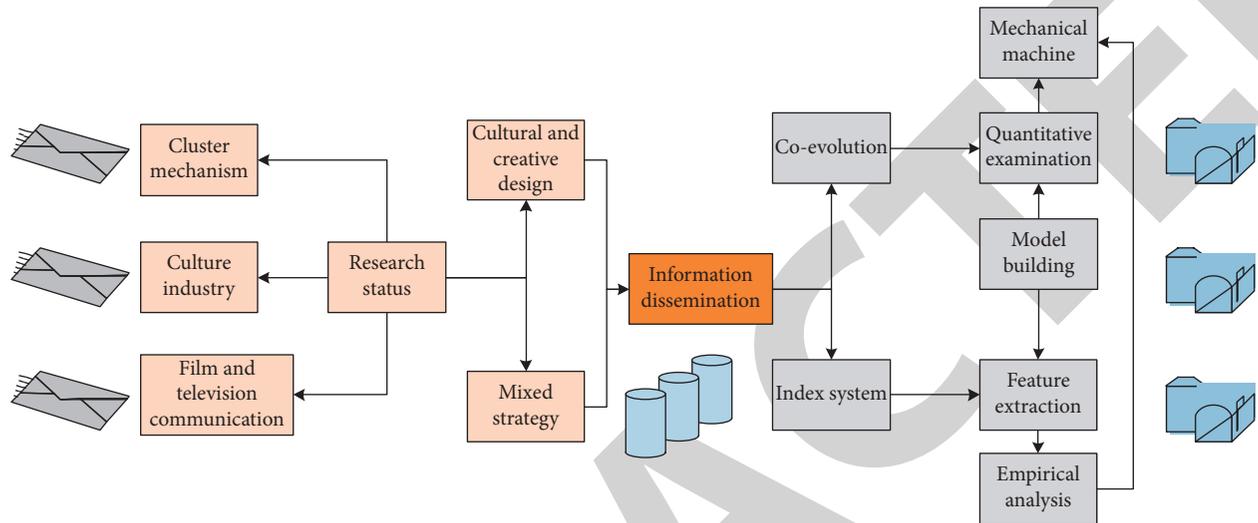


FIGURE 2: The framework of the cultural communication model based on evolutionary game theory.

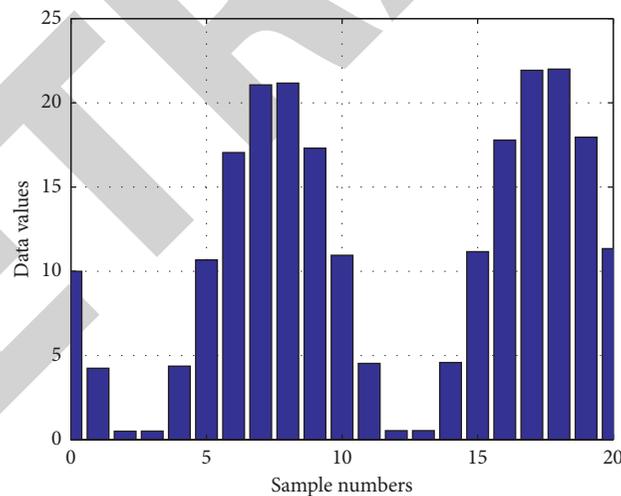


FIGURE 3: Simulation of cultural transmission data value.

other's strategy with a certain probability. Record the proportion of the number of individuals participating in cultural communication in the entire group at each time step, set the noise coefficient to  $k=0.1$ , and draw the curve as shown in Figure 5.

It reflects the dissemination of general cultural events and the dissemination of hotspots and major cultural events on the Internet. The effect of cultural dissemination is not only related to the degree of trust between participants but also depends on the value of the culture itself. The cultural value is

the average, which means that there is not much connection with the users in the group, and the communication efficiency is not high, so the scope of communication is also limited. Therefore, it can spread rapidly in a short time and can often achieve cross-group and cross-regional transmission, which has attracted widespread attention from the whole society. When analyzing the influence of network scale on cultural communication, under the condition that other initial conditions remain unchanged, three networks were examined when the network scale  $N$  was 500, 1,000, and 2,000,

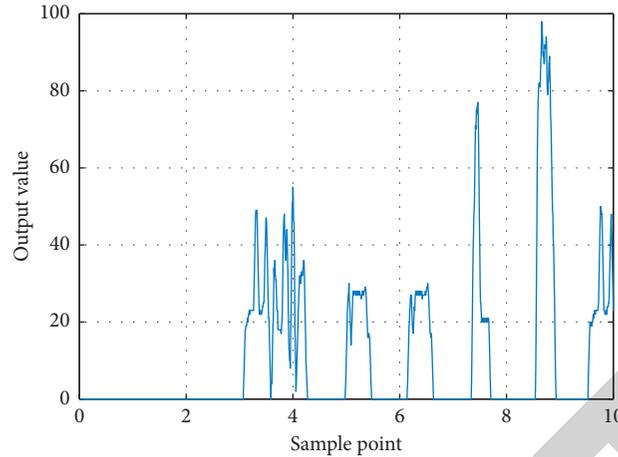


FIGURE 4: The output of the network node during the game.

respectively. According to the set game psychology and set update rules in the simulation, the number of people involved in cultural communication accounted for 41 groups. The time step of each simulation is  $T=200$ . For each case, 50 simulations are performed to take the average value to reduce the error.

