The Evolutionary Public Opinions on Social Media in the Context of Infodemic: an SD modelling approach

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Abstract: In the context of infodemics, negative opinions were rapidly fermented on the Internet, causing significant mental damage to general public, especially when developed into cyberbullying. Therefore, it is of significant importance to study the evolution of public opinions on social media. The SHI_AI_BOR model is developed to investigate the propagation of negative opinion during pandemic. The model considers the competitive spread of both position and negative opinion from the general public, and social media and government participation. Simulation results showed that increasing the conversion rate of the general public can alleviate the overwhelming spread of negative opinion, while social media participation might cause a second wave of negative opinion. Moreover, government participation can not reduce the peak of negative opinion but can reduce the time period that negative opinion prevalence.

Keywords: Public Opinions, sentiment analysis, social media participation, government participation, SEIR model

Introduction

COVID-19 pandemic is the most severe public health crisis in a century. In addition to the serious health threat it posed to the general public, COVID-19 produced adverse psychological impacts mostly through the excessive information on social media, which is referred as infodemic [1]. Infodemic refers to the rapid spread of excessive information (both correct and incorrect) through social media and other communication technologies during the pandemic, making it difficult for people to find trustworthy sources of information and reliable guidance [2]. The infodemic consisted mainly of rumors, cyberbully, and others. The Director-General of the World Health Organization emphasized that "we are not just fighting a pandemic, we are also fighting an infodemic." [3]

In the era of social media, everybody is able to disseminate information online. The excessive and fragmented information sometime can trigger extreme public opinion. During the COVID-19 pandemic, the uncertainty on the spread of the virus has intensified negative emotions among the public, including anxiety, panic, and concerns [4, 5]. This, in turn, led the irrational public to magnify certain aspects of a social event and negatively judge the people involved, causing significant harm to the physical and mental well-being of the individuals [6]. Some social media platforms, driven by the desire to attract attention and profit, deliberately create hotspots and spread negative information of the events, leading to a further surge in negative online sentiment [7]. Understanding the mechanism by which public opinions evolve in the context of COVID-19 is important to fight against and build a healthy Internet, especially during turbulent times [8].

2. Method

Based on the traditional SEIR model [9, 10], we constructed the SHI$_A$I$_B$OR model of online public opinion dissemination to investigate the competitive spread of various opinions. The general public were categorized the following six groups and their relationship is illustrated in Figure 1.

1) Susceptible (I): People who have not been exposed to the information, but they may be exposed to and participate in information dissemination in the future.

2) Hesitation (H): People who has been exposed to the information, but have not yet spread the information.

3) Spreader A (I_A): People who hold and disseminate a negative opinion.

4) Spreader B (I_B): People who hold and disseminate a positive opinion.

5) Spreader (O): People who hold and disseminate an objective opinion.

6) Stiffler (R): People who do not disseminate the information anymore.

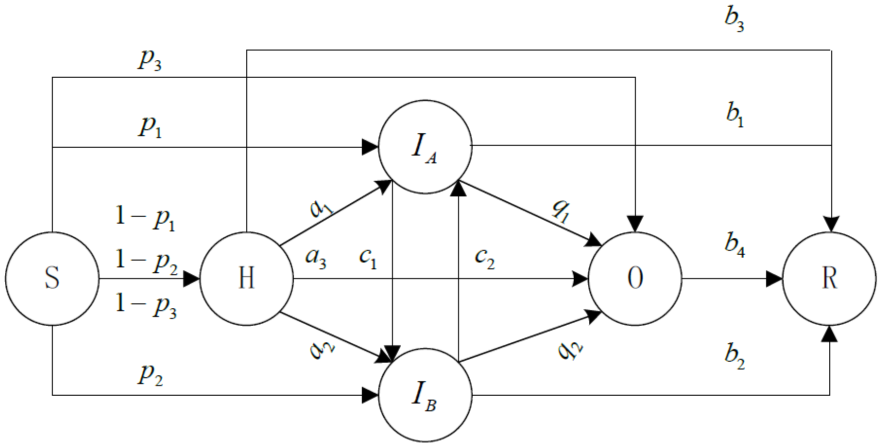


Figure 1 Model Structure

When S contacts I_A, I_B and O, they will be transformed into the spreader of positive, negative and objective opinion with the probability of p_1, p_2, p_3, respectively, or transformed into H with the probability of 1- p_1, 1- p_2, 1- p_3, respectively. H will be transformed into the spreader of positive, negative and objective opinion with the probability of a_1, a_2, a_3, respectively, when contacted with the views of A, B and O, or become R with the probability of b_3. The positive and negative opinions may transform into each other with the probability of c_1, c_2, or transformed into the spreader of objective opinion with government guidance with the probability of q_1, q_2, or transformed into R with the probability of b_1, b_2. O will be transformed into an R with probabilities of b_4. The equations of the model are listed below:

$$\begin{cases} \frac{dS(t)}{dt} = -p_1 S(t) I_A(t) - p_2 S(t) I_B(t) - p_3 S(t) O(t) - S(t)[(1-p_1)+(1-p_2)+(1-p_3)] \\ \frac{dH(t)}{dt} = S(t)[(1-p_1)+(1-p_2)+(1-p_3)] - (a_1+a_2+a_3+b_3)H(t) \\ \frac{dI_A(t)}{dt} = p_1 S(t) I_A(t) + a_1 H(t) + (c_2-c_1) I_A(t) I_B(t) - b_1 I_A(t) - q_1 I_A(t) O(t) \\ \frac{dI_B(t)}{dt} = p_2 S(t) I_B(t) + a_2 H(t) + (c_1-c_2) I_A(t) I_B(t) - b_2 I_A(t) - q_2 I_B(t) O(t) \\ \frac{dO(t)}{dt} = p_3 S(t) O(t) + a_3 H(t) O(t) + q_1 I_A(t) O(t) + q_2 I_B(t) O(t) - b_4 O(t) \\ \frac{dR(t)}{dt} = b_1 I_A(t) + b_2 I_B(t) + b_3 H(t) + b_4 O(t) \end{cases}$$

Where $S(t)$, $H(t)$, $I_A(t)$, $I_B(t)$, $O(t)$, $R(t)$ represents the density of each group of the people at time t. Thus, $S(t)+H(t)+I_A(t)+I_B(t)+O(t)+R(t)=1$. The conversion of positive and negative opinions is presented in the following equations:

$c_1 = 0.01 + y * [I_A/(I_A+I_B) - 0.5]$

$c_2 = 0.01 + y * [I_B/(I_A+I_B) - 0.5]$

Where, the constant 0.01 indicates the spontaneous conversion rate of public opinions between positive and negative. $I_A/(I_A+I_B)$ and $I_B/(I_A+I_B)$ are the proportion positive and negative opinions on social media. If $I_A/(I_A+I_B) > 0.5$, it means that positive view points dominant on the social media and individuals will be affected with more people changing into positive view and less people changing into negative view. y represents the strength of social media impact.

3. Model of a case during the COVID-19

3.1 Case background

On December 8, 2020, it was officially announced that a woman was diagnosed with COVID-19 in Chengdu and before her diagnosis, she had visited many crowded public venues such as a park, a restaurant and several bars. Many people were angry about the girl's action as they felt the danger of being infected or being quarantined. In the early morning of December 8, increasing number of people discussed this event online and negative opinions pervaded. As the girl had visited several bars, there were speculations about her private life while it turned out her work is for marketing and improving ambience of bars. Insulting personal attacks were widely seen on social media and the girl's personal information, such as her name, phone number, and family address, was exposed on the Internet. At 13:14 on Dec 8, a Weibo post by the official Weibo account of Sina News (@新浪新闻) "Chengdu confirmed girl suspected of being cyberbullied" was discussed 1523 times, receiving exposure of 90.49 million times. This post surged to the top of Weibo's hot search list. At 20:24 the same day, CCTV (China Central Television) commented on the personal information leakage regarding the Chengdu girl. The post by official Weibo account of CCTV News (@央视新闻) "Anxiety over the epidemic should not be a reason for cyberbullying," was exposed 560 million times, with 27,000 discussions, attracting significant attention from netizens.

3.2 Data collection

1) Public opinion

We collected the weibo posts by general public from the start of the “chengdu girl event” to 48 hours after the event when the public sentiment is gradually calming down. A total of 7307 posts were collected after deleting the duplicated posts. Using the Baidu API sentiment analysis model, we extract the opinion polarity of the Weibo posts and its confidence level, as shown in table 1. High confidence level means that the identification results is of high credibility. The average confidence level is 0.86 for the total 7303 weibo posts, which showed that the sentiment analysis results is highly credible.

Table 1. The public sentiment

Time	Content	Opinion polarity*	Negative possibility	Positive possibility	Confidence level
7:42	Wear mask and protect yourself	2	0.0227	0.9773	0.9496
7:49	It teared me apart. 😳	0	0.9657	0.0343	0.9237
8:26	I have been searching information on mobile since yesterday afternoon. Finally, it came out in the early hours.	1	0.4817	0.5183	0.6340

* Opinion polarity: 0 represents negative opinion, 1 represents positive opinion and 2 represents positive opinion.

By calculating the frequency of negative posts across different time intervals, we derived the proportion of negative opinion over time. Due to the uneven number of posts in different time intervals, the amount of data in some time intervals are so small that are not enough to support the calculation of negative opinion. In order to improve the accuracy, we utilized an uneven time series set as the x-axis, ensuring adequate data sizes while minimizing time intervals. This approach aimed to make our studied data as dense as possible, and the final proportion of negative public opinion over time is presented in Figure 1.

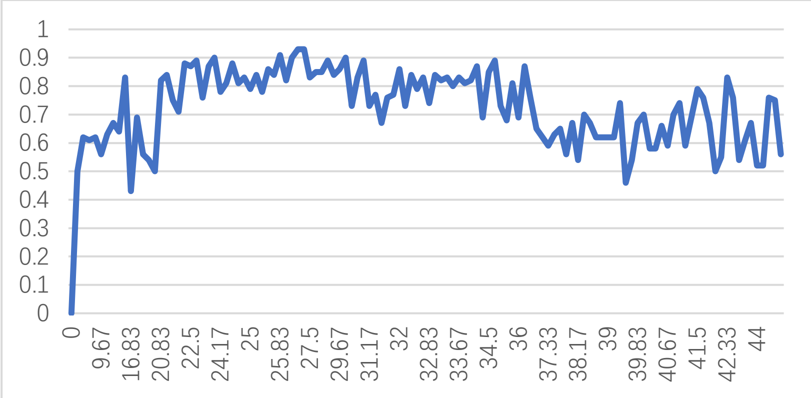


Figure 1 The evolution of negative public opinion over time

2) Social media participation and government intervention

The public opinion monitoring platform, Zhiweishijian （https://ef.zhiweidata.com/） summarized the dissemination of the event related information. We collected the data on related information from social media and the government. Government posts were mainly from official accounts such as People's Daily, CCTV News, China.com.cn, and China.org.cn. The content of government posts revolved around object opinion such as "Chengdu girl is also a victim; " and "Cyber violence should be avoided." A total of 35 official government posts were collected. For social media, a total of 426 posts were identified, much larger than the government post, as shown in Figure 2.

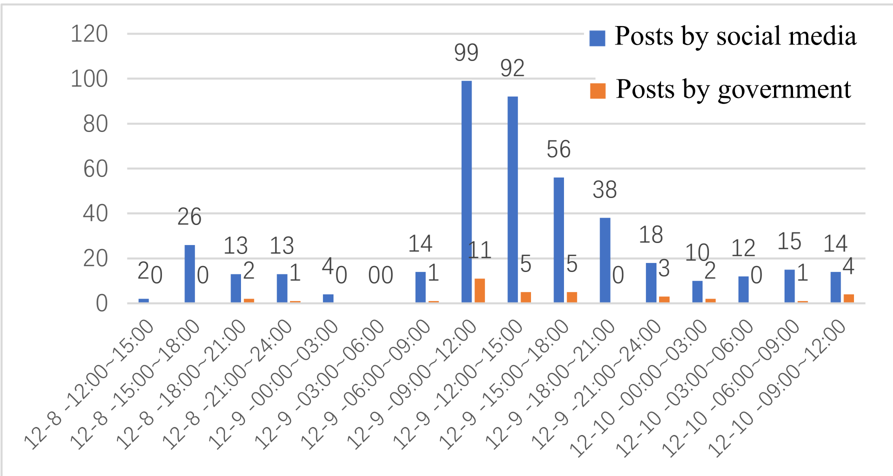


Figure 2 The participation of government and social media

3.3 Parameter setting

During the pandemic, public were all anxious about event or information related to COVID-19 spread. Therefore, we set the initial negative opinion and the spread of the negative opinion 10 times that of positive opinion. As a result, the initial value is set as following:

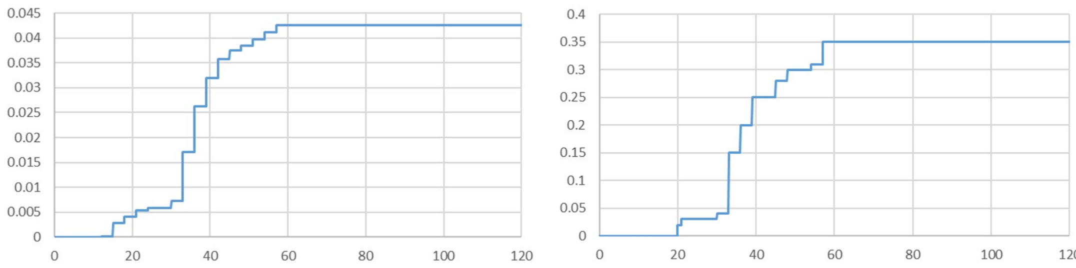
$$S(t)=0.9995,\quad H(t)=0,\quad I_A(t)=0.0004,\quad I_B(t)=0.00005,\quad O(t)=0.00005,\quad R(t)=0$$

The fraction for spread the negative opinions were set 10 times higher than the spread of the positive and objective opinions. Therefore,

p1=0.6， p2=p3=0.06； a1=0.6， a2=a3=0.06

The recover rates are set as equal, where b1=b2=b3=b4=0.01

The impact of social media and government (y and q) are set according to the number of posts they published. As the government official post are more influential than posts of social media, we set government post impact times high than that of social media, as shown in Figure 3 (a) and (b).



(a) the impact of social media (y) (b) the impact of government (q)

Figure 3 The impact of government and social media

3.4 Model validation

First of all, the model structure is an extension based on the traditional SEIR model, which has been widely used to model the spread of public sentiment. Secondly, the model parameter setting is according to the data published on social media. Finally, the model simulation result fits the real-world data, as shown in Figure 4, which also adds confidence to the model.

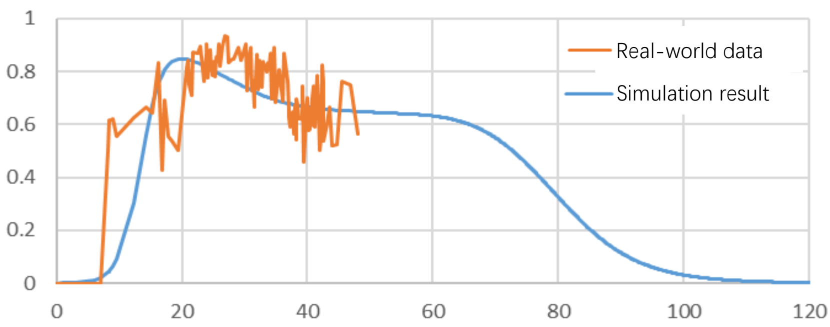


Figure 4 The negative public opinion: real-world data and simulation result

4. Policy analysis

4.1 The impact of the spontaneous conversion rate (SCR) of general public

In the base scenario, the SCR of public opinions between positive and negative were set as 0.01. In this section, we tested two scenarios with C1 and C2 with the spontaneous conversion rate set as 0.03 and 0.06 respectively.

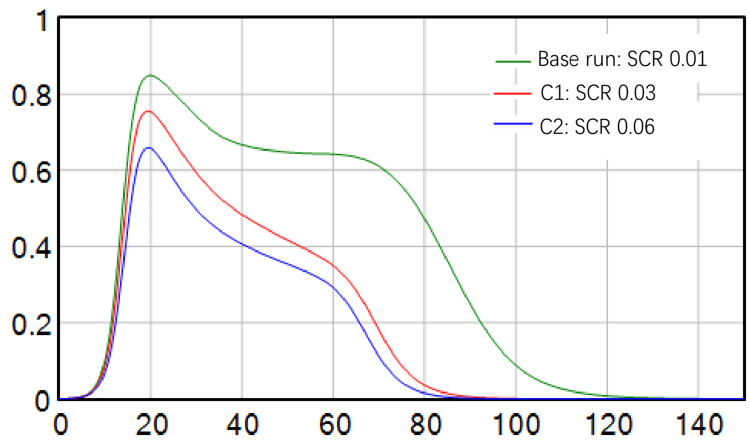


Figure 5 The negative public opinion under different spontaneous conversion rate

The model simulation result shows that the increase of SCR can reduce both peak of public negative opinion and the duration of the strong negative opinion. Meanwhile, as the SCR becomes larger, the impact becomes smaller. A diminishing marginal effect can be identified. The simulation result indicated that if the netizens could be more open-minded and were more willing to accept object and spread opposite opinion, the view point domination online will be less severe.

