

## Research Article

# Research on the Emotional Evolution Mechanism of Network Public Opinion Based on an Information Ecosystem

Ying Qu , Hongmei Tian , and Hong Chen 

*School of Economics and Management, Hebei University of Science and Technology, Shijiazhuang 050018, Hebei, China*

Correspondence should be addressed to Hong Chen; 2503596708@qq.com

Received 12 April 2022; Accepted 2 August 2022; Published 29 August 2022

Academic Editor: Manuel De la Sen

Copyright © 2022 Ying Qu et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

As an important carrier of public emotion expression, public opinion spreads on a large scale with the continuous upgrading of social networks, and effectively controlling the spreading process of public opinion is an essential topic of contemporary social research. In view of the competition between positive and negative information in the process of public opinion dissemination, this paper introduces the theory of emotional infection and proposes a network public opinion communication model based on emotional contagion, considering the reinforcement effect of different individual mentalities and the influence of government intervention. Based on the data from the COVID-19 epidemic situation, MATLAB simulation technology is used to verify the validity of the model, and the effect of strengthening the validity and government intervention on public opinion control is discussed. According to the experiment, three conclusions have been come up with. First, a positive reinforcement effect can enhance the ignorant participants' ability to maintain the same emotion as the infected information. When positive information repeatedly stimulates the ignorant, it will positively strengthen the ability of people with a positive mentality to maintain positive emotions, which is significantly beneficial to public opinion control. Its essence is to increase the effect of positive information's belief factor on the dynamic infection rate. When negative information repeatedly stimulates an ignorant person, it will positively strengthen the ability of the person with a negative attitude to maintain negative emotion, which is not conducive to public opinion control. Second, a negative reinforcement effect will strengthen the ignorant ability to change the same emotion as the infected information. When negative information repeatedly stimulates the ignorant, the negative reinforcement effect will strengthen the positive people's ability to change negative information into positive emotion, which is significantly beneficial to public opinion control. Its essence is to increase the effect of suspicion factor on the dynamic immunization rate. It will strengthen the positive mentality and negative mentality into the path of immunization, which is beneficial to epidemic control. When positive information repeatedly stimulates the ignorant, it will negatively strengthen the ability of the negative mentality to change the positive information into negative emotions, which is not beneficial to the control of public opinion. It will be harmful to strengthen the path of positive and negative mentality into immunization, which is beneficial to epidemic control. Third, the earlier the government intervenes in public opinion, the better it will be. The essence of intervention is to decrease the dynamic incitement rate.

## 1. Introduction

The rapid development of information technology and the Internet has greatly enriched the dissemination of public opinion information. Due to the virtual and anonymous nature of the Internet [1], the Internet has become an important gathering place to express public interests, emotions, and thoughts [2]. When public expression gradually accumulated and externalized into attitudes, netizens' opinions collided with each other in

communication and discussion, thus promoting the formation of online public opinions [3]. In essence, the development of online public opinion is the result of competition between positive and negative emotions [4]. If negative emotions prevail on the Internet, public opinion will develop negatively; otherwise, public opinion will develop positively. Infection with negative emotions is more likely to stimulate the spread and fermentation of public opinion. If it is not guided and controlled in time, it will have a negative impact on social stability [5].

Many scholars have carried out related research on the emotional issues of online public opinion information in recent years. From the perspective of emotional dimension theory, some scholars believe that personal preference [6], personal opinion [7], and personal intimacy [8] are the biggest drivers of public opinion, and group emotions and emotions are essential deciding factors in the change of public opinion. From the perspective of dynamic model theory, other scholars have conducted dynamic theme analysis [9], emotional clustering [10], and emotional classification [11] on public opinion texts. The most commonly used models are the LDA theme model [12], BTM two-word theme model [13], and Count Vectorizer model [14]. The existing research not only identifies the factors that affect public opinion information emotion at the microlevel but also reflects the development trend of public opinion at the macrolevel.

At the microlevel, there are still many factors that affect public opinion. Based on the theory of emotional contagion, starting from the positive and negative aspects of the information itself, we construct an improved SIR model based on the theory of emotional contagion. And we use the tool named MATLAB to intuitively display the impact of different information reinforcement on positive and negative emotional people. Based on this, relevant suggestions are put forward to help the government control public opinion.

The novel point is that this manuscript not only introduces the theory of emotional infection into public opinion communication, and discusses the differences in the communication of information of different emotions, considering the emotional factors carried by public opinion information, but also divides the infected people into those with positive emotions and those with negative emotions to study the dynamic strengthening effect of positive and negative information on netizens' emotions and the impact of government's positive and negative intervention on public opinion dissemination. The main contributions can be summarized as follows. On the basis of the improved SIR model, we use MATLAB to simulate the dynamic strengthening effect of positive and negative information on public opinion dissemination, and the impact of government's positive and negative intervention on public opinion dissemination, and demonstrate the effectiveness of the model through examples. Based on the simulation results, we summarize three findings. First of all, when positive unknown person ( $S^+$ ) touches more positive information about the event, the ability of the unknown person to maintain positive emotions towards public opinion will be strengthened. When the positive unknowns are exposed to negative information many times, they still maintain a positive attitude towards public opinion, which is negative reinforcement. Secondly, the essence of positive reinforcement is to increase the effect of the belief factor on netizens, and the essence of negative reinforcement is to increase the effect of the suspicion factor on netizens. Finally, the government's timely positive guidance of public opinion can reduce the impact of the incitement rate on netizens and improve the effect of the purification rate on netizens.

## 2. Related Works

For the definition of network public opinion, Rousseau, a famous French thinker, put forward the concept of "public opinion" in his book on a social contract. Later, scholars Noell Neumann and Braucher Birgit found that the views of the minority in the network would be submerged in the public opinion from the perspective of communication, forming a consistent network public opinion [15, 16]. With the development and change of the times, the concept of network public opinion is gradually enriched and extended. At the present stage, scholars generally believe that online public opinion is a collection of cognition, attitude, emotion, and behavioral tendency generated by people spreading related events through the Internet after various social events are stimulated [17].

The evolution of Internet public opinion is developing with the growth of hot events discussed by netizens. According to the development process of hot events, scholars focus on prevention in advance, response in the event, and handling after the event.

Firstly, monitoring and early warning in advance of transmission. In recent years, scholars' research on network public opinion monitoring and early warning has two characteristics: the number of research results has soared and the theoretical level has extended to the practical level. But if we want to prevent it beforehand, the most important thing is the choice and application of technology [18]. Some scholars tend to study from experiments and theories, and the information technology method of network public opinion monitoring is obtained [19]. Some scholars focus on building networks that use big data technology to predict [20]. At present, the cloud-based monitoring system [21] is hot research area because it improves the shortcomings of traditional public opinion monitoring data collection and analysis. Li G proposed a cloud computing framework for Internet detection [22].

The second is the research on the mechanism of medium-term communication. Most scholars still focus on the disseminating and controlling of information after the incident, preferring to respond to public opinion after the incident. To study the communication mechanism of online public opinion, we must first understand the life cycle of public opinion. At present, the widely accepted life cycle theory of online public opinion is the four-stage theory put forward by Huang et al. [23]. According to the different stages of the life cycle, the law of online public opinion has been extensively studied, such as early warning mechanism [24], evolution mechanism [25], coupling mechanism [26], collaborative governance mechanism [27], emergency mechanism [28], and so on.

The third is the guiding governance in the later stage of communication. The guidance and governance of network public opinion are mainly the guidance of mainstream media, government, and multi-agent collaborative governance. Mainstream media and government guidance complement each other. The mainstream media communicate with government functional departments, predict the trend of events [29], and the government links the media's public

opinion forces to start the social coordination mechanism and functions [30] and guide the trend of online public opinion. Collaborative governance is mainly studied from the concept [31], collaborative mechanism [27], and collaborative purpose [32]. At present, the focus of research is how to promote the participation of collaborative topics and strengthen cooperation among various subjects [33].

Through the above analysis, we can find that scholars have done extensive research on online public opinion, which has laid a theoretical foundation for the discussion in this paper. However, there are relatively few studies on the evolution of public opinion and sentiment, and further research is needed. The main innovation of Dhiman's literature is to propose a meta-heuristic algorithm that considers the cooperative behavior of animals and their social relations, which improves the accuracy of the algorithm to a certain extent and is more in line with the reality [34–36].

This study draws on Dhiman's ideas in the improvement of the algorithm, considers the positive and negative effects of information on the positive and negative emotions of netizens, describes the dynamic evolution process of the interaction of positive and negative information, and explores the nature of emotional contagion. Vaishnav et al. analyzed the impact in terms of total cases, total recovered cases, and total deaths reported during the COVID-19 epidemic by utilizing machine learning algorithms [37].

The manuscript draws on the data of Weibo during the COVID-19 epidemic, and uses an improved algorithm to analyze and study the data. The recovered and the deceased are regarded as those who are immune to public opinion ( $R$ ), and the ignorant ( $S$ ) refers to people who are not involved in public opinion originally spread. According to the different attitudes of individuals toward things, they are divided into positive ( $S+$ ) and negative ( $S-$ ).

The manuscript has found a useful way to control the spread of public opinion. Finally, the "COVID-19 epidemic" data are used to verify the effectiveness of the improved model.

### 3. Model

**3.1. Information Ecosystem.** The information ecosystem in social media generally adopts the "three elements theory," which mainly includes the information subject, information object, and information environment [22]. In this study, the information subject is the netizen who uses mobile information technology to participate in public opinion communication to express their views, attitudes, and tendencies. Public opinion is information. It is the specific content that netizens use to express their emotions, cognition, attitudes, and opinions in the public opinion space for topical events or phenomena. The information environment is the scene of public opinion spreading on the Internet.

**3.1.1. Netizen.** Based on the infectious disease model, all people are divided into four categories: ignorant, positive, negative, and immune. The ignorant ( $S$ ) refers to people who are not involved in public opinion originally spread.

According to the different attitudes of individuals toward things, they are divided into positive ( $S+$ ) and negative ( $S-$ ). A positive spreader ( $P$ ) is a person who spreads positive information. A negative propagator ( $N$ ) is someone who spreads negative information. Immune ( $R$ ) is someone who no longer spreads information (see Table 1).

**3.1.2. Information.** Information can be divided into positive information and negative information. Positive information refers to positive opinions that reflect the actual situation of objective facts and safeguard the interests of most people. Negative information refers to one-sided and distorted opinions that harm society. Positive information and negative information can be transformed into each other, mainly influenced by government intervention. Government positive intervention of information means objective and positive information released by the government, while government negative intervention of information means vague, uncertain, and negative information released by the government (see Table 2).

**3.1.3. Information Environment.** Because the same ignorant is infected with the same emotional information at different times, the information environment of online public opinion is divided into static and dynamic scenes. The static state is when the same ignorant is infected by an item of positive or negative single information and then passes the information on. The main parameters are static infection rate, purification rate, incitement rate, and immunization rate (see Table 3). The dynamic state is a scene where the same ignorant is infected with positive or negative information for many times. The main parameters are the positive infection rate, negative infection rate, purification rate, and incitement rate under dynamic conditions.

- (1) *Static Environment.* Parameters in the static scene mainly include positive and negative infection rate, purification rate, incitement rate, and immunization rate.
- (2) *Dynamic Environment.* Belief factor is the degree to which the same ignorant person believes and is willing to accept this emotion after being repeatedly infected by the same emotional spreaders, indicated by  $b$ .

Suspicion factor: the degree to which the same ignorant person is suspicious and bored after being repeatedly infected by the same emotional spreaders and feels a certain risk in public opinion, represented by  $r$ .

Positive emotional transfer factor: the degree to which negative spreaders are purified to be positive due to government intervention, represented by  $k_1$ .

Negative emotional transfer factor: the degree to which positive spreaders are incited to be negative due to government intervention. It is represented by  $k_2$ .

(1) *Dynamic Infection Rate.* It is mentioned in public relations that the more times a person touches certain information, the easier to accept it [12]. When the same ignorant

TABLE 1: Different states of netizens.

	Condition	Name	Describe
S	S+	Positive ignorant	Be optimistic about things
	S-	Negative ignorant	Be pessimistic about things
P	P	Positive spreader	Spreads positive information
N	N	Negative spreader	Spreads negative information
R	R	Immune	Ignores and stops spreading information

TABLE 2: Description table of different information.





Legend	Name	Characteristic
	Positive information	Be objective, safeguard the interests of most people and be positive
	Negative information	One-sided, distorted facts, negative influence
	Government positive intervention information	Government releases objective and positive information
	Government negative intervention information	Government releases ambiguous, uncertain, and negative information

TABLE 3: Description table of parameters in the static state.

Parameter	Name	Meaning
$\lambda$	Positive infection rate	The probability of the ignorant being exposed to positive information and becoming a positive spreader
$\gamma$	Negative infection rate	The probability of the ignorant being exposed to negative information and becoming a negative spreader
$\mu$	Purification rate	The probability of a negative spreader purified into a positive spreader
$\beta$	Incitement rate	The probability of a positive spreader incited to become a negative spreader
$\alpha$	Immunization rate	The probability of ignoring or quitting the ecosystem

person is repeatedly stimulated by positive information, the easier it is for him to accept positive information and transform into a positive spreader. Similarly, if you are repeatedly stimulated by negative information, it is easier for you to accept it and transform into a negative spreader. The effect can strengthen the ignorant person's ability to maintain the same emotion as the infected information is defined as the positive reinforcement effect, defined by indicated. The dynamic infection rate is the most direct embodiment of the positive reinforcement effect, which has a certain quantitative relationship with belief factor  $b$ , suspicion factor  $r$ , and contact times  $n$ . It can be expressed dynamically by the following formula:

$$\lambda_n = \begin{bmatrix} \lambda_1 = \lambda_0(1+b) - r\lambda_0(1+b), \\ \lambda_2 = \lambda_1(1+b) - r\lambda_1(1+b), \\ \dots \\ \lambda_n = \lambda_{n-1}(1+b) - r\lambda_{n-1}(1+b). \end{bmatrix} \quad (1)$$

That is,  $\lambda_n = \lambda_0 ((1+b)(1-r))^n$

$b$  is the belief factor and  $b \in [0, 1]$ ,  $r$  is the suspicion factor and  $r \in [0, 1]$ ,  $k$  is the emotion transfer factor and  $k \in [0, 1]$ ,  $n \in [1, 3]$ , and  $n$  is the number of times that the ignorant person comes in contact with the information of different infected persons.  $\lambda_n$  represents the probability that the unknown person is exposed to  $n$  times of positive

information and turns into a positive spreader.  $\gamma_n$  represents the probability that the unknown person is exposed to  $n$  times of negative information and turns into a negative spreader. The calculation formula of  $\gamma_n$  is the same as that of  $\lambda_n$ . If it is a negative number, the absolute value is taken, indicating the magnitude and degree of the negative infection rate.

(2) *Dynamic Immunization Rate*. In contrast, when the same ignorant person is repeatedly stimulated by positive information, gets bored and becomes an immune person, or becomes a negative spreader due to a negative mentality. Similarly, if you are repeatedly stimulated by negative information, feel bored and become an immune person, or become a positive spreader because your mind is actively changed. This ability to strengthen the ignorant person's ability to change the same emotion as the infected information is defined as a negative reinforcement effect, defined by  $\rightarrow$  indicated. The negative reinforcement effect of the dynamic immunization rate is the primary embodiment. By analyzing the internal mechanism of the transmission threshold, there is a certain negative relationship between the infection rate and the immunization rate. There is a certain quantitative relationship with belief factor  $b$ , suspicion factor  $r$ , and contact times  $n$ . It can be expressed dynamically by the following formula

$$\alpha_{n=} \begin{bmatrix} \alpha_1 = \alpha_0(1+r) - b\alpha_0(1+r), \\ \alpha_2 = \alpha_1(1+r) - b\alpha_1(1+r), \\ \dots \\ \alpha_n = \alpha_{n-1}(1+r) - b\alpha_{n-1}(1+r). \end{bmatrix} \quad (2)$$

Namely,  $\alpha_n = \alpha_0((1+r)(1-b))^n$ .

