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RESEARCH ARTICLE

Agent-based modeling approach for group polarization behavior considering conformity and network relationship strength

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Summary

Currently, group behaviors happen frequently with the development of network technology. As a typical social group behavior, group polarization has been attracted more and more academic attention due to its significant disturbance to public's daily lives. At present, the classic J-A (proposed by Jager and Amblard) and D-W (proposed by Deffuant and Weisbuch) models are used to analyze group polarization process. However, the main shortcomings existing in these models are that the individuals' psychology and their network relationships are rarely considered. In order to overcome the limitations, this article integrates the influence factors such as conformity and network relationship strength integrated into the polarization model. Besides, the BA (proposed by Barabasi and Albert) network model is used as the agent adjacency model due to its closer to the real social network structure. Subsequently, the experimental simulations are carried out with the multi-agent Monte-Carlo method so as to testify the efficiency and effectiveness. The results indicate that different information interaction modes have essential influence on group attitude polarization. Moreover, conformity parameters and the intensity of relationship have dual impacts on both speeding up and slowing down the polarization process.

KEYWORDS

conformity, group polarization, information interaction mode, relationship strength

1 | INTRODUCTION

With the popularization of the Internet and the development of communication, people's activities are changed from face to face to online gradually.[1] Consequently, more and more attentions are paid to the activities of Internet users. Also, the interaction between the Internet and the real world has often led to the fact that the real social event has been fermenting through the great diffusion of the Internet. According to statistics from the historical "society blue book," since 1993 up to 2006 in China, the mass incidents have increased from 8709 to 90 000. However, from 2007 to 2009, the number was over 90 000. Since 2010, it has been increased to over 100 000 every year. Generally, the mass incidents come with some fuse ones such as "Guo Meimei incident," "Yihuang compulsory demolition incident," "Luo Yixiao incident," and "Lei Yang incident," which straightly pointed to the real social problems. Their impact goes from cyberspace to real life and from virtual to reality. The main feature of these events is shown as follows: after a trigger incident was revealed over the Internet, it quickly aroused the attention and discussion of a large number of netizens as well as the public's long-repressed memory of the long-repressed "Hatred of officials, rich and police."

It would promote the development of events and accelerate the spread of events, which will cause widespread concern on all sectors of society. Finally, the government has to intervene, clarify, and handle the incident properly. It is clear that without the Internet, it is impossible for society to show its influence during a very short period and further control the development of the situation. As a result, the mass behavior of the Internet has become a hot topic of social concern, which is related to social stability and harmony. In this article, we study the group polarization behavior, which is a typical phenomenon in mass incidents. It appears in the whole development process of group events. Over the process, the group attitude evolves from the initial dispersed state to the extreme after the event continues to advance, and ultimately from emotional extremes to action extremes. The issue has become one of hot topics in the academic world. Some typical research outcomes are as follows: Margit and Lisbeth[2] used the group polarization theory to discuss the life cycle of network public opinion, and the evolution trend and existence form of group polarization caused by netizens' arguments on sensitive issues. Han[3] named the polarized public attitude and the phenomenon that synchronization makes social events from small to big as “making big.” The public widely believed that they can get greater social attention after “making big,” and then a lot of social concerns would be obtained, which would help solve the problem. Therefore, in the current period of social transformation in China, the “making big” events occurred frequently, covering various fields. At the same time, “making big” had become the most direct way for people to express their requests, meaning that people want to prompt the government to pay attention to the livelihood of the people and then improve social functionalities through the manifestation of social contradictions. In the process of tracking polarization, we find that netizens can get a lot of information about mass events. But such information is usually filtered and screened. Therefore, they will inevitably get access to the websites which hold their same or similar opinions. Meanwhile, these websites will also tend to link to like-minded websites and rarely to those with different opinions. Each netizen is in one or several highly homogeneous groups under the influence of this information. The information acquired by them is the same angle after screening and filtering, which will naturally enhance their own original opinions and lead to extreme.[4] Therefore, it is critical to explore the whole process of social mass events from their initialization to propagation, and eventually to the final polarization, and also to explore the internal mechanism to resolve the events as well. Through the exploration, the mass events can be handled timely and properly during the fermentation period. In addition, the social instability and economic losses caused by these extreme events can be avoided.

So far, the polarization behavior of group events is relatively poorly studied.[5] The existing research mainly starts from the phenomenon. By qualitative analysis, the outline of the reason for polarization phenomenon and the corresponding preventive strategies are proposed. Apparently, current research rarely works on quantitative analysis for the polarization phenomenon with any specific models.[6] They are mainly based on the classic D-W[7,8] and J-A model.[9,10] Subsequent studies follow up and expand these classical ones, but some shortcomings still exist. For example, these classic models are not close enough to the real cases. Moreover, the psychological factors and interaction modes of the participating groups are all issues to be considered.

Based on the current study, this article considers the individuals' psychological factors in the model, and then introduces a very important individual psychological characteristic-conformity psychology.[11] As we all know that the existence of individual conformity can significantly promote the creation of group polarization behaviors. Therefore, the consideration of individual conformity is very necessary in the construction of polarization model. Furthermore, in the interaction modes among individuals presented in this article, each individual will collect information from the surrounding individuals with a one-to-many manner similar to network forum, instead of the traditional random face-to-face interaction. Finally, the pure BA network[12] reveals only the connection between individuals thus lacks the description of the relationship between the intersections. Consequently, it is possible to give a better description of the different closeness of the individual,[13] making the polarization simulation more rational and realistic.

The structure of this article is organized as follows: Section 2 is the literature review, which introduces the limitations of existing research and points out the significance of this article. In Section 3, the improved attitude polarization model is presented based on the J-A model. Simulation analysis is given in Section 4. Section 5 explores the rationality and reliability of the simulation experiment by discussing the parameters in the model. Finally, Section 6 summarizes the article and proposes the future work.

2 | LITERATURE REVIEW

According to the analysis of existing work, this section mainly analyzes the relevant literatures from public opinion propagation, group psychology, and polarization model.

From the perspective of public opinion propagation, Mongeau and Garlick[14] found in a study on group polarization that social comparison information would affect people's perception of persuasive demonstration information. Cho[15] studied the evolution of opinions where people were not sure of their own opinions and/or their opinions might be conflicting to others' in social networks. In addition, some researcher used swarm intelligence methods[16] to study information propagation from viewpoint of network structure. In fact, the typical swarm intelligences include particle swarm optimization,[17] cuckoo algorithm,[18] ant colony optimization,[19] bat algorithm,[20] artificial neural networks,[21] artificial bee colony,[22] and pigeon-inspired optimization algorithm.[23,24] Swarm intelligences have been widely used in many fields, including personalized recommendation,[25] privacy protection,[26] logistics distribution,[27] Internet of Things,[28] product design and development,[29] and so on. For example, Wang et al[30] investigated the characteristic of error distribution between the estimated and real distance in the DVHop algorithm and proposed a Gaussian error correction multiobjective positioning model with nondominated sorting (NSGA-II). The experimental results demonstrated that it was significantly superior to other four algorithms in both positioning precision and robustness. Chen et al[31] explored the network topology of group event propagation and used artificial immune algorithm to get the network structure characteristics of promoting or inhibiting group synchronous behavior propagation. Cai et al[32] presented a hybrid multi-objective cuckoo search under-sampled software defect prediction model based on SVM (HMOCS-US-SVM) and eight datasets from Promise database were selected to verify the proposed software defect predication model. Jiang et al[33] presented a new extended ant colony labor division model for Traffic flow network in order to improve the efficiency of traffic and the simulation result showed that their proposed model was superior to other methods. Cui et al[34] designed a new evolutionary algorithm named oriented cuckoo search (OCS) algorithm and simulation results demonstrated that their modification achieved better precision performance when compared with three other DV-Hop algorithms. Qi et al[35] introduced MinHash, an instance of locality-sensitive hashing (LSH), into service recommendation, and further put forward a novel privacy-preserving and scalable mobile service recommendation approach based on two-stage LSH, named SerRec (two_isH). Finally, the experimental results showed that both the service recommendation accuracy and the scalability had been significantly improved while privacy preservation was guaranteed. Huang et al[36] adopted and improved the D-W model. By studying two kinds of initialization, the article found out people would have distinct opinion after propagation in the context of nonintervention. Furthermore, when intervention was taken into consideration, the result showed the finite influence of changing individuals' opinion by important nodes, suggesting the steadiness of propagation in a certain network. These studies mainly discussed the polarization phenomena of mass incidents from some macroscopic perspectives. Consequently, neither the search for the cause nor the proposal of the strategy has reliable experimental analysis or data support.

In the study of group attitude polarization, two factors need to be described accurately because they are of great significance to the research results. One is the evolution of participating groups' psychological process; the second is the group members' psychological trends for each choice. For example, the sorting of individuals into areas with like-minded neighbors had led to considerable geographic polarization in the United States. Truglia[37] argued that this phenomenon was exacerbated by conformity, defined as the tendency of individuals to be more politically active when surrounded by like-minded neighbors. Through a large number of simulations, Dong et al[38] studied the dynamic influence of network agent on the formation of public opinion, revealing that network agent shortened the steady-state time, reduced the number of public opinion clusters, and made the change of public opinion in the dynamic trend of public opinion tend to be stable. Fersini et al[39] proposed approval network as a novel graph representation to jointly model homophily and constructuralism, which was intended to better represent the contagion on social networks. Asch[40] conducted such research and performed related experiments. He concluded that in the highly ambiguous situation, people showed conformity behavior. Chen et al[41] integrated social preference theory and revenue function into the model of public opinion polarization and analyzed the influences of individuals with different preferences on public opinion polarization. Finally, they obtained several interesting observations through simulation experiments.

