Modeling and simulation of microblog-based public health emergency-associated public opinion communication

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ABSTRACT

With the advent of the era of "we media," many people's opinions have become easily accessible. Public health emergencies have always been an important aspect of public opinion exchange and emotional communication. In view of this sudden group panic, public opinion cannot be effectively monitored, controlled or guided. This makes it easy to amplify the beliefs and irrationality of social emotions, that threaten social security and stability. Considering the important role of opinion leaders in micro-blogs and users' interest in micro-blog information, a SIR model of public opinion propagation is constructed based on the novel coronavirus pneumonia model and micro-blog's public health emergencies information. The parameters of the model are calculated by combining the actual crawl data from the novel coronavirus pneumonia epidemic period, and the trends in the evolution of public opinion are simulated by MATLAB. The simulation results are consistent with the actual development of public opinion dissemination, which shows the effectiveness of the model. These research findings can help the government understand the principles that guide the propagation of public opinion and advise an appropriate time to control and correctly guide public opinion.

1. Introduction

The world has entered a period of major public health epidemics as serious environmental pollution increases, the number of drug resistant variants to novel biological pathogens grows and the emergence of new infectious diseases. According to statistics from the World Health Organization (WHO), the number of newly discovered viral infectious diseases in the world has increased fourfold in the past 30 years, including more than 40 kinds of viruses causing major infectious disease outbreaks. For example, there was severe acute respiratory syndrome (SARS) in 2013, the H1N1 influenza pandemic in 2009, poliomyelitis in 2014, the Ebola epidemic in 2014, Middle East respiratory syndrome (MERS) in Korea in 2015, the Zika virus epidemic in 2015-2016, the Ebola epidemic in the Congo from 2018 to 2019, and COVID-19 in 2019. The outbreak of each epidemic not only poses a serious threat to public health and human safety, but also has a great impact on the economy and society.

Major epidemics generally have the following basic characteristics: sudden onset, diverse causes, rapid transmission, complex hazards, and close contact with public health and daily life. Compared with natural disasters and accidental disasters in a city,

epidemics have both national and global effects, pose a threat to people's lives and safety, and impact social and economic operations and the quality of social life. These characteristics garner public attention, leading to the spread of mass panic and the expansion of harmful consequences of the epidemic. Such outcomes can even stimulate a series of derivative events, which can more easily become the focus of public opinion and are more likely to incite major public opinions about the epidemic.

The effective response to and governance of public opinion during epidemic situations is an important issue to be solved in the field of social emergency management. General Secretary Xi Jinping, in guiding COVID-19 epidemic prevention and control in Beijing, stressed that we should strengthen the guidance of public opinion, publish accurate information in a timely manner, respond to the concerns of the masses openly and transparently, enhance the pertinence and effectiveness of public opinion guidance, and consolidate the strong positive messaging. Therefore, in the prevention and control of epidemics, the appropriate response and governance of network-based public opinion is very important. The analysis of network-based public opinion can help the government understand people's thoughts and wishes in a more timely manner, accurately ascertain and control the development of trends in public opinion, resolve complaints in a timely manner, answer questions and address doubts, and guide and correct the development of the situation in order to make networks have a good ecological environment.

On February 3, 2021, the 47th statistical report on the development of China's internet indicated that by the end of December 2020, the number of internet users in China had reached 989 million, and the internet penetration rate had reached 70.4%. With the rapid development of the internet, social network platforms have swiftly risen and penetrated all aspects of people's lives. They have become a means for human beings to release pressure, express feelings and vent negative emotions. With the sudden popularization of social media software, the threshold for the public to express themselves online is becoming increasingly lower, and public opinion is becoming increasingly difficult to control. Microblog platform user groups encompass many classes and types of people, and different sources often contribute to public opinion on public health matters. The universality of a microblog's main argument can represent the evolution of a society's attitude. The high degree of public attention to major epidemics and the accessibility of online communication platforms jointly promote the challenges of responding to public opinion and of governance of the public. If the government handles such emergencies improperly or fails to respond correctly and quickly to public opinion, its credibility will be questioned, triggering extreme public emotions, and even endangering public security and social stability.

With the increasing number of public opinions about major epidemics being shared on social networks, research on network-based public opinion has become an indispensable part of public emergency management research. However, research on network-based public opinion of epidemics started late and has achieved few results. Based on previous relevant research, this paper conducts an in-depth study on the propagation and evolution of public opinion on major epidemic situations. By collecting public opinion text, pictures and social relations data related to the epidemic from the microblog platform, this paper studies various epidemic prevention and control measures, social and livelihood issues, degree of public concern, and attitudes held by the public toward the problem during the evolution of the epidemic to provide the government with an overall portrait of the public's emotional attitude toward public health. By analyzing the public health opinion communication process, this paper can help the government control public opinion and understand the characteristics of public opinion communication to find a more appropriate period for public opinion intervention and guidance. The paper is composed as follows: the first part is the introduction; the second part is the related work introduction; the third part is the construction of the public opinion communication model based on the SIR model; the fourth part is the model simulation and analysis, as well as the corresponding policies and suggestions; the last part is the research conclusion.