$b \in [0, 1]$  is the belief factor,  $r \in [0, 1]$  is suspicion factor, and  $k \in [0, 1]$  is the emotion transfer factor;  $n \in [1, 3]$  is the number of times that the ignorant person comes in contact with the information of different infected persons.  $\alpha_n$  represents the probability that the unknown person is exposed to  $n$  times of positive or negative information and turns into the immune.

(3) *Dynamic Purification Rate and Incitement Rate.* Government intervention can be divided into two categories: positive intervention and negative intervention. When the information released by the government is positive, it will purify some negative spreaders into positive spreaders. The more times it is released, the more obvious the purification effect. When the information released by the government is negative, it will incite some positive spreaders into negative spreaders, and the more times it is released, the more obvious the incitement effect. At this point, the purification rate  $\mu$  and the incitement rate  $\beta$  have a specific quantitative relationship with belief factor  $b$ , suspicion factor  $r$ , emotion transfer factor, and intervention times  $i$ . It can be expressed dynamically by the following formulas:

$$\begin{aligned} \mu_i &= \mu(1 - \log_b(1 + K_1)^i), \\ \beta_i &= \beta(1 - \log_r(1 + K_2)^i). \end{aligned} \quad (3)$$

### 3.2. State Transition Rules

#### 3.2.1. Transfer under the Stimulated by Positive Information.

Assuming that ignorant people with positive mentality prefer positive information, ignorant people with negative mentality prefer negative information. When ignorant people with different mentalities are infected by certain emotional information, it is generally difficult to change their preferences, so without government intervention, we will not consider the change of ignorant people's preferences for the time being. That is, the ignorant will not turn into a spreader contrary to the preference.

- (1) *Static Transfer.* When the ignorant person (S) is stimulated by a piece of positive information, if the ignorant person (S) has a positive mentality (S+), he will be infected as a positive spreader (P) with a probability of  $\lambda$ . If the ignorant person (S) has a negative mentality (S-), he will become a negative spreader (N) with a probability of  $\gamma$  (see Figure 1).
- (2) *Dynamic Transfer.* Some positive information repeatedly stimulates the ignorant person (S), the positive ignorant person (S+) is more willing to believe the positive information and accept it, and the  $S+ \rightarrow P$  path is positively reinforced, or it may

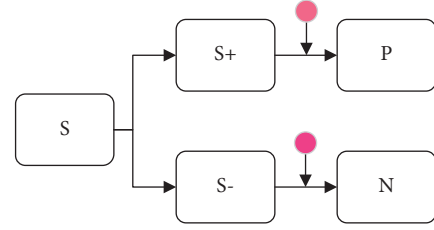


FIGURE 1: Static transfer rule diagram of positive information stimulation.

be ignored, and the  $S+ \rightarrow R$  path is negatively reinforced. However, the negative ignorant person (S-) will doubt the positive information, and the  $S- \rightarrow N$  path and the  $S- \rightarrow R$  path are negatively reinforced. When public opinion spreads, the positive information will increase. An effective measure to control public opinion is to increase the number of positive spreaders and reduce the number of negative spreaders. Therefore, the positive reinforcement path of  $S+ \rightarrow P$  is significantly beneficial. From the formula of the dynamic infection rate, it can be concluded that the essence is to improve the function of the belief factor. The negative reinforcement of the  $S+ \rightarrow R$  path and the  $S- \rightarrow R$  path is beneficial (see Figure 2).

#### 3.2.2. Transfer under the Stimulation of Negative Information.

There are two transfer forms: (1) Static transfer: When the ignorant person (S) is stimulated by a certain negative message, if the ignorant person (S) has a negative mentality (S-), it will be infected as a negative spreader (N) with a probability of  $\gamma$ . If S has a positive mentality (S+), it will become a positive spreader (P) with a probability of  $\lambda$  (see Figure 3). (2) Dynamic transfer: Some negative information repeatedly stimulates the ignorant person (S), the negative ignorant person (S-) is willing to believe the negative information and accept it, the  $S- \rightarrow N$  path is positively reinforced, or it may be ignored, and the  $S- \rightarrow R$  path is negatively reinforcement. However, the positive ignorant person (S+) may doubt negative information, and the  $S+ \rightarrow P$  path and the  $S+ \rightarrow R$  path will be negatively reinforced. When public opinion spreads, negative information increases. An effective measure to control public opinion is to increase positive and reduce negative information. Therefore, the negative reinforcement path of  $S+ \rightarrow P$  is significantly beneficial. From the dynamic immune formula, it can be concluded that the essence is to improve the role of the suspicion factor. Negative reinforcement of the  $S- \rightarrow R$  path and the  $S+ \rightarrow R$  path is beneficial (see Figure 4).

#### 3.2.3. Interactive Transfer Rules between P and N under Government Intervention.

There are two transfer rules: (1) Static interaction: After a positive spreader (P) and a negative spreader (N) contact, they will transform into each other. If the government intervenes positively, the negative

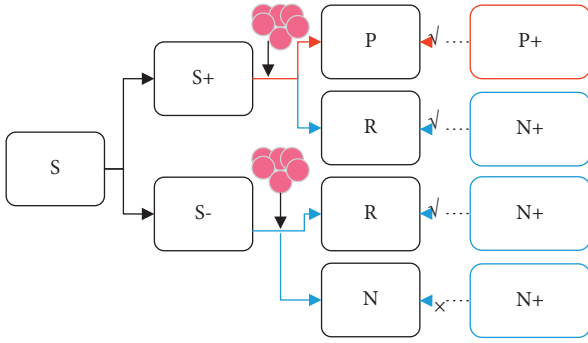


FIGURE 2: Dynamic transfer rule diagram of positive information stimulation.

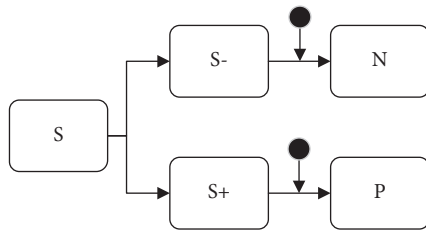


FIGURE 3: Static transfer rule diagram of negative information stimulation.

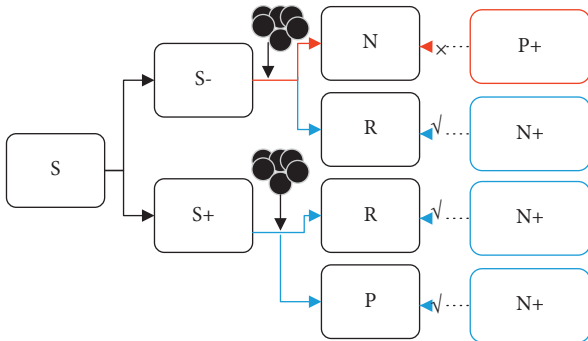


FIGURE 4: Dynamic transfer rule diagram of negative information stimulation.

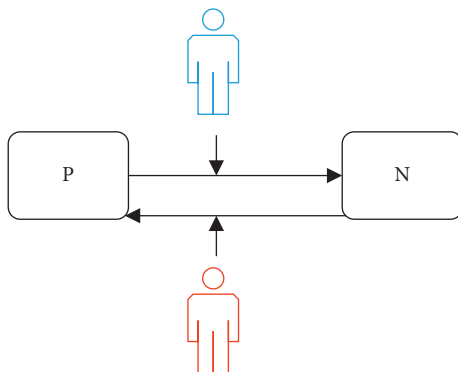


FIGURE 5: Static N-P interaction rule diagram.

spreader ( $N$ ) will be purified into a positive spreader ( $P$ ) with a probability of  $\mu$ ; if the government intervenes negatively, the positive spreader ( $P$ ) will be incited into a negative spreader ( $N$ ) with the probability of  $\beta$  (see Figure 5). (2) Dynamic interaction: When the government intervenes positively many times, the  $N \rightarrow P$  purification path is reinforced. When the government repeatedly intervenes negatively, the path of  $P \rightarrow N$  incitement path is reinforced. The essence of governance of public opinion is to increase positive spreaders, reduce negative spreaders, and make public opinion spread in a positive trend. Improving the purification rate and reducing the incitement rate will achieve the governance effect. According to the purification rate formula, the essence of improving the purification rate is to improve the function of the positive emotion transfer factor. According to the formula of the incitement rate, the essence of reducing the incitement rate is to reduce the function of the negative transfer factor (see Figure 6).