To analyze the groups' polarization phenomenon from the perspective of psychology, it is possible to describe individuals' psychological progress accurately over the whole event. However, it is difficult to explore the overall development trend if the study is merely performed from the psychological angle. Moreover, such research does not accurately grasp other factors except the factor of groups' psychology.

From research on polarization model, the classical polarization models mainly include the D-W model proposed by Deffuant et al and the J-A one developed by Jager and Amblard. D-W model considered that when the individual attitudes were relatively close, their attitude would be gradually closer together. Based on the principle, the influence of different attitude threshold on the group attitude polarization was discussed in this model. Its simulations indicated that a high threshold tended to make the attitude uniform and a lower threshold tends to produce a small group of attitudes. Unlike the D-W model, Jager and Amblard designed the J-A one based on the social evaluation theory, and discussed the rule of group's attitude evolution through the simulation calculations. Moreover, Interian and Ribeiro[42] proposed and explored a new quantitative characterization of the polarization phenomenon in networks and new tools for evaluating the polarization of a network were also presented. In addition, Li and Xiao[43] used the adjustable BA network model, which was closer to the real social network structure as the agent adjacency model. Meanwhile, on the basis of the J-A classic model, the individual attitude values were extended from single dimension to multidimensions. However, these typical models are not associated close enough with reality. For example, they treated all individuals as homogeneous individuals, but each individual had different characteristics in reality. Besides, the corresponding affinity among individuals was not presented in these models either. Moreover, their simulation results differed from the reality very much, resulting in low applications. For instance, the values of individual's final attitude were distributed in one or several values, while in practice, even after polarization, the attitude values of a few individuals were scattered.

Through the analysis mentioned above, this article constructs an improved model of group polarization attitude evolution and uses the multiagent Monte Carlo method under the social framework calculation[44-46] to carry out the simulation. Compared with the classic J-A model, this one uses the BA network model as the agent adjacency model and integrates the different relationship strength[47] in the network to depict the relationship between individuals in the network. Furthermore, the conformity parameters are introduced to describe the individual psychological characteristics, making each individual have different characteristics. Subsequently, this article adopts the information interactive mode of network forum instead of the rules of the traditional face-to-face social mode.[48] In this new mode, the individual interacts with all the neighbors and then makes a comprehensive judgment. In doing so, the model proposed here not only describes the physical connection between individuals but also integrates psychological and emotional factors, which is closer to the reality.

3 | MODEL CONSTRUCTION

3.1 | Classical D-W and J-A models

The most classical polarization models are D-W and J-A. The J-A one is improved by D-W model. It not only considers the assimilation effect of social evaluation theory but also considers the repulsion and neutral conditions, which is more appropriate to the reality. The basic model is defined as follows:

- *Assimilation rules*

If the difference of the attitude distance between two selected random nodes a and b is less than d_1, that is,

$$| x_a - y_b | < d_1. \tag{1}$$

Then, the attitude values of the two nodes of a and b are changed accordingly, and the updating formula is shown as follows:

$$\left\{ \begin{array}{l} x'_a = x_a + \mu(x_a + x_b) \\ x'_b = x_b + \mu(x_a + x_b) \end{array} \right\}, \tag{2}$$

where $i = 1, 2, 3, \dots, n$, $\mu \in (0,0.5]$, is the influence parameter.

- *Repulsion rules*

If the difference of the attitude distance between a and b is more than d_2, that is,

$$|x_a - y_b| > d_2. \tag{3}$$

The attitude values of a and b are updated as follows:

$$\begin{cases} x'_a = \xi(x_a - \mu(x_b - x_a)) \\ x'_b = \xi(x_b - \mu(x_a - x_b)) \end{cases}, \tag{4}$$

where $\mu \in (0,0.5]$, ξ is the influence parameter, and it has a definition as follows:

$$\xi(x) = \begin{cases} x & 0 \le x \le 1 \\ 0 & x < 0 \\ 1 & x > 0 \end{cases}. \tag{5}$$

- *Neutral rules*

In other cases, the attitude values of a and b are unchanged.

3.2 | Improved attitude polarization model

In the existing D-W and J-A models, the interaction evolution of attitude values among individuals is expressed merely by distance, meaning as long as the difference between the attitude values of two individuals falls into the threshold of a certain definition, it will be changed accordingly. Obviously, this has a deviation from the actual situation. The mutual influence and change of attitude among individuals involves many factors, such as the overall atmosphere created by the surrounding individuals, the distance between individuals, the conformity of individuals, and so on. Under the circumstance, this article proposes an improved attitude polarization model. The main ideas for improvement are shown in Figure 1: (i) Figure 1A shows the individual interaction of the classic model, which picks up two connected individuals from the network to

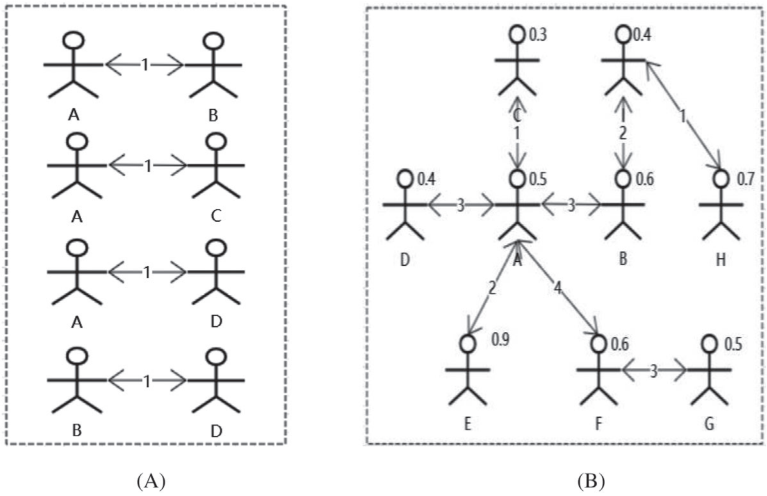


FIGURE 1 Schematic diagram before and after model improvement. (A) The original model (one-to-one interaction). (B) The improved model (one-to-many interactive mode)

TABLE 1 Description of parameters

No.	Name	Description
1	R_i	Represents the threshold value of the individual change attitude value. When R_i is greater than 1, the attitude value changes; otherwise, the attitude value remains the same.
2	z_{ij}	Represents the relationship strength between individual i and j
3	$X_j(t)$	Represents the attitude value of individual j at time t
4	$X^+{}_j(t)$	Represents the attitude value of positive views in $X_j(t)$
5	$X^-{}_j(t)$	Represents the attitude value of negative views in $X_j(t)$
6	α	Represents the adjustment parameter
7	C_i	Represents the conformity parameter of individual i
8	β	Represents the assimilation degree
9	γ	Represents the coefficient of repulsion
10	d_1	Represents the assimilation effect distance
11	d_2	Represents the repulsion effect distance
12	$\dot{x}_i(t)$	Represents the comprehensive average attitude of individuals around individual i at time t

interact with each other randomly. Figure 1B shows an interactive mode in the improved model, where each individual in the network needs to combine the attitude of all the individuals around it, meaning that single individual collect the tries to collect the attitude of all the individual connected to it in order to make judgment according to the general attitude trend. (ii) The intensity index to describe the different relationship between individuals in the real world is incorporated. Apparently, when individuals make decisions, ones who have the greatest impacts on the others are those who are close to each other, that is, stronger relationships generate greater influence. In Figure 1A, the intensity index of relationships between all individuals is 1, meaning the relationships between all individuals are the same. While in the improved model, the relationship strength between pair of individuals is assigned by a random function, which is used to reflect the difference in the relationship between individuals. (iii) The individual conformity parameter to determine whether one changes its attitude value is introduced. In the improved model, each participant has a different conformity parameter, which is combined with the attitude values of the surrounding individuals to determine whether to adjust its own attitude value. When the condition reaches the threshold, the participant will synthesize all others' attitudes to obtain the final average value. It further multiples the conformity coefficient and the coefficient of acceptance capacity as the variance of the individual's attitude value.

The parameters involved in the model are defined in Table 1.

Through the above analysis, the specific building process of the model is as follows:

1. Randomly select an individual and then evaluate the overall information of all the ones around it, and decide if the attitude needs to be changed or not. First of all, we need to judge the trend of the comprehensive attitude of all the individuals connected to the selected individuals. After that, the threshold value of the individual is expressed as:

$$R=\begin{cases} c_i+\alpha\dfrac{\left|\sum_{j=1}^{n} z_{ij}X_j^{+}(t)\right|}{\left|\sum_{j=1}^{n} z_{ij}X_j(t)\right|} & \sum_{j=1}^{n} z_{ij}X_j(t)>0 \\ c_i+\alpha\dfrac{\left|\sum_{j=1}^{n} z_{ij}X_j^{-}(t)\right|}{\left|\sum_{j=1}^{n} z_{ij}X_j(t)\right|} & \sum_{j=1}^{n} z_{ij}X_j(t)<0 \end{cases}. \tag{6}$$

In this model, the relationship strength z_{ij} is divided into four levels, ascending from 1 to 4, which is assigned with a certain level according to a random function. $X_j(t)$ represents the attitude value of individual j at time t, $X^{+}{}_j(t)$ represents the attitude value with positive views in $X_j(t)$, $X^{-}{}_j(t)$ represents the one with negative views in $X_j(t)$, and α represents an adjustment parameter in order to control the tendency of polarization to occur. The value of R_i determines whether the individual's altitude makes a change. If $R_i > 1$, then proceed to the next step, otherwise no operation will be performed. In other words, whether an individual changes his/her original attitude depends on his/her conformity and the influence of people around him/her. Usually, there exist three main situations: the first one is that the individual's conformity is extremely strong, which is completely influenced by the surrounding environment. If any side takes the initiative, the individual will be inclined to the strong side, and then it will always follow the environment to adjust his attitude; the second one is that the surrounding environment of an individual is not balanced. Most individuals who are connected with others have reached the same view and the view of one party has dominated. At that point, the individual will turn to a strong side; the last one is that, the individual combines its own conformity with environmental factors, and then makes itself movement towards one side.

