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Temporal and spatial evolution of online public sentiment on emergencies

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ABSTRACT

The transmission of online emergency information has become an active means of expressing public opinion and has vitally affected societal emergency response techniques. This paper analyzes interactions between three groups in time and space using a classic SIR (susceptible, infected, and recovered) epidemic model. Through social network theory and analog simulation analysis, we utilize data from China's Sina Weibo (a popular social media platform) to conduct empirical research on 101 major incidents in China that occurred between 2010 and 2017. We divide these emergencies into four types—natural disasters, accidents, public health events, and social security events—and conduct a simulation using three examples from each group. The results show that government control of public opinion is both cheaper and more effective when it occurs at the initial stages of an incident. By cooperating with the government, the media can facilitate emergency management. Finally, if netizens trust the government and the media, they are more likely to make cooperative decisions, maintain interest, and improve the management of online public sentiment.

1. Introduction

Online public sentiment refers to the sum of various attitudes, opinions, and emotions expressed via the Internet within a certain time and space, reflecting social conditions (Cao, Liu, Fang, Duan, & Li, 2014; Zhang, & Li, 2016). Online public sentiment on emergencies refers to how netizens use a network platform to express their opinions and views on emergencies (Soffer & Gordoni, 2017). Our study categorizes these emergencies as natural disasters, accidents, public health events, and social security events. The evolution of online public sentiment on emergencies is a dynamic process and involves three main bodies: a government, network media, and Internet users (Wang, Li, & Li, 2016). If emergencies themselves drive public sentiment, then Internet users are the producers, and online media drives the development of public sentiment. The government, meanwhile, regulates and guides public sentiment and attempts to understand how it evolves to play an active role in guiding future public sentiment (An, 2019; Lan & Zeng, 2013; Xia, 2019). This process is driven by the public need to know the truth about events and a general sentiment of social justice, both of which require that the public receive adequate information. However, public sentiment has become progressively more complicated and uncertain over time, arousing widespread concern in academic circles.

Government and public netizens coexist in a social network. When an emergency occurs, online rumors spread quickly and take

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diverse forms, thereby affecting decision making and information dissemination via official media (McGregor, 2019). Tang, Chow, Breen, and Prigerson (2019) argue that to understand the relationship between individuals and the media during the spread of online rumors, it is necessary to construct a simulation model of how public opinion develops. To this end, Lebensztayn and Rodriguez (2013) use a Markov chain to depict the interactions between the spread of online public sentiment and official activities in order to simulate the propagation of crisis information in online media. They accomplish this through the utilization of a multi-agent modeling method, guided by the theory of complex adaptive systems and Repast and Netlogo platforms. They found that the media's initial authoritative release of information after an emergency has a substantial influence on the behavioral decisions of all social groups, making media a powerful tool for official management over a situation. Zhu and Li (2012), meanwhile, established a new public opinion communication and control model that starts from the network public opinion communication environment, compared an intervention and control group at the initial stage of public opinion formation, and verified the effectiveness of the control method through simulation. Other scholars carry out simulations of the evolution of public opinion based on complex multi-agent networks in order to verify the influence of each factor on the overall transmission and effect of various public opinions. Such studies adjust the parameters of influencing factors, such as governmental credibility, and examine the differences between individuals and the media (Zhao et al., 2012). Hegselmann and Krause (2002) proposed a dynamic and bounded Deffuant model based on an analysis of the characteristics of public opinion transmission among netizens within social networks, and they analyzed the relationship between the number of netizens and the speed of consensus formation. Utilizing actual interactions between network users, they proposed a network evolution model that comprehensively considers the influence between users, the trust threshold, and an individual persistence strategy that better portrays the actual evolution of online public sentiment. Hu and Dong (2016) used Netlogo simulation software to simulate the behavior of the government, media, and netizens after China's Weng'an Riot. The riot involved a siege of government buildings in Weng'an County, Guizhou Province, following the tragic death of a female student, and resulted in fire damage and physical destruction. They discovered the value of network environment attributes of government, media, Internet users, and other Internet subjects as well as the weight of their respective influences. That is to say, by changing the relationship intensity among subjects, the influence of changes in network relations among government, media, and Internet users on the dynamic evolution of network public opinions can be measured and analyzed.

To the end of understanding the transmission of online public sentiment, social network analysis (SNA) allows researchers to analyze the comprehensive or interconnected space formed as a result of the interactions among individual users, at individual and systemic levels. Therefore, SNA better explains the change in main bodies and how these factors affect the relationship structure of the overall social network. The formation and evolution of online public sentiment are inseparable from communication relationships between people, the topological structure of public opinion networks, and the relationships among various public opinion participants. Hridoy, Ekram, Islam, Ahmed, and Rahman (2015) propose that social network data are one of the most effective and accurate indicators for studying public sentiment since platforms like Facebook, Twitter, and other social media websites are filled with people's opinions and comments. Examples include Twitter users' views on Barack Obama's Nobel Peace Prize nomination (Urban & Bulkow, 2013) and comments on Instagram and Flickr mentioning the word "Ebola" (Seltzer, Jean, Kramer-Golinkoff, Asch, & Merchant, 2015). SNA is also a valuable tool for understanding perceptions of emergencies, though Wei-Wei-Dong, Qian, and Jie (2018) are among the few scholars who have carried out research on this topic. Because of the complexity of influencing factors and the difficulty of obtaining adequate data, developing an accurate model is a challenge, and few studies have attempted to verify the results of theoretical research through case studies. Too much emphasis has been placed on unilateral changes in government attitudes, and fewer studies have focused on the effect of multiple agents such as network media and netizens in addition to governments (Zeng & Chen, 2018).

Based on previous studies, this paper analyses the characteristics of how public opinion about emergency networks evolves over from the perspective of time in cyberspace. The current view of the evolution of online public sentiment, netizens, media, and government all participate as subjects; therefore, multi-agent modeling is used to simulate the interaction between netizens and netizens, media and netizens, and the media and government. The interactive influence problem is simulated, and Baidu index data is used to obtain a number of statements expressing public sentiment from a particular period of time to apprehend both the evolution of public sentiment and the effect of governance on that evolution. Then, using the method by which Sina Weibo analyzes social networks, the characteristics of the key node and the important actors in the network during an emergency are analyzed spatially to provide a scientific basis for the government to respond effectively to online public opinion.

Our findings provide quantifiable data that will aid the government in effectively responding to online public sentiment. It is hoped that the model will accomplish four things. First, it will guide the handling of actual accidents and strengthen interactions of the media and netizens with the government. Second, it will allow the public to rapidly determine the status of emergencies and how they are developing and to appropriately guide trends in online public sentiment. Third, it will enable the government to publicly intervene in incidents as well as effectively and decisively control adverse effects. Fourth, it will guide network dissemination, maximize the use of rapid and effective media reporting to amplify the government's voice, facilitate the spread of positive messages on the Internet, and issue timely communication to the public and the media.

2. Methods

2.1. Model description

We utilized an SIR virus propagation model consisting of three differential equations with three state variables (susceptible, infected, and recovered—SIR) to determine the behaviors of various agents of online public sentiment. We applied the SIR model to

public opinion by involving three main actors: the government, media, and netizens. SIR allowed us to explore the number of participants in the middle segment, the participation of the media and the government, and the impact of various factors that influence the behavior of each subject and the interactions between subjects. This allowed us to summarize the influence of the government, media, netizens, and their interactions by adjusting the parameters of public opinion attributes. We suggest the following two hypotheses:

- H1: The attributes of the three subjects change simultaneously.
 H2: Netizen democracy is limitedly rational.

2.2. Model governmental attributes

The following governmental attributes can be understood through the formula:

$$G[G_a, G_b, G_c, G_d, G_e] \quad (1)$$

Government attitudes (G_a): The natures of sudden crises differ, as do the time and intensity of governmental interventions, which directly influence official media attitudes and netizens' views of the event. As public opinion on a sudden crisis continually evolves, the public sentiment of media and netizens pressures the government to accelerate its disclosure of information and improve information transparency. To understand this effect, G_a expresses the government's attitude toward a specific emergency at a given time. There are two possible values for $G_a(t)$ in the model: $G_a(t) = 1$ represents government support of communication, and $G_a(t) = -1$ represents government limitation of communication.

Government credibility (G_b): Netizens' and the media's trust of the government and the distribution of credibility at a given point in time can be represented as $G_b(t) \in [0, 1]$. Both the initial and ongoing credibility values differ for each specific example since the government takes different attitudes toward a crisis.

Government disclosure speed (G_c): The speed at which the government discloses information is represented as $G_c(t) \in [0, 1]$. This study assumes that all media publish information on a crisis; therefore, the information disclosure speed is never 0. In the simulation model, the closer $G_d(t)$ is to 1, the faster disclosure speed is.

Government transparency (G_d): As emergencies continue to develop, the government either discloses information as an effect of the netizens' and media's public opinion or it does not. This transparency can be represented by $G_d(t) \in [0, 1]$. When $G_d(t) = 0$, information is not disclosed and when $G_d(t) = 1$, information is entirely disclosed.

Supervision and leadership (G_e): The government supervises and publicizes the extent of the emergencies as reported by network media. This is expressed as $G_e(t) \in [0, 1]$ in the simulation model, which takes values in consecutive intervals of (0, 1).

2.3. Model media attributes

Media adopt different attitudes toward emergencies, and these attitudes determine public opinion trends. However, the attitude of the media is also affected by netizens and the government. The formula for the media attribute is as follows:

$$M[P_n(t), U_n(t), Md_n(t), Mi_n(t)] \quad (2)$$

where the function values of the four attributes, the attitude, credibility, authority, and influence of the media, at time t are sequentially represented from left to right.

Media attitudes: There are only two attitudes for the media, and media attitudes toward emergencies vary according to motives. The two attitudes mentioned in this article are extremes. In the simulation model, media attitudes are represented by $P_n(t)$, where $P_n(t) = 1$, which indicates support for the spread of opinion and $P_n(t) = -1$, which indicates opposition to the spread of opinion. The attitudes of the media vary from -1 to 1.

Range of influence: In addition to different attitudes, the credibility of media vary when it comes to the spread of information about incidents. In the simulation model, media credibility can be represented by $U_n(t) \in [0, 1]$, where $U_n(t)$ represents the credibility of media n at time t . When $U_n(t) = 0$, the media's credibility is quite low, and the probability of information dissemination is small. When $U_n(t) = 1$, the media's credibility is extremely high, as is the probability of information dissemination.

Media credibility: Different media have different levels of authority. When the media has greater authority, it has a greater influence on netizens and the government, resulting in the higher credibility of information provided.

In the simulation model, the media's authority is represented by $Md_n(t) \in [0, 1]$. The larger this value, the more influence a media source has on both netizens and the government.

Media influence: The simulation model divides media influence into three levels. $Mi_n(t) \in [0, 0.4]$ indicates that the media's influence is minimal in a given emergency, $Mi_n(t) \in [0.4, 0.7]$ indicates that the media has a moderate influence, and $Mi_n(t) \in [0.7, 1]$ indicates that the media has a significant influence. The greater the scope of influence of the media, the greater the credibility and authority of information about an event. The formula below represents the influence value of the media at time t :

$$Me_n(t) = Me_i(t_0) - d(t - t_0) \quad (3)$$

where $Me_i(t_0)$ represents the initial value, t is the time when the netizen starts to participate in the emergency event, and d remains a constant when the unit is decreased, and its value can be adjusted by the actual state of emergency.

2.4. Model netizen attributes

The following netizen attributes can be understood through the formula:

$$N [P_i(t), Q_i(t), X_i(t), Y_i(t), Z_i(t)] \quad (4)$$

Netizen attitudes: Individual netizens have different ideologies that affect whether and how they share information about an emergency. In the simulation model, $P_i(t) = 1$ refers to netizens' inclination to disseminate emergency information. If $P_i(t) = 0$, then a netizen will accept information and focus on emergencies; while if $P_i(t) = -1$, a netizen will neither focus on the emergency nor follow the development of the event.

Netizen influence: This refers to a netizen's ability to spread information during an emergency and can be understood as $Q_i(t) \in [0, 1]$. When $Q_i(t)$ is between 0 and 0.07, then the netizen is not very capable of spreading information. If $Q_i(t) = 0.7-0.9$, then a netizen has a moderate ability to spread information. If $Q_i(t) = 0.9-1$, a netizen has a significant influence.

Level of trust: This refers to the extent to which netizens believe information about emergencies and whether they spread such information. In the simulation model, this is conveyed through $X_i(t) \in [0, 1]$; credibility is randomly assigned a value between 0 and 1. If $X_i(t) = 0$, then a netizen i during event t will not believe information nor spread it. If $X_i(t) = 1$, then a netizen will believe the information and disseminate it to others.

Rate of dissemination: This refers to netizens' dissemination of information due to the effects of government, media, or other netizens. This is described in the simulation model as $Y_i(t) \in [0, 1]$. If $Y_i(t) = 0$, where a netizen is not affected by other subjects. $Y_i(t) = 1$ implies that the netizen is affected by other subjects and adapts his/her behavior accordingly.

Netizens' desire to disseminate: Netizens each have their own concerns and preferences; so, their enthusiasm over sharing information in the face of an emergency differs. This can be expressed as $Z_i(t) \in [0, 1]$. Since the desire to disseminate information changes over time and based on the emergency $Z_i(t)$, $Z_i(t)$ is used to express the distribution desire i of netizens at time t . The initial test value is randomly selected in the continuous interval of (0, 1). While 0 indicates that the netizens have no desire to spread information about the incident, and will therefore not spread information after receiving it, 1 indicates that the netizens have a strong desire to spread information about the incident. The following formula indicates that the netizen's desire to spread information changes with time:

$$Z_i(t) = d_i - \alpha^*(t - t_0) \quad (5)$$

where d_i indicates the initial value of the netizen's desire to spread information, d_i is a constant, and the value of d_i varies with the actual situation. The desire of the netizens to communicate changes over time. The constants here are changed. Through these parameters, depending on the actual situation, data on the interaction of different subjects can be obtained. α is a constant, and the value of α can be adjusted depending on the actual situation.

2.5. Emergency attributes

Event importance: Every netