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Modelling network public opinion polarization based on SIR model considering dynamic network structure

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Abstract Under the dispute between China and the United States, the international field of public opinion is dominated by increasing tensions, and the network rumors triggered by the COVID-19 epidemic are intensifying. In view of the above-mentioned context, this paper focuses on the development and the evolution process of public opinions. Since the evolution of public opinion is often accompanied by the spread and diffusion of information, this paper combines the process of information diffusion with the development process of polarization behavior, and brings in the dynamic network and the timeliness factor of public opinion dissemination, so as to better explore the polarization process of public opinion under the dynamic network. Then, this paper focuses on the analysis of the parameters of the model and through the dynamic adjustment of parameters, finding out the main factors that affect the trend and development of network public opinion. In addition, this paper introduces an actual case, and takes the actual case data as the support to demonstrate the reliability and practical application value of the model. Finally, based on the simulation results and analysis of actual cases, this paper puts forward the corresponding preventive measures to alleviate the polarization behavior of the group.

1. Introduction

New media, under the context of rapidly-developing Internet technology, is gradually replacing traditional media as the primary channel of information spread. Netizens tend to express opinions and make comments on topics in which they are interested, and the collaborative filtering and recommendation algorithms based on big data satisfy different demands of netizens for news topics, enabling netizens with similar interests to interact on the online platforms. In this way, network groups with similar characteristics or similar concern can be gathered to a certain extent to focus on topics of interest, so that public opinion can be expanded rapidly to draw social attention to the event. Most mass incidents have become hot social events after being spread on new media platforms as

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TikTok, Toutiao, and Weibo, and their influence has gradually expanded in public discussions. For example, on December 24, 2019, a female doctor in a Beijing hospital was stabbed to death by a patient's family. On January 20, 2020, Dr. Tao Yong of Beijing Chao yang Hospital was cut by a patient's family, leading to permanent damage to his right hand. On July 7, 2020, a woman in Hangzhou went missing. In 2020, there were many large incidents of buses falling into lakes due to collisions [1].

Effective dissemination of public opinions can attract the attention of relevant government departments, thus facilitating efficient handling of the incident and maintaining the fairness and justice of the society. However, continuous heavy stress from public opinion and the inefficient implementation of policies will also seriously weaken the credibility of the government. Therefore, this study focuses on how online mass emergencies spread in the new media era, and the timely and effective analysis of netizens' concerns about the incidents and how they vent feelings. Meanwhile, effective strategies are proposed from the perspective of decision-making of relevant departments to solve online mass incidents, to contain online rumors, to control the further simmering of public opinions, to reduce the consumption of public resources, and to help the government to grasp the opportunity for dealing with the incident to maintain credibility, so as to eventually satisfy the demands of netizens behind online public opinions.

In this paper, a polarization model of network groups based on the mechanism of dissemination and interaction of public opinions in the context of new media was developed, where the susceptible infected recovered (SIR) model and JA model were introduced to realize information spread and interaction among network groups on the new media platforms. Besides, in view of the situation where network individuals withdrew due to the immunity to hot events and public opinion, the interaction network was dynamically adjusted in real time to adapt to the dissemination mechanism of online public opinions.

This paper proceeds as follows: the second section is literature review, and the scientificity and innovation of this study is confirmed by analyzing studies at home and abroad; the third section describes the proposed model, including its innovation and the practical application value; the experimental simulation and the analysis of the important parameters of the proposed model is presented in the fourth section; the fifth section verifies the validity of the model and the practical application value of this research based on case analysis and data support. The final section involves conclusions and outlook, in which the main conclusions are drawn and the limitations of the research are analyzed.

2. Literature review

At present, the academic circle is quite interested in the research of online public opinion, and certain achievements have been made in the research of the synchronization of public opinion and the polarization phenomenon. The research mainly focuses on the following three aspects: first, the influence of network topology on the spread of online rumors; second, the application of epidemic model in the spread of public opinion; third, the model innovation and simulation of the polarized attitudes of the network groups.

The network topology is the foundation of the spread of rumors. Different network topologies based on different environment and platforms of public opinion spreading with different network groups and network relationships will produce different effects on the spread of information. Liu et al. [2] transformed the dissemination process of breaking news into a dissemination network, to build a weighted oriented complex network with new media as the node, the communication relationship as the edge and the number of times of communication as the weight of the edge. The study showed that the dissemination network has strong accessibility and small-world characteristics. Wu et al. [3] constructed a new public opinion model. And the simulation verified that the model can fully reflect the evolution of formed or unformed public opinion. Zhu et al. [4] studied the dynamics of opinion spread on Barabási–Albert(BA) scale network from the perspective of physics through Monte Carlo calculations and mean-field approximation. It was found that phase transition from ordered to disordered states occurs when the value of parameter q is changed steadily. Yuan and Liu [5] developed an evolutionary network model with mixed connection rules, including log-normal adaptation priority and random connections, nearest-neighbor interconnections within the same community and global random connections in different communities, and analyzed and compared the statistical characteristics of two real networks and two artificial networks, but irregular users were not taken into account. Xuan et al. [6] investigated the dynamics of opinion formation on the duplex scale-free network. The study showed that the underlying network enhances or weakens the diversity of opinion systems due to the presence of multiple complexities compared to non-interactive single-factor network. Xiao et al. [7] proposed a social computational method for modeling evolution, and then simulated the dynamics of dissemination under three ideal network topologies.

The extensive application of epidemic models in online opinion spreading exerted enormous impact, thereby greatly stimulating the development of this research field. Zhu et al. [8], based on the susceptible exposed infected and recovered (SEIR) model, constructed a model that incorporates opinion evolution into the process of topic dissemination. They explored the information diffusion through model simulation, revealing how opinion evolution affects information diffusion, but only the qualitative influence has been discovered. Zan et al. [9] built a susceptible infectious counterattack-refractory (SICR) model of rumor spread based on the counterattack mechanism of rumor spread, so as to explore the peak value of rumor spread and the final scale of rumor under different parameters. Wang [10] presented a new susceptible infected recovered (SIR) model, and the results indicated that the rumor outbreak rate and the number of final infected nodes drop significantly when the differences in node's recognition ability are considered. However, in this study, the network nodes were only classified into three categories, leading to a lack of generality. Jiang and yan [11] established a new model of rumor spread by expanding the traditional SIR model. The simulation results demonstrated that immune susceptible individuals are an effective way to curb rumors. However, the potential stages of rumors were not included in the study. By introducing the concept of indepesndent spreaders into the classical SIR rumor spread mode. Wu and Gergely [12] proposed a new Susceptible-Exposed-Infected-Resistant

(SEIR) model, in which infection time depended on the distribution of infection age and had infinite delay. Qian et al.[13] found that independent spreaders can spread rumors to areas far from the current area of rumor infection, thus effectively strengthening the rumor spreading process. Xie et al. [14] applied big data of public opinion to corporate governance and studied how to integrate resources through internationalization and business diversification to improve the innovation performance of open economies.

Many scholars have made remarkable contributions to the innovation and simulation of polarization models. They have continuously expanded and enriched the classical basic models such as Deffuant-Weisbuch (DW) model [15,16] and JA model [17,18] by incorporating relevant influencing factors, such as psychology, sociology, game theory according to the actual situation, so as to make the simulation results consistent with the actual situation of public opinion polarization. Huang and Song [19] constructed a new model by taking the node preference and memory effect into consideration, and performed simulations in ER, BA and real Facebook networks respectively. The results revealed that the preference strategy promotes the non-uniform network to converge to a consensus, and the memory effect can promote the consensus of the network. Chen [20] adopted the Deffuant model to experimentally analyze the evolution of public opinion, and discovered that the convergence of opinions in CTAN-based social acquaintance network is not only correlated with the parameters of the evolutionary model, but also affected by the topology of the interpersonal relationship network caused by genetics and 20 variance ratios. However, the impact of subject heterogeneity on the evolutionary process was not considered in the research. Zhang and Hong [21] developed and analyzed two generalized DW models, and verified the nearly reliable convergence of the SMDW model. Bu et al.[22] proposed a game theory-based algorithm for predicting the evolution of emotions, using game theory to model the emotional interactions between web users. Li and Xiao [23] used the adjustable BA network model as the Agent adjacency model, and expanded the attitude values of individuals from unidimensional to multidimensional based on the JA classical models. However, these classical models are insufficiently combined with real scenarios. Xin et al.[24] studied the effect of individual persuasiveness on opinion interactions and developed a new opinion interaction model based on the Deffuant model and its improved model. They analyzed the effect of opinion interactions between individuals possessing different persuasive powers on opinion evolution. Shu et al. [25] proposed a strong agile response task scheduling optimization algorithm, which can effectively improve the efficiency of public opinion network information transmission Dong et al. [26] extracted news abstracted by machine learning method, and realized the monitoring of network public opinion through the data analysis of network text.