When $R_i > 1$, the evolution rule of the individual is:

- *Assimilation rules*

When the difference between the altitudes held by an individual and comprehensive average attitude of the surrounding individuals is less than d_1, the attitude of individual i is updated:

$$x_i(t+1)=X_i(t)+\beta[\dot{x_i}(t)-X_i(t)],\ |\dot{x_i}(t)-X_i(t)|<d_1, \tag{7}$$

where $x_i(t)$ is shown in formula (8), and β represents the assimilation degree of attitude change, ranging from 0 to 1.

$$\dot{x_i}(t)=\frac{\sum_{j=1}^{n} z_{ij}X_j(t)}{\sum_{j=1}^{n} z_{ij}}. \tag{8}$$

- *Repulsion rules*

When an individual's opinion is larger than comprehensive average one of the surrounding individuals, the attitude of individual i is updated as:

$$x_i(t+1)=X_i(t)+\gamma[\dot{x_i}(t)-X_i(t)],\ |\dot{x_i}(t)-X_i(t)|>d_2. \tag{9}$$

- *Neutral rules*

In other cases, the individual i does not change its attitude value.

When $R_i < 1$, the individual does not make any changes.

Note that, in this model, the information interaction among individuals is a one-to-many mode. In such a mode, the information collection is relatively more comprehensive. Hence, the difference between the individual and the overall environment is smaller than that one-to-one mode. Therefore, the values of d_1, d_2 are different. The flow chart of group attitude polarization is shown in Figure 2.

4 | EXPERIMENTAL SIMULATION

This article studies the whole evolution process by setting different parameter values. First, the BA network can better describe the real social network, so it is selected as the evolution network. Subsequently, many different parameters values are considered and ones that can obtain the better polarization effect are selected. Related parameters are set as follows: network node size is set as 100 with $d_1 = 0.3$, $d_2 = 0.7$, $\beta = 0.1$, and $\gamma = 0.2$. After 400 interactions, the attitude tends to polarize according to the surrounding environment, where some individuals still maintain their original attitude, some become polarization, and others adjust their attitude to adapt to the surrounding environment so as to achieve balance. The evolution result of individual attitude value with interaction time is shown in Figure 3.

The horizontal and vertical axes represent the number of interactions and individual attitude values, respectively. According to the simulation results, after the intense interaction, the individuals gradually develop the polarization trend, and the attitude values begin to shift towards the two

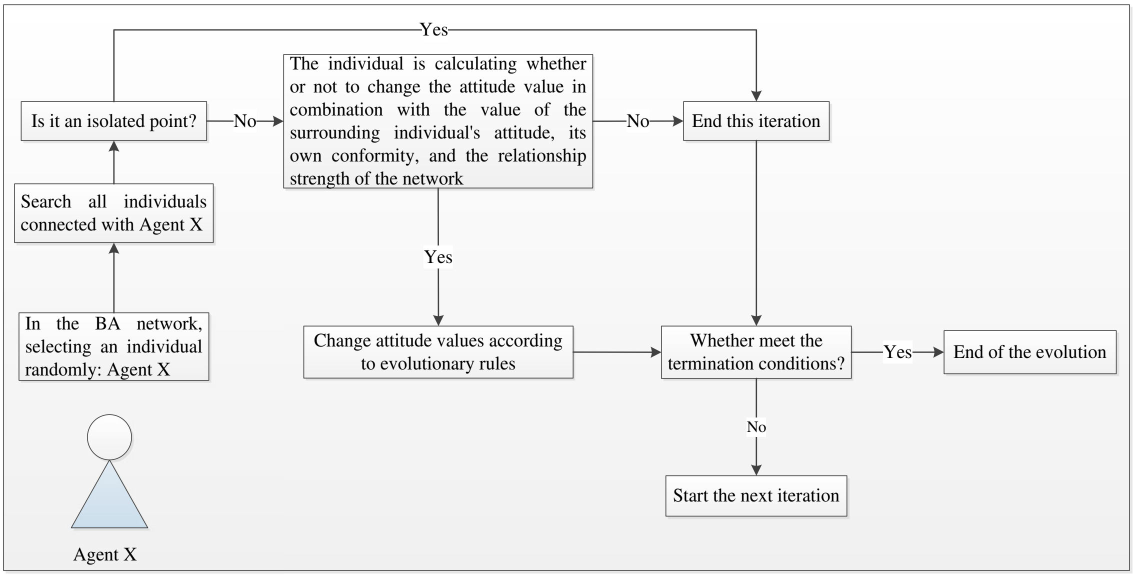


FIGURE 2 The flow chart of group attitude polarization

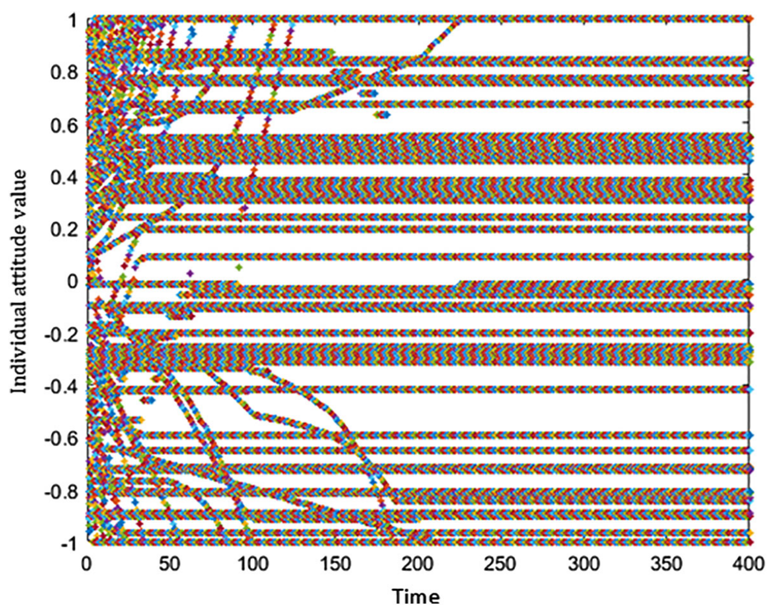


FIGURE 3 Individual attitudes' evolution with the number of interactions (the BA network)

extreme directions 1 and – 1. At the same time, there are a few individuals who are not affected by the influences of the surrounding individuals and insist on their own views, which are scattered between −1 and 1 on behalf of the individual attitude values. However, the overlapped part of the evolution process of individual attitude value cannot be presented in Figure 3 directly. Therefore, we give Figure 4 to show the distribution of individuals' attitude values under different interaction times.

When initial state time is 0, the individual attitude distribution is shown in Figure 4A. In this figure, the horizontal and vertical axes represent the individual's attitude value and the number of individuals, respectively. The simulation results show that the individual's attitude values are more diffuse and the distribution is not relatively uniform in the initial stage. It shows that the group contains various views for the event, meaning there is no clear consensus or more unified consensus. Each individual judges and gives an attitude value for the judgment of the event purely by itself. So at an early stage, the group's attitude towards an event does not produce a significant polarization phenomenon. With the increase of interactions, when time is equal to 50 100 and 400, respectively, the distribution of individuals' attitude values starts differentiation gradually. The specific experimental results are shown in Figure 4B-D. The number of individuals in the middle is less, while ones with values close to 1 and −1 are under constant accumulation, showing significant polarization. With the increment of interactions, it is easy to see that the attitude distribution presented in Figure 4D has been stable, among which a few individuals still