3.3. Construction of the Improved SIR Model Based on Emotional Contagion. The proportion of ignorant, positive, negative, and immune people at time  $t$  is  $S(t)$ ,  $P(t)$ ,  $N(t)$ , and  $R(t)$  respectively, in which  $\lambda$  is the positive infection rate,  $\gamma$  is the negative infection rate,  $\mu$  is the purification rate, and  $\beta$  is the incitement rate (see Figure 7).

This research not only provides theoretical references and ideas for the research direction of public opinion dissemination from the dynamic changes of netizens' emotions in theory, but also provides relevant departments to further understand the dissemination characteristics of network public opinions in real life, grasp the laws of public opinion dissemination, and formulate the management and control of public opinions. By studying the dynamic strengthening effect of positive and negative information on netizens' emotions and the impact of government's positive and negative intervention on public opinion dissemination, it is helpful for the government, the media, and netizens to grasp the development context of public opinion events and the law of public opinion information dissemination in an all-round way, so as to guide and manage public opinion. Provide detailed reference basis to enhance its scientific decision-making ability.

### 4. Case Analysis

Pneumonia caused by novel coronavirus infection, which broke out in the South China Seafood Market in Wuhan in mid-to-late December 2019, is also challenging the government's governance capacity in a very short period of time as the situation is becoming increasingly serious, and the epidemic is rapidly spreading to the whole country as a result of the movement of people during the Spring Festival travel rush. In the face of surging Internet Public Opinion, countless netizens quickly pushed public opinion about the "epidemic situation" to the focus of national and even global attention. On January 20, 2020, Academician Zhong Nanshan said that the "novel coronavirus" had the characteristics of human-to-human transmission. The public became upset

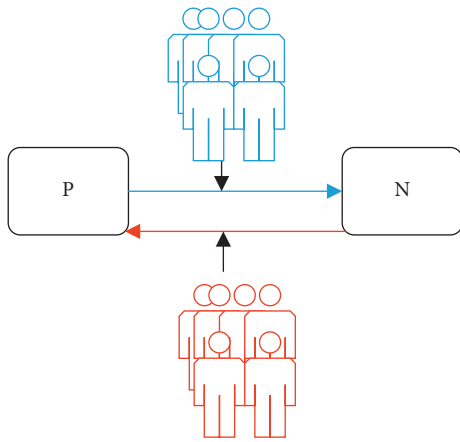


FIGURE 6: Dynamic  $N$ - $P$  interaction rule diagram.

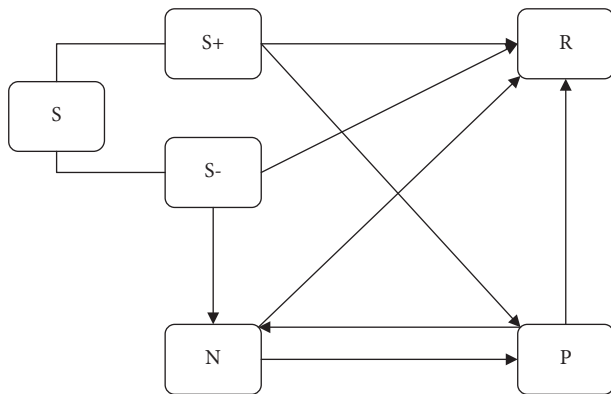


FIGURE 7: Improved SIR model based on emotional contagion.

and conveyed their panic through online public opinion. On January 23, the closure of Wuhan resulted in negative public opinion reaching a climax. During this period, the National Health and Health Commission released daily data on the number of confirmed cases and deaths in COVID-19, which was forwarded by the official media. The public mood was stable. After March 10th, the epidemic situation in Wuhan was under control. Xi Jinping arrived in Wuhan to inspect the prevention and management of the COVID-19 epidemic situation, and medical staffs returned home. The epidemic situation in China was stable, and most people ignored it, and public opinion became calmer and calmer.

**4.1. Data Acquisition and Processing.** Sina Weibo is currently the largest blog site in China and one of the representatives of social networks in China. According to the data as of December 2020, the monthly active number of Sina Weibo reached 521 million, and the daily active users reached 225 million. Weibo users use Weibo for an hour on average every day, and the degree of data openness is relatively high, so users could freely express their views on emergencies. Therefore, the Weibo information of the Sina Weibo platform can represent the emotional trend of online public opinion to a certain extent.

Taking the Weibo public opinion of new coronavirus pneumonia as an example, using “new-type coronavirus pneumonia, Wuhan epidemic situation, and China epidemic situation” as the keywords, we have found 29,324 popular Weibo texts from January 1, 2020 to March 20, 2020; these texts on Sina Weibo platform are crawled in Python, including the nickname and ID of Weibo publishers, release time, collection number, forwarding number, comments number, likes number, and context. Preprocessing the collected Weibo data is conducted by first using the Jieba library in Python to segment the Weibo text, and common stop words are filtered to make the text suitable for naive Bayesian classification. Second, duplicate data are removed. Data with the same name and content in Weibo on the same day are removed to ensure that each message represents a spreader. Third, advertisements are eliminated. Weibo containing promotions such as “movie,” “constellation,” and “diviner” are deleted. Fourth, the emotion of each Weibo is classified. The Snow NLP library and the TF-IDF algorithm are both used to train the classifier text classification to mark the emotional tendency of each Weibo text. Finally, based on the time series, Weibo’s emotional attitude change is visualized to obtain the emotional trend graph of COVID-19 public sentiment (see Figure 8).

**4.2. Data Analysis.** Using Weibo data marked by emotion, we can calculate the positive infection rate  $\lambda$  and the negative infection rate  $\gamma$ , immunization rate  $\alpha$ , purification rate  $\mu$ , and incitement rate  $\beta$  in static and dynamic environments every day. When calculating the positive infection rate  $\lambda$ , the negative infection rate  $\gamma$ , and immunization rate  $\alpha$ , we set the number of contacts  $n$  to be 1, 2, 3. Because of the deletion of repeated data every day, every emotion on Weibo represents the emotion of every spreader, and the number of Weibo represents the number of spreaders. The belief factor  $b$ , the suspicion factor  $r$ , and the emotional transfer factor  $k$  can be expressed dynamically by the following formulas:

$$b = \frac{F_i * L_i}{W_i}, \tag{4}$$

$$r = \frac{T_i * L_i}{W_i}, \tag{5}$$

$$k = \left( \frac{P_{i+1}}{S_{i+1}} - \frac{P_i}{S_i} \right) + \left( \frac{N_{i+1}}{S_{i+1}} - \frac{N_i}{S_i} \right). \tag{6}$$

The number of Weibo likes on day  $i$  is expressed as  $L_i$ , the number of comments is expressed as  $T_i$ , the number of forwarding is expressed as  $F_i$ , and the total number of Weibo in two days is expressed as  $W_i$ . The three behaviors of liking, forwarding, and commenting can reflect the views of netizens on a certain Weibo.