In summary, the existing studies focus less on the dynamic evolution of the network and the information dissemination in the evolution process. Based on this, a dynamic network structure was firstly introduced in this paper, and the entry and withdrawal mechanisms of individuals in the interaction of public opinion were established. Meanwhile, the SIR epidemic model was employed to better simulate the spread of public opinion. Finally, combining the simulation experiments, the influence of the adjustment of dynamic network, the infection rate of participating individuals, and the immunization rate on the polarization of public opinion was analyzed, and the rationality and effectiveness of the model were verified by actual case study.

3. Model construction

The emergence, simmering, and outbreak of online mass incidents are increasingly dependent on the new media platforms and media under the development of the Internet. The collision of views and the exchange of ideas in the network groups are all carried by the new media platform, and the ideas and emotions are expressed through the words. Existing studies rarely focus on the mechanism of information interaction in the new media era, ignoring the interaction of information and the transient and instantaneous interaction of opinions. Existing models, whether the JA model, DW model or other innovated models based on both or the combination of multiple models, are all based on pre-set interaction networks. However, these models are based on interaction networks planned in advance according to the characteristics of the online groups. With the further evolution of online public opinions, new individuals will enter and the individuals with immunity will exit. Therefore, the network topology is constantly changing with the participation of individuals in public opinion. The reesearch ideas diagram is shown in Fig. 1.

What the existing JA models solve is the polarization problem produced by the interaction of opinions and the game of positions among individuals in the public opinion. However,

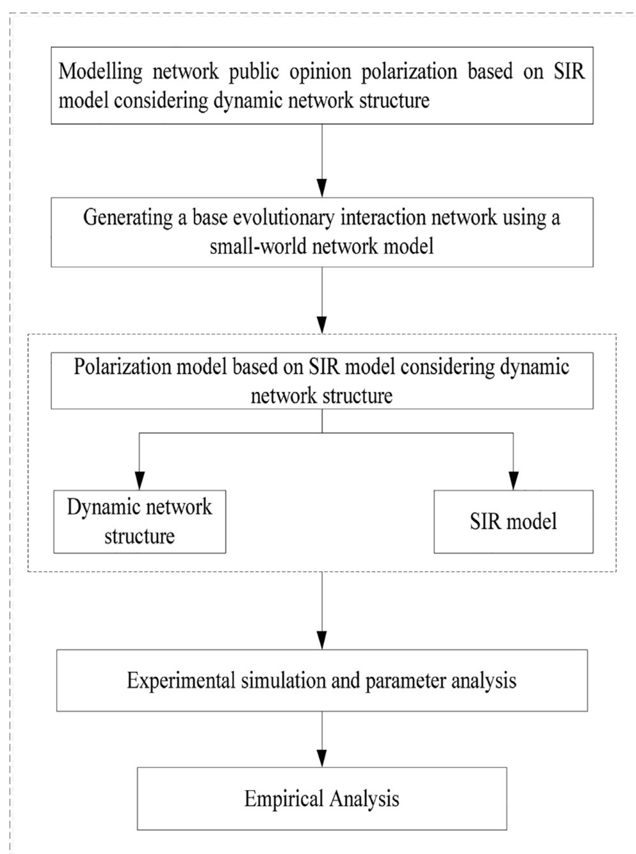


Fig. 1 Research ideas diagram.

it fails to the consideration of the following four aspects: (1) the spread and diffusion of information in the process of opinion evolution, (2) not all individuals will become the spreaders and exporters of information, (3) new individuals will join and immune individuals will exit in the process of opinion interaction, and (4) network topology structure of interaction is not always unchanged and will be dynamically adjusted as new individuals join and the immune individuals exit. Therefore, based on the combination of the JA model and the SIR model, this paper adopted a dynamically adjusted interaction network to reflect the dynamic adjustment of inter-individual relationship, as well as the entry and exit of participants in the process of online opinion interaction. The principle of interaction is displayed in Fig. 2.

1) The SIR epidemic model was used to simulate information dissemination between individuals, with the initial number of infected individuals I_0 set. The conversion between the SIR states is as follows.

$$\begin{cases} \frac{dS(t)}{dt} = -\alpha n(S) \\ \frac{dI(t)}{dt} = -\beta n(I) + \alpha n(S) \\ \frac{dR(t)}{dt} = -\beta n(I) \\ N = n(S) + n(I) + n(R) \end{cases} \tag{1}$$

2) The SIR model was metaphorically applied to the field of dissemination of online public opinions, so that the state of the participating individuals at different stages of opinion can be better distinguished. Individuals with state S passively participate in information interaction, without actively spreading information to the surrounding individuals; individuals with state I actively spread online public opinions; individuals with state R are immune individuals, who exit the interaction network.
3) The actual process of public opinion interaction is often accompanied by the participation of new individuals and the withdrawal of old individuals. Therefore, the entry and exit mechanisms of individuals were set in this paper to dynamically adjust the groups participating in the dissemination of public opinions while at the same time ensuring the dynamics of the interaction network. The main idea is that individuals' interest in public opinion information caused by mass incidents will increase first and then decrease as time goes by. When the individual's interest in the public opinion decreases to a certain threshold, there will be greater immunity. At this time, the individual will temporarily withdraw from receiving and spreading the public opinion, and the interaction chain based on the public opinion with the surrounding connected individuals will be broken. Eventually the individual and the connected edge exit the network. As long as the public opinion caused by the event does not dissipate, there will still be new individuals to join the network, generating new interactive connections, and maintaining a dynamic state of balance. The adjustment rules are as follows.

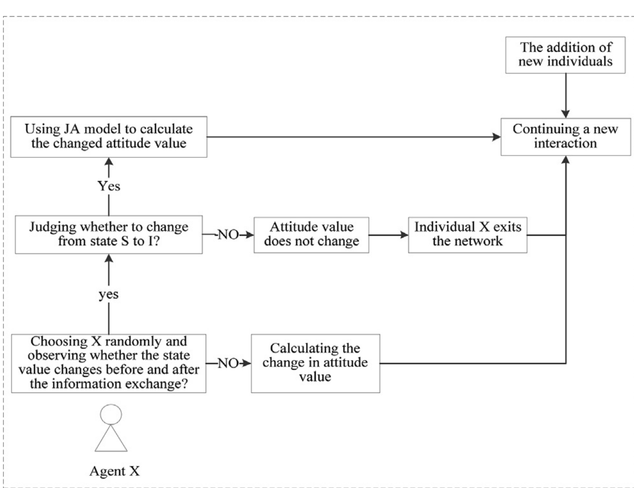


Fig. 2 Model schematic.

In the initial stage, individuals have great interest in the public opinion caused by the event, and at the same time, due to the large amount of information generated in this period, the infection rate of individuals is high. However, with the repeated appearance of public opinion, the acceptance and interest of individuals to public opinion begin to show a downward trend with the passage of time t, while the immunity rate begins to rise. Therefore, the SIR model is adjusted as follows:

$$\begin{cases} \frac{dS(t)}{dt} = -P^i_{acc} n(S) \\ \frac{dI(t)}{dt} = -P^R_{acc} n(I) + P^i_{acc} n(S) \\ \frac{dR(t)}{dt} = P^R_{acc} n(I) \\ N = n(S) + n(I) + n(R) \end{cases} \tag{2}$$

$$P^i_{acc} = \frac{P_i}{\lg(10 + (t - t_0))} \tag{3}$$

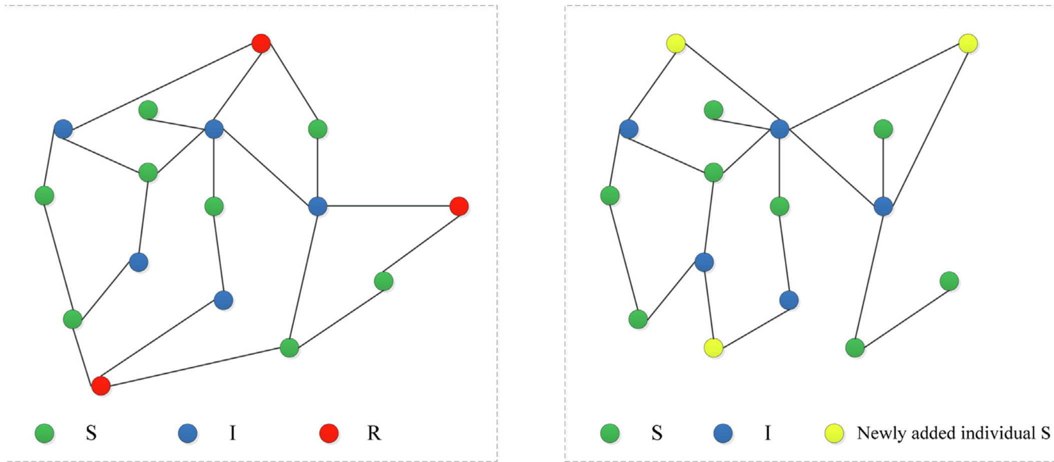
$$P^R_{acc} = \lg\left(10 + (t - t_i)\right) * P_R \tag{4}$$

