


Article

A Novel Public Opinion Polarization Model Based on BA Network

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Abstract: At present, the polarization of online public opinion is becoming more frequent, and individuals actively participate in attitude interactions more and more frequently. Thus, online views have become the dominant force in current public opinion. However, the rapid fermentation of polarized public opinion makes it very easy for actual topic views to go to extremes. Significantly, negative information seriously affects the healthy development of the social opinion ecology. Therefore, it is beneficial to maintain national credibility, social peace, and stability by exploring the communication structure of online public opinions, analyzing the logical model of extreme public attitudes, and guiding the communication of public opinions in a timely and reasonable manner. Starting from the J–A model and BA network, this paper explores the specific attributes of individuals and opinion network nodes. By incorporating parameters such as individual conformity and the strength of individual online relationships, we established a model of online group attitude polarization, then conducted simulation experiments on the phenomenon of online opinion polarization. Through simulations, we found that individual conformity and the difference in environmental attitude greatly influence the direction of opinion polarization events. In addition, crowd mentality makes individuals spontaneously choose the side of a particular, extreme view, which makes it easier for polarization to form and reach its peak.

Keywords: online public opinion; group polarization; influencing factors; power relations



Citation: Ye, Y.; Zhang, R.; Zhao, Y.; Yu, Y.; Du, W.; Chen, T. A Novel Public Opinion Polarization Model Based on BA Network. *Systems* **2022**, *10*, 46. <https://doi.org/10.3390/systems10020046>

Academic Editors: Philippe Mathieu, Fernando De la Prieta, Alfonso González-Briones and Juan M. Corchado

Received: 13 March 2022

Accepted: 7 April 2022

Published: 9 April 2022

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1. Introduction

In recent years, with the rapid development of China's self-media platforms, the polarization of online public opinion has become more frequent, for example, the Tesla car brake failure incident, the self-explosion "0 sugar" incident in Genki Forest, and the China Express blind box pet incident, all of which have aroused widespread social concern. It can be noted that in the process of spreading online opinions, due to the reduction of transmission cost, the amount of information received by individuals increases. At the same time, information homogenization and fragmentation are serious, which makes it difficult for individuals to maintain a neutral and objective attitude toward their actual output. As a result, the information views of the surrounding environment tend to be consistent and then become a driver of polarizing events in online public opinion. In fact, in the process of information sharing and decision making, individuals' actual behaviors are generated by their objective cognition together with psychological activities. Consequently, it is very easy to collide with the surrounding environment and group views. Furthermore, the original decision is biased, leading to different degrees of polarization. Moreover, individuals have differences in age, occupation, family, education level and other various aspects. These differences make them have various sensitivities to the polarization of public opinion and

fluctuations of their own opinions and attitudes, resulting in a complex trend of public opinion polarization events.

Existing studies on opinion polarization usually use a relatively small and simple network structure to analyze changes in the attitudinal values of social groups and focus on the influence of individual heterogeneity on the connections between individuals. In fact, the polarization process of individual attitudes relies on a complex network structure in which complex mechanisms of opinion polarization arise.

Distinguishing from existing research tools, this paper considers the heterogeneity properties of nodes and defines them specifically based on the J–A model, as well as the threshold changes between individuals, adding parameters such as individual consistency and strength of network relationships, forming a complex network structure of the group, and using its basic characteristics of growth and preferential attachment, the BA scale-free network is selected for the study, which can be used to investigate the sensitivity problem of the model correction.

We denote the number of edges formed by individuals and their neighbors as ‘degree’ (P) and use the BA scale-free network to present the power law of the distribution of complex networks. After matching the degree, relationship strength, and attitude values with the relevant data, it is confirmed that the group communication behavior between individuals will make the opposing parties continuously reinforce their own views, and the trend of bifurcation of online opinions is obvious.

Further, we try to put the connections between nodes into the set network model, fully discuss the relationship between the polarization process of individual attitudes and the complex network structure, and comprehensively consider the network public opinion propagation mechanism and polarization prediction laws. Based on the opinion polarization model of the BA network, we simulated the collision process of individual opinions on the network and predicted the values of public attitudes after more than 400 collisions. In the evolutionary process, it was found that most individuals would actively choose extreme views to battle in the evolution of time. Moreover, when they are in a network group with the same interests as their own, they will keep looking for similar views to their own in the mutual communication with members to reinforce their original ideas.

In terms of social organization, the negative impact of public opinion polarization reversal will intensify contradictions in a disguised way. This makes the output effect of superimposed views one-sided and extreme, with less output space for the positive and effective viewpoint information. Based on the BA network’s opinion polarization model, this paper predicts the trend of public attitudes toward online events. In general, it is conducive to control and govern online opinion polarization events by clearly understanding the dynamics and process of online opinion polarization, simulating public opinion and attitude, and controlling the heat of online public opinion in a timely fashion.

2. Literature Review

2.1. Literature Review Based on J–A Model

The J–A model refers to a new social attitude judgment model proposed by Jager and Amblard [1], which shows that the subject’s attitude structure determines the occurrence of assimilation and alienation effects, which in turn lead to the phenomenon of consensus and polarization. Since then, there have been many studies related to the J–A model. Barash et al. [2] found that the complex infection model could produce highly nonlinear infection diffusion dynamics, and its critical mass had potential practical significance for the prediction of the early stage of transmission activities. Li and Tang [3] proposed the threshold model of group behavior and considered group spatial factors and the strength of social influence relationships among individuals. Based on the group polarization effect, Gabbay et al. [4] added a new explanation, that was, the interaction between individuals with the same interests will trigger the change of attitude to extremes in disguise. Chen et al. [5] used the J–A model to study the rumor diffusion process with

the consideration of individual heterogeneity. Subsequently, they took the imported food safety issue as an example during the COVID-19 pandemic and testified to the efficiency of the proposed model.

From the above analysis, it can be seen that the existing literature uses a relatively small and simple network structure to analyze the changes in social group attitude value, which is different from the structure in complex social networks. In addition, many articles do not give node heterogeneity attributes and do not consider the change of threshold between individuals, which is also far from reality. Based on this, this paper integrates the parameters such as individual conformity and network individual relationship strength into the classical J–A model, which makes the model well adapted to complex, real-world events.

2.2. Literature Review of BA Models

The BA model, or scale-free model, was proposed by Barabasi and Albert in 1999 [6]. They pointed out that the network produced by the BA model had the characteristic of no scale, and the distribution of its network degree values followed a power-law distribution, which was closer to most actual networks. Liu et al. [7] conducted further research and found that the BA model could only generate a network model in which the distribution of degrees follows a power index of 3, while the value in the actual network was usually between 1 and 3. Chen et al. [8] explored a multi-dimensional public opinion process based on a complex network dynamics model in the context of derived topics, and they found that information intensity was the most important influence factor. Zhou et al. [9] found that the network generated by the BA model did not have obvious small-world characteristics, while the actual network usually had both unscale and small-world characteristics. In addition, a large number of scholars have found that the BA model is prone to isolated nodes in the application process and has the characteristics of only “first rich” and not “later rich”, which are not in line with the evolutionary characteristics of the actual network.