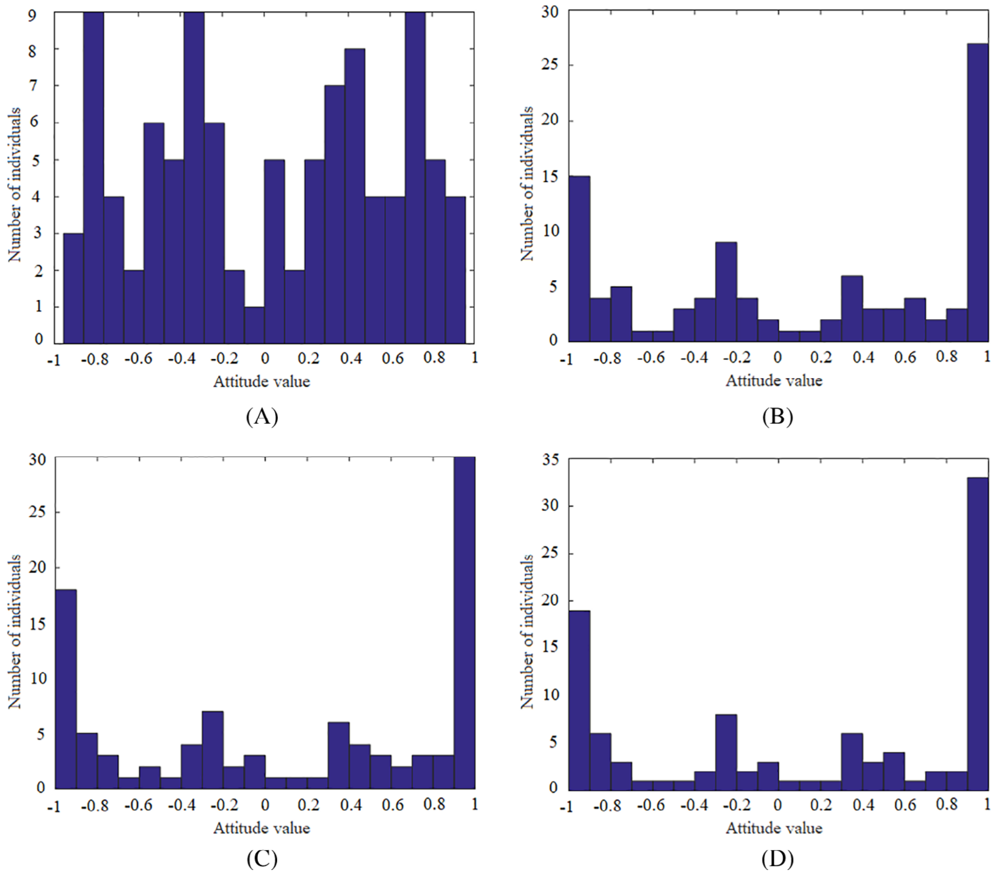


FIGURE 4 Individual attitude distributions under different interaction times. (A) Time = 0. (B) Time = 50. (C) Time = 100. (D) Time = 400

maintain their initial attitude values all along. This phenomenon lies in two reasons: (i) the conformity of the individual is very low so that it has not reached the threshold value of $R > 1$ set by the model yet. Therefore, it has never been affected by the attitude value of peripheral individuals. Rather, it even maintains its attitude value to the initial event. (ii) The positive and negative sides draw a tie, making it difficult for the individual to decide which side should be trusted. Therefore, the individual may remain neutral instead of changing its attitude value.

In the actual scene, after an event is moving toward polarization, there are always some individuals who will maintain their own opinions and show their attitude by the definition of the event through their own judgment. Similarly, there will also be individuals who are unable to infer the truth behind the events and have to stay on the sidelines. In addition, just as experiment results show, most of them will be driven by psychological effect, thus choosing a polarization direction, which illustrates that most individuals show that they are not willing to be isolated when facing group events, but choose to integrate into a more powerful side and seek safety instead.

Except for the above analysis process, another classic social network named small world network is also used to explore the group polarization. The experimental results are shown in Figures 5 and 6. They demonstrate that the polarization effect is obvious. Meanwhile, the neutral individuals and the ones holding the initial attitudes are all relatively uniform, which reflects the scientific nature and applicability of the proposed polarization model.

The results of the simulation experiment are summarized as follows: (i) in Figure 6, there are a few individuals who always maintain the original attitude values during the whole polarization process. This is because these ones have less conformity, which can be understood as a few stubborn or extreme rational people in the reality, who are not affected by the surrounding individuals, and always maintain a consistent attitude and do not any changes. (ii) Some individuals change from original positive attitudes to final negative ones. On the other side, others change from negative attitudes to positive ones. The reason is as follows: the individuals are convinced by other group members after interactions and then give up their own standpoints. In reality, mass incidents often involve more rumors, and individuals in the public opinion field often change their standpoints due to the changes of event news. (iii) The attitudes of very few individuals gradually tend to one side after a certain fluctuation. The internal reason is that the positive side and negative one are in equal strength. After many sharp collisions of opposite opinions, one party wins in fierce interactions.

Note that due to different group polarization degrees under the above two network structures, this article compares these two group polarization effects through a large number of simulation experiments. The results show that the influences of different network structures on the polarization process have no significant regularity. Also, the different networks created by the same nodes and edges have different polarization process. Therefore, next, analysis and discussion will be focused on the factors that influence the group polarization process.

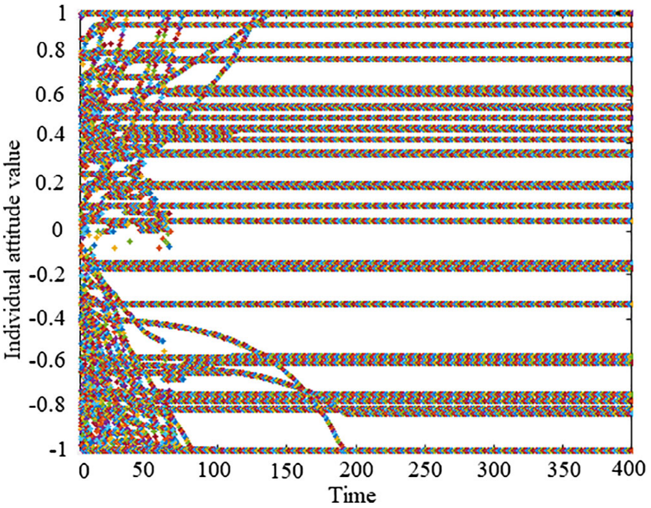


FIGURE 5 Individual attitudes' evolution with the number of interactions (the small world network)

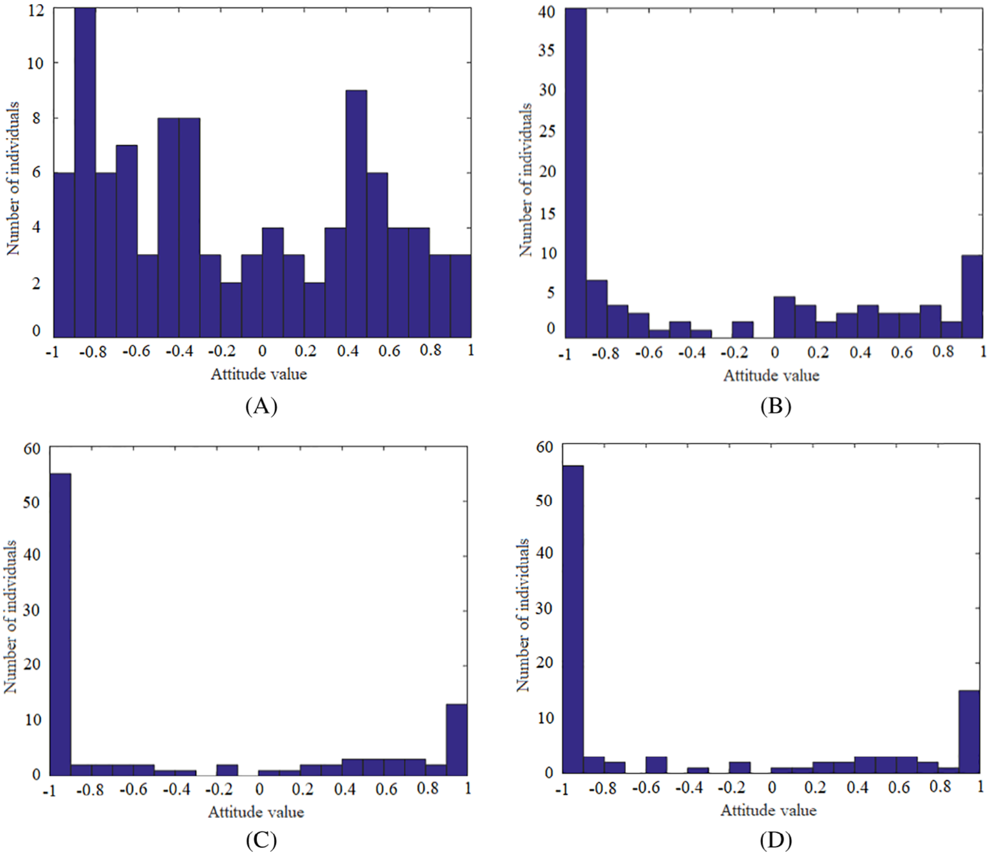


FIGURE 6 Histogram of individual attitude distribution under different interaction times. (A) Time = 0. (B) Time = 50. (C) Time = 100. (D) Time = 400

5 | ANALYSIS AND DISCUSSION OF SIMULATION RESULTS

Based on the results of the experimental simulation, this article analyzes the impact of interaction modes, the conformity, and the relationship intensity on the group polarization process.

5.1 | The influence of information interaction on polarization process

In this section, we mainly compare the effect of pairwise random interaction mode and the one-to-many interaction one on polarization. Pairwise random interaction is suitable for the traditional face-to-face social modes (ie, point-to-point interactive mode), while one-to-many one is more appropriate for similar network forum, community interaction modes, and so on. With the development of the network, we are no longer limited to the interaction with a certain individual at a specific moment in facing and receiving information. Instead, each individual can observe the attitudes of a large number of other ones at the same time. Therefore, the change in its attitude can be considered to be influenced by multiple neighboring individuals simultaneously. A one-to-many interactive mode enables individuals to obtain information of multiple nodes at the same time so as to make more accurate judgments based on the acquired information. As a result, the experimental simulation results are more stable and more appropriate to the actual situation. In the viewpoint of the pairwise interactive mode, each interaction is randomly combined. The simulation result is fluctuating, and it is actually deviating from reality. After that, the polarization phenomena of different interaction models are compared by experiments, in which the proportion of polarization individuals is recorded via pairwise random interactive mode and one-to-many interactive one, respectively. The average value of the calculated results is calculated in the following 10 times, as shown in Figure 7.