$P_i$  indicates the total number of forwarding Weibo on day  $i$ .  $P_{i+1}$  indicates the total number of Weibo forwards on the  $i + 1$ st day.  $N_i$  indicates the total number of negative Weibo on day  $i$ .  $N_{i+1}$  represents the total number of negative Weibo on day  $i + 1$ .  $S_i$  indicates the total number of Weibo

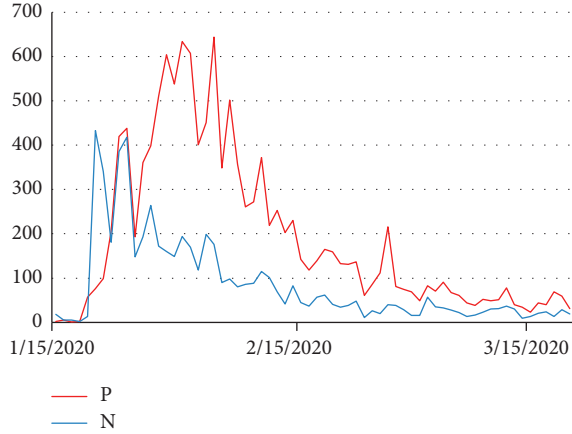


FIGURE 8: “Covid-19 epidemic” network public opinion emotion trend.

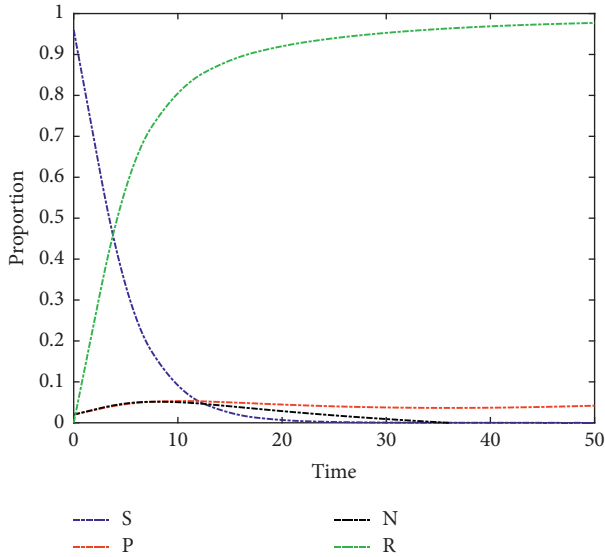


FIGURE 9: “Covid-19 epidemic” public opinion communication simulation figure.

on day  $i$ .  $S_{i+1}$  indicates the total number of Weibo on day  $i$ .  $R_i$  represents the total number of neutral Weibo on day  $i$ .  $R_{i+1}$  represents the total number of neutral Weibo on day  $i + 1$ . We can calculate the value of the emotional transfer factor using equation (6).

**4.2.1. Calculation of Parameter Values.** According to the above formula, the daily parameter values can be calculated, but the daily values are discrete. Now, to calculate the average value of the parameters in time, the following steps are required:

- (1) Using the Fourier function to fit, a smooth fitting curve is obtained, reflecting the changing trend of parameters to a certain extent.
- (2) Several points with large deviations are removed to make the parameter error smaller, and then fit the

linear curve which is fit to obtain the range of parameter values.

- (3) Observe the distribution of the processed parameters with the Weibull distribution. The abscissa of the Weibull function represents the value of the parameters, and the ordinate represents the probability of the values. Generally, the maximum probability value is taken as the parameter to obtain the average probability value, representing the numerical probability value in this period. However, there are also cases of an uneven probability distribution, and hence it is necessary to choose according to the actual situation of the parameters.

With the above method, the probability average of each parameter is as follows:  $\lambda_0 = 0.38$ ,  $\gamma_0 = 0.42$ ,  $\mu = 0.16$ ,  $\beta = 0.06$ , and  $\alpha_0 = 0.15$ . The values of the above variables are the average of probability, which are used as the initial value in the static environment.

**4.2.2. Inspection Effectiveness.** We substitute the obtained parameter values into the model, and then use MATLAB to simulate the public opinion propagation simulation diagram of the COVID-19 epidemic (see Figure 9). Comparing the actual data graph with the simulation graph, the trend changes are generally consistent, proving that this model is effective.

**4.3. Reinforcement Effect on Public Opinion Communication.** The trend chart of public opinion propagation simulated by the probability average is taken as the control group, and the infection rate and immunization rate tables obtained from daily public opinion data are taken as the experimental group to analyze the influence of the reinforcement effect on public opinion propagation.

On January 20, “China Telecom” released “there is a responsibility to stick to the front line, there is a warmth to work together, there is a power to unite as one. During the special period of fighting COVID-19, China Telecom is sparing no efforts to ensure unimpeded communication and maintain communication security concerns.” Take positive emotion Weibo for example. Considering that the popularity of a certain Weibo lasts for a very short time, assuming that the popularity of this Weibo lasts only one day, the number of likes and retweets after that can be ignored. This Weibo received 1250000 likes, 8100 forwards, and 50000 comments on that day. Through calculation, it is concluded that the belief factor is 0.14 and the suspicion factor is 0.001. When the contact times is 1, the dynamic positive infection rate is 0.43, when  $n$  is 2, the dynamic positive infection rate is 0.49, and when  $n$  is 3, the dynamic positive infection rate is 0.56. The contact times of 1 is used as the control group, and the others are used as the experimental group (see Table 4).

With the increase in the positive infection rate,  $S(t)$  rapidly decreases to 0, and the ignorant person becomes a spreader in a short time. The speed of public opinion spread is accelerated.  $P(t)$  increases rapidly to the peak in the early stage and then falls back to the steady state higher than the



TABLE 4: Dynamic positive infection rate.

	Control group	Experiment group 1	Experiment group 2
Date		January 20	January 20
The static positive infection rate ( $\lambda_0$ )	0.38	0.38	0.38
Belief factor ( $b$ )	0.14	0.14	0.14
Suspicion factor ( $r$ )	0.001	0.001	0.001
Contact times ( $n$ )	1	2	3
The dynamic positive infection rate ( $\lambda_n$ )	0.43	0.49	0.56

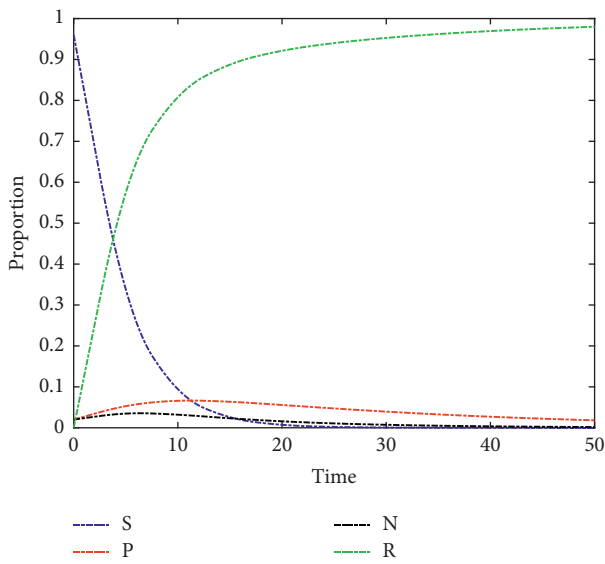


FIGURE 10: The control group.

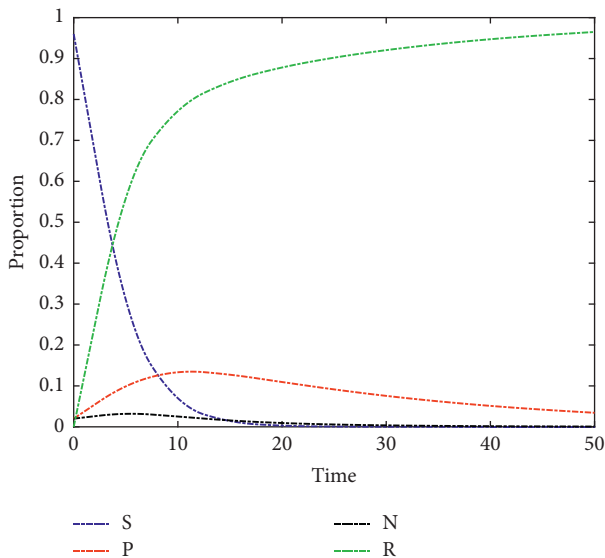


FIGURE 11: Influence of the positive infection rate on public opinion transmission.

control group in the later stage, accompanied by a decrease in negative propagator  $N(t)$  (see Figures 10 and 11). The reason is that on January 20th, the online big V (people with strong influence) “Baihuaxiang Shuai” jointly launched the topic of “health care action” on Weibo with other network people, which attracted 41.05 million people, causing

netizens to forward it crazily. On January 25th, General Secretary Xi Jinping delivered a speech to actively respond to the epidemic situation, which was actively forwarded by netizens. The behavior of forwarding increases the number of times that the ignorant person touches the positive information, such that the  $S+ \rightarrow P$  path is positively enhanced. Opinion leader’s positive comments increase the belief factor of positive information, and online public opinion is developing toward a positive trend, which is beneficial to public opinion control.