Combined with existing research, we find that most scholars focus on the interaction between nodes, emphasizing that the heterogeneous characteristics of individuals themselves will affect the connections between individuals. However, we notice that the connections between nodes are not only related to the properties of the nodes but also the network structure. Taking the BA model as the background, the model degree distribution is generally similar to the power-law distribution, and the connection between nodes has the characteristics of merit. This study will try to give a specific definition of the node's own attributes according to the characteristics of the actual network and emphasize the node characteristics in the network background in order to improve the adaptability of the model in the existing research.

2.3. The Prediction Law of Online Public Opinion Dissemination and Polarization

More and more people have been connected to the world through digital technology in recent years. As a result, public opinion can spread quickly. It is difficult for the public to identify and judge what they want from a large amount of data. At present, more scholars have already conducted in-depth studies on social network structures and the phenomenon of opinion polarization. For example, Wang [10] dissected the dynamic relationship between the factors influencing group attitudes. Chen et al. [11] analyzed the panic emotion propagation process and further identified the emergence process of group panic buying behavior under the COVID-19 pandemic. Wang et al. [12] considered the components of group polarization formation of online public opinion, quantitatively analyzed the mechanism of public opinion polarization dynamics and regulation strategies, and strongly argued the relevance of the main factors of public opinion development through an example simulation. Zhang et al. [13] proposed the intertextual characteristics of the process of generation, diffusion, and polarization in self-media online public opinion. Hatton [14] proposed that preference and significance are related to different individual-level characteristics through the analysis of the European Social Survey and European barometer data. Heizler and Israeli [15] proposed that the tragedy of a specific individual

is more likely to cause the polarization of public opinion than the tragedy of a group. Blake et al. [16] believe that the neutrality and polarization of people's views vary according to sociodemographic characteristics, including age, gender, and education.

The above-mentioned literature has summarized the general law of the polarization phenomenon of online public opinion groups. However, the influencing factors and network structure in the polarization process are seldom analyzed. Based on this, this paper relies on a specific network structure to study the complexity of the polarization mechanism and the process of individual attitude polarization. By fully discussing the relationship between the two, we can understand the communication mechanism of network public opinion and the law of polarization prediction.

3. A Novel Public Opinion Polarization Model Based on BA Network

3.1. Basic J–A Model

Much of the existing research is discussed based on the D–W or J–A models. Both originate from social judgment theory. Social judgment theory analyzes the phenomenon of how an individual's position changes when confronted with different points of view. It is founded on the idea that a person's attitude changes depending on the information that causes the change. If the positive information is close to the individual's initial position, then the information is within the individual's range of acceptance. The view is that the individual is likely to move to the advocated position. That is, individuals are more likely to assimilate similar information. We brought this perspective to the J–A model as an example and obtained the following conclusions.

Individual i and individual j interact with information. The attitude values are based on the distance between them. The rule of attitude value change is related to the difference between the two attitude values. Individuals tend to prefer information close to themselves and reject information farther away, although the quality of attitudes affects the degree of individual interaction. The specific rules are as follows [1].

$$\text{If } |x_i - x_j| < u_i dx_i = \mu \cdot (x_j - x_i) \quad (1)$$

$$\text{If } |x_i - x_j| > t_i dx_i = \mu \cdot (x_i - x_j) \quad (2)$$

where u_i is the threshold when individual i decides to accept the message, t_i is the threshold when individual i rejects the message, and μ is the intensity of the control influence.

3.2. Improved Ideas

The J–A model provides a theoretical basis for information exchange simulation. However, the model does not consider factors such as environmental climate, individual affinity, and individual subordination. This deviates from the actual situation. For example, when the individual's herding is strong, the individual will move towards the stronger party. If the individual's herding is weak, they will adjust and move in a specific direction according to their own and the environmental attitude value. Obviously, the J–A model does not consider the population characteristics and individual attributes, and it does not have practical application value.

At the same time, we assigned the corresponding initial network structure, which aims to meet the environmental conditions in the process of individual interaction. Society is intricate and complex, with varying views on opinion events. In existing studies, small-world networks and BA scale-free networks (from now on referred to as BA networks) are often invoked to simulate realistic social networks to restore real individual attitudinal interaction processes. Small-world networks are derived from the regular network model, in which N nodes relate to probability p on broken edges. Its "degree" distribution is in line with normal distribution. The BA network has a power-law distribution of degrees characterized by a growth mechanism and meritocratic connectivity. The BA network grows while the nodes move to the nodes with a higher degree. In general, both network

structures are closer to reality, and both preserve the diversity in real networks. They both guarantee faster convergence of the algorithm and meet the requirements of the model.

Based on the above considerations, the network group attitude polarization model is improved based on the J–A model. For the attributes of individuals and networks, parameters such as individual followership and strength of personal network relationships are added to the J–A model. The model can be adapted for actual complex events. Moreover, in real society, the network distribution law is mostly reflected in the power-law distribution, and the BA network is used as the agent adjacency model. In addition, we set the effect interval parameters d_1 and d_2 to illustrate the positive or negative effects of relationship strength distribution and followership parameters on group attitude polarization.

3.3. Methodology

3.3.1. J–A Model

The J–A model refers to the new model of social attitude judgment proposed by Jager and Amblard. The main conclusions of the J–A model are as follows: first, the attitude structure of the subject determines the inevitability of its assimilation effect and alienation effect; second, the assimilation effect and the alienation effect have a counter-effect, which will lead to the subject reaching consensus, polarization, and other phenomena. The core idea of the J–A model is based on the theory of social judgment, whereby a person's attitude changes depending on the location of the persuasive information he receives. For example, commentators will be more inclined to make statements with similar views. The idea of this study is to explore the polarization of network public opinion, and the idea is to create a model adapted to different group characteristics and individual attributes, specifically by integrating parameters such as individual conformity and network individual relationship strength into the classical J–A model, so that the model is more suitable for complex, real-world events. The method of model simulation can more intuitively see the assimilation and alienation effects that occur in individual attitudes and the final polarization results.

3.3.2. BA Network

The BA network refers to the scaleless network proposed by Barabasi and Albert that follows power-law distribution. The BA network is based on the growth mechanism and the preferential connection; that is, the size of the BA network shows an increasing trend, and the network nodes will be connected to the nodes with higher proximity. In this study, under the rules of individual attitude interaction, the corresponding initial network structure is assigned to meet the simulation environment. Compared with the intricate interactive networks in reality, the BA network not only retains the diversity of the actual network but also standardizes and simplifies the individual interaction process.

3.3.3. Multi-Agent System

A multi-agent system is a collection of multiple agents that coordinate and serve each other to complete a task together. Its goal is to build large, complex systems into small, easily managed systems that communicate and coordinate with each other and has wide uses in many fields such as platform management [17], the effect of policy implementation [18,19], and so on. A multi-agent system has the following characteristics: first, each agent is independent, autonomous, and can solve a given sub-problem and affect the environment in a specific way; second, agents communicate and coordinate with each other.