2. Related work

Many experts and scholars have conducted research about the control of public opinion communication in social networks and have achieved notable research results. Lin Lin et al. conducted text mining on related public opinion with the 5 W communication model from public opinion evolution, text content, communication media, audiences, and public opinion influence, and used grounded theory to build a development model of the generation of network public opinion (Lin et al., 2021). Li Qing et al. proposed a new public opinion evolution HK-SEIR model that combined the opinion fusion HK and the epidemic transmission SEIR models, the topic interest degree is added to the opinion fusion HK model, and the interaction behavior between the users under the interest and confidence threshold is analyzed (Qing et al., 2021). Based on the traditional SEIR warehouse model of internet public opinion communication, Cheng Quan et al. constructed an improved SEIR model considering users' subject interest, and through the establishment of an internet public opinion evolution model, the key factors influencing the evolution of public opinion events were simulated and verified (Quan et al., 2020). Gao Shan et al. extended risk-information communication theory from the perspective of the type of emergency, explored the causes of rebounded online public opinion regarding public emergencies, and provided policies and suggestions for risk-information communication and online public-opinion governance during emergencies (Shan et al., 2021). Shiyue Li analyzed the characteristics of how public opinion about emergency networks evolves from the perspective of time in cyberspace (Li et al., 2020). Han S. C. et al. studied the impact of human activity patterns on information diffusion and conducted quantitative research on the impact of user behavior on information dissemination using the SIR propagation model and empirical data (Han et al., 2016). Xu Jiuping et al. established a novel dynamic dissemination model to systematically study the recurrence of online public opinion (Jiuping et al., 2020). Xiwei Wang et al. chose "network attack" as the research topic and extracted 23,567 relevant messages from Sina Microblogs to study the structure of nodes for public opinion dissemination and the characteristics of propagation paths on mobile internet (Wang et al., 2020). Cheng Quan et al. analyzed the influence factors of the Internet public opinion events in the public health emergencies and proposed the Internet public opinion stochastic resonance model considering the topic relevance (Quan et al., 2021). Lifan Zhang et al. investigated the diffusion effect of information in a coupled social network environment, Using an improved SIR model (Zhang et al., 2018). Jinghua Zhao et al. based on the complex network theory, information spread theory and

disease spread theory, as well as a study of the Wenling doctor murdering case, constructed a model about the spread of information on emergencies by combining empirical data and simulation experiments (Zhao et al., 2021). Many experts and scholars have also turned their attention to the research of opinion leaders, the leader of public opinion communication such as, Su Yan found that opinion leaders generally reinforce Weibo users' subjective assessment (e.g., attitudes and emotional responses) of the incident (Yan, 2019). Wang Yinying et al. found that most opinion leaders were those who expressed negative sentiment toward the CCSS on Twitter (Yinying and J, 2019). Zhang Yuexia et al. proposed the Media and Interpersonal Relationship-SEIR (MI-SEIR) model, which considered the impact of media transmission and interpersonal relationships on opinion propagation (Yuexia et al., 2019).

In conclusion, researchers are aware of the importance of controlling social network-based public opinion and pay attention to the different effects of group characteristics on public opinion communication. Microblogs are currently the most important interactive network platform in China. With independent and public information release, fast communication speed and great influence, microblogs became the main battlefield of public opinion communication. Therefore, based on novel coronavirus pneumonia models and previous studies, the subject of this research is the propagation of public opinion regarding new coronavirus pneumonia outbreaks. Variables such as opinion leader status and user interest in communication were introduced through microblog platform data crawling to analyze the evolution of public health emergency communication. To some extent, this can help to better understand and control the spread of popular public health opinions, avoid panic caused by false or malicious public opinions, maintain social stability and assist the government in governance.

3. Model building

3.1. SIR model

The assumptions of SIR model are as follows:

(1) The state of the population is divided into the susceptible state S, the infectious state I and the recovered state R. At any given time t, their proportions in the total population are S(t), I(t) and R(t), respectively.
(2) When the infectious state I is successfully exposed to the susceptible state S, the probability of being turned from the susceptible state into the infected state is α.
(3) The infectious state, I, can be expressed in terms of γ, the probability of recovering from infection and becoming recovered. Recovered individuals can no longer be infected by those in the infectious state, I, and no longer participate in the transmission process.
(4) Initial conditions of the model: when t = 0, $I(0)=I_0$, $S(0)=1-I_0$, $R(0)=0$.

A schematic diagram of the state transformation process of the traditional SIR model is shown in Fig. 1, and its corresponding differential equation is shown in Formula (1).

$$\begin{cases} \dfrac{\partial S(t)}{\partial t} = -\alpha S(t)I(t) \\[2mm] \dfrac{\partial I(t)}{\partial t} = \alpha S(t)I(t) - \gamma I(t) \\[2mm] \dfrac{\partial R(\mathrm{t})}{\partial \mathrm{t}} = \gamma I(t) \end{cases} \tag{1}$$

3.2. SIR-based public opinion communication model

The classical SIR model is similar to the process of disseminating public opinion during public health emergencies, but in the process of public opinion information dissemination, the dominant opinions will often prevail over alternative opinions. Due to fear of isolation, people with different opinions will turn to either silence or mainstream opinions (Weizhe et al., 2014). Under the conditions of this hypothesis, opinion leaders, as a popular source of public health opinion in the microblog communication platform, seriously affect the communication of public health opinion. Because different users have different interests in public health opinion information, there are some differences in the probability of forwarding such information, which also affects the dissemination of public health opinion. Therefore, based on the classical SIR model, this paper considers microblog public opinion leaders and user interests, ω, to construct a public opinion communication model of public health emergencies. This study is based on the following assumptions:

(1) "Susceptible state" S refers to users who have not participated in the process of public opinion communication. They may not have the opportunity to receive relevant information, or they may not participate in public opinion communication due to lack of interest.
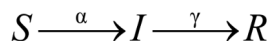
$$S \xrightarrow{\quad \alpha \quad} I \xrightarrow{\quad \gamma \quad} R$$

Fig. 1. SIR Model Diagram

(2) "Infectious state" I refers to the state of users who are interested in receiving and disseminating public opinion information, including users who disseminate public opinion information to others by publishing, commenting, forwarding and/or other behaviors. As mentioned earlier, opinion leaders can play an important role in public opinion communication. Their communication ability is quite different from that of ordinary users. Often, a few opinion leaders can influence a large group of people. Based on this, this paper further divides the infectious state I into the infectious state of opinion leaders I_1 and the infectious state of the ordinary citizen I_0.