In the pairwise random interaction mode, the group attitude polarization changes with the distance parameter d_1 and d_2, but the aggregation of the final individual attitude values are mainly divided into three situations: (i) Figure 7A shows the absolute polarization phenomenon, that is, all individuals' attitudes present two extreme distribution states. The reason for the complete polarization is that the range of the assimilation distance in the model is too small, and the one of repulsion distance is too large. In the individual interaction process, the effect of the repulsive action is obviously greater than that of the assimilation action. Its corresponding realistic scenario is that the individual differences are very easy to result in contradictions because individuals with different opinions are not tolerant to each other, which is extremely to lead to polarization phenomenon. (ii) Figure 7B,D shows the coexistence and neutralization of extreme and neutral states. From the viewpoint of the parameters, the assimilation and the repulsion ranges are essentially constant. The two forces are mutually tied so that some individuals tend to be extreme states and some remain their neutralization. (iii) Figure 7C shows a completely neutral, or nonpolarization state, and the assimilation range is greater than repulsion range. In this scenario, individuals are more conservative. They are not easy to collide with others' viewpoints but tend to integrate with interactive individual views. Therefore, when individuals are willing to adjust their views to each other, seeking common ground while putting aside differences, the polarization phenomenon rarely takes place.

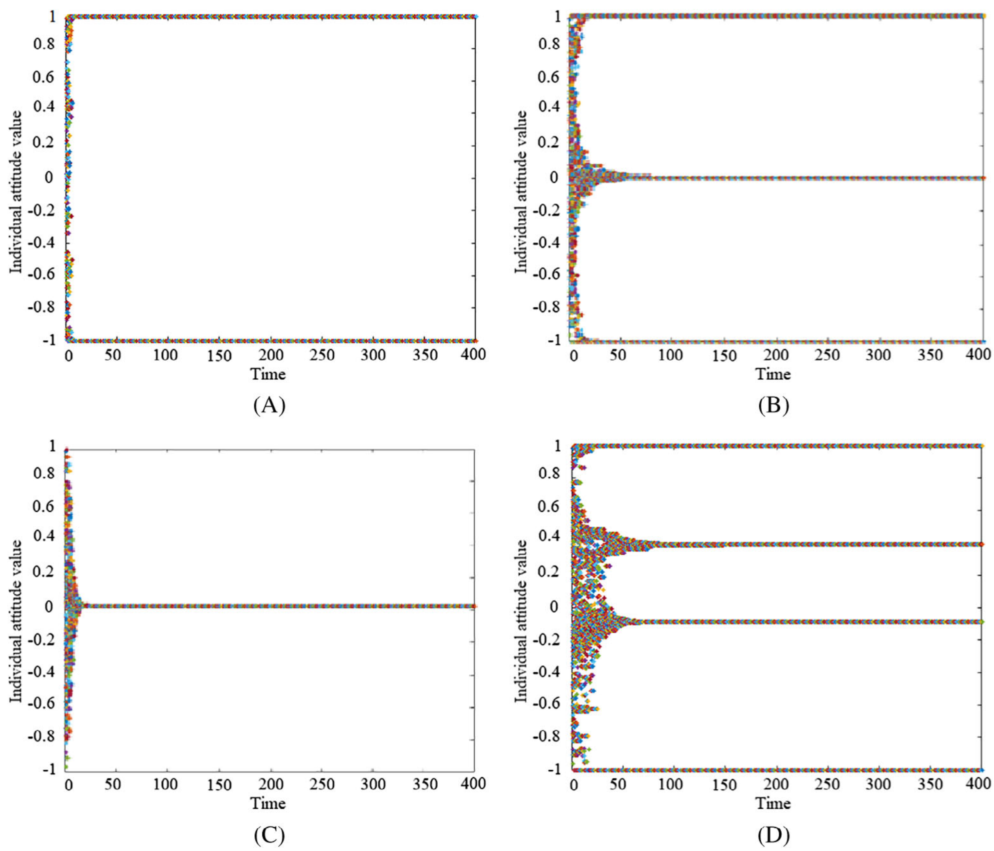


FIGURE 7 Individual attitude evolutions with pairwise random interactions under different distance parameters. (A) $d_1 = 0.4, d_2 = 0.8$. (B) $d_1 = 0.6, d_2 = 1.2$. (C) $d_1 = 0.9, d_2 = 1.5$. (D) $d_1 = 0.3, d_2 = 1.5$

In the one-to-many interactive mode, we set up four sets of attitude distance parameters d_1 and d_2, and obtain four different evolution results in Figure 8, which are corresponding to the attitude distributions of different evolution moments in Figures 9-12. These evolution results are similar to the results generated from the pairwise random interactive mode. The one-to-many interactive mode determines that the difference in the average attitude value between the individual and the surrounding ones overall environment will obviously be less than that in the attitude values in one-to-one interaction mode. Therefore, the values of d_1, d_2 in the one-to-many interactive mode are different from those of the pairwise random interaction mode. For example, (i) in Figures 8A and 9 ($d_1 = 0.3$, $d_2 = 0.7$), the final attitude value evolution results show that there exist extreme attitudes and other different attitudes at the same time, which means some individuals are in an attitude polarization state. (ii) In Figures 8B and 10 ($d_1 = 0.3$, $d_2 = 1.3$), the attitude values between the final evolution result and initial stage are little different. It indicates that the group is in an equilibrium state, and both assimilation and repulsion effects are relatively weak. Combined with the actual scene, it can be understood as: people have their own understandings of the events that occur, or they have less attention to the events. (iii) In Figures 8C and 11 ($d_1 = 0.6$, $d_2 = 1.3$), the assimilation effect is extremely strong, resulting in the vast majority of individuals obeying the views of the general environment and maintaining neutral opinions. In Figures 8D and 12 ($d_1 = 0.2$, $d_2 = 0.4$), the final result is a fully polarized state. Since the range of the repulsion distance parameter far exceeds the range of assimilation, the individual is very prone to fight against the individual who conflicts with the viewpoint, and to polarize his own opinion extremely.

The common features of two above experiment simulations from the two different information interactions are: with the adjustment change of d_1 and d_2, the overall trend of the evolution results are the same. The difference is that the latter is closer to reality. When considering that a group of people come up with the opinions on an event, and their attitudes and opinions are supported with each other at the same time, there must be the individuals who propose their own opinions. Due to the uniqueness of each individual, there must be a scattered view of each dimension of attitude value. Based on simulation results of the pairwise random interactive mode, after all individuals interact with each other in several attitude dimensions, they keep the same attitudes and lack of decentralized views. As a consequence, the model and information interactive mode proposed in this article better match reality. At the same time, according to the experimental results, it is not difficult to find that compared with face-to-face social mode, the information exchange modes such as online forums help reduce the occurrence of polarization. Under the same conditions, point-to-point interactions are more prone to the generation of extreme attitude, while in the one-to-many interactive mode with more comprehensive information, the individuals are relatively rational in the choice of attitudes.

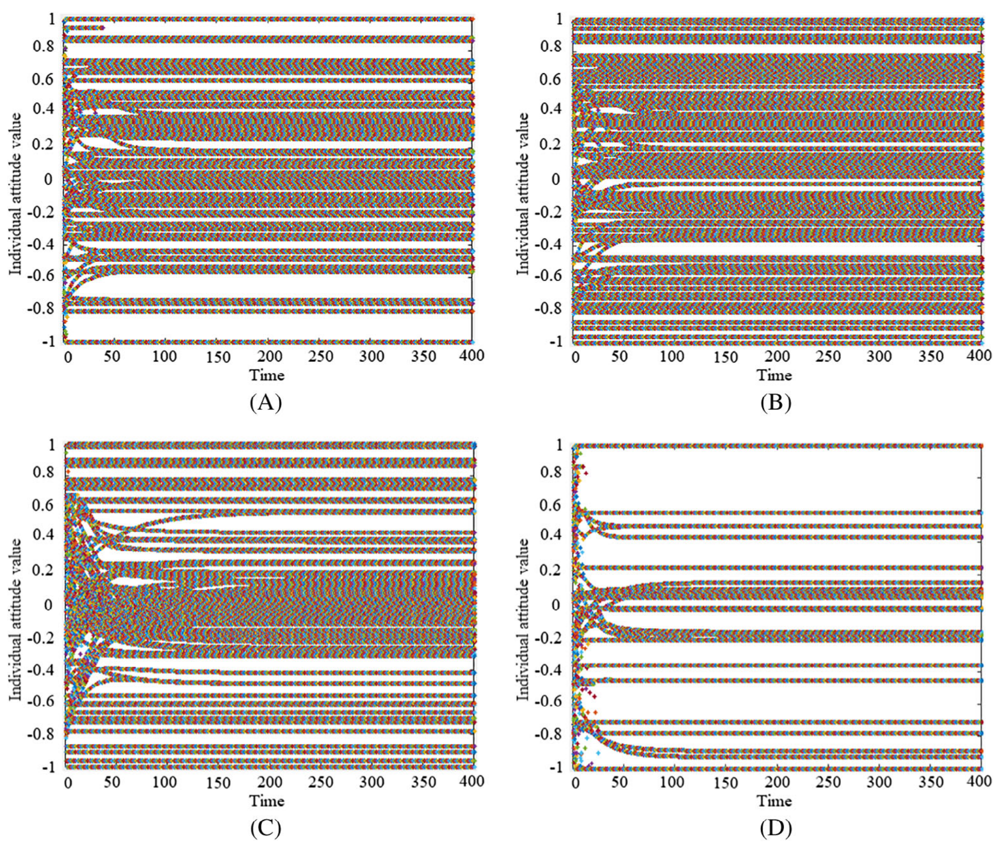


FIGURE 8 Individual attitude evolutions with one-to-many interactions under different distance parameters. (A) $d_1 = 0.3, d_2 = 0.7$. (B) $d_1 = 0.3$, $d_2 = 1.3$. (C) $d_1 = 0.6, d_2 = 1.3$. (D) $d_1 = 0.2, d_2 = 0.4$