The reason why a multi-agent system is selected for this study is precisely because it is suitable for complex and open distributed systems and meets the setting conditions of this paper.

3.4. The Novel Public Opinion Polarization Model

3.4.1. Model Construction

The individuals and connections between the individuals form a population-complex network structure. We define the parameters and features in the network. The model parameters are shown in Table 1 as follows.

Table 1. Model parameters.

| Parameters | Definition |
|------------|--|
| P_i | Degree |
| k_{ij} | Strength of relationship between individuals |
| $X_i(t)$ | Individual attitude value |
| $S_i(t)$ | Environmental attitude value |
| C_i | The clustering coefficient of individuals |
| C | The clustering coefficient of the network |
| M_i | Impact threshold |
| d_1 | Assimilation effect interval |
| d_2 | Exclusion effect interval |
| β | Assimilation degree coefficient |
| γ | Exclusion degree coefficient |
| L | Average distance length |

(1) Degree (P_i)

The number of edges formed by individuals and their neighbors is called the degree. The size of the degree reflects the number of individuals in the nearby area. The higher the number of nearby individuals, the higher the importance of individuals. In social relationships, the higher the importance of the individual, the higher the level of information, with considerable power of speech and definition.

(2) Strength of relationship (k_{ij})

The strength of the relationship describes the closeness of the relationship between individual i and individual j . The model assigns a value to k by a random function. The k -value reflects the extent to which individuals influence each other. The range of the k -value is between integers 1 and 4. The strength of the relationship increases sequentially as the value increases.

(3) Individual attitude value ($X_i(t)$)

The individual attitude value is a quantitative indicator of the individual's attitude at the moment t . $S_i(t)$ is the average of all individual attitude values near individual i at the moment, also known as the integrated environmental attitude value. The expression for $S_i(t)$ is as follows.

$$S_i(t) = \sum_{j=1}^n \frac{2k_{ij} - 1}{4(n-1)} X_j(t) \quad (3)$$

where $S_i^+(t)$ is the summation of positive attitude values, and $S_i(t)$ is the summation of negative attitude values. The distribution of $X_i(t)$ conforms to the Gaussian distribution.

(4) The clustering coefficient of individuals (C_i)

The clustering coefficient of individuals is the ratio of the actual number of edges formed by individual i and neighboring individuals to the maximum number of possible edges. The maximum number of possible sides is $(n^2 - n)/2$. C_i reflects the aggregation of individuals. In general, individuals tend to build groups with a high degree of collection. The expression is as follows.

$$C_i = \frac{2n}{n(n-1)} \quad (4)$$

(5) The clustering coefficient of the network (C)

The clustering coefficient of the network C is the average of the clustering coefficients of all individuals in the network, which quantifies the degree of individual aggregation. The expression is as follows.

$$C = \frac{1}{n-2} \sum_{i=1}^n C_i \quad (5)$$

(6) Impact threshold (M_i)

The impact threshold M_i determines whether an individual's attitude has changed, directly responding to the level of information in the neighborhood. If $M_i \geq 1$, the individual attitude value has changed. Otherwise, the individual does not change. α is the adjustment parameter. The expressions are as follows.

$$\text{If } S_i(t) \geq 0 \quad M_i = \alpha S_i^+(t) + C_i \quad (6)$$

$$\text{If } S_i(t) < 0 \quad M_i = \alpha S_i^-(t) + C_i \quad (7)$$

The interpretation of M_i is as follows. According to the rule, whether an individual's attitude value changes depends on its subordination and the degree of environmental influence. There are three main scenarios. In the first case, the individual is highly submissive, entirely influenced by the environment. The individual will always follow the environment and adjust their attitude. In the second case, the environment around the individual is unbalanced, and there will be a view recognized and dominated by more individuals. In this case, the individual will also favor the strong side. In the third case, the individual's subordination combined with the environment drives the individual to move towards a particular side of the camp.

(7) Effect interval parameters (d_1/d_2)

Effect interval parameters specify the range of individual attitude value changes. If the distance between $X_i(t)$ and $S_i(t)$ is less than d_1 , the individual does not follow the rule of exclusion. Otherwise, individuals do not follow the rules of assimilation.

(8) Assimilation/exclusion degree coefficient (β/γ)

The assimilation/exclusion degree coefficient is the degree of control over the value of individual attitude change. β is the degree coefficient of the assimilation rule, and γ is the degree coefficient of the exclusion rule: both range between 0 and 1.

(9) Average distance length (L)

The average distance length is the average number of distances between individuals in the network [20]. The distance between individuals is the sum of the edges connecting both. The maximum distance is the diameter of the network. The L -value reflects the ability and efficiency of information transfer between individuals. Let the path length between individual i and individual j be l_{ij} . The expression of l_{ij} is as follows.

$$L = \frac{2}{n(n-2)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n-1} l_{ij} \quad (8)$$

3.4.2. Simulation Process

To reveal the mechanism of individual attitude polarization, we established a social networking platform. Research has shown that most complex, real-world networks exhibit power-law distribution, which indicates that most individuals have a small degree, and only a few offer a large degree. Barabasi and Albert proposed BA scale-free networks to study this class of networks that exhibit power-law distributions. The basis of the network is Growth and Preferential attachment. Growth means that the complex network structure will continue to expand. Preferential attachment means that the additional individuals are more inclined to connect with individuals of a higher degree. The specific construction method is as follows.

Step1. Growth: We randomly construct the initial network containing m_0 individuals. Next, we constantly increase the number of individuals, and individuals are randomly connected to the original model.

Step2. Preferential attachment: The probability (π_i) that an individual is connected to the network is positively correlated with the degree (p_i) of nearby individuals. The expression is as follows [6].

$$\pi_i = \sum_{j=1}^n \frac{p_i}{p_j} \tag{9}$$

BA scale-free networks conform to the characteristics of self-organization, synchronization, and emergence mechanisms in actual society. Therefore, we choose the BA scale-free network to study and make corrections for issues such as model sensitivity.

3.4.3. Interaction Rules

In individual interaction, the impact threshold M_i is calculated by first considering the environmental attitude value, relationship strength, and clustering coefficient. Next, a judgment is made: if $M_i \geq 1$, the interaction takes place; otherwise, the individual attitude value does not change in any way.

We set the effect interval d_1/d_2 as the discriminate condition. A discussion of the interaction process follows.

(1) Assimilation rules

If the distance between $X_i(t)$ and $S_i(t)$ is less than d_1 , it is considered that assimilation of individual and environmental attitudes occurs. The rules of attitude value evolution follow the following rules.

$$X_i(t + 1) = (1 - \beta)X_i(t) + \beta S_i(t) \tag{10}$$

(2) Exclusionary rule

If the distance between $X_i(t)$ and $S_i(t)$ is greater than d_2 , the individual and the environmental attitude values are considered in exclusion. The rules of attitude value evolution follow the following rules.

$$X_i(t + 1) = (1 - \gamma)X_i(t) + \gamma S_i(t) \tag{11}$$

(3) Neutrality rules

If none of the above conditions are met, the individual is considered not to make any changes.