P^i_{acc} is the dynamic adjustment probability of individual i state changing from S to I. With the increase of interaction time (Times), the probability of individual being infected decreases dynamically, where P_i is the initial infection probability of individual i, which is determined by the assimilation of the infected individuals adjacent to t_0 represents the initial interaction time.

P^R_{acc} is the dynamic adjustment probability of the state of individual i changing from I to R. With the increase of interaction time (Times), the probability of individual immunity presents a dynamic increasing trend, where P_R is the initial immunity probability of individual i, and t_i represents the initial infection time. If the status of the participating individual i changes from I to R, it indicates that the individual has become immune to the public opinion caused by the event, and loses the interest level of participation, and individual i withdraws from the network.

New individuals who gain interest in the public opinion will re-enter the information interaction. The interaction rules are exhibited in Fig. 3.

4) After the change in the state of the individual is determined through the SIR epidemic model, the polarization model is used to quantitatively calculate the attitude variable. The rule of the evolution of individuals' attitude value is expressed as follows.



(*a*) Schematic diagram of network structure before dynamic adjustment (*b*) Schematic diagram of network structure after dynamic adjustment

Fig. 3 Dynamic network structure adjustment diagram.

When the probability of infection P^{i}_{acc} and the probability of immunity P^{R}_{acc} do not reach the set threshold, that is, the individual status does not change, the attitude value of the individual will fluctuate in a small range due to the transmission of the attitude value of the surrounding individuals. The interaction rules are as follows:

1) Assimilation rules

The attitude value of individual i is updated when the difference between the opinion held by individual i and the combined opinion of the surrounding individuals with state I is less than d_1.

$$w_i(t+1) = w_i(t) + \theta\left[\dot{w}_i(t) - w_i(t)\right], \text{when}\left(\left|\dot{w}_i(t) - w_i(t)\right|\right) < d_1 \quad (5)$$

Where $\dot{w}_i(t)$ is expressed as formula (4), θ represents the assimilation degree of attitude change, and $\theta \in (0, 0.5)$.

$$\dot{w}_i(t) = \frac{\sum_{j=1}^{n} w_j(t)}{n} \quad (6)$$

2) Repulsion rules

When the difference between the attitude value of individual i and the average attitude value is greater than d_2, the attitude value of individual i is updated to:

$$w_i(t+1) = w_i(t) - \vartheta\left[\dot{w}_i(t) - w_i(t)\right], \text{when}\left(\left|\dot{w}_i(t) - w_i(t)\right|\right) > d_2 \quad (7)$$

3) Neutral rules

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

When the infection probability P^{i}_{acc} exceeds the set threshold, namely, the individual state from S to I, it indicates that the individuals' perceptions and positions on the event have changed more. At the same time, the assimilation between individuals will weaken with the increase of interaction times, while the repulsion will increase with the increase of interaction times, so the interaction rules are as follows:

1) Assimilation rules

The attitude value of individual i is updated when the difference between the opinion held by individual i and the combined opinion of the surrounding individuals with state I is less than d_1.

$$w_i(t+1) = w_i(t) + \frac{1}{\lg(10 + (t - t_i))} * \varnothing * \left[\dot{w}_i(t) - w_i(t)\right], \quad \text{when}\left(\left|\dot{w}_i(t) - w_i(t)\right|\right) < d_1 \quad (8)$$

Where $\dot{w}_i(t)$ is expressed as formula (4), $\varnothing$represents the assimilation degree of attitude change, and $\varnothing \in (0.5, 1)$.

2) Repulsion rules

When the difference between the attitude value of individual i and the average attitude value is greater than d_2, the attitude value of individual i is updated to:

$$w_i(t+1) = w_i(t) - \lg(10 + (t - t_i)) * \delta * \left[\dot{w}_i(t) - w_i(t)\right], \quad \text{when}\left(\left|\dot{w}_i(t) - w_i(t)\right|\right) > d_2 \quad (9)$$

Where δrepresents the repulsion degree of attitude change, and $\delta \in (0.5, 1)$

3) Neutral rules

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

4. Experimental simulation and results analysis

4.1. Experimental simulation

In order to show how online public opinions polarize in a more intuitive manner, the evolution process of the attitudes of network groups was stimulated. The simulated network was determined to be a dynamically adjusted network according to the above model, and the structure of the network changes as individuals join and leave the topic of public opinion. In this paper, the initial node size of the network was set to 300, and the setting of the initial attitude value was divided into two steps: first, 50% of the individuals obey the random distribution of [−1,1]. Second, the remaining 50% initializes the attitude value of the individuals according to the nature of the event itself. For example, if the nature of the event is negative, the distribution of attitude value was biased to [−1,0]. And after 400 interactions, the opinions and attitudes of individuals tended to be polarized due to the changes in the surrounding individuals. Some individuals will retain their original attitudes, while some will develop polarized attitudes. The results of evolution with the duration of interaction are shown in the following figure.

From Fig. 4, the horizontal axis represents the number of interactions, and the vertical axis represents the proportion of individuals who participate in group polarization and change their attitude in the process of information interaction. It can be seen that the proportion of infected individuals decreases gradually with the increase of the number and time of interactions, and after 100 interactions, it basically stabilizes around 0.1. Obviously, this is in line with the actual interaction of public opinions. When the group's discussion and communication of an event reaches a certain level, the enthusiasm of the participating groups will gradually decline over time. In addition, because the influence of the event itself still exists, there will be constant withdrawal of immune individuals and entry of new individuals to maintain the dynamic balance of public opinion in a short period of time. Therefore, after 100 interactions, infected individuals and uninfected individuals keep dynamic and stable fluctuations. Fig. 5. reveals that individuals' attitudes gradually polarize after intense interactions. As is shown in the simulation results, the individuals are more aggressive and their attitudes are more deviated in the first 100 interactions. After 100 interactions, the intensity of interaction slows down, but still tends to polarization. Some individuals' attitudes begin to evolve towards the two extreme directions, 1 and −1, while most individuals maintain their own opinions without being affected by the surrounding environment, with the values of attitude distributing between −1 and 1. However, because the overlap in the evolution of the attitude values of individuals cannot be visually reflected in the figure, the distribution of the attitude values of individuals under different interactions is provided in this paper, as shown in Fig. 6.

Fig. 6 shows the three-dimensional diagram of different interaction periods. We can intuitively see that in the initial stage, the cuboids representing the degree of polarization are uneven, indicating that the attitude distribution is relatively scattered. With the increase of interaction times, the number of individuals inclined to the poles of 1 and − 1 began to increase, indicating that individuals began to form small groups with different views. And the individuals with the same views began to persuade the individuals who were not firm in their positions and the newly added individuals to continuously expand the advantages of their own views. From the final result, the whole participating group formed three opinion groups: positive polarization, negative polarization and neutrality.