4.2 The impact of the social media participation

To investigate the impact of the social media participation on the public opinion, another two scenarios, M1 and M2 are tested besides the base scenario. In M1, the social media participation is set at 120% that of the base scenario while in M2 the social media participation is set at 80% that of the base scenario, which represents a 20% increase and decrease of social media participation.

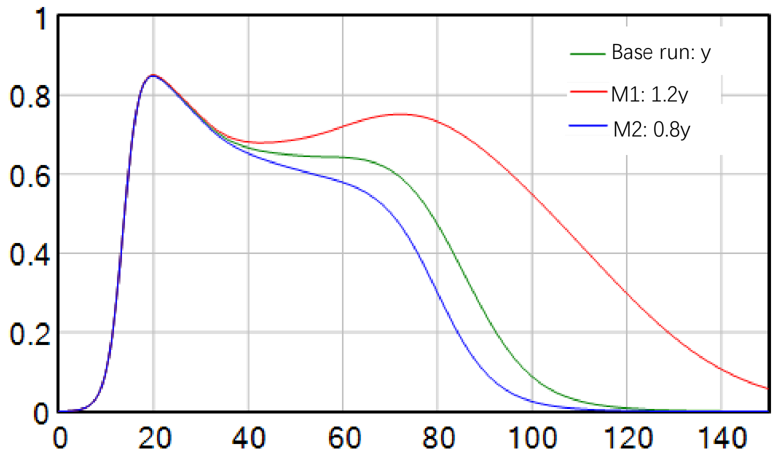


Figure 6 The negative public opinion under different social media participation

The model simulation result shows that the change of social media participation can not change the peak of the negative opinion, but will extend the duration of the public opinion domination. With high social media participation, a second wave of strong public opinion can be observed. While with low social media participation, the dominant of public opinion will end faster.

4.3 The impact of the government intervention

To investigate the impact of the government participation on the public opinion, another two scenarios, G1 and G2 are tested besides the base scenario. In G1, the government participation is set at 120% that of the base scenario while in M2 the government participation is set at 80% that of the base scenario, which represents a 20% increase and decrease of government participation.

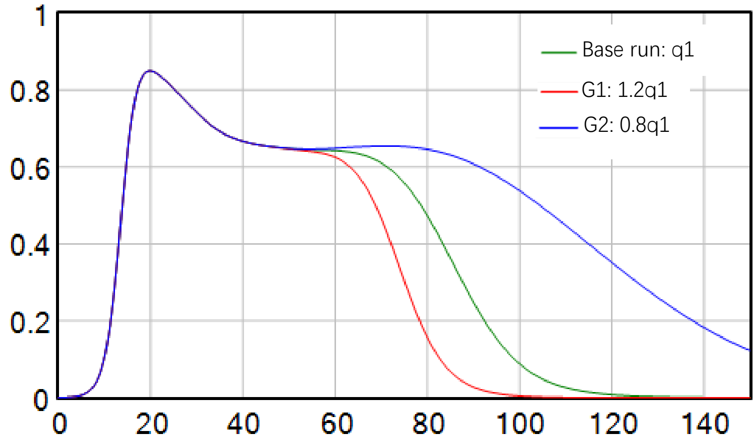


Figure 7 The negative public opinion under different government participation

The model simulation result shows that the change of government participation can not change the peak of the negative opinion, but will affect the duration of the public opinion domination. With high government participation, the dominant of public opinion will end faster. On the contrary, a low government participation will extend the time period of strong negative public opinion, which might cause panic or anxiety, or even lead to cyber violence.

5. Conclusion

This study explored the evolution mechanism of public opinion on social media applying the system dynamics method. Text mining and sentiment analysis are used to collect data of a real-world case, “Chengdu girl event”. This case is adopted first for model parameter setting and then for model validation. Finally, the model is used to investigate the impact of the spontaneous conversion rate of the general public, social media participation, and government intervention.

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