The following flow chart (shown in Figure 1) outlines the discriminatory process of the polarization model.

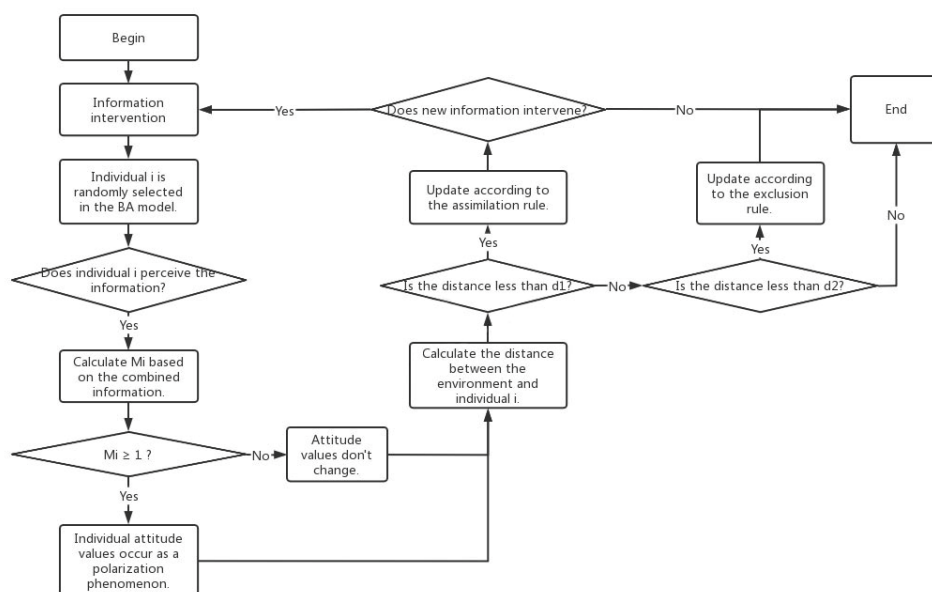


Figure 1. Network population attitude polarization model discrimination process.

4. Experiment Simulation

Because the BA network can present the social network well, this paper defines the BA network as the basis of evolution. By setting different parameter values, this paper makes an intensive study of the evolution process. First, this paper sets the scale of network nodes as 100 and takes $d_1 = 0.3, d_2 = 0.7, \beta = 0.1, \gamma = 0.2$. Through practical operations, this paper finds that after 400 interactions, the individual's attitude will tend to polarize with the surrounding environment, and their attitude value will gradually shift to the two extreme directions of -1 and 1 . However, some individuals will still maintain their original attitude. Furthermore, some individuals will constantly adjust their attitude value in the range of -1 to 1 to achieve a balanced state by adapting to the external environment. Specifically, in the process of attitude evolution, the quantitative distribution of different attitude values under different interaction times is shown in Figure 2 below:

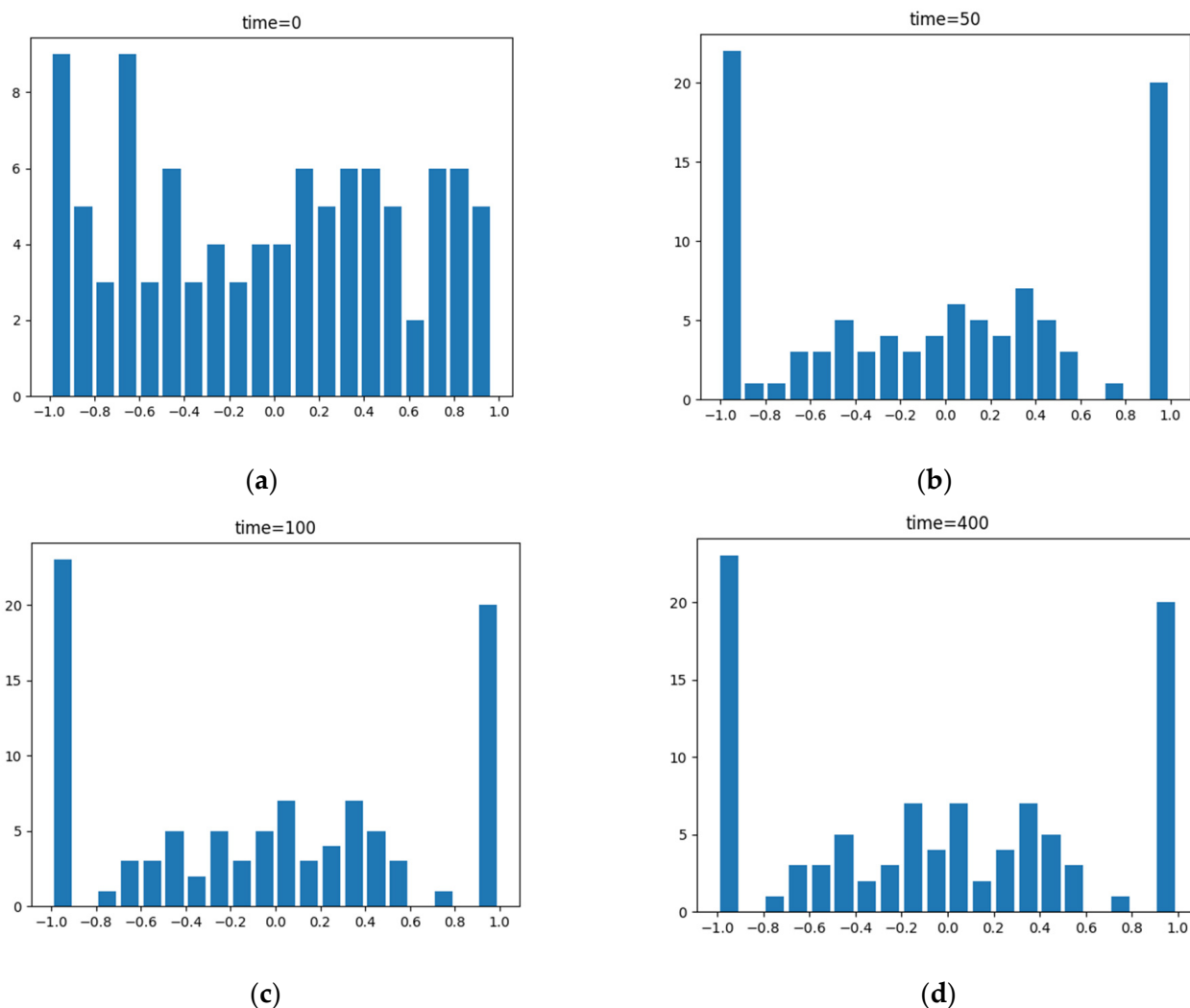


Figure 2. Quantitative distribution of attitude values under different interaction times.