(3) "Recovered state" R refers to the group that has participated in the dissemination of public health opinion but has since lost interest and will no longer participate in its dissemination.

(4) R is the final state of propagation in the model. For a specific user, their probability of infection α, their probability of recovery γ, and their degree of interest in the process of public health opinion dissemination ω always maintain a constant value.

(5) To simplify calculations, it is assumed that the overall number of microblog users during the epidemic period is maintained at a constant value N. By analyzing these users at any time t, the three states S, I, and R are divided according to the rules outlined above, and the corresponding proportions of the number of users are $S(t)$, $I(t)$ and $R(t)$.

(6) The opinion leaders I_1 always maintain the infectious state. If the proportion of opinion leaders I_1 is constant, it cannot be transformed from S or into R. The model demonstrating the transition from each state is shown in Fig. 2:

According to the research hypothesis, $S(t)+I(t)+R(t)=1$ and $I(t)=I_0(t)+I_1(t)$. In this model:

(1) The source of the opinion message comes from the opinion leader I_1 or the ordinary user I_0. Referring to reference [16], users with more than 300000 fans and more than 300 message forwards are opinion leaders; otherwise, they are determined to be ordinary users. The number of opinion leaders' and ordinary users' fans are expressed as a_1 and a_2, respectively.

(2) Users' forwarding behavior is affected by users' degree of interest (expressed as ω) in the public opinion information; the closer the value of ω is to 1, the more interested the user is in the public opinion information and the higher the forwarding tendency is. The closer the value of ω is to 0, the less interested users are in the public opinion information and the lower the forwarding tendency is. Based on the similarity of user groups, the degree of interest ω follows the normal distribution of (0, 1).

(3) When the opinion information is communicated to the user of interest, the user propagates this information with probability P_1. Including the influence of user interest, the probability that the information is propagated is ωP_1. When the information is communicated to subsequent uninterested users, the user will decide whether to terminate the propagation based on the degree of disinterest, and the probability of terminating the propagation is $(1-\omega)P_2$. In this process, the opinion leaders I_1 always maintain the infectious state. This process is represented as follows:

$$P_1 = \frac{Number\,of\,forwards}{Number\,of\,Readers} = \frac{Number\,of\,forwards}{Number\,of\,Fans} = \frac{pnum}{fanum} \tag{2}$$

$$P_2 = \frac{Number\,of\,subsequent\,no\,longer\,forwarded}{Number\,of\,forwards} = \frac{nrpnum}{pnum} \tag{3}$$

According to the analysis, the undetermined user base S will be reduced due to exposure to the infectious states I_1 and I_0, and the number being reduced per unit time is:

$$\Delta S = -\omega P_1 a_1 NS(t)I_1(t) - \omega P_1 a_2 NS(t)I_0(t)$$
$$= -\omega P_1 NS(t)(a_1 I_1(t) + a_2 I_0(t)) \tag{4}$$

The change in quantity per unit time of the infectious state I is:

$$\Delta I = \omega P_1 NS(t)(a_1 I_1(t) + a_2 I_0(t)) - (1-\omega)P_2 NI_0(t) \tag{5}$$

The change in quantity per unit time of the recovered state R is:

$$\Delta R = (1-\omega)P_2 NI_0(t) \tag{6}$$

The differential equation corresponding to the model is described as follows:
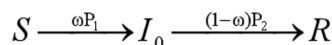
$$S \xrightarrow{\omega P_1} I_0 \xrightarrow{(1-\omega)P_2} R$$

Fig. 2. Public Opinion Communication Model of Public Health Emergencies Based on SIR

$$\begin{cases} \dfrac{\partial S(t)}{\partial t} = -\omega P_1 a_1 S(t) I_1(t) - \omega P_1 a_2 S(t) I_0(t) \\[2mm] \dfrac{\partial I(t)}{\partial t} = \omega P_1 S(t)(a_1 I_1(t) + a_2 I_0(t)) - (1-\omega) P_2 I_0(t) \\[2mm] \dfrac{\partial R(t)}{\partial t} = (1-\omega) P_2 I_0(t) \end{cases} \tag{7}$$

4. Model simulation and analysis

According to the actual development stage of public opinion during COVID-19, Python was used to crawl 192330 microblog-related data from December 8, 2019, to March 1, 2020 and to deal with anticlimbing by setting up a longer delay event. It uses key words and dates to construct advanced search links, traverses search pages and pagination, and keeps its forwarding information, comment information and release time, etc. Then, it extracts the user link, crawls the user's relevant information, and finally exports it to Excel for saving. A total of 35737 original microblogs and 156591 forwarded microblogs were screened out. The total number of forwarded microblogs was 2.271761 and the average forwarding volume of each microblog was approximately 65. The format of the crawled data is shown in Fig. 3:

This paper provides statistics on the number of fans, a_1 and a_2, of publishers of all original microblog posts in the collected dataset. Considering that the microblog platform disseminates information in a timely manner and users receive information on time, and that this paper uses days as the interval of change in state, the sum of the number of fans of all original content can be regarded as the original microblog's *fanum*. At the same time, the sum of the forwarding numbers of all original microblogs produces the overall forwarding number, *pnum*. Out of the above novel coronavirus pneumonia-related microblog forwarding users, crawling of the microblog's home page was used to determine whether the blog content contains public opinion keywords after a day to get the number of people *nrpnum* who will not participate in forwarding. The total number of users N participating in public opinion communication is obtained by eliminating duplicate usernames. According to the rules used to designate opinion leaders, the number of ordinary users I_0 and opinion leaders I_1 in the incubation period of public health opinion are counted. Through the above calculation process, the parameters of the SIR-based public health public opinion communication model are $P_1=0.406$, $P_2=0.117$, $a_1=6458951$, $a_2=7358$, $I_0(0)=0.00583$, $I_1(0)=0.00237$, $N=112821$. Degree of interest ω obeys the normal distribution between (0,1). In order to simulate the overall public interest in the public's opinion on public health, the interest ω takes the mean value of 0.5.