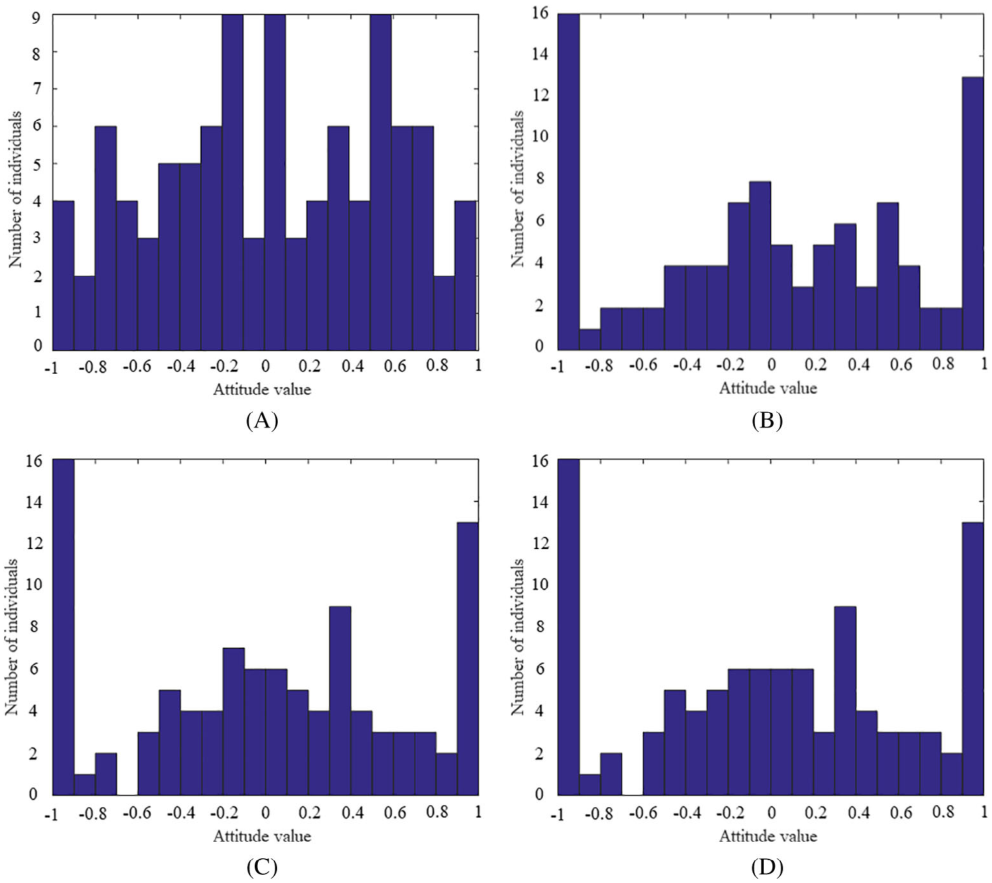


FIGURE 9 Individual attitude distributions under different interaction times (corresponding to Figure 8A) (A) Time = 0. (B) Time = 50. (C) Time = 100. (D) Time = 400

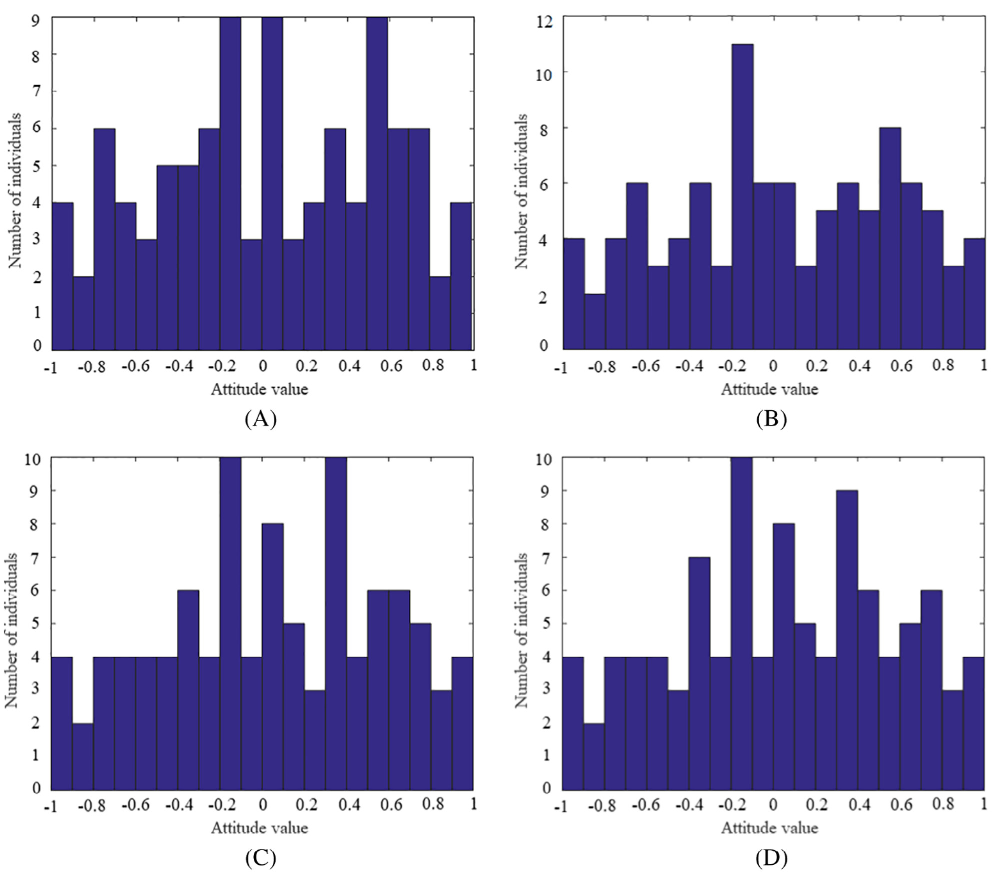


FIGURE 10 Individual attitude distributions under different interaction times (corresponding to Figure 8B). (A) Time = 0. (B) Time = 50. (C) Time = 100. (D) Time = 400

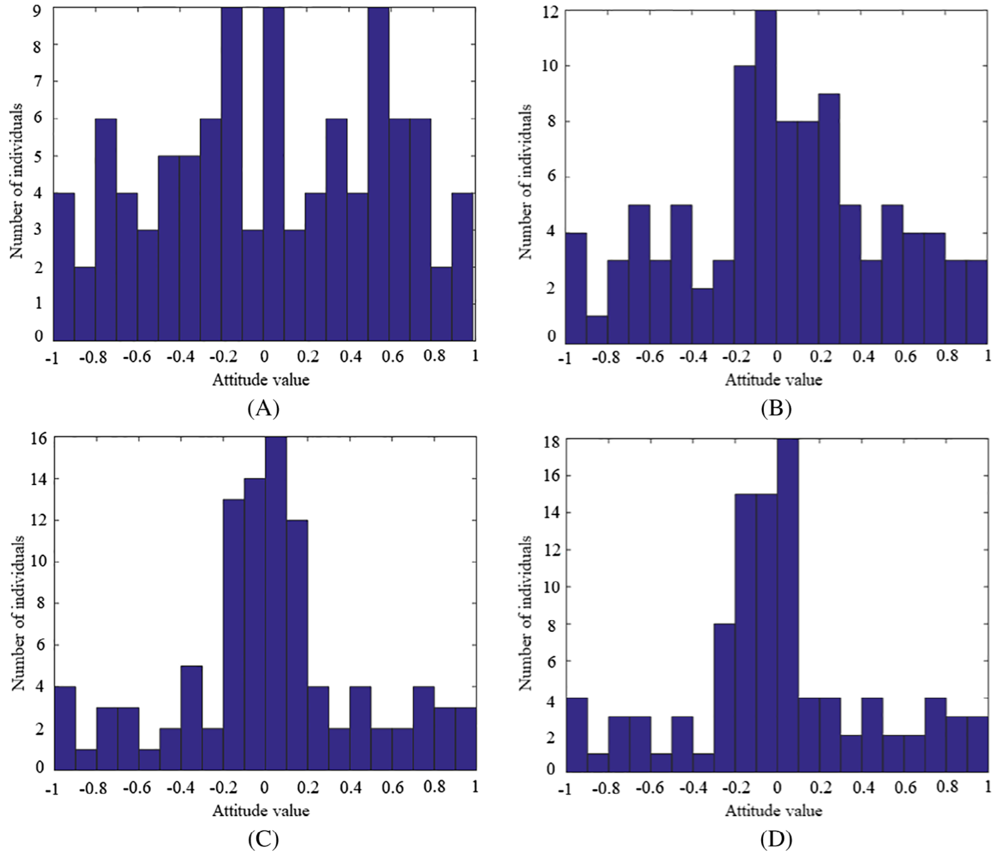


FIGURE 11 Individual attitude distributions under different interaction times (corresponding to Figure 8C). (A) Time = 0. (B) Time = 50. (C) Time = 100. (D) Time = 400

5.2 | The influence of conformity on attitude polarization process

In research on group polarization behavior, the conformity is one of the important influencing factors, which is of great significance to the generation and development of polarization behaviors. Every person has a certain degree of herd mentality, which, in turn, is transformed into conformity behavior. The size of an individual's conformity tendencies depends on individual's inherent personality and his (her) awareness of an event.