In the initial state, time = 0: the individual attitude value distribution diagram is shown in Figure 2. The abscissa in the diagram represents the individual attitude value, and the ordinate represents the number of individuals corresponding to the attitude value. The simulation results show that in the initial state, the individual attitude value is relatively scattered and evenly distributed. In the initial state, individuals in the group hold their views on events, and there is no clear view of which is right or wrong, or there is a relatively unified opinion. Everyone makes judgments and forms attitude values purely through their views on events. Therefore, in the early stage of event development, there will be no

obvious extreme phenomenon in the attitude value of the group towards an event. With continuous interaction between individuals, when the time is 50, 100, and 400, the attitude value of individuals begins to show a differentiation trend. The specific simulation results are shown in Figure 2.

The number of individuals with a neutral view decreases, while the number of individuals close to 1 and -1 attitude values increases. These changes can obviously show a polarization phenomenon. In the process of increasing the number of interactions, it can be found from the four simulation results that the attitude distribution diagram presented in Figure 2 has been relatively stable. Even a few individuals did not change their attitude values. This paper lists two reasons:

- (1) The low conformity of individuals leads to the failure to reach the threshold of $R > 1$ set by the model. Therefore, the attitude value of other individuals has not influenced them, so their attitude value has been maintained as their initial attitude value.
- (2) Due to the network structure, the gap between the positive and negative sides is very close, making it difficult for the individual to make a choice under the influence of this evenly matched environment. As a result, a few individuals remain neutral from beginning to end, so they never change their attitude value.

In a real event, after each event is polarized, some people will always define the event according to their judgment to maintain their original point of view. Similarly, some individuals will hold a wait-and-see attitude because they cannot understand the truth of the event. However, as the simulation results show, driven by herd mentality, most individuals actively choose an extreme point of view to stand in line, which shows that most individuals show a phenomenon of joining the powerful party to seek security in the face of group events to avoid isolation.

5. An Empirical Case

In this paper, the public opinion polarization model based on the BA network is used to predict the trends in public attitudes towards network events. Based on the 4.1 simulation study, this paper selects the network event of “Hua Chenyu and Zhang Bichen having children unmarried” as a research sample to predict the attitude of online groups. The original data of the case sample is shown in Table 2.

Table 2. Case Sample Public Raw Attitude Values.

| Interval | Count | Interval | Count | Interval | Count | Interval | Count |
|-------------|-------|-------------|-------|-----------|-------|-----------|-------|
| (−1.0,−0.9] | 972 | (−0.5,−0.4] | 488 | (0.0,0.1] | 551 | (0.5,0.6] | 549 |
| (−0.9,−0.8] | 633 | (−0.4,−0.3] | 538 | (0.1,0.2] | 680 | (0.6,0.7] | 1399 |
| (−0.8,−0.7] | 608 | (−0.3,−0.2] | 521 | (0.2,0.3] | 541 | (0.7,0.8] | 768 |
| (−0.7,−0.6] | 514 | (−0.2,−0.1] | 507 | (0.3,0.4] | 658 | (0.8,0.9] | 849 |
| (−0.6,−0.5] | 519 | (−0.1,0.0] | 1511 | (0.4,0.5] | 690 | (0.9,1.0] | 3083 |

Data source: Zhang Bichen’s long article posted on Weibo at 17:51 on 22 January 2021.

On 21 January 2021, an unknown netizen broke the news on the Internet: a top male star in the entertainment industry married and had children, the woman was also an insider, and the child was registered when he was one year old. Another netizen revealed that the male star was Hua. On the same day, Hua’s cousin posted a denial. At 17:45 on 22 January 2021, Hua admitted to having a child with Zhang. At 17:51, Zhang also confirmed this by posting a long article on Weibo under his real name.

The incident of “Hua and Zhang having a child out of wedlock” caused an uproar on the Internet. With the continuous revelation of news related to the incident, netizens had a heated discussion, and the public view gradually became distinct and polarized. In this paper, the BA network simulates the state of a real social network, and we use the polarization model of public opinion to simulate and predict the evolution of this event. Through web crawlers, this article obtained the original data set of public attitudes under Zhang’s long post on Weibo at 17:51 on 22 January 2021. In this paper, Python

NLP natural language processing and machine learning are used to obtain 16,579 valid data, thereby determining the size of the instance network nodes. According to the actual situation of the case, this paper determines that the assimilation degree coefficient is 0.005, the repulsion degree coefficient is 0.01, the assimilation effect band distance is 0.3, and the repulsion effect band distance is 0.7. Based on existing stop word rules and machine learning recognition methods, this article assigns a positive or negative attitude value to the initial valid comment. With the soaring heat of the incident, the matter has aroused heated discussion among the public. In the environment of constantly revising the direction of public opinion, the views of network individuals collide, resulting in different degrees of change in their attitudes. This article regards this transformation as a process of individual interaction. Based on the polarization model of public opinion based on the BA network, this paper simulates the process of the collision of individual views on a network and predicts the value of public attitude after the occurrence of 10, 50, 100, and 400 such situations. The forecast statistics are shown in Table 3.

Table 3. Polarization predictions of public attitude values after interaction.

| Time | Attitude Value | | | |
|------|----------------|------------|-----------|-----------|
| | (−1.0,−0.9] | (−0.1,0.0] | (0.0,0.1] | (0.9,1.0] |
| 10 | 1570 | 972 | 1113 | 3477 |
| 50 | 2926 | 976 | 1152 | 4121 |
| 100 | 3058 | 965 | 1154 | 4230 |
| 400 | 3071 | 913 | 954 | 4269 |

We captured 16,579 valid comments from Zhang’s statement at 17:51 on 22 January 2021. Figure 3 is valid comments from eight hours after the long article was published. This paper uses certain rules to assign different attitude values to different comments, and the distribution of individual attitude values is shown in Figure 3. The original public attitude value from the case sample was analyzed as follows: 2062 people held a neutral attitude towards the incident, and 4055 people held an absolute positive or negative attitude. At this time, the distribution of public attitude values was relatively even. Network individuals expressed their opinions on the event, and there was no obvious polarization tendency in network public opinion and no clear and unified view. For the incident, many network users still held a wait-and-see attitude and looked forward to the follow-up development of the event; at the same time, there were also a considerable number of netizens who held a “blessing” support attitude or a “not optimistic” opposition attitude.

Based on the model above, the prediction results of the attitude value distribution of the sample dataset after different interactions are shown in Figure 4. After 5 h, 1 day, 2 days, and 8 days of simulated interaction, the polarization trend of public attitudes gradually became obvious, and the number of neutral network individuals began to decrease. From the forecast results, it can be seen that from the beginning of Zhang’s statement at 17:51 on 22 January 2021 to 8 days after the statement was released, the proportion of network users with an absolute positive or absolute negative attitude rose from 24.46% to 44.27%, while the proportion of neutral internet users decreased from only 12.44% to 11.26%. Obviously, the proportion of network individuals who show an absolute attitude has increased significantly, and the polarization trend of network public opinion has become more and more obvious, while the numbers of netizens who indicate a neutral attitude has remained at a low level, and the range of changes is small. With the clarity of the incident, the views of netizens have become more distinct. However, there are still some who hold a neutral attitude, such as “eating melons”, and do not express personal views with a clear attitude.