Take the negative emotion Weibo of “2 Novel Coronavirus cases confirmed in Xinjiang” released by CCTV News on January 23 as an example. Considering that the popularity of a certain Weibo lasts for a very short time, assuming that the popularity of this Weibo lasts only one day, the number of likes and retweets after that can be ignored. This Weibo received 1400 likes, 178100 retweets, and 2700 comments on that day. According to the formula defined above, the belief factor is 0.002 and the suspicion factor is 0.2. When the contact times is 1, the dynamic immunity rate is 0.18, when  $n$  is 2, the dynamic immunity rate is 0.22, and when  $n$  is 3, the dynamic immunization rate is 0.26. The contact times of 1 is used as the control group, and the others are used as the experimental group (see Table 5).

With slight increases in the immunization rate, the time for  $S(t)$  to decrease to zero is not obvious compared with the control group, the peak value of  $P(t)$  becomes smaller, and the peak value of  $N(t)$  becomes larger (see Figures 12 and 13). This shows that the speed of public opinion spread slows down. The reason is that after a series of rumors before February 6th, The Supreme People’s Court, the Public Security Bureau, and other relevant departments jointly formulated the Opinions on Punishing Offenses that hinder the Prevention and Control of Pneumonia Epidemic in novel coronavirus according to law, which pointed out that those who fabricate and spread incorrect epidemic information and seriously disturb social order will be convicted and punished for fabricating and deliberately spreading false information. Once this opinion was specified, the major media and WeChat official account quickly forwarded it, and netizens learned that rumors and spreading rumors should bear corresponding legal responsibilities and felt a great risk. Therefore, the number of negative spreaders decreased and turned into immunizers or positive spreaders, and the  $S- \rightarrow P$  path was negatively strengthened. Public opinion is developing toward positive emotions. It is beneficial to public opinion control. On March 10th, the epidemic situation in Wuhan was brought under control. Xi Jinping arrived in Wuhan to inspect the prevention and control of the COVID-

TABLE 5: Dynamic immunization rate.

	Control group	Experiment group 1	Experiment group 2
Date		February 23	February 23
Static immunization rate ( $\alpha_0$ )	0.15	0.15	0.15
Belief factor ( $b$ )	0.002	0.002	0.002
Suspicion factor ( $r$ )	0.2	0.2	0.2
Contact times ( $n$ )	1	2	3
Dynamic immunization rate ( $\alpha_n$ )	0.18	0.22	0.26

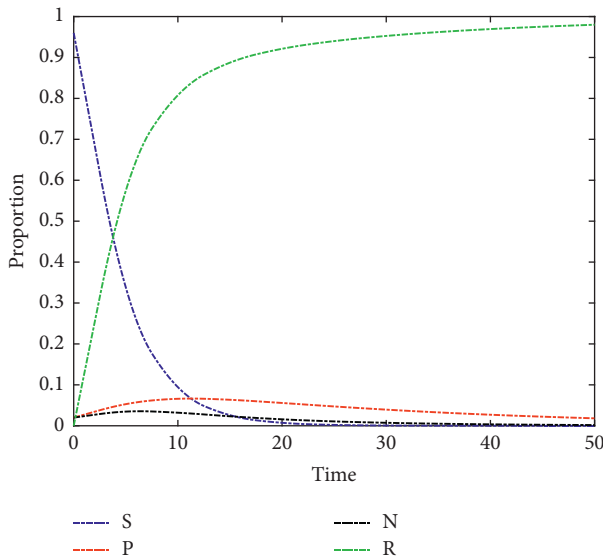


FIGURE 12: The control group.

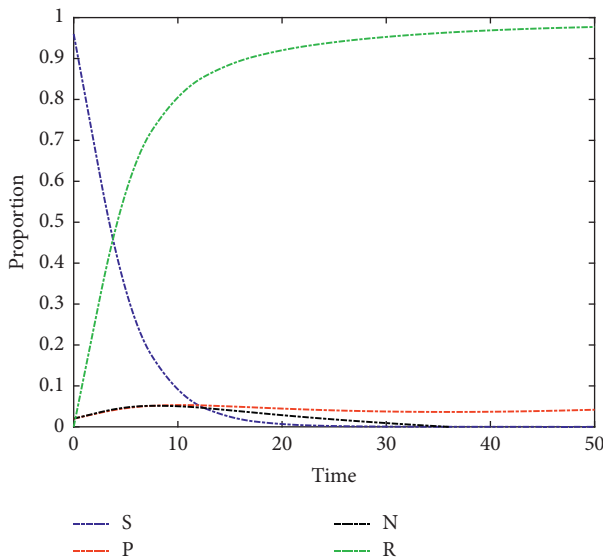


FIGURE 13: Influence of the immunization rate on public opinion transmission.

19 epidemic, and the medical staffs returned. After that, the national epidemic was basically in a stable state, and the netizens stopped paying attention to it and turning into immunizers; therefore, the  $S+ \rightarrow R$  path strengthened negatively, which was beneficial to public opinion control.

TABLE 6: Dynamic purification rate.

	Control group	Experiment group 1
Date		January 31
Static purification rate ( $\mu$ )	0.16	0.16
Belief factor ( $b$ )	0.52	0.52
Suspicion factor ( $r$ )	0.48	0.48
Positive emotion transfer factor ( $k_1$ )	0.25	0.55
Number of interventions ( $i$ )	1	2
Dynamic purification rate ( $\mu_i$ )	0.18	0.21

TABLE 7: Dynamic incitement rate.

	Control group	Experiment group 1
Date		February 20
Static incitement rate ( $\beta$ )	0.06	0.06
Belief factor ( $b$ )	0.52	0.52
Suspicion factor ( $r$ )	0.48	0.48
Negative emotional transfer factor ( $k_2$ )	0.37	0.56
Number of interventions ( $i$ )	1	2
Dynamic incitement rate ( $\beta_i$ )	0.09	0.13

4.4. *The Influence of Government Intervention on Public Opinion Dissemination.* The trend chart of public opinion propagation simulated by the probability average is taken as the control group, and the purification rate (see Table 6) and incitement rate (see Table 7) obtained from daily public opinion data are taken as the experimental group to analyze the influence of government intervention on public opinion propagation.

With the increase in purification rate,  $S(t)$  slowly decreases, and as time increases, the gap between  $P(t)$  and  $N(t)$  becomes larger, and  $P(t)$  is much larger than  $N(t)$ . This shows that the speed of public opinion spread slows down, and the number of positive spreaders increases (see Figures 14 and 15). The reason is that on January 31, the “Shanghai Institute of Pharmacy and Wuhan Institute of Virology jointly discovered that Shuang-huang-lian Oral Liquid, a Chinese patent medicine, can inhibit COVID-19,” which caused netizens to rapidly spread information. Shuang-huang-lian oral liquid instantly became “magic water,” and the inventory held by significant e-commerce platforms was exhausted. The Health Commission immediately took measures to clarify through major media, stating that until now, there had been no special medicine for the prevention and treatment of a new

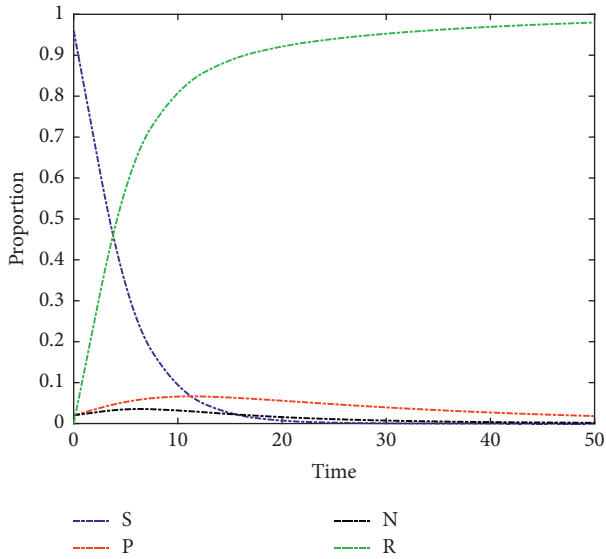


FIGURE 14: Control group.