	keyword	content	time	forward	comment	user name	fans	identity	Whether it is certified	gender	district	
1	keyword	content	time	forward	comment	user name	fans	identity	Whether it is certified	gender	district	
2	Novel coronavirus	[Henan information and com	January 28th, 2020, 22: 45 am			China Electronics Newspap	442201	Blue V	Yes:	Female		
3	Novel coronavirus	Xinhuanet client: Shanghai	January 28th, 2020, 22: 45 am			Ice bergWolf	1218		No:	Male	Fuzhou, Fujian Province	
4	Novel coronavirus	Rumor: N95 mask with Respi	January 28th, 2020, 22: 45 am			one111zero	10		No:	Female	Ningxia Province	
5	Novel coronavirus	# Novel Coronavirus infect	January 28th, 2020, 22: 45 am			Steam ball WSHJ	431		No:	Female	Chengdu, Sichuan Province	
6	Novel coronavirus	How to prevent and control	January 28th, 2020, 22: 45 am			Like Dream wagmeg	3		No:	Female	Others	
7	Novel coronavirus	[China Center for Disease	January 28th, 2020, 22: 45 am	1	1	Love Me Daxing Community	174303	Blue V	Yes:	Male		
8	Novel coronavirus	Medical expenses for C OVI	January 28th, 2020, 22: 45 am			Zhong Ruiyang	439		No:	Male	Chaoyang District, Beijing	
9	Novel coronavirus	[Novel coronavirus science	January 28th, 2020, 22: 45 am			User 6506359786	1		No:	Female	Others	
10		Hengshui [Note! "Hengsh										
11												
12		After investigation, wang										
13												
14	Novel coronavirus	The police once again remi	January 28th, 2020, 22: 45 am	1		Hengshui Tong	246205		No:	Female	Hengshui,	
15	Novel coronavirus	Forward it to Weibo	January 28th, 2020, 22: 45 am			Fast Xiao Bao	709		No:	Male	Jiangsu Province	
16	Novel coronavirus	On June 26, 2000, US Presid	January 28th, 2020, 22: 45 am			Moonxiao 201810	15		No:	Male	Hengshui, Hebei Province	
17	Novel coronavirus	# We fight against new 19	January 28th, 2020, 22: 45 am	1	4	First broadcast	150651		No:	Female	Shaanxi Province	
18	Novel coronavirus	# Lanzhou revealed # # fig	January 28th, 2020, 22: 45 am			Lanzhou All-wide Media	109256		No:	Female	Gansu Province	
19	Novel coronavirus	Jiao Yahui, director of th	January 28th, 2020, 22: 45 am			Lijiang	232581		No:	Male	Others	
20	Novel coronavirus	//@Begins-happy: ask for h	January 28th, 2020, 22: 45 am	1		Kitties on the Moon _	372		No:	Female	Beijing: Beijing	
21	Novel coronavirus	//@ West Zai: If, really i	January 28th, 2020, 22: 45 am			4157tudou	900		No:	Female	Overseas:	
22	Novel coronavirus	Forward it to Weibo	January 28th, 2020, 22: 45 am			Longnan Cheng County Hong	3225	Blue V	Yes:	Male		
23		Last night, the first batc										
24		On the same day, experts f										
25		Fan Hua is the head nurse										
26		"The epidemic is orders, a										
27		As a Party member with 24										
28		"When I came to the superm										
29	Novel coronavirus	In the face of the sudden	January 28th, 2020, 22: 45 am	1		Zhongan Online	32061	Blue V	Yes:	Female		
30	Novel coronavirus	Forward it to Weibo	January 28th, 2020, 22: 45 am	5		ollydbgMan	335		No:	Male	Overseas USA	
31	Novel coronavirus	Forward it to Weibo	January 28th, 2020, 22: 45 am			1 Nie Yimeng's List MKe	324		No:	Female	Hami, Xinjiang Province	
32	Novel coronavirus	Forward it to Weibo	January 28th, 2020, 22: 45 am			Gansu Provincial Health C	2852646	Blue V	Yes:	Male		
33	Novel coronavirus	[# Raise 3.4 million prote	January 28th, 2020, 22: 45 am			User 6911107015	1		No:	Male	Others	
34	Novel coronavirus	Rumor: Wearing a multi-lay	January 28th, 2020, 22: 45 am			one111zero	10		No:	Female	Ningxia Province	
35	Novel coronavirus	//@ Qin Yi ink: //@Tiger c	January 28th, 2020, 22: 45 am			Autumn White Hope for Aut	207		No:	Female	Others	

Fig. 3. Display of Blog Data Format

4.1. Analysis of information dissemination stage

In this paper, MATLAB R2021a was used for simulation. The novel coronavirus pneumonia model was used to simultaneously interpret the above parameters in the model. Trends in user transmission state ratios during the public opinion epidemic situation were determined.

From Fig. 4, we can see that for the data collected from the COVID-19 dataset, the percentage of those in the undetermined state S is below the proportion of those in the infectious state I at (39.0529, 0.3724) for the first time. The proportion of those in the undetermined state S is for the first time lower than that of those in the infectious state I at (46.5592, 0.4065), and the point of symmetry falls at approximately 60. The point with the highest proportion of individuals in the infectious state I is (51.5592, 0.3952), and the first point of rapid increase of the three curves in the figure occurs at approximately the *19th* day.