Fig. 7 more clearly shows the proportion of opinion polarized individuals in the interaction process. It can be found that in the initial stage, the proportion of extreme opinion individuals is 0, indicating that in the embryonic stage of network public opinion, the public's evaluation of the events behind public opinion is relatively conservative, and they will not easily express complete positive or negative statements, The opinions and attitude values of network groups are relatively scattered, and there is no extreme attitude value group. With strengthened interactions among individuals, the proportion of polarized individuals expands obviously, occupying nearly 50% after 400 interactions. It can be found that (1) the event triggered the public opinion was inflammatory and guided netizens' sentiment to a cer-

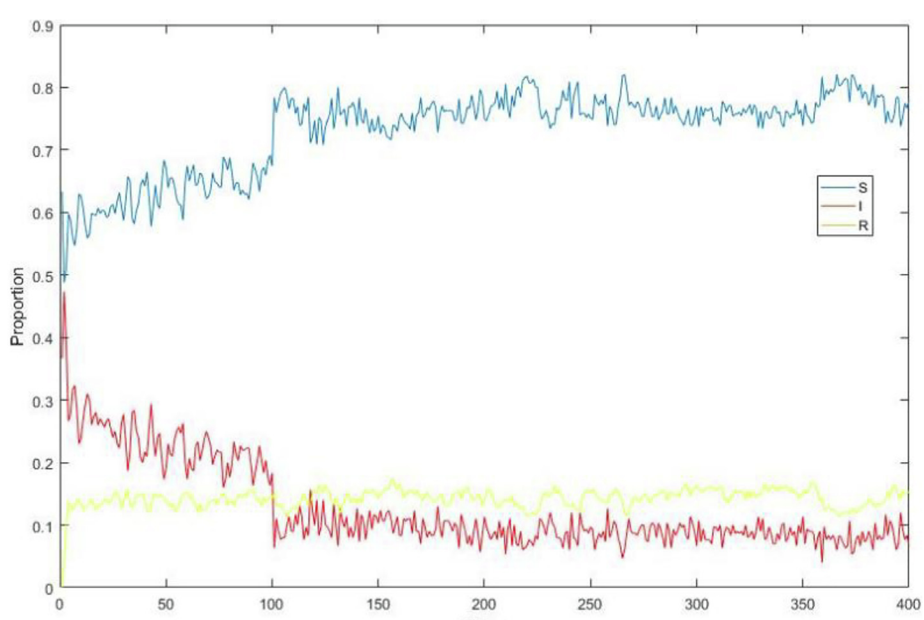


Fig. 4 The proportion of infected individuals.

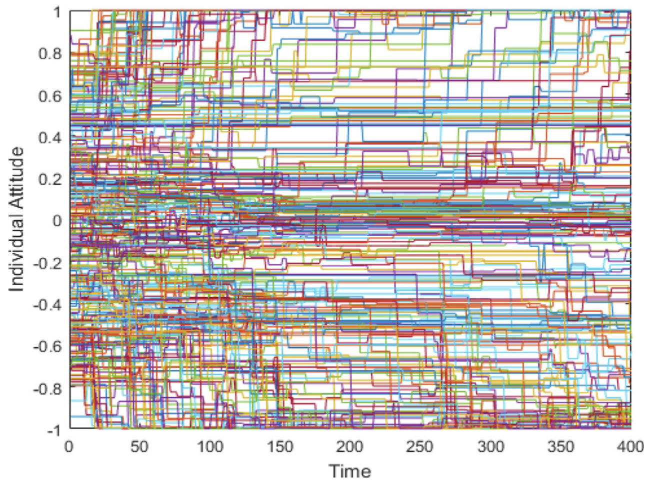
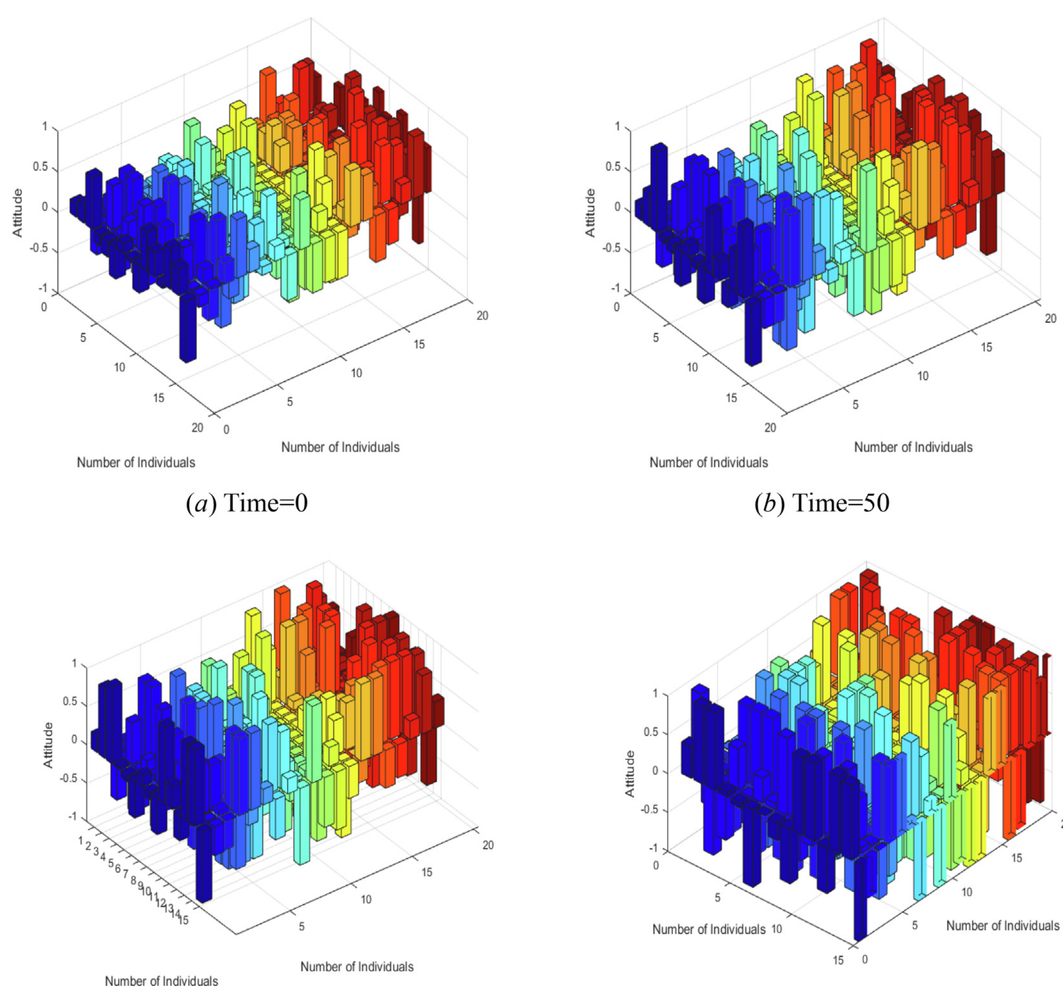


Fig. 5 Evolution of individual attitudes with the number of interactions.

tain extent, (2) the harm caused by the event was within the controllable range, and nearly half of the individuals could still maintain a neutral attitude after sufficient discussions and interactions, (3) the new attitudes of newly joined individuals mitigated the original relationship network and polarized opinions, thereby slowing down the process of attitude polarization. Based on the simulation results, when dealing with the polarization of network public opinion caused by network group events, first of all, we need to fully grasp the golden time of public opinion germination period and effectively guide the trend of public opinion. Secondly, in the middle of the development of public opinion, the real situation of the incident is released in a timely manner, and we have to use the new individuals added in the middle and late stages to buffer the extremist trend of public opinion.

4.2. Results analysis

In this section, the model was analyzed and discussed from the following aspects: (1) Exploring the polarization effect before and after integration into dynamic networks. (2) With the dynamic adjustment of the network, individuals with immunity in the network will continuously exit and new individuals will join, then how the initial attitude values of the newly joined individuals affect the polarization process of public opinion overall? (3) Exploring the relationship between group



(*a*) Time=0 (*b*) Time=50

(*c*) Time=100 (*d*) Time=400

Fig. 6 Three-dimensional histogram of individual attitude distribution under different number of interactions.

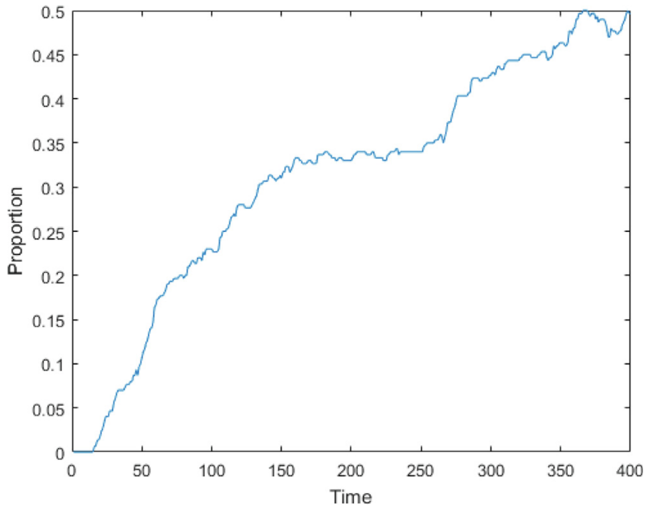


Fig. 7 The polarization process of attitudes.

polarization by adjusting the immunization rate β. (4) Investigating the impact of the infection rate α of new individuals on the degree of polarization. The exploration of the above three aspects can help to further analyze the important factors affecting the development and spread of group's polarized behaviors, so that corresponding measures can be proposed to alleviate the social harm brought by it.