Figure 6 shows the cultural dissemination situation in BA networks of different scales. It can be seen that when the network scale  $N$  is equal to 500, 1,000, and 2,000, there is no significant difference in the rate of participation in cultural dissemination within the group, and cultural dissemination reaches a stable state. The number of steps difference is very small. After the 100th round, the proportion of cultural communication has reached almost 100%. It can be seen that the law of cultural communication under the scale-free network is not affected by the distribution of the network scale and has nothing to do with the network scale.

The effects of cultural communication show relatively large heterogeneity under different network structures. When the trust between individuals is set to 0.48 and the individuals make decisions based on the psychology of the game model, the four types of networks have significant differences in the changes in the communication ratio. Among them, the proportion of the number of people participating in cultural communication under the scale-free network structure is at the beginning of the game. After the 50th round, it rose rapidly and remained at 99.9%. Almost everyone participated in cultural dissemination, followed by the small-world network, with a relatively stable growth trend. After 50 rounds, the proportion of people involved in dissemination reached 30%; again, it is a regular grid network, and its changing trend is similar to that of a small-world network; the proportion of the number of people participating in communication under a random network has gradually decreased since the beginning of the game and remained at 0 after the 55th round.

The greater the number of people disseminating information in a group, the more widespread the information can be disseminated. It is obvious from Figure 7 that the proportion of the number of people spreading culture in random networks is on a downward trend. Information stops after a

certain number of spreads, and the degree of cultural spread is low. The two common network topologies of social networks, namely, the scale-free network and the small-world network, have shown an upward trend in the proportion of people disseminating culture, and cultural dissemination is more widespread because both networks have better connectivity. Therefore, it is a key factor in whether cultural information can be spread on a large scale. It can be seen that when the group density is 0.7, in most cases, the hybrid movement mechanism will promote the system's cooperation level to be higher than the mechanism and evolve into a fully cooperative state, and the system evolves compared with the case where the group density is 0.2. The speed is faster, and the system is stable in about 70 steps.

This article models the interaction between individuals in social network groups from the perspective of bounded rational games. This article analyzes the evolution process of culture and the evolutionary stability strategy of the group. Then, the individual strategy updates rules of this evolutionary game, and the topological model of the social network is determined. Finally, the computer simulation method was used to demonstrate the process of cultural diffusion, and several key factors affecting cultural communication were analyzed. The experimental results show that the proportion of spread under the scale-free network and the small-world network is significantly higher than the random network and the regular grid network, and the cultural spread is more widespread. At the same time, when examining the influence of the network structure of the scale-free network and the small-world network on cultural communication, it is found that the culture can be spread more widely under the scale-free network. The network scale  $N$  of these two networks has an impact on the outcome of the game. In addition, the communication benefits in the communication intensity and the initial distribution of individual opinions are positively correlated with the communication ratio, and the trust threshold has a significant impact on the results of cultural communication within a certain range. The specific error distribution is shown in Figure 8. Under the scale-free network structure, when  $\beta > 0.47$ , there is a positive relationship between the spread ratio and the level of the trust threshold.

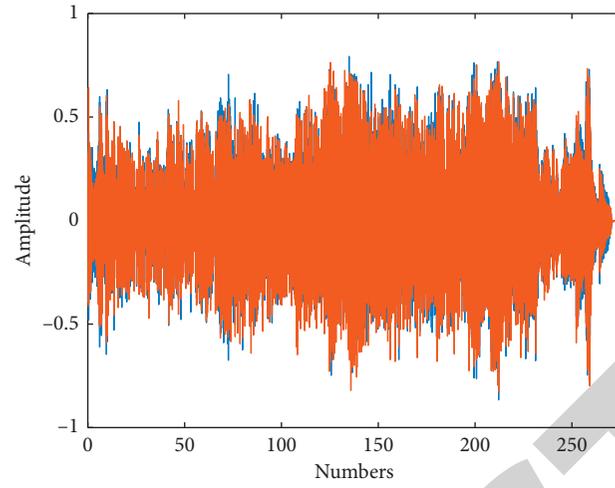


FIGURE 5: Propagation signal response spectrum.