From Day 1 to Day 19, the proportion of communicators in the initial stage is very low, and there are almost no recovered people in the period of 0-10 days. At this time, the number of communicators is small, the coverage is low, and it is difficult to forward information. Most users do not have access to public health information, and the credibility of the information has not been confirmed. The public has low trust in the public's opinion of public health information. In reality, this time period corresponds to December 8 to December 27. During this period, although a small proportion of public opinion can be formed on microblogs, its dissemination scope is narrow, its credibility is limited, and most microblog users are still in the undetermined state. This stage can be defined as the latent stage of communication of public health opinion information.

From Day 20 to Day 46, after the suspected epidemic was reported to the Jianghan CDC (Centers for Disease Control), the spread of COVID-19 public opinions increased. More than half of the undetermined users had been transformed into a infectious state. Because the interest degree ω of the paper took an average of 0.5, in theory, most microblog users had been informed of the epidemic situation. In addition, some users who participated in public opinion forwarding no longer forwarded information after losing interest and becoming recovered. This time period corresponds to the actual dissemination of COVID-19-related public opinion that took place from December 28, 2019, to January 24, 2020. On January 23, 2020, Wuhan was closed, and all parts of the country subsequently launched the first-class response to the major public health emergency by comprehensively carrying out epidemic prevention and control. The spread of public health opinion information based on COVID-19 epidemic data ushered in the fastest growth period, which was consistent with the period of the fastest spread of public health opinion information in the model. At this stage, public health opinion was not only limited to the microblog platform, but also was driven by the joint publicity and discussion in traditional media and other new media, and evolved into the outbreak stage of national discussion. Therefore, this paper defines the 19th-46th day as the outbreak stage of public health opinion communication.

From Day 47 to Day 60, the spread of public opinion about COVID-19 gradually slowed down and reached its apex on the 51st day, and the rate of transformation from the infectious state to the recovered state gradually increased, corresponding to the data from January 25th to February 7th. At this stage, state and local agencies actively promoted the prevention and control of the epidemic, actively developed COVID-19 detection products, built the Raytheon Hill Hospital—where academic Zhong Nanshan and many medical staff struggled on the front line of the epidemic—and implemented a series of behavioral measures to gradually stabilize public opinion. Although occasional rumors and new cases attract the public's attention, most public opinions can be controlled in time. Therefore, this paper defines the time period from Day 46 to Day 60 as the shock stage of public health opinion communication.

During the 61st Day to the 100th Day, the speed of public opinion communication about COVID-19 showed a steady downward trend. More than half of microblog users turned into the recovered state. The public's enthusiasm for public health and public opinion declined, corresponding to the actual data from February 8th to March 1st. During this period, newly confirmed cases in various parts
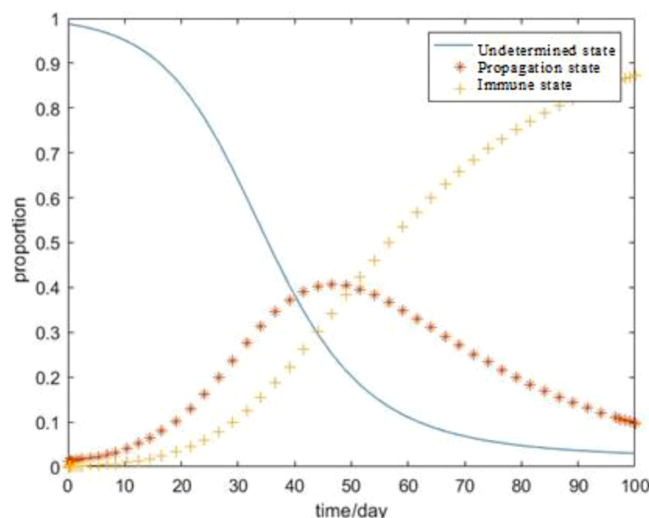

Fig. 4. COVID-19 Public Opinion Propagation Model Based on SIR

of China decreased, confirmed cases were cleared from isolation, epidemic risk decreased, and people decreasingly participated in the forwarding of public health opinion. Therefore, this paper defines the period from the 61st Day to the 100th Day as the regression stage of public health opinion communication.

To intuitively understand the characteristics of each stage in the propagation of public health opinion based on COVID-19 data, and to verify the simulation results of the model, this paper selects the daily microblog keywords from the crawl data and uses the statistics from the amount of forwarding from microblog users to establish a histogram with time as the horizontal axis and posting volume as the vertical axis, shown in Fig. 5 below:

According to Fig. 5, the spread of COVID-19 public opinion demonstrated 20 days of incubation, 27 days of outbreak and a relatively long time of extinction. Before official information was released, public health opinion spread and user participation was extremely low. In the medium-term communication process, with an increasing number of relevant reports from major media and government agencies, the communication speed of public health opinion has increased rapidly, and the number of posts has shown a sharp increasing trend. Later in the communication process, due to the efforts of national and local institutions in "prevention, control and treatment" of the epidemic situation, the public's attention toward public health opinion information gradually decreased and the number of posts shows a decreasing trend, which is consistent with the simulation results of our public opinion communication model.

4.2. Opinion leader analysis

In the process of public opinion communication about public health, opinion leaders often have more fans than ordinary users. The information associated with them also indicates that they have a stronger ability to spread public health opinions. This paper assumes that opinion leaders with more fans have a stronger ability to communicate public opinion about public health, so we chose to increase the number of fans a_1 of opinion leaders to determine the impact opinion leaders have on public opinion communication of public health events. The COVID-19 public opinion propagation model based on the SIR where the number of fans $a1$ is adjusted to a specific value that is 1.5 times larger than $a_1 = 6458951$ is shown in Fig. 6.