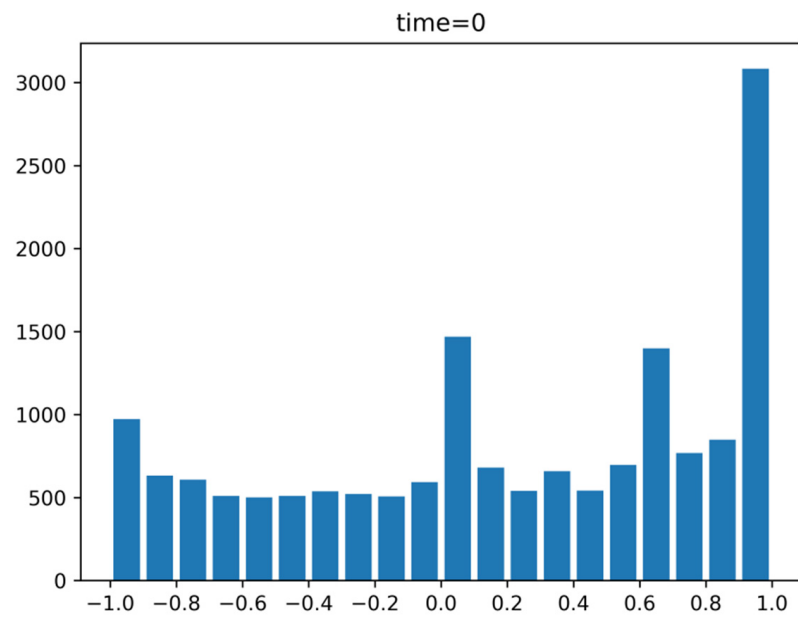


Figure 3. Distribution of public raw attitude values.

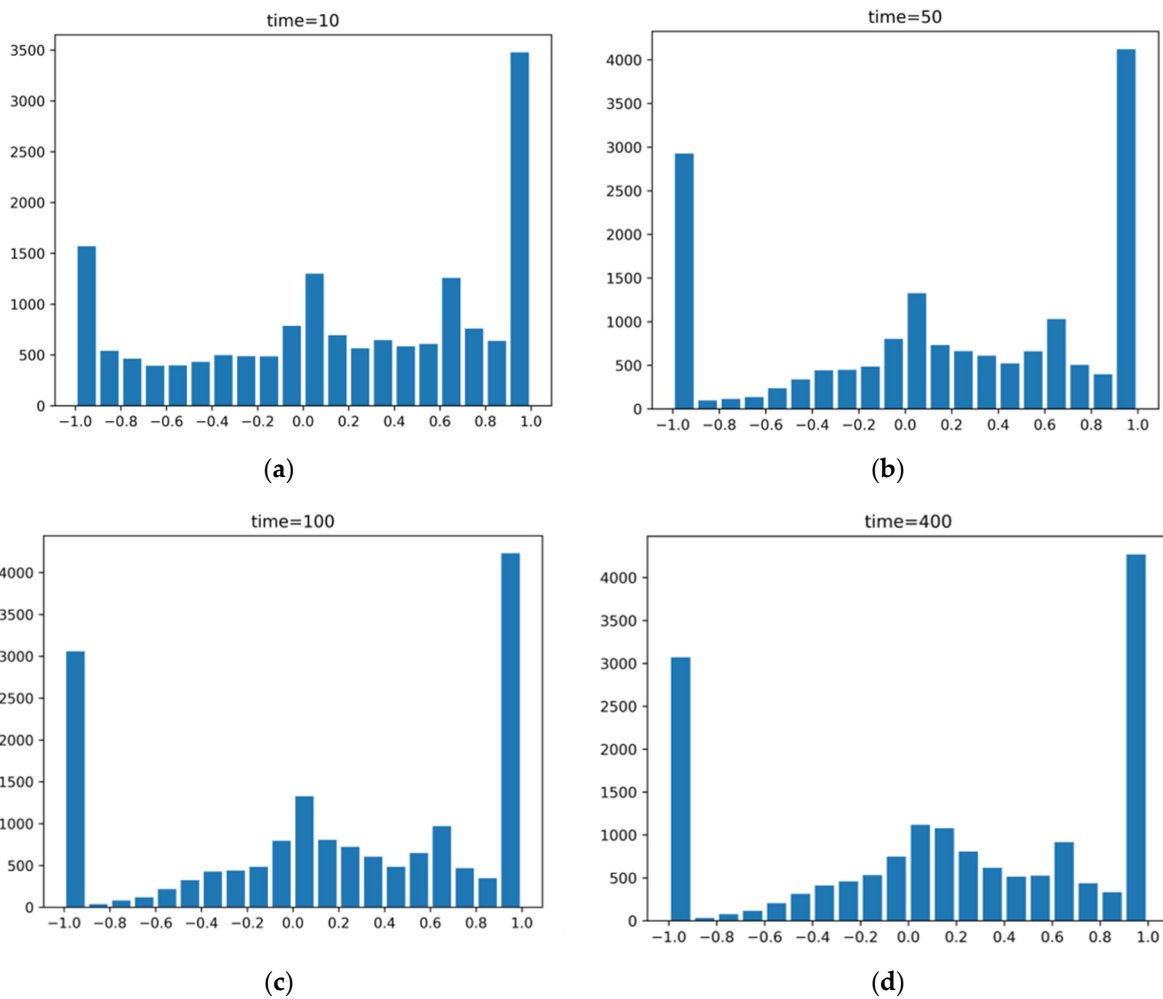


Figure 4. Prediction of attitude value distribution under different interactions.

From the prediction results of attitude value distribution, it was found that with the continuous occurrence of interaction, the growth rate of the proportion of network

individuals with an absolute attitude is from fast to slow, while the proportion of someone with a neutral attitude does not change much. From the simulated interaction results of the four time nodes of 5 h, 1 day, 2 days, and 8 days, it can be seen that from the beginning of Zhang's long article at 17:51 on 22 January 2021 to one day after the incident, the growth rate of the proportion of users who showed an absolute attitude increased from 24.45% to 39.64%, and after the incident, the growth rate slowed down from 39.64% to 0.71%. In summary, after one day of simulated interaction, the trend of the attitude distribution map stabilized.

Individuals participating in the evolution of network public opinion have the characteristics of subjective judgment and labeling processing, as well as passive acceptance and loss of subjectivity. There are countless exchanges of opinions between individuals, which eventually form group behavior, and individual behavior is affected by group behavior. The phenomenon of polarization of online groups mostly occurs in the field of opinions, and the result is mostly that the views are further differentiated and opposed, and the opposing parties continue to strengthen their views in the group discussion, and it is obvious that they cannot merge. At the same time, when a person is in a network group with similar interests or views as a link, he will exchange common ideas and understandings with other members of the group or constantly look for views like his, trying to obtain psychological comfort and strengthen his original concepts.