4.2.1. Comparison of the polarization effect before and after the dynamic network was incorporated

In the research of the polarization of online opinions, the network structure, as the basis for the interaction and connection between participants, has huge significance to the evolutionary outcome. Different types of network topology exert tremendous influence on the spread of information, interaction and polarization of opinions, and play different roles in guiding the actual cases. By comparing the polarization process of public opinions under dynamic and static networks, adjusting the values of the assimilation and dissimilation bands respectively, and conducting multiple simulations, the visualized results were obtained, as shown in the following figure.

Two different results were produced by the experimental simulations. First, Fig. 8(a) shows the simulation results obtained under the condition $d_1 = 0.4$ and $d_2 = 1.1$. Under the same condition, the polarization degree of network group in the static network is significantly higher than that in the dynamic network. This is because under the parameters $d_1 = 0.4$ and $d_2 = 1.1$, the assimilation band is short, and the space for the alienation rejection band is large, so that network group is easy to polarize. The dynamic adjustment of the network encourages some extreme individuals to withdraw from the original solidified network, and the newly joined non-extreme individuals can alleviate the polarization trend to a certain extent. Therefore, under the same conditions, the dynamic adjustment of the network can mitigate polarized online public opinion to a certain extent.

Second, Fig. 8(b) shows the simulation results obtained under the condition $d_1 = 0.6$ and $d_2 = 1.3$. Under this parameter, online group tends to be neutral, and individuals tend to have a similar choice. It can be seen that the polarization process demonstrated in Fig. 8(b) is relatively slow, with the polarization rate of about 35% in the static network, and approaching 50% in the dynamic network. Obviously, in the situation where the online group is relatively conservative and tends to pursue similar strategy of attitude evolution, the dynamic adjustment of the network motivates the participation of new individuals with polarized attitudes, thus enhancing the degree of polarization of online group to some extent.

From the above simulation results, we can draw the following conclusions. Firstly, compared with the static network, the polarization trend of the dynamic network is not completely determined after the model and parameters are constructed. The addition of new attitude individuals and the withdrawal of old individuals will affect the topology of public opinion interaction network, and the attitude value distribution of new individuals will greatly affect the trend of group polarization. Secondly, public opinion will be further strengthened or smoothed over time. The addition of new individuals can maintain the individual's latest attitude towards public opinion and make the outside world change dynamically due to the change of public opinion caused by the event.

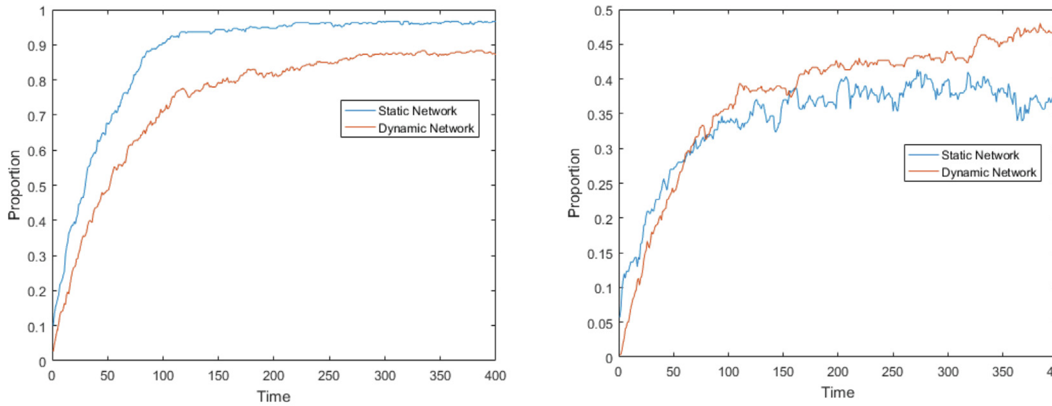
4.2.2. The impact of the distribution of initial attitude values of newly joined individuals on the polarization effect

As some participants gradually become immune to the topic and withdraw from the network, the initial attitude values of the newly joined individuals will affect the trend of public opinion. In this paper, the initial attitude values of the newly joined individuals were set as values randomly distributed in the range $[-0.7, 0.7]$, $[-0.8, 0.8]$, $[-0.9, 0.9]$ and $[-1, 1]$, and the following results were obtained when other conditions remain unchanged.

It can be seen from Fig. 9 that as the gap in the distribution of the initial attitude values of the newly joined individuals widens, individuals with extreme attitudes will gradually appear, which remarkably promotes the overall polarization of opinions. For example, new individuals whose initial attitude values are randomly distributed in the range $[-0.7, 0.7]$ have relatively mild opinions on the event and little impact on the original public opinion, and the final degree of polarization is about 55%. When the initial attitude values tend to be distributed in the range of $[-1, 1]$, the probability of the appearance of individuals with extreme attitudes increases sharply, and these individuals will greatly stimulate the polarization trend of opinions, improving the proportion of final polarized individuals to 85%. Therefore, under the same conditions, the difference in the distribution of the initial attitude values of newly joined individuals will have a huge influence on the polarization process of online public opinions.

4.2.3. The influence of immunization rate β on the polarization effect

In this section, the influence probability of an infected individual who transforms into an immunized individual on the final polarization effect was investigated. Considering individuals with immunity will withdraw from the network and no longer interact, which will affect the original atmosphere of the opinion field to a larger extent, in this paper, the immune individuals were controlled by adjusting the value of β with other conditions kept unchanged, so as to observe the curves of



(a)d_1=0.4, d_2=1.1 (b)d_1=0.6, d_2=1.3

Fig. 8 The degree of polarization of public opinion in dynamic and static networks under different parameters.

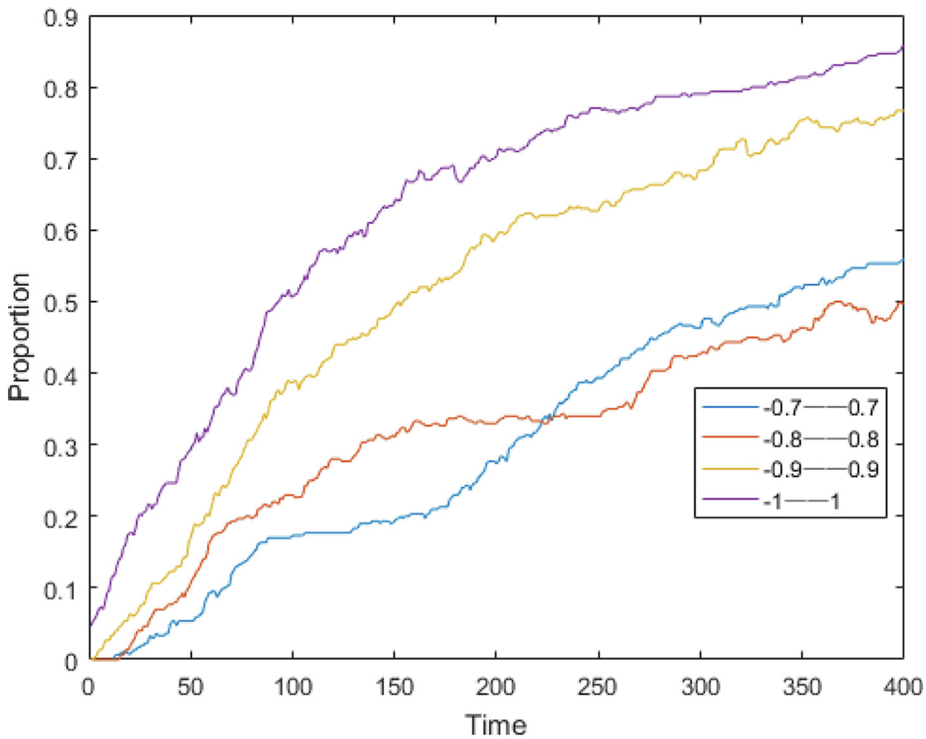
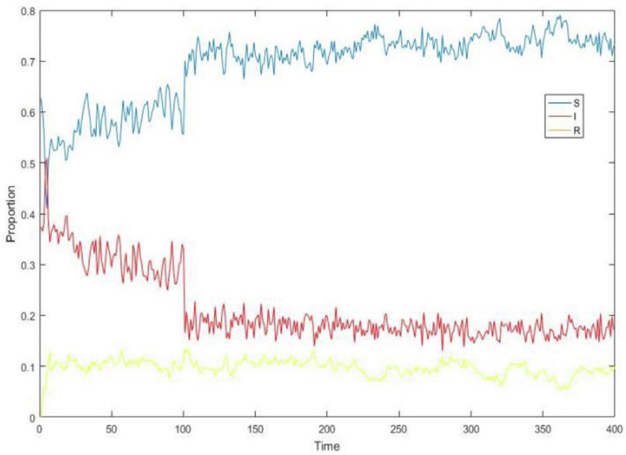


Fig. 9 The impact of new individuals with different distributions of initial attitude values on the polarization process.