In Fig. 6, the point where the proportion of those in the undetermined state S is lower than that of those in the infectious state I for the first time is (21.2033, 0.4166); the point where the proportion of those in the undetermined state S is lower than those in the infectious state I for the first time is (38.7811, 0.4821); and the point where the proportion of those in the infectious state I is the highest is (29.3401, 0.5488). Comparing the intersection coordinates of Fig. 4 with Fig. 6, the start time of the microblog public opinion outbreak stage in Fig. 6 is approximately 17 days ahead of Fig. 4. At the same time, the value where the proportion of individuals in the transmission state reaches its peak is 0.1423 units greater in Fig. 6 than in Fig. 4, and the transmission rate is faster. Compared with Fig. 4, in the specified time interval, the undetermined users in Fig. 6 are transformed more rapidly and at a greater rate, and the overall time of public health opinion communication is significantly shortened.

In Fig. 7, we assign a_{11}, a_{12} and a_{13} to I1 and satisfy $a_{13} > a_{11} > a_{12}$ to visualize the outbreak of COVID-19. The coordinates where the three curves reach the peak proportion of those in infectious states are (29.3401, 0.5488), (36.1653, 0.4799), and (46.5592, 0.4065) for a_{13}, a_{11}, and a_{12}, respectively. Accordingly, the higher the number of opinion leaders' fans, the earlier the outbreak period of public health opinion, the higher the peak proportion of the infectious state, and the faster the spread of public health opinion. On the 100th day, it can be observed that the higher the number of fans, the lower the intersection point between the curve and the Axis X = 100. This indicates that the higher the number of fans, the faster the user's conversion from susceptible state to other states. Therefore, increasing the number of fans of opinion leaders—that is, increasing the influence of microblog opinion leaders—makes public opinion
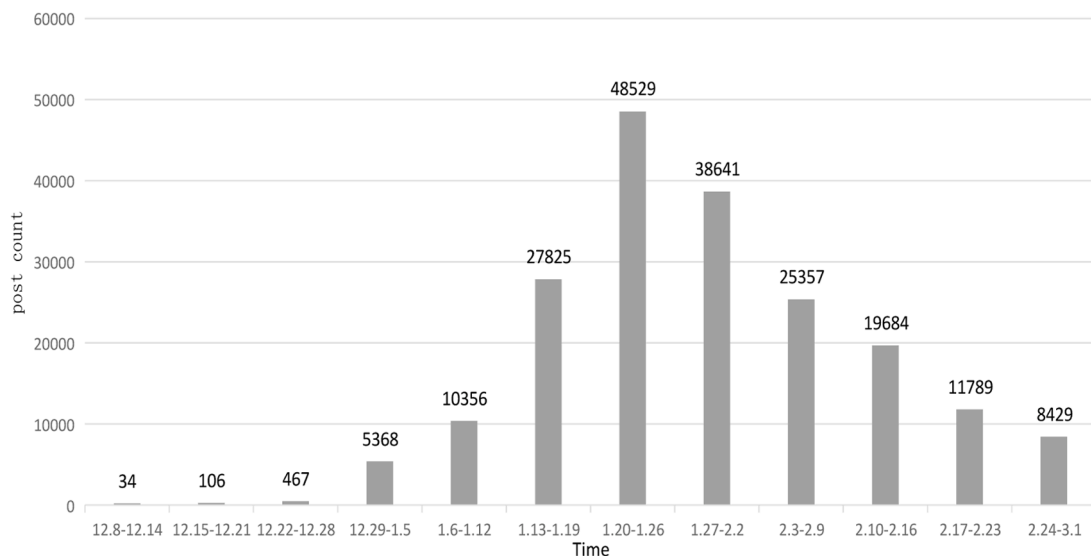

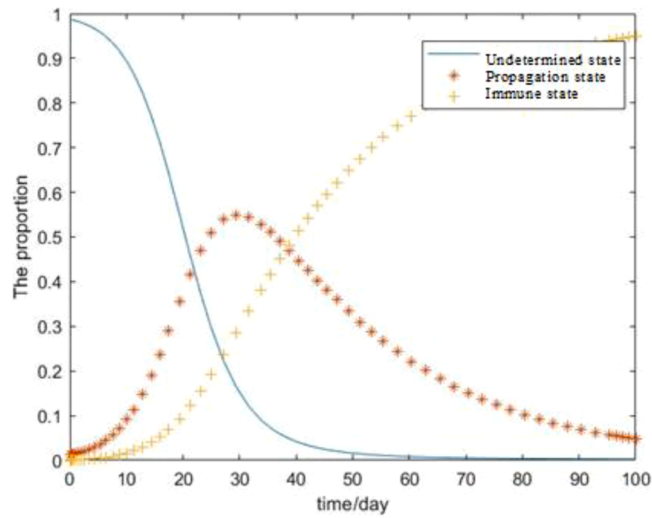**Fig. 5.** Posting Statistics for Different Time Periods

Fig. 6. COVID-19 Public Opinion Propagation Model with Increased Numbers of Opinion Leader Fans
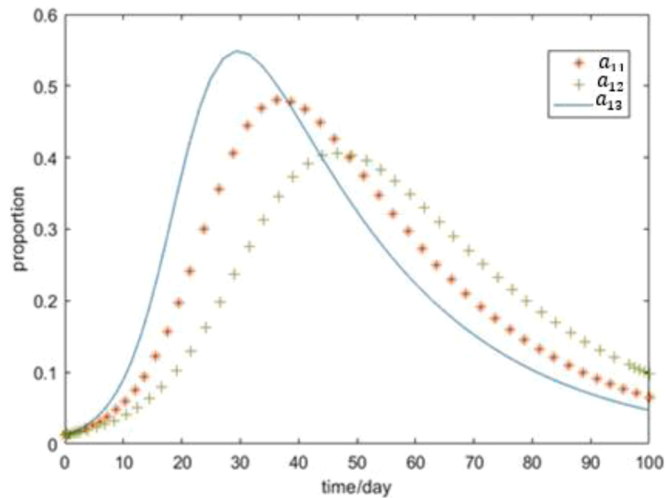

Fig. 7. Variation of Infectious State I_1 with the Number of Fans

about public health information spread more widely and have greater influence in a shorter time.