6. Conclusions

6.1. Summary

In order to explore the propagation structure of online public opinion and analyze the logic of extreme public opinion in the social context of the big data era and the developed self-media network, we constructed a BA network model, simulated and analyzed the trend of public attitudes toward online events and the polarization mechanism of individual attitudes, verified the propagation mechanism and polarization prediction law of online public opinion through experiments, confirmed the validity of the BA model, and obtained the following conclusions through simulation experiments.

- (1) Individuals' attitudes toward public opinion are related to their surroundings. When an individual's attitude changes toward an event, it is often due to the influence of other perspectives in communicating with other individuals. Through the J–A model, we can understand that the value of an individual's attitude at a particular moment depends on their attitude and the surrounding environment at the last moment. Based on this principle, we investigated the specific changes in attitude values.
- (2) The discrimination of attitudinal values depends on distance. Based on the difference in attitude values, the model specifies interaction rules to determine the attitude preference for the next moment. However, there are different positive effects between two individuals. The degree of influence is also inconsistent between individuals. It is worth discussing in what form the surrounding environment impacts the individual. The J–A model provides an idea. We consider parameters such as individual followership, the strength of network relationships, etc., and assign the corresponding values by specific rules. To obtain the final polarization algorithm, we need to combine the law of related network distribution and choose the BA network as the agent adjacency model.
- (3) The group communication behavior between individuals makes the opposing sides continuously reinforce their views and gradually form the polarization of online opinions. The evolutionary results show that there is a clear polarization phenomenon at the beginning of the evolutionary stage. As the polarization process proceeds, the fluctuations level off, and the level of inter-individual following is low. It fails to reach the influence threshold, causing the attitudes of several individuals to stay in the initial state. Moreover, the difference in network structure makes the change of individuals always within a local interval, even when some individuals have difficulty making a choice and remain neutral. With the deepening of polarization, the proportion of

network individuals with absolute attitudes increases significantly, and the trend of polarization of double-linked opinions becomes more and more obvious. On the other hand, the proportion of Internet individuals who expressed neutral attitudes remained low and slightly changed. With the development of the event, the Internet users' ideas about the event become more and more distinct. Based on the results of this simulation, we give policy recommendations and discuss the problems in the experimental process in the following sections.

6.2. Policy Recommendations

With the prevalence of the trend of network intelligence and the expansion of network coverage, the predicament of information blocking has changed, and human networked society has risen rapidly. At the same time, a large amount of true and false information causes confusion, and false information spreads to the public, misleading moral values, laying down hidden danger for the maintenance of a harmonious environment for online public opinion. The government should take timely measures for the real-time, changing, networked environment to create a just and harmonious network environment for citizens and eradicate some unsettling hidden social dangers. To better cope with the polarization of network public opinion, this paper puts forward the following suggestions:

- (1) Improve the public opinion monitoring mechanism and build a harmonious network order

Internet public opinion is easy to use to guide the views of the masses, and if it is not properly supervised, it is easy to mislead the masses. Even the evolution of online public opinion may cause the masses to fall into a vicious circle of emotional or even group polarization. At the same time, freedom of speech on the Internet promotes the interaction of people's information and the collision of thinking and produces a situation in which false information and misinformation affect the emotions and thoughts of viewers to achieve the publisher's personal, bad goals. Therefore, the normality of online public opinion requires the cooperation of a strong monitoring mechanism to ensure the safety and order of cyberspace to some extent.

Although there are some online information reporting platforms, the government's use of them is inefficient, and even the processing and feedback of reporting information is not timely. The government should further improve the monitoring mechanism of network public opinion, not only relying on computer keyword recognition and big data processing technology but also mobilizing social forces to help network monitoring. Reporting information is more accurate than keyword recognition technology. Only by screening false information and reasonably guiding the direction of public opinion can some netizens who have difficulty judging information be protected and not misled or suffer some losses due to being deceived. The government actively participates in the governance of cyberspace. It will contribute to the harmonious co-construction and sharing of the network.

- (2) Rebuild the accountability mechanism for public opinion and crackdown on online anomie

Every occurrence of online public opinion polarization is a test of the government's credibility. Whether the government's accountability mechanism is sound and whether other aftermath measures are appropriate and timely will affect the government's image. As a public servant of the people, the government should actively investigate disharmonious factors or improper regulation by the government itself after the negative impact of online public opinion and safeguard the legitimate interests of the people. Only in this way can the credibility of the government be maintained.

The reconstruction of the network public opinion accountability mechanism is a necessary part of the government's governance of the network environment. Relevant government departments can start by conducting satisfaction surveys on network individuals related to the governance of the network environment. Through this post-mortem investigation, the government can clarify its image positioning in the eyes of the public and

understand its own problems. Only when the crisis is handled properly and the masses are satisfied will the negative influence of online public opinion be weakened, and the rebound will be avoided. At the same time, relevant government departments should also be held accountable for illegal acts that maliciously affect public order and damage the interests of others. Only by thoroughly cracking down on online anomie can we give a warning to criminals and, at the same time, put an end to attempts to conduct anomie because of luck.

(3) Guide netizens' values and transmit positive energy of public opinion

Internet public opinion has both positive and negative effects, and in the contemporary era, when the Internet closely links everyone, positive and negative emotions are more likely to spread and affect the public. Therefore, it is particularly important to guide netizens' values in a timely and positive manner and transmit positive energy of public opinion.

For different network groups, different measures should be taken to guide and pass on the "right medicine". Neutral internet users with many fans and high membership levels not only have a stable stance but also have a relatively large fan base, a high degree of activity, and a strong potential to control public opinion. Therefore, such network users can be used as a key group for public opinion dissemination guidance and polarization intervention, and the background of social platforms should increase efforts to maintain key groups, promote content that is conducive to guiding the development of netizens' values in a positive direction, and transmit positive public opinion. For some network users who pay less attention to hot events because their sources of information are relatively closed and single and passive, they can push comprehensive information to this group in a targeted manner, which helps the group form an objective and comprehensive understanding of hot events. At the same time, increasing the frequency of pushing positive content to enhance the positive experience of network users helps to transmit positive public opinion. In addition to paying attention to the above two parts of network users, high-impact and highly active groups can be found through background big data, and advanced technology can be used to seize the opportunity of positive information exposure and play and enhance leadership.

(4) Enhance the image of the government and maximize the interests of society

Internet public opinion is usually inextricably linked to civil rights, people's livelihood, and real society and the problems it exposes or the focus of discussion are related to this. Therefore, the government plays an important role in the management of network public opinion, which is conducive to enhancing the image and playing a more decisive role in maximizing the interests of society.

The government can use advanced technology and big data platforms to strengthen the management of the two major sources of information dissemination, official media and self-media. First, to standardize the operation and management mechanism of official media, we should put social benefits in the first place, standardize and restrain professional journalists, and correct the one-sided pursuit of traffic realization by some bad official media; at the same time, increase support for official media in terms of policies, funds and talent introduction. Second, through the public or industry associations to regulate the development of self-media in the right direction, guide them to carry out activities to produce and disseminate positive energy information, and create a positive atmosphere of public opinion and emotion among the public.