The simulation experiment is based on BA network and compares group polarization processes under different conformity parameters to visually demonstrate the effects of individual conformity. Considered the randomness of the experimental individuals' selection, group conformity obeys the normal distribution and it is more scientific. Meanwhile, the conformities of different groups are different. The group with higher educational background has relatively lower conformity, and the middle-aged group with lower education levels has relatively higher conformity. Therefore, four different parameter values are selected. The conformity parameters obey the normal distributions of 0~1.3, 0~1.1, 0~1, and 0~0.9, respectively, to represent different conformity groups. In the experiment simulations, we find that, under different assimilation and repulsion effects with parameters d_1 and d_2, the conformity parameters have different influences on the polarization process. When the overall environment is conductive to the occurrence of polarization phenomena, the conformity parameter takes as a catalyst to promote the polarization. When the overall environment tends to be conservative and neutral, the conformity parameter can inhibit the occurrence of polarization. As a result, we set $d_1 = 0.3$, $d_2 = 0.5$ and $d_1 = 0.45$, $d_2 = 1.0$, respectively, to observe the effects of conformity parameters on the attitude of polarization process. The simulation results are shown in Figures 13 and 14.

The 4-fold lines in Figures 13 and 14 represent the evolution process of attitude polarization under different conformity parameters, where the horizontal and vertical axes represent interaction times and the ratio of individuals with extreme attitudes to total ones. In this experiment, we measure the group polarization degree in terms of the ratio of the extreme individuals to the whole, and then we also evaluate the speed of group polarization in terms of time-to-stability. As shown in Figure 13, when the group overall tendency of polarization is higher (ie, the assimilation effect is smaller and the repulsion effect is larger), the group polarization degree is positively correlated with the group's conformity size. In a certain range, the group polarization ratio increases with the increase of the group's overall conformity. According to the overall trend of the 4-fold lines, in the early interactions, the change of groups' attitude and the speed towards the extreme evolution are basically the same, and the group with lower conformity is the first to achieve a stable polarization state after a period of time. Therefore, the polarization speed is negatively correlated with the group conformity as a whole. From the perspective of the model, the larger the conformity parameter is, the probability that the attitude is affected by the surrounding individuals is greater. Also, the more the interaction will be required to achieve the polarization stable state, the higher the final polarization degree will be and the slower the polarization will be arrived. From a psychological point of view, in a group with high

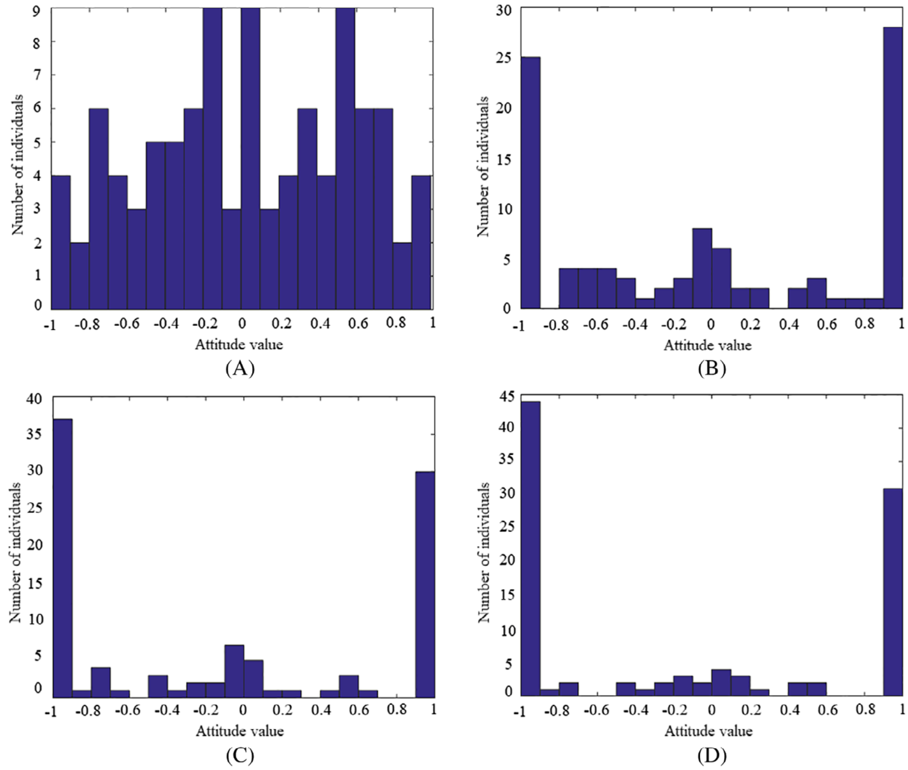


FIGURE 12 Individual attitude distributions under different interaction times (corresponding to Figure 8D). (A) Time = 0. (B) Time = 50. (C) Time = 100. (D) Time = 400

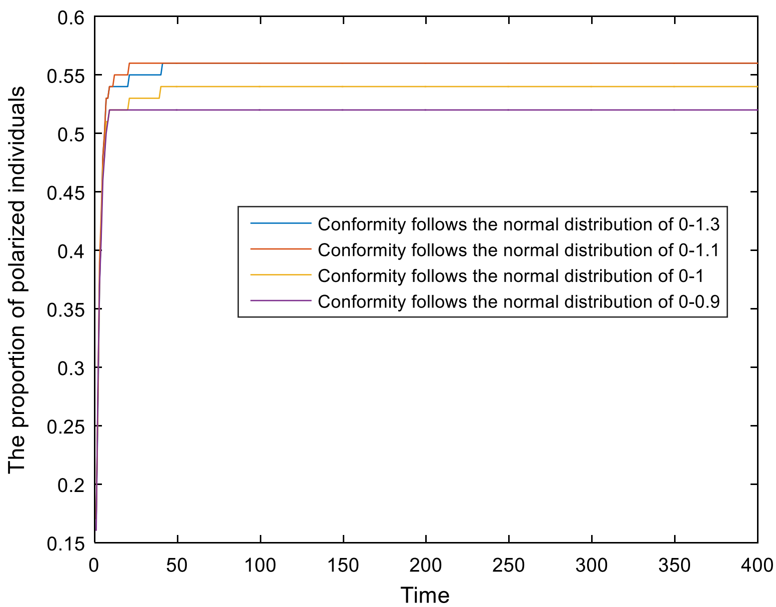


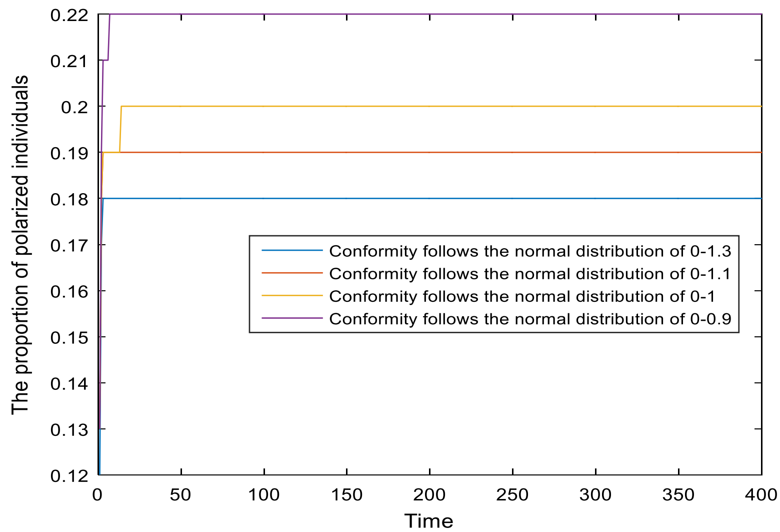
FIGURE 13 Conformity parameters promote polarization process

conformity, individuals are very vulnerable to the influence of the external environment. Obviously, as interactions increase, there appear more and more extreme individuals. Psychology plays a role in forming a higher group polarization degree. Meanwhile, in the process of polarization formation, the individual perspectives are prone to repeat, so the groups with higher conformity need more interactions to reach stable state.

In addition, as shown in Figure 14, when the group polarization tendency is low (ie, the assimilation effect is larger and the repulsion effect is smaller), the group polarization degree is negatively correlated with the group's conformity. Within a certain range, the group polarization ratio decreases with the increase of the group's overall conformity. When the whole group tends to seek common ground while reserving differences, individuals will tend to learn from a wide range of perspectives that can coexist, with small-scale repulsion of opposing views. In addition, the overall view of the group is prone to the neutral. Therefore, the group with higher conformity will become less polarized.