4.3. Analysis of public interest

This paper simulates the public's influence on the spread of COVID-19 public opinion by changing the degree of interest ω. The trend of COVID-19 information dissemination where the value of ω is raised to 0.7 is shown in Fig. 8.

In Fig. 8, the point where the proportion of those in the undetermined state S is lower than that of those in the propagating state I for the first time is (20.9599,0.4313); the point where the proportion of those in the undetermined state S is lower than that of those in the propagating state I for the first time is (45.5151,0.4785); and the point where the proportion of those in the propagating state I is the highest is (30.5436, 0.6166). Compared with Fig. 4, the outbreak stage of public opinion communication is approximately 18 days earlier, the time it takes for the proportion of those in the infectious state to peak is shortened by 16 days, the peak proportion of those in the infectious state is increased by approximately 0.2101 units, the speed of public opinion communication is accelerated, and the communication cycle of public opinion information is further prolonged. If other values remain unchanged while the value of ω is changed, and $\omega_1 > \omega_2 > \omega_3$, then the law of infectious state I varies according to the degree of interest of ω, as shown in Fig. 9:

In Fig. 9, the coordinates of the highest proportions of infectious states are (30.5436, 0.6166), (36.1653, 0.4799), and (49.8141,0.2615) for ω_1, ω_2, and ω_3, respectively. In observing the coordinate data, we find that the larger the degree of interest ω is, the earlier the outbreak period of public health opinion information is, the higher the peak proportion of the infectious state is, and the faster the spread of public opinion information is.
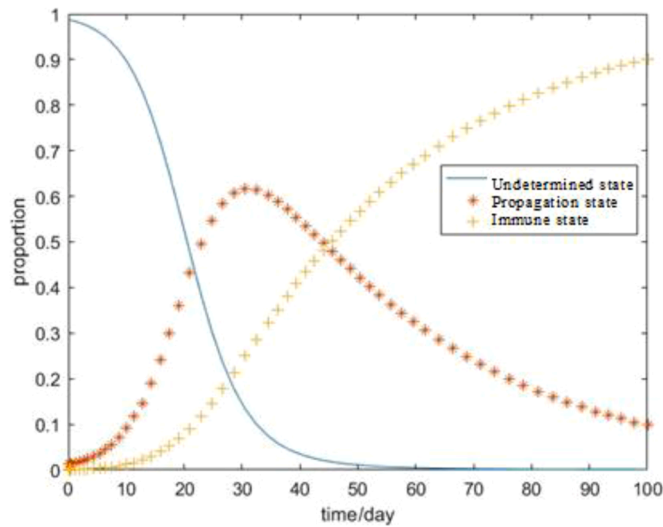
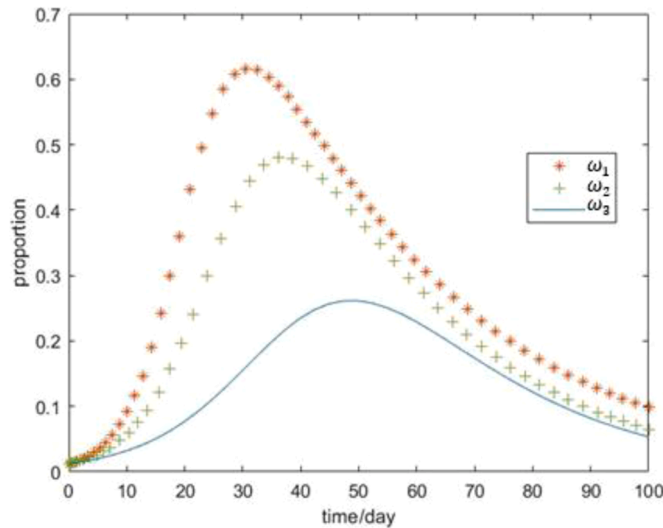**Fig. 8.** COVID-19 Communication Model after Increasing User Interest

Fig. 9. Trends in Infectious State with Varying the Degrees of Interest

The increase in public interest in the dissemination of public health emergency information causes more users to be interested in public opinion and participate in the dissemination of information about public health events. This speeds up the dissemination of public opinion, improves the popularity of public opinion, and hastens the dissemination of public health opinion.

4.4. Analysis of users' continuous attention

The users' continuous attention degree refers to the probability that users pay continuous attention to public opinion and carry out secondary communication. In the model, it is easier to maintain the infectious state than to transition to the recovered state. Therefore, the higher the continuous attention of users, the lower the probability that users will be transformed into the recovered state. By increasing P_2, this paper simulates the impact of users' continuous attention on the public opinion communication of public health events. The results are shown in Fig. 9.

In Fig. 9, the point where the proportion of those in the undetermined state S is lower than that of those in the infectious state I for the first time is (33.2227,0.2577); the point where the proportion of those in the undetermined state *S* is lower than that of those in the infectious state *I* for the first time is (43.2227,0.2758); and the point where the proportion of those in the infectious state I is the highest is (38.2017, 0.2868). Compared with Fig. 4, the outbreak stage of public opinion communication was delayed by approximately 6 days, the time when the proportion of those in the transmission state peaked was delayed by 8 days, the peak proportion decreased by

approximately 0.1158 units, the duration of the outbreak period was shortened, and the regression stage was significantly lengthened If other values remain unchanged while only the values of P_2 change, then the trends in COVID-19 propagation vary, as shown in Fig. 11.