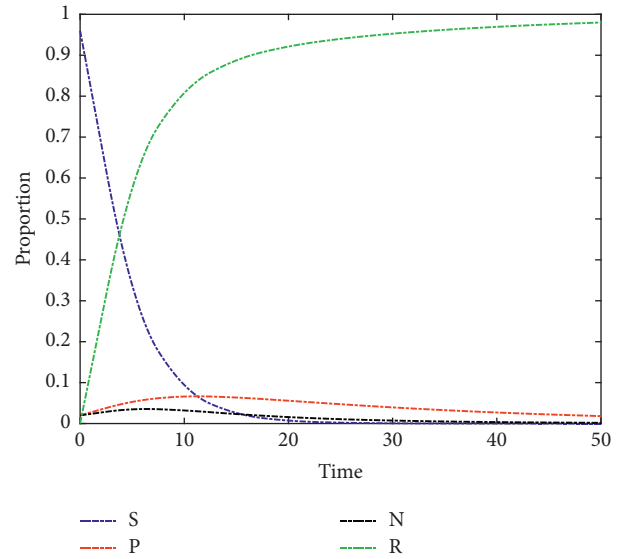


FIGURE 16: Control group.

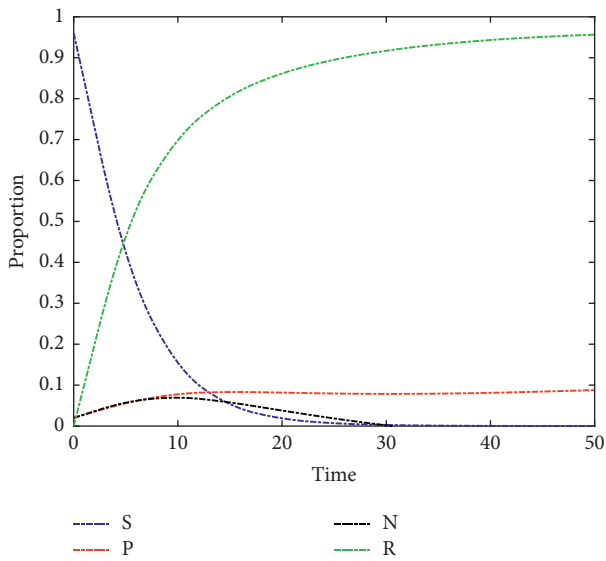


FIGURE 15: Effect of the purification rate on public opinion transmission.

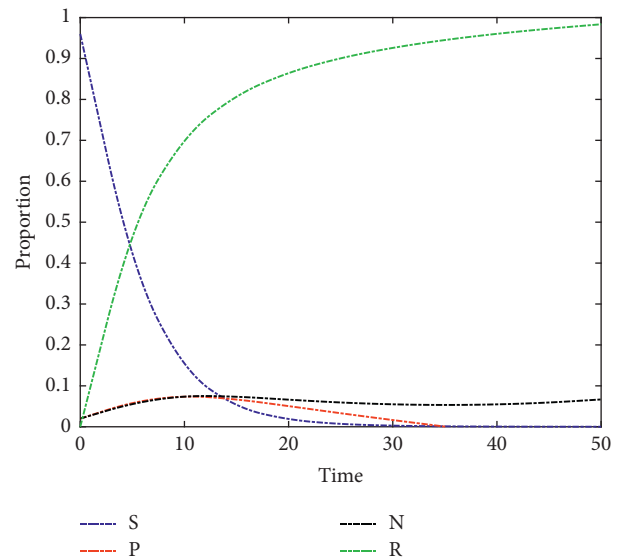


FIGURE 17: Influence of the incitement rate on public opinion communication.

type of coronary pneumonia. Soon, the negative emotions of netizens showed a significant downward trend. From February 4th to 12th, when the increased number of infections and deaths was reported on the Internet, Raytheon Mountain and Huoshen Mountain were built rapidly, and medical staffs began to go to various places on the front line. After that, Weibo such as “China speed” and “the most beautiful retrograde” were quickly forwarded by officials, media, and individuals, and spreaders of negative emotions felt the government’s intense credibility. The netizens turned into spreaders of positive emotions and no longer felt panicked. Therefore, it is effective to improve the purification rate to control the public opinion.

With the increase in incitement rate,  $S(t)$  slowly decreases, and as time increases, the gap between  $P(t)$  and  $N(t)$  becomes larger, and  $N(t)$  is much larger than  $P(t)$  (see Figures 16 and 17). The reason is that on February 20, the official Microblog reported that the Diamond Princess had confirmed 634 cases of COVID-19, and two Japanese passengers died. This news caused some panic among netizens. The negative emotions of netizens are rising again, negative information spreaders are increasing, and public opinion is developing in a negative direction. Therefore, increasing the incitement rate to control the spread of public opinion has a negative effect.

## 5. Conclusions

Based on the SIR model, this paper introduces positive spreaders, constructs an improved SIR model based on emotional contagion, and studies the interaction between positive and negative emotions of online public opinion. Among them, positive and negative reinforcement effects and the influence of government intervention on the interaction of positive and negative public opinions are considered. MATLAB simulation shows that the improved SIR model can better reflect the interaction of positive and negative emotions and public opinion communication closer to the actual situation. Based on this, this paper draws the following conclusions: A positive reinforcement effect enhances the ignorant participants' ability to maintain the same emotion as the infected information. When positive information repeatedly stimulates the ignorant, it will positively strengthen the ability of people with a positive mentality to maintain positive emotions, which is significantly beneficial to public opinion control. Its essence is to increase the effect of positive information's belief factor on the dynamic infection rate. When negative information repeatedly stimulates an ignorant person, it will positively strengthen the ability of the person with a negative attitude to maintain negative emotion, which is not conducive to public opinion control.

A negative reinforcement effect will strengthen the ignorant ability to change the same emotion as the infected information. And when the negative information repeatedly stimulates the ignorant person, the negative reinforcement effect will strengthen the positive people's ability to change negative information into positive emotion, which is significantly beneficial to public opinion control. The essence is to increase the effect of the suspicion factor on the dynamic immunization rate. It will strengthen the positive mentality and negative mentality into the path of immunization, which is beneficial to epidemic control. When the positive information repeatedly stimulates the ignorant, the negative will strengthen the ability of the negative person to change the positive information into negative emotion, which is not conducive to public opinion control. It will be harmful to strengthen the path of positive and negative mentality into immunization, which is beneficial to epidemic control.

The earlier the government intervenes in public opinion, the better it will be. The essence of intervention is to decrease the dynamic incitement rate.

Despite such effectiveness, several weaknesses of the current study must be highlighted. First, there are many factors that affect the dissemination of online public opinion. This study only considers the emotions of the information itself, the emotions of netizens, and the government's positive and negative interventions. The consideration is not comprehensive enough, and other influencing factors need to be further studied. Second, due to the different attention of different platform users to events, the speed and way of public opinion dissemination will be slightly different, and this study only selects the data of Weibo, a platform for empirical research, and hence there are certain limitations. Multiple platform data should be selected for verification

analysis, such as Facebook, Twitter, and other platforms. Third, the dynamic strengthening process is considered a bit one-sided, and we will further study this aspect later.

## Data Availability

The data were collected by an Internet web crawler technology and are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Acknowledgments

This work was supported by the National Social Science Foundation of China (no. 21BSH072), Natural Science Foundation of Hebei Province Project "Building a Risk Knowledge Management Model for Software Projects Driven by Subject Behavior Data" (no. G202120800) and the Soft Science Research Special "Resilience cultivation and improvement countermeasures of rural supply chain in Hebei Province under the background of digital economy" (no. 22557663D).