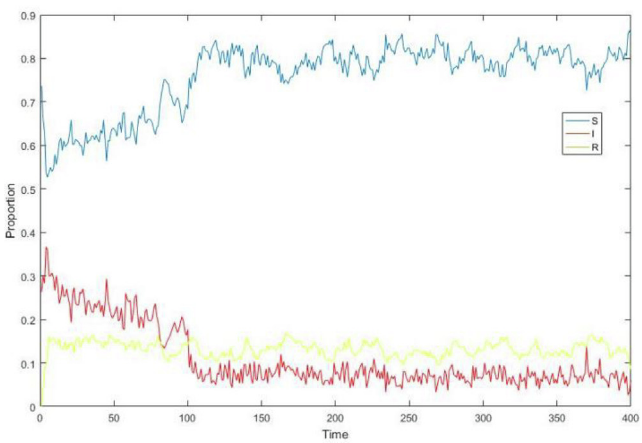
the proportion of healthy, infected, and immune individuals and the graph of polarization effect.

Fig. 10 shows that at the immunization rate of 9%, information spread gradually strengthens. All the individuals tend to be stable, and with the disappearance of the information spreaders, only healthy individuals exist. At the immunization rate of 5% and 7%, the individuals play three roles alternatively, and the information spreads always exist in the group, just like strong infectious viruses. Overall, when the infection rate remains unchanged, the number of individuals with immunity surges while the number of infected individuals reduces dramatically with the increasing immunization rate β. Therefore, by weakening the interest of individuals in the topic and intensifying the efforts of refuting rumors, the channels of rumor spread can be effectively cut off, allowing participating individuals to quickly develop immunity to the topic, thus bringing the spread and discussion of the topic to an end.

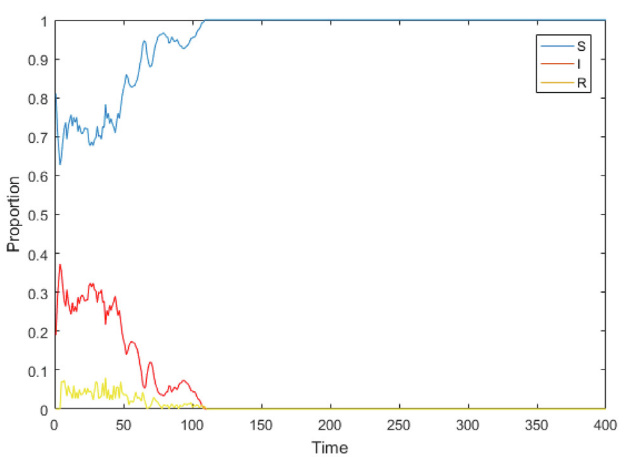
Figs. 11 and 12 present the comparison at the immunization rate β = 5%, β = 7%, and β = 9%. It can be found that as the immunization rate rises, the overall polarization of public opinions is effectively reduced. Based on this, measures can be taken to prevent or solve mass incidents, including: enhancing their immunity to wrong information by effectively releasing authoritative information through various channels, so that individuals can accurately distinguish the true information from the untrue news, thus preventing individuals from becoming spreaders of untrue information. Besides, we can



$(a)\beta = 5\%$



$(b)\ \beta = 7\%$



$(c)\beta = 9\%$

Fig. 10 Infection rate of the participating groups at different immunization rates.

also use effective method to identify individuals with extreme attitudes that spread public opinion, cut off information spread, and cultivate immunity of these individuals, thereby curbing the polarization trend of online public opinions.

4.2.4. The impact of infection rate α on the polarization effect

The spread of the public opinion triggered by a network event largely depends on the degree of attraction of the event to the participating groups. When an online mass event involves people's welfare, the online participants will be easily infected by the opinion spreaders and become new spreaders of information. This section focuses on the impact of the infection rate of individuals who have become spreaders after they were attracted by public opinion on the polarization process of online public opinions. First, with all other conditions kept fixed, the infection rate α was adjusted from 6% to 10%, and then increased to 12% to obtain the line graph of the polarization degree of individuals' attitudes, as exhibited in the figure below.

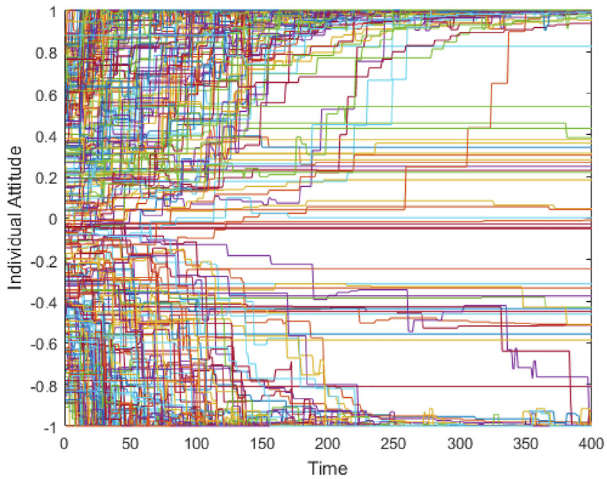
The larger the infection rate α, the more related the public opinion is to the immediate interests of netizens, and the easier it is to make them empathize with the opinion, thus arousing public attention. The smaller the infection rate α, the less influential the event, and the less the participation of netizens. It can be seen from Fig. 13 that the greater the infection rate α, the more intense the discussion on the event, and the more frequent the interaction of opinions and the exchange of ideas among netizens, resulting in a more obvious polarization trend of online public opinions. Therefore, it is necessary to reduce the heat of online public opinions triggered by online mass incident in a timely and early manner to decrease the probability of infection, so as to effectively prevent the extreme public opinion and extreme behaviors caused by online mass events.

5. Empirical analysis

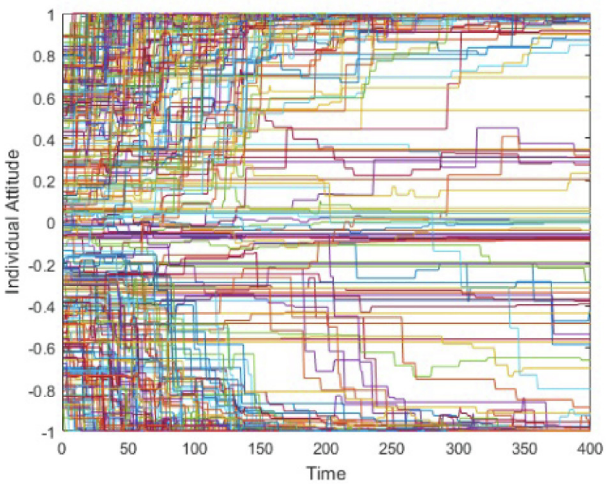
5.1. Background

In this paper, the typical case of "Ant Group's Suspended IPO" was analyzed to verify the polarization model based on the dynamic network structure constructed in this study.