Fig. 10

In Fig. 11, $p_{21} > P_{22} > p_{23}$, and the corresponding peak points are (38.2227, 0.2868), (37.1943, 0.3422), and (36.5743, 0.4060), respectively. The lower the continuous attention of users is, the higher the immunization rate, the lower the propagation rate and the lower the propagation peak.

Reducing users' continuous attention to public health events can effectively slow down the transmission speed of public health opinion, reduce the scope of public health opinion transmission, and reduce the number of people who know public opinion information, thus further limiting transmission of public health opinion.

4.5. Public opinion control strategies and suggestions

Based on the above simulation results, variables including microblog opinion leader status, user interest in public health emergencies, user continuous attention level and other factors can greatly affect the dissemination of public health opinion. Social network public opinion information can be controlled in the following ways:

(1) Microblog opinion leaders can do the following: accelerate the speed of public opinion dissemination and expand their influence on others, especially in the initial stage of public opinion; control the key sources of public opinion dissemination in a timely manner; guide trends in and speed of public opinion dissemination with great efficiency at a low cost, which is of great benefit to government management; and establish a prediction and identification system for opinion leaders. After identifying opinion leaders, the government should strengthen guidance of opinion leaders to manipulate trends in public opinion. Mainstream media should actively take on the role of the opinion leader, intervening immediately after an emergency outbreak occurs, acting as the figurehead of public opinion information, giving professional interpretation and authoritative communication, and playing the role of public opinion guides.

(2) The greater the public's interest ω in public health public opinion is, the faster the spread of public health public opinion is, the higher the intensity is, and the wider the dissemination is. Therefore, leaders can choose to reduce the public's interest in public health public opinion to limit its transmission speed and reduce the intensity of public health opinion.

(3) The resolution of events triggered by public health opinion is closely related to users' degree of continuous attention. The higher $P2$ is—that is, the lower the degree of continuous attention of users—the lower the total number of users who are maintained in the infectious state. The slower the communication speed of public health opinion is, the smaller the scope of communication is, and the faster the intensity subsides. The government should gradually establish and improve mass feedback channels in a universal manner, set up a platform for responding to public health opinion information to address the needs of the masses on time, and effectively reduce the anxiety of the masses to mitigate users' continuous attention towards public opinion on public health events.

5. Conclusion

This paper constructed a public health emergency public opinion communication model based on the classical infectious disease
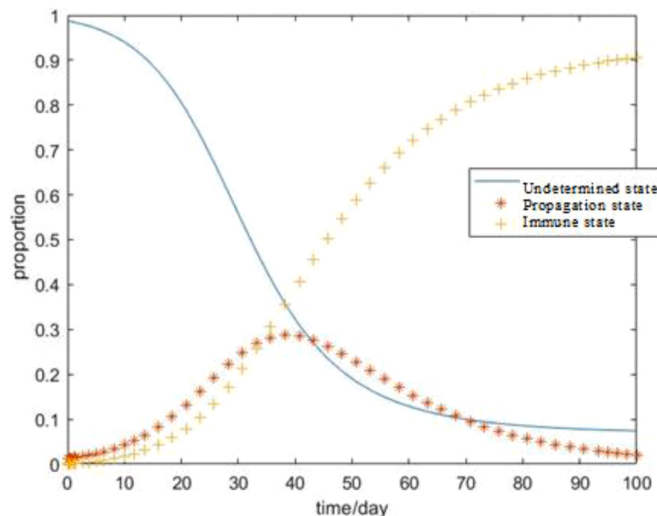

Fig. 10. COVID-19 Propagation Model of Increase User Continuous Attention
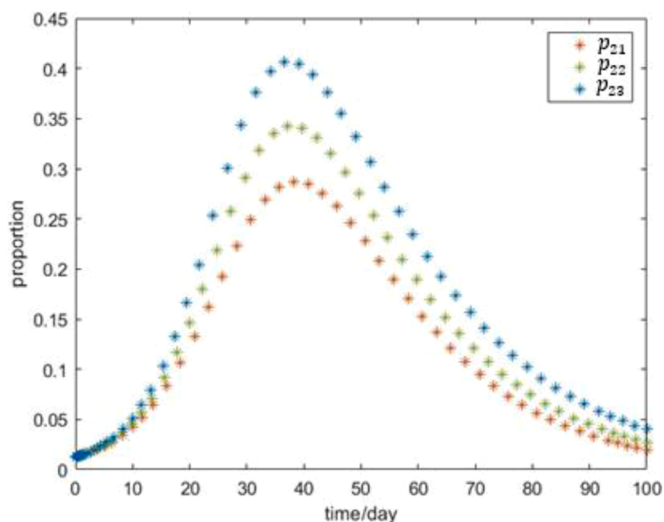
Fig. 11. Trends of the Infectious state with Varying P2 Values

model—the SIR model—combined with the characteristics of public opinion communication on microblogs. This model took into consideration the difference between opinion leaders and ordinary users on the social network platform as well as the interest of network users in public opinion information. Defining the dissemination of network-based public opinion about the novel coronavirus pneumonia as a case, the model is verified by analyzing the actual microblog data and using the actual calculated parameters. Through computer simulation experiments, this paper studied the impact of microblog opinion leaders, public interest in public health opinion and the effect of continuous attention on the communication process of microblog public health opinion information. It provides the government with control and guidance opinions to manage public health microblog opinion information. In the future, studies should focus on how to build a fast and effective public health opinion monitoring system, model the dynamic microblog network structure and accurately predict the spread of public health opinion information.

CRediT authorship contribution statement

Jinghua Zhao: Writing – review & editing. **Huihong He:** Data curation, Writing – original draft. **Xiaohua Zhao:** Visualization, Investigation. **Jie Lin:** Conceptualization, Methodology, Software.

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