Let us recall the event of “salt robbing” in 2011 in China. It is a typical mass event, which includes synchronization and polarization behaviors. When analyzing the crowd and psychology of panic-salt-buying, we find that the main group of the panic-salt-buying is more than 40 years old

FIGURE 14 Conformity parameters inhibit polarization process



women. The main motivation of their actions is that they are worried about the shortage of salt due to seawater pollution after the nuclear radiation. These individuals are limited to the deficiencies of social cognition and lack of information channels. Hence, they become the main group for panic-salt-buying-and-hoarding. Second, the main reason for their unquestioning salt-panic-buying is that all the surrounding ones are snatching salt. Take the salt-panic-buying group as an example, the event has a strong polarization tendency, and the group has a very high conformity character. In the process of salt-panic-buying, it is greatly influenced by the surrounding individuals and the environment, so people blindly join in the salt-panic-buying behavior. The polarization degree is high. Simultaneously, it has lasted for a long time until the government clarified to clear up the crisis.

5.3 | The influence of relationship intensity distribution on polarization process

In the research of social network, the relationship exists in the network as a crucial factor. Individuals rely on affection, friendship, love, and other emotions to maintain. The connections between individuals are closely related and often measured by the depth of the emotion between two ones. In the social network model, it represents the relationship strength between two connecting nodes. In the case of the panic-salt-buying incident in 2011, statistically, more than 60% of people who purchased salt have joined the group through the spread of friends and relatives around them. That is, when the individual changes his perception or judgment for a certain event, he or she often has a strong dependence on the individuals around him (her) with strong relationships and also has a strong trust degree for them.

Compared with the network model of different relationship intensity distribution, the network structure with the weight (ie, the relationship strength) of 1 cannot reflect the interpersonal factors in the decision-making of real individuals. After introduced different weights (ie, incorporating different intensity distributions of relationships), the change in attitude value will be greatly influenced by the intimate individuals while ignoring the ones with smaller intimacies. This will greatly affect the polarization process. Therefore, this section explores the influences of the distributions of different relationship intensities on the polarization process. Here, the relationship strength is divided into four levels, quantified as integers of 1-4, that is, the network weights are assigned to the number from 1 to 4 and compared with the group with the network weight value of 1. We set the assimilation and repulsion effect parameters $d_1 = 0.3$, $d_2 = 0.5$ and $d_1 = 0.4$, $d_2 = 1.1$, respectively, and take the number of nodes $n = 100$, and then perform time = 400 iterations on different weighted network. We record the proportion of the polarized individuals and take the average of the 10 calculations. The obtained curves are shown in Figure 15.

In Figure 15, we see that in the case of relatively small assimilation effect range and larger repulsion effect range, the introductions of different relationship intensities significantly increase the group polarization degree, and the extreme individuals' proportion increases significantly. It indicates that the attitude values of the surrounding intimate individuals directly affect the ultimate polarization degree of the whole group. Obviously, the role of the relationship strength is to strengthen the influence of intimate individuals and to weaken that of non-intimate ones. Under the circumstances of encouraging differentiation as well as inhibiting view assimilation, relationship strength is easy to strengthen the polarization degree. Correspondingly, if the assimilation effect is large and the repulsion effect is small, introducing the relationship strength will have the opposite effect on the polarization result. The experimental results are shown in Figure 16.

Figure 16 shows that when the parameters $d_1 = 0.4$ and $d_2 = 1.1$, after introducing the intensity distributions of different relationships, the polarization phenomenon is weakened, the proportion of polarized individuals goes down as well. The reason is that the individuals in the group generally have less extreme views on the event. When two opinions are inconsistent, there are more individuals who choose mutual assimilation strategies

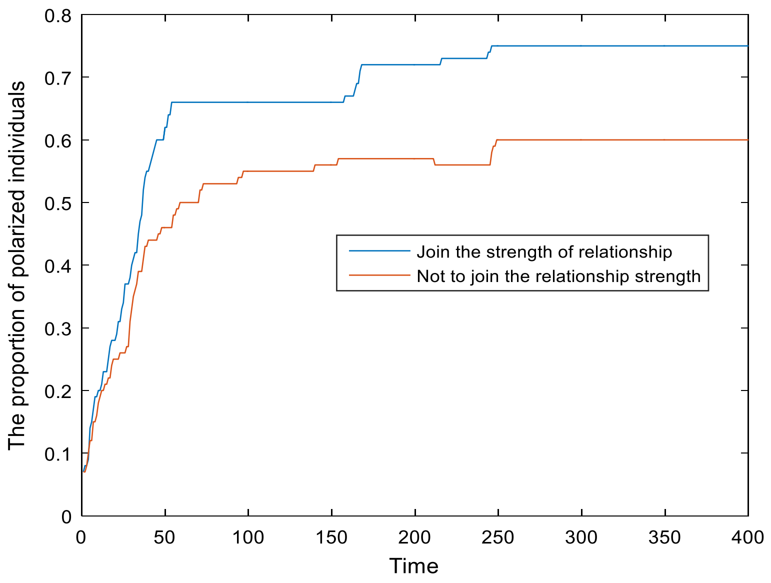


FIGURE 15 Comparison of polarization processes before and after introducing relationship strength ($d_1 = 0.3, d_2 = 0.5$)

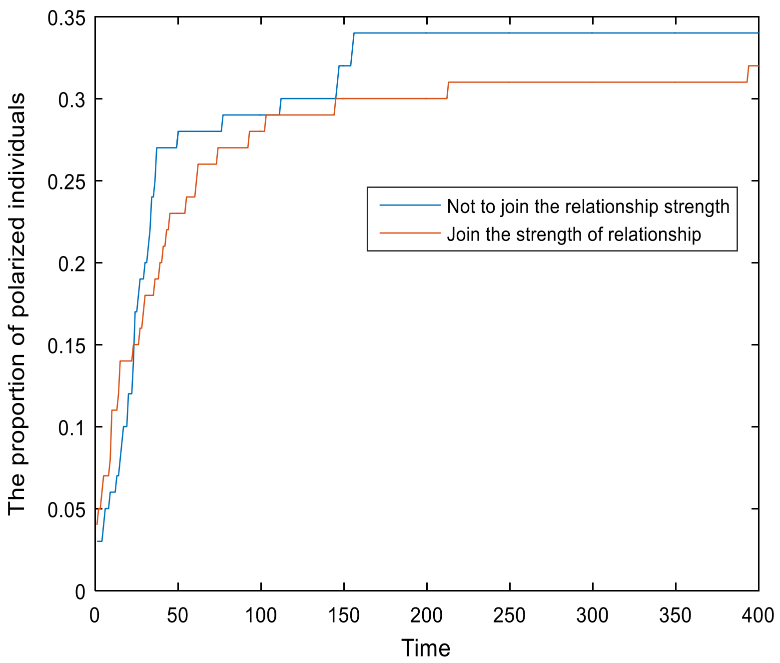


FIGURE 16 Comparison of polarization processes before and after introducing relationship strength ($d_1 = 0.4, d_2 = 1.1$)

than mutual repulsion individuals. Therefore, the overall polarization ratio is low. Furthermore, the conservative viewpoints of the surrounding close individuals (the connected individuals with strong relationship strength) will also influence individual's decision-making more strongly and make it tend to the nonextreme direction.

As a result, the relationship strength of the polarization model describes the influence of the intimacy-alienation relations among individuals on the polarization process after the occurrence of the mass incidents in a real society.

6 | CONCLUSION

In view of the polarization phenomenon in mass events, the evolution process simulation of group attitudes is implemented through improved polarization model and multiagent Monte Carlo method. Meanwhile, the main factors that influence polarization process are also discussed. The main work in this article is as follows.

(1) A multifactorial polarization model was established based on classic J-A polarization model. By introducing individual psychological factors, changing the relationship intensity among individuals as well as the information interactive mode, the proposed polarization model was closer to the reality, and its evolution effect was also superior to the traditional ones.

(2) The evolution process of group attitude polarization was studied under different information interaction modes. The experimental results showed that the one-to-many interaction mode was better to alleviating the occurrence of polarization phenomenon. The main reason may be that individuals can obtain more information through one-to-many interaction mode and their attitudes are more objective. Moreover, our mode solved the irrationality of the distribution for individual attitude values after the formation of polarization in the original model. Hence, the attitude values with dispersive views were distributed in various dimensions.

(3) The influence of individual conformity factor on group attitude polarization is also explored. The experimental results stated that according to the differences of group events, the conformity parameters had different effects. When there exist fierce arguments about the event among individuals and smaller mutual tolerances after communication, the greater the conformity of the group was, the higher the degree of polarization was, and the longer duration of polarization from starting to stability was. Based on the fact, when facing such group polarization event, the government needed to make an active voice, and the TV media needed to take the initiative to "neutralize" the public opinion so as to weaken the polarization. On the contrary, it was difficult to generate polarization, and the larger conformity could inhibit the polarization tendency.

(4) Based on relationships among individuals who exist in a real society, our mechanism assigned different relationship strengths to the links across groups to reflect the influence of the intimate individual's opinion when making decisions. Therefore, the influences of different relationship strengths on the polarization process were explored under the same conditions.

However, the development of mass events is extremely complex.[49] Also, many factors are involved in the polarization phenomenon. In the future work, the impacts of opinion leaders and nonbidirectional factors of interindividual relations and so on are future research hotspots,[50] which will not only make the model closer to the reality, but also make the results of simulation experiments more reasonable and practical. In addition, this article mainly targets the major issues of China. Therefore, the future work should apply this model to the world-wide and use the issues of China as an example.

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CONFLICT OF INTERESTS

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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