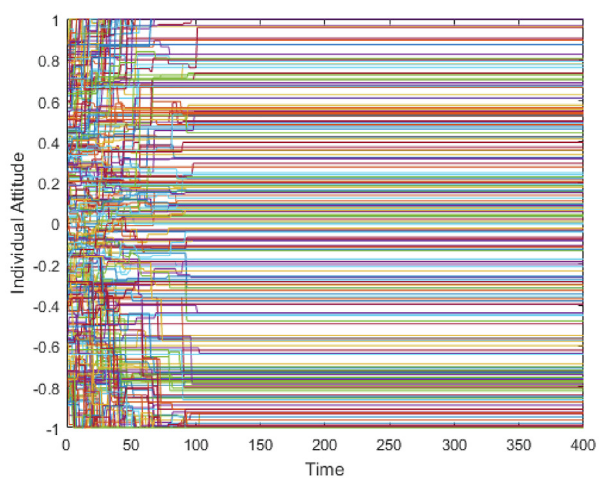
On the evening of November 3, 2020, the IPO of Ant Group, which was supposed to be the largest IPO in history, was suspended. The SSE explained the reason for the suspended listing is that the state's top financial regulators held a joint regulatory talk with the top management of Ant Group, and Ant Group has reported significant issues such as the change in supervision environment concerning fintech. Due to these changes, Ant Group may not be able to meet listing requirements or to meet related information disclosure requirements. Immediately, "suspended listing of Ant Group" and "Alibaba's stock price plunged" became the hot topics. The following day, the incident continued to heat up, with the topic "Suspended IPO of Ant Group" appearing on the real time trends on Weibo; at the same time, the largest shareholder of Ant Group, Alibaba, saw its opening price plummeting over 9% in Hong Kong, and "Alibaba share price plunged" also became a hot topic on Weibo, attracting continuous public attention to the event. Based on this, Python crawler was used in this paper to obtain the information of posts related to "Ant Group's suspended listing" from Nov. 2 to Nov. 8, 2020, and a total of 83,369 comments were obtained, including the name of the user, time of the post, number of comments, number of likes, etc. The form of the crawled field is shown in Fig. 14.



$(a)\beta = 5\%$



$(b)\beta = 7\%$



$(c)\ \beta = 9\%$

Fig. 11 The evolution of attitude values of individuals at. different immunization rates.

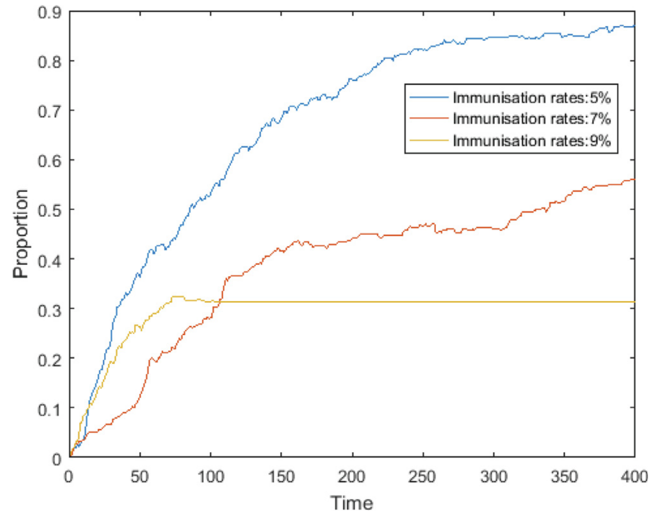


Fig. 12 Proportion of polarized attitude values of network groups at different immunization rates.

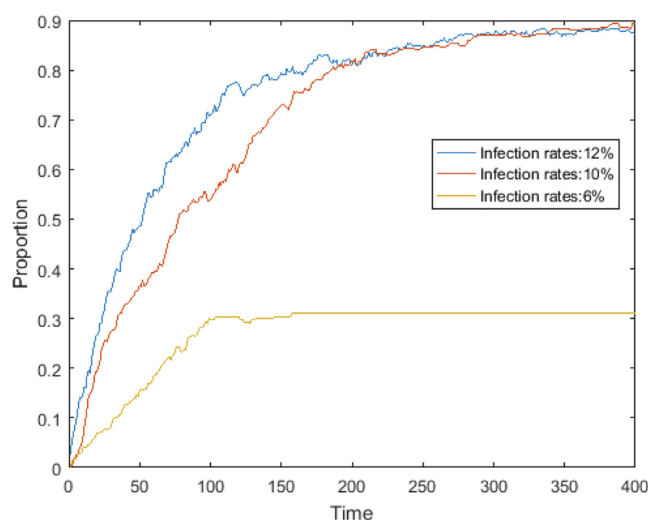


Fig. 13 The impact of infection rate on the polarization process.

5.2. Analysis of empirical results

The analysis results of the crawled data are shown in Fig. 15. It was found that netizens have formed various views on the event in the discussion of this topic, which can be summarized in the following three aspects from the perspective of the distribution of sentiment: (1) Social neutral sentiment for "Ant Group's suspended listing" occupies 50.2%, mainly involving the spread of the information on the event, discussion on the operation or profitability model of Ant Group, and the speech delivered by Jack Maat Shanghai Bund Summit. (2) Negative comments on the incident account for 30.2%, with netizens expressing their dissatisfaction with Ant Group's high-leverage circular lending model and questioning the regulators' sudden suspension of Ant Group's listing. 3 Positive sentiment accounts for 19.6%, with netizens expressing their support for the decision of state's financial regulators.

id	Comments	Number of comments	likes	Time
ktr02	The well is down, the wall is down	8	49	2020-11-3 12:03
ylrh19286	Next year, we should focus on supporting the standardized development of financial technology in accordance with the law, firmly oppose monopoly and unfair competitive practices, and prevent disorderly expansion of capital.	77	196	2020-11-3 12:06
xlent	Taking away people's money is like killing your father, especially or moving the bank which has assets to make money in China	6	11	2020-11-4 08:33
jv	Originally the valuation is inflated, just cut leeks. Still really think they are worth that much?	26	33	2020-11-6 21:06
TripleS_Wong	Doing finance should be like doing finance	34	92	2020-11-03 22:45
hy366	Who would have thought that the special event, Anthem, which passed the meeting in 30 days, had the day of suspension!	3	31	2020-11-03 21:32
delehai918	Li Ka-shing and Ma Yun fell from the altar before and after. The reason for this is that they have finally exposed the nature of capitalists, one is an enemy of the state, one is an enemy of the people!	546	1053	2020-11-05 11:13
cxs	If Anthem becomes a bank, then its imagination is greatly limited	7	62	2020-11-06 00:39
lcpk	Ant Group's suspension of listing demonstrates strong determination to protect investors' interests	73	238	2020-11-06 20:53

Fig. 14 Part of the content of Weibo posts on "suspended IPO of Ant Group" crawled.

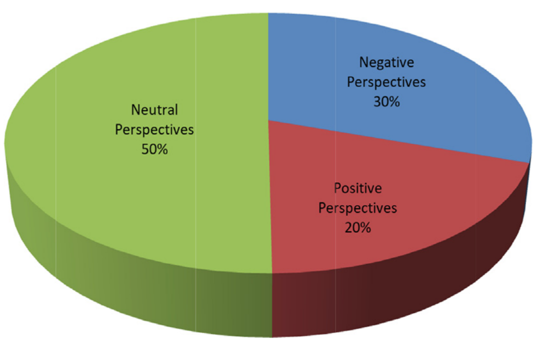


Fig. 15 Social Emotion Distribution Chart.

According to the statistics of the heat and the dissemination of the topic shown in Fig. 16, the discussion on Ant Group started to heat up from November 2, and reached the peak on November 4, after which the heat of the topic started to fall. The phenomenon is in line with the trend of public opinion spread in the SIR epidemic model.

Through the analysis of the "Ant Financial suspended listing" incident, it can be seen that the main factors influencing the evolution of the incident are: (1) Ant Technology is a financial company, but listed under the guise of technology, so as to avoid regulation. (2) expressed support for the decision to suspend the listing of Ant Group, believing that strict state control is a responsible approach to investors and the market. (3) believe that Ant lending has solved the problem of many procedures and high threshold for bank loans for some people who urgently need loans, and do not support too much government intervention in the market.

With the actually crawled texts as the data source, the distribution of public opinions on the event "suspended listing of Ant Group" was analyzed. As can be seen in Fig. 17, the opinions of netizens are not overly concentrated, and those who hold neutral opinions believe that it is normal to suspend the listing of Ant Group because the company failed to meet the listing requirements of regulators, and the suspension has little correlation with the company itself. The group with negative and extreme views expressed their dissatisfaction with the Ant Group's highly leveraged circular lending model, and questioned the excessively high interest rates of Ant Group's products, namely, Huabei and Jiebei, which are suspected of usury; those who hold a positive attitude support the regulators' decision to suspend Ant Group's listing, saying that there is a huge problem with the model of Ant Group, and a smooth listing of the company may harm investors, and may even lead to a "subprime crisis" if it collapses. Therefore, the regulators deferred the listing of Ant Group in order to protect the interests and rights of investors.