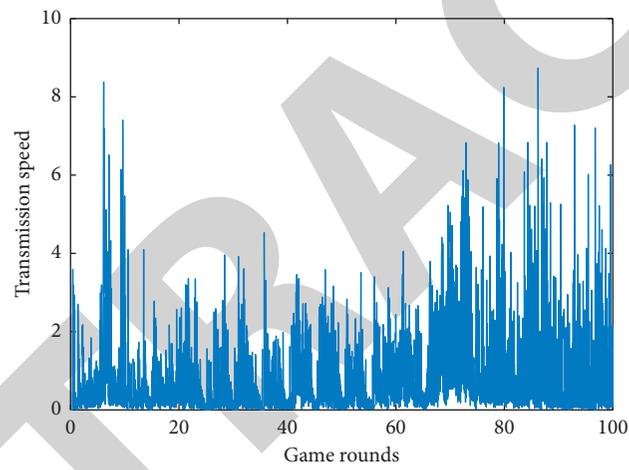


FIGURE 6: Changes in propagation speed with game rounds.

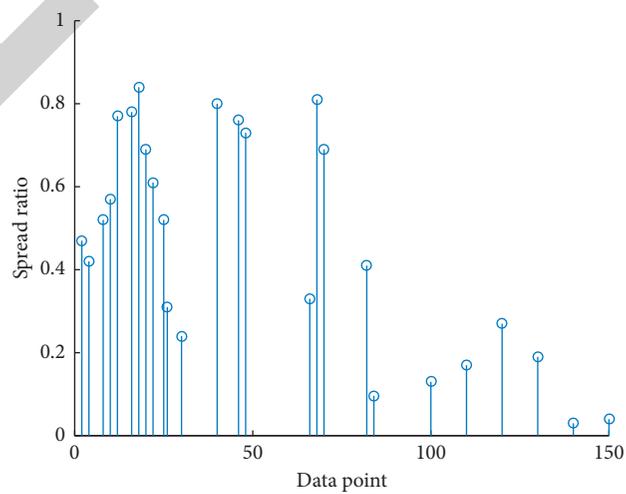


FIGURE 7: Dependence of model data points and propagation ratio.

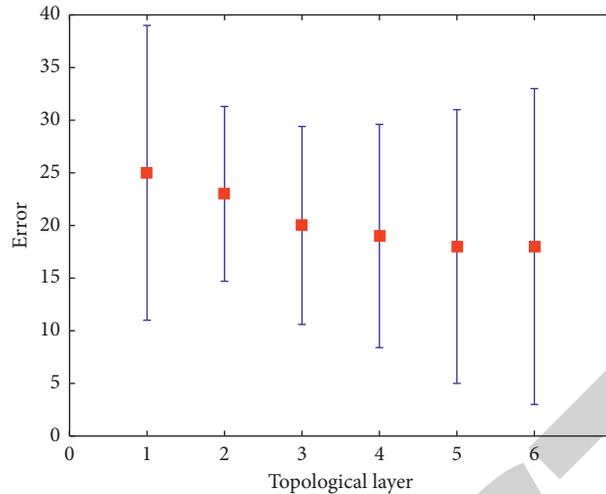


FIGURE 8: The error distribution of the number of layers in the propagation model structure.

## 5. Conclusion

By summarizing the current research progress of complex social networks and cultural communication, this paper first models the interaction behaviors between individuals in social network groups from the perspective of a completely rational game. Under the hypothesis of “complete rationality,” the information dissemination behavior of microindividuals in social networks is examined, the costs and benefits faced by users in cultural dissemination are analyzed, the trust between individuals is added as an important variable to the model, and the completeness is established for information static game model. Based on the analysis of the current situation of complex social network theory and cultural communication research at home and abroad, it can be seen that there are fewer documents for quantitative analysis of cultural communication, especially less quantitative analysis of cultural communication within complex social networks. This paper studies the cultural communication activities of users in social networks based on completely rational and bounded rational games, presents two models of cultural communication under two hypotheses, simulates cultural communication activities in complex networks, and then masters social networks. Based on this, the influence of network structure, communication intensity, social deterrence, and trust threshold factors in complex social networks on the results of cultural communication has been studied using mathematical analysis and computer simulation methods to create harmony for the supervision and guidance of culture. A stable social environment provides theoretical support and then analyzes the pure strategy Nash equilibrium and the mixed strategy Nash equilibrium under the two users, respectively. Finally, an experimental simulation was carried out, and it was found that the important parameters in the two game models, namely, the trust degree between individuals in social relations and the importance of culture, are positively correlated with the proportion of participation in cultural dissemination.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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