## References

- [1] X. G. Chen, S. Duan, and L. d. Wang, "Research on trend prediction and evaluation of network public opinion," *Concurrency and Computation: Practice and Experience*, vol. 29, no. 24, Article ID e4212, 2017.
- [2] T. Chen, L. Peng, and J. Yang, "Modelling, simulation, and case analysis of COVID-19 over network public opinion information with individual internal factors and external information characteristics," *Concurrency and Computation: Practice and Experience*, vol. 33, no. 17, pp. 1–26, 2021.
- [3] P. Fu, B. Jing, T. Chen, J. Yang, and G. Cong, "Modeling network public opinion propagation with the consideration of individual emotions," *International Journal of Environmental Research and Public Health*, vol. 17, no. 18, p. 6681, 2020.
- [4] Y. Song, Y. Xia, D. Fang et al., "Positive and negative network public opinion information dissemination model and simulation based on improved SIR," *Computer Application Research*, vol. 38, no. 11, pp. 25–33, 2021.
- [5] G. Yu and B. Li, *Public Opinion Management in Social Network Era*, pp. 111–112, Jiangsu People's Publishing House, Nanjing, 2015.
- [6] H. Chen and T. Chen, "A research of propagation stage feature and the warning method for the government to intervene network public opinion," *Research on Library Science*, vol. 1, pp. 24–30, 2015.
- [7] Y. C. Chen and T. C. Hsieh, "Big data for digital government: opportunities, challenges, and strategies," *International Journal of Public Administration in the Digital Age (IJPADA)*, vol. 1, no. 1, pp. 1–14, 2014.
- [8] J. Wei, L. Ding, H. Zhu et al., "Research on social network public opinion communication model based on emotion and affinity," *Information Science*, vol. 39, no. 4, pp. 37–47, 2021.
- [9] C. Lin and Y. He, "Joint sentiment topic model for sentiment analysis," in *Proceedings of the 18th ACM Conference on Information and Knowledge Management*, pp. 375–384, ACM, New York, September 2004.

- [10] F. Wen, J. Xiao, C. Huang, and X. Xia, "Interaction between oil and US dollar exchange rate: nonlinear causality, time-varying influence and structural breaks in volatility," *Applied Economics*, vol. 50, no. 3, pp. 319–334, 2018.
- [11] J. Wiebe and E. Riloff, "Finding mutual benefit between subjectivity analysis and information extraction," *IEEE Transactions on Affective Computing*, vol. 2, no. 4, pp. 175–191, 2011.
- [12] Y. W. Teh, D. Newman, and M. Welling, "A collapsed variational bayesian inference algorithm for latent dirichlet allocation advances in neural information processing systems 19," in *Proceedings of the Twentieth Annual Conference on Neural Information Processing Systems*, Vancouver, Canada, December 2006.
- [13] X. Yan, J. Guo, and Y. Lan, "A Biter Topic Model for Short Texts," *International Conference On World Wide Web*, ACM, Rio de Janeiro Brazil, 2013.
- [14] Y. Tripath, A. Agrawal, and K. Rath, "Classification of Sentiment Reviews Using N-Gram Machine Learning Approach," *Expert Systems with Applications*, vol. 12, pp. 117–126, 2016.
- [15] N. N. Elisabeth, *The Spiral of Silence: Public Opinion—Our Social*, pp. 50–56, University Chicago Press, Chicago, 1993.
- [16] B. Braeuchler, "Public sphere and identity politics in the Moluccan Cyberspace," *Electronic Journal of Communication*, vol. 14, no. 3, pp. 9–12, 2004.
- [17] Q. Qiu, J. He, H. Chen, and J. Qiu, "Research on the evolution law of emergency network Public Opinion," *International Symposium on Computational Intelligence and Design*, pp. 157–161, 2019.
- [18] D. Yan, *Research on Online Public Opinion in Mass Incidents*, Xinhua Publishing House, Beijing, 2013.
- [19] K. Guo, L. Shi, W. Ye, and X. Li, "A survey of internet public opinion mining," *International Conference on Progress in Informatics and Computing*, pp. 173–179, Shanghai, 2014.
- [20] M. A. Saad, A. C. Bovik, and C. Charrier, "Blind prediction of natural video quality," *IEEE Transactions on Image Processing*, vol. 23, no. 3, pp. 1352–1365, 2014.
- [21] Z. T. He, X. Q. Zhang, F. W. Zhao, and T. K. Ji, "Internet Public Opinion monitoring model based on cloud computing," *Applied Mechanics and Materials*, vol. 404, pp. 744–747, 2013.
- [22] G. Li, X. Q. Zhang, Z. T. He, and T. K. Ji, "Analysis and design on cloud computing monitoring framework of Internet Public Opinion," *Applied Mechanics and Materials*, vol. 442, pp. 511–514, 2013.
- [23] S. Huang, W. Si, and T. Mu, "Innovation and research of online public opinion control and guidance mechanism in universities in the self-media era," *Information Science*, vol. 39, no. 4, pp. 62–67, 2021.
- [24] Y. Lan and R. Zeng, "Study on the law of public opinion propagation and early warning stage of emergency events," *Journal of Information*, vol. 32, no. 5, pp. 16–19, 2013.
- [25] P. Liu, "Information dissemination mechanism based on cloud computing cross-media public opinion network environment," *International Journal of Information Technologies and Systems Approach*, vol. 14, no. 2, pp. 70–83, 2021.
- [26] C. H. Lee, "Mining spatio-temporal information on micro-blogging streams using a density-based online clustering method," *Expert Systems With Applications*, vol. 39, no. 10, pp. 9623–9641, 2012.
- [27] K. Emerson, T. Nabatchi, and S. Balogh, "An integrative framework for collaborative governance," *Journal of Public Administration Research and Theory*, vol. 22, no. 1, pp. 1–29, 2012.
- [28] J. Qi, H. Liu, and Y. Zhang, "Study on the coupling mechanism of Internet Public Opinion in sudden public crisis events," *Information Science*, vol. 35, no. 9, pp. 102–108, 2017.
- [29] M. J. Bryson et al., "The Mainstream media Communicate with Government Functional Department, Predict the Trend of Events," *Public Administration Review*, vol. 1, pp. 44–55, 2006.
- [30] B. Brauchler and M. Erb, "Introduction eastern Indonesia under reform: the global, the national and the local," *Asian Journal of Social Science*, vol. 39, no. 2, pp. 113–130, 2011.
- [31] J. Wang, *China's Public Opinion Control in the Platform Era: News, Media Power, and State-Platform Collaborative Governance*, University of Warwick, United Kingdom, 2019.
- [32] P. Mie, *Challenges of Collaborative Governance: An Organizational Discourse Study of Public Managers' Struggles with Collaboration across the Daycare Area*, Copenhagen Business School, Frederiksberg, Denmark, 2015.
- [33] J. Hartley, E. Sorensen, and J. Torfing, "Collaborative innovation: a viable alternative to Market competition and organizational entrepreneurship," *Public Administration Review*, vol. 73, no. 6, pp. 821–830, 2013.
- [34] G. Dhiman and V. Kumar, "Spotted hyena optimizer: a novel bio-inspired based metaheuristic technique for engineering applications," *Advances in Engineering Software*, vol. 114, pp. 48–70, 2017.
- [35] G. Dhiman and V. Kumar, "Emperor penguin optimizer: a bio-inspired algorithm for engineering problems," *Knowledge-Based Systems*, vol. 159, pp. 20–50, 2018.
- [36] G. Dhiman and A. Kaur, "STOA: a bio-inspired based optimization algorithm for industrial engineering problems," *Engineering Applications of Artificial Intelligence*, vol. 82, pp. 148–174, 2019.
- [37] P. K. Vaishnav, S. Sharma, and P. Sharma, "Analytical review analysis for screening COVID-19," *International Journal of Modern Research*, vol. 1, pp. 22–29, 2021.