The government focuses on governing online public opinion to further consolidate its position and enhance its image. At the same time, in the process of standardization and guidance, the interests of all parties maximize social interests after the game.

This paper discusses the extreme model of public opinion based on the BA network, enriches the theory and method of polarization of online group attitudes, and predicts the network public opinion of hot events through empirical analysis, providing practical guidance for the intervention and guidance of network public opinion, which is of great significance for promoting the modernization of national governance capabilities.

6.3. Limitations and Future Research Directions

The present study has limitations in some respects. First, the model is a poor fit for the phenomenon of group attitude reversal. Internet public opinion changes rapidly, and as events develop, the final direction may not always be consistent with the initial state. People's attitudes will undergo drastic shifts in the process, which is often difficult to simulate by polarization models. Later, we will enrich and extend the model to address the conditions and trends of public opinion reversal. Second, the example simulation process includes only one public opinion event with a small sample size. This study can conduct practical simulation experiments by collecting different events and a larger sample size. By simulating multiple occasions, we can effectively improve the model's generalizability. Third, there is some bias in analyzing attitude values during the experiment. This study uses a machine-learning algorithm to assign attitude values to event comments. It is crucial to extract group attitudes from the text effectively. The algorithm's limitations primarily influence the encoding operation of the training set. If the algorithm can accurately extract attitude values from buzzwords, expressions, and punctuation, the error of the model will be significantly reduced. There is still room for improvement in the example algorithm piece.

Author Contributions: Conceptualization, T.C.; data curation, R.Z.; formal analysis, Y.Z.; software, W.D.; visualization, Y.Y. (Yuanyuan Yu); writing—original draft, Y.Y. (Yuanjian Ye). All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Zhejiang Provincial Natural Science Foundation of China (Grant No. LY22G010003), the 2020 National Innovation and Entrepreneurship Training Program (No.202010353008), the 2020 Science and Technology Innovation Activity Program for College Students and New Seedling Talent Program of Zhejiang Province (No.2021R408050), and the 2019 University-level College Student Innovation and Entrepreneurship Project of Zhejiang Gongshang University (No.CX202002021).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

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

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Jager, W.; Amblard, F. Uniformity, bipolarization and pluriformity captured as generic stylized behavior with an agent-based simulation model of attitude change. *Comput. Math. Organ. Theory* **2005**, *10*, 295–303. [\[CrossRef\]](#)
2. Barash, V.; Cameron, C.; Macy, M. Critical phenomena in complex contagions. *Soc. Netw.* **2012**, *34*, 451–461. [\[CrossRef\]](#)
3. Li, Z.; Tang, X. Threshold model of collective action. *J. Syst. Sci. Math. Sci.* **2014**, *34*, 550.
4. Gabbay, M.; Kelly, Z.; Reedy, J.; Gastil, J. Frame-induced group polarization in small discussion networks. *Soc. Psychol. Q.* **2018**, *81*, 248–271. [\[CrossRef\]](#)
5. Chen, T.; Rong, J.; Yang, J.; Cong, G. Modeling Rumor Diffusion Process with the Consideration of Individual Heterogeneity: Take the Imported Food Safety Issue as an Example during the COVID-19 Pandemic. *Front. Public Health* **2022**, *10*, 781691. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Barabasi, A.L.; Albert, R. Emergence of scaling in random networks. *Science* **1999**, *286*, 509–512. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Tao, L.; Zhong, C.; Chen, X. Overview of Rehydration Network Theory and Application Research. *Syst. Eng.* **2005**, *23*, 1–7.
8. Chen, T.; Yin, X.; Yang, J.; Cong, G.; Li, G. Modeling Multi-Dimensional Public Opinion Process Based on Complex Network Dynamics Model in the Context of Derived Topics. *Axioms* **2021**, *10*, 270. [\[CrossRef\]](#)
9. Zhou, T.; Bai, W.J.; Wang, B.H.; Liu, Z.J.; Yan, G. A brief review of complex networks. *Physics* **2005**, *34*, 31–36.
10. Wang, G. Dynamic Model and Simulation Analysis of Group Polarization of Online Public Opinion. *J. Intell.* **2012**, *3*, 20–24.
11. Chen, T.; Jin, Y.; Yang, J.; Cong, G. Identifying emergence process of group panic buying behavior under the COVID-19 pandemic. *J. Retail. Consum. Serv.* **2022**, *67*, 102970. [\[CrossRef\]](#)
12. Wang, F.; Zhang, S.; Wei, Y. Simulation of the Dynamics of Group Polarization Phenomenon in Online Public Opinion and Strategies for Regulating It. *Police Technol.* **2017**, *4*, 37–40.

13. Zhang, J.; Zhang, Y.; Zhao, F. Inter textuality: An Energy Logic Model for the Generation, Diffusion and Polarization of Self-media Network Public Opinion. *Inf. Sci.* **2020**, *38*, 3–9.
14. Hatton, T.J. Public opinion on immigration in Europe: Preference and salience. *Eur. J. Political Econ.* **2021**, *66*, 101969. [[CrossRef](#)]
15. Heizler, O.; Israeli, O. The identifiable victim effect and public opinion to ward immigration; a natural experiment study. *J. Behav. Exp. Econ.* **2021**, *93*, 101713. [[CrossRef](#)]
16. Blake, K.D.; Gaysynsky, A.; Mayne, R.G.; Seidenberg, A.B.; Kaufman, A.; D'Angelo, H.; Roditis, M.; Vollinger, R.E., Jr. US public opinion to ward policy restrictions to limit tobacco product placement and advertising at point-of-sale and on social media. *Prev. Med.* **2022**, *155*, 106930. [[CrossRef](#)] [[PubMed](#)]
17. Chen, T.; Peng, L.; Yang, J.; Cong, G.; Li, G. Evolutionary Game of Multi-Subjects in Live Streaming and Governance Strategies Based on Social Preference Theory during the COVID-19 Pandemic. *Mathematics* **2021**, *9*, 2743. [[CrossRef](#)]
18. Chen, T.; Qiu, Y.; Wang, B.; Yang, J. Analysis of Effects on the Dual Circulation Promotion Policy for Cross-Border E-Commerce B2B Export Trade Based on System Dynamics during COVID-19. *Systems* **2022**, *10*, 13. [[CrossRef](#)]
19. Chen, T.; Peng, L.; Yin, X.; Jing, B.; Yang, J.; Cong, G.; Li, G. A policy category analysis model for tourism promotion in china during the COVID-19 pandemic based on data mining and binary regression. *Risk Manag. Healthc. Policy* **2020**, *13*, 3211. [[CrossRef](#)] [[PubMed](#)]
20. Fang, J.; Wang, X.; Zheng, Z.; Bi, Q.; Di, Z.R.; Xiang, L. New Interdisciplinary Science: Network Science. *Prog. Phys.* **2007**, *27*, 239.