Then, the incident, "Ant Group's suspended IPO" was simulated based on the polarization model of online public opinions which incorporates dynamic network and SIR model proposed. For visualization, the size of the simulated network was set to 1000 and the initial number of infected individuals was set to 5%, and 10 individuals with node degree less than 5 were randomly selected as immune individuals to exit from the network in each interaction. The assimilation and rejection parameters were set to $d_1 = 0.5$ and $d_2 = 1.4$, and the number of interactions T = 200. The results are shown in Fig. 18.

As can be seen from Fig. 18, the analysis of the public opinion on the event, "Ant Group's suspended IPO" based on the model proposed in this paper is closer to the actual data. The model shows that a majority of individuals hold neutral attitudes and most groups hold positive attitudes, which is basically consistent with the distribution of netizens' attitudes towards the event. In general, the polarization model of multi-dimensional public opinion proposed in this paper can simulate the event triggering public opinion in reality, and offers certain practical significance for analyzing the causes of multidimensional public opinion and predicting the evolution of public opinion.

In order to verify the scientific validity of this model, further comparisons are made with other models in this paper. The model in the literature [17] is used to simulate the event of "Anthem's suspension of listing", and the results are shown in Fig. 19.

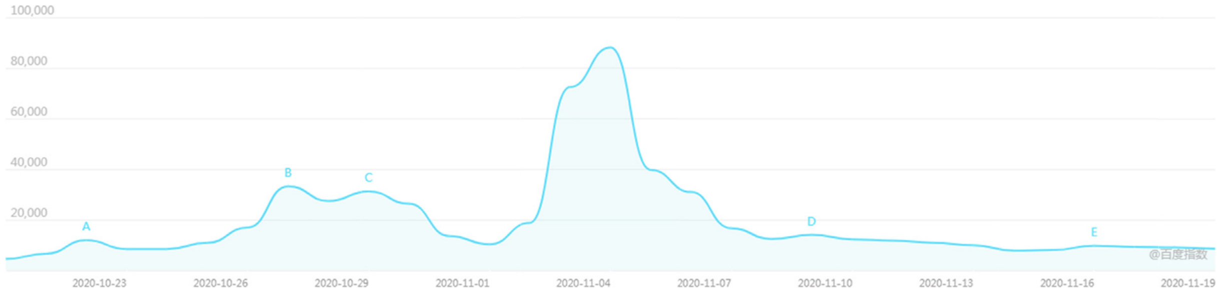


Fig. 16 Public opinion dissemination trend chart.

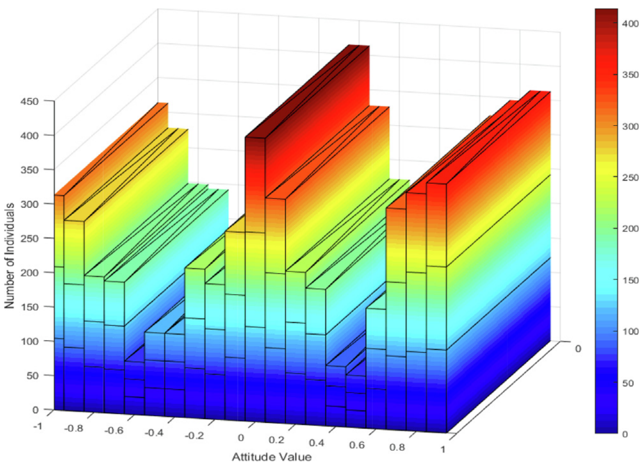


Fig. 17 Distribution of public opinion on "suspended IPO of Ant Group"

As can be seen from Fig. 19, the simulation of the model in the literature [17] reflects the positive, neutral, and negative directions of public opinion triggered by the "Anthem's delayed IPO" event as a whole. However, the attitude values are too concentrated and do not reflect the individual views of neutral positive and neutral negative attitudes, which does not accurately describe the overall development of public opinion and differ significantly from the case data, and do not reflect the distribution of extreme individuals in this topic.

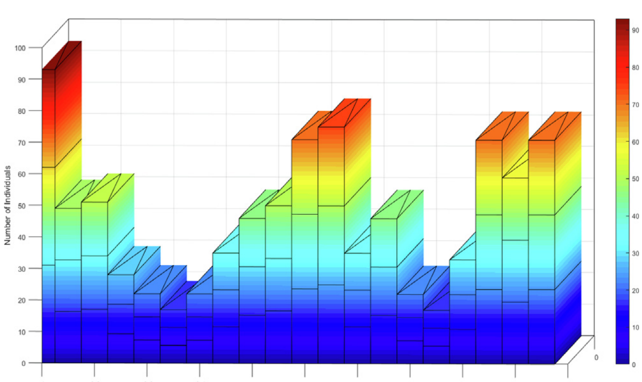


Fig. 18 Simulated distribution of public opinions on "Ant Group's suspended IPO" based on the proposed model.

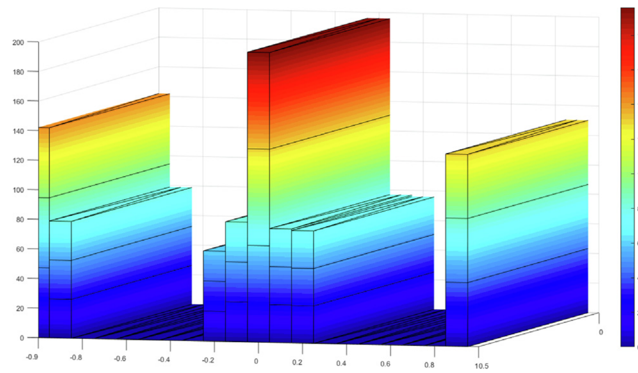


Fig. 19 Distribution of public opinion on the event of "Ant Financial suspended listing" simulated by using the model proposed in the literature [17].

Therefore, the comparison shows that the model proposed in this paper is more consistent with the evolution of public opinion in reality.

6. Conclusion

With the continuous popularization of network informationization, network mass incidents frequently occur, involving various aspects in the society. The appearance of public opinion, the spread of information, the emergence and disappearance of polarization phenomenon reflect the process where mass event occurs, evolves and disappears. The polarization behavior, as a specific manifestation of the evolution of public opinion, involves more internal mechanisms, and has great theoretical significance for exploring the complex connotation of mass events. In addition, the study on the mechanism of the emergence of online groups' behavior has important practical significance for improving the vulnerable social systems and realizing the effective management of a complex society.

To address the phenomenon of polarization in online public opinion, this paper based on SIR model considered dynamic network structure to simulate the evolution process of group's attitudes through multi-agent Monte Carlo method. Meanwhile, the main factors causing the polarization phenomenon were analyzed through the model parameters, which provides certain reference for solving the polarization phenomenon in reality. The main research work and conclusions of this paper are as follows.

(1) In this paper, the static network in the traditional study was transformed into a dynamically adjusted network, which can better reflects the changes in public opinions in each period as new individuals join and old individuals exit. The results of relevant simulation experiments further verified that the polarization model based on the dynamic network with the epidemic model incorporated is more consistent with the actual scenario.
(2) The immunization rate β directly affects the overall process of polarization. As the value of β increases, the polarization phenomenon mitigates instead. Therefore, relevant departments need to effectively release authoritative information through various channels, helping audiences to accurately identify the true information, increasing the β value, preventing individuals from becoming spreaders of untrue information, thereby curbing extreme events or extreme public opinion.
(3) The distribution of initial attitude values of new individuals directly affects the polarization process of public opinion in the original network. The emergence of some extreme individuals will further intensify the polarization of public opinion. Some of the newly joined extreme individuals will shake the attitudes of individuals who hold a neutral opinion originally but tend to have polarized opinions.
(4) The increase of the infection rate α also directly drives the polarization trend of public opinion. It can be found that the increase in the infection rate means that the event arouses much public attention, and netizens are likely to close ranks in the process of interaction, thus triggering the polarization of public opinion.

Data Availability Statement

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

Author contributions

J.Y. described the proposed framework and wrote the whole manuscript; J.S. implemented the simulation experiments; W.L. collected data; J.W. revised the manuscript. All authors have read and agreed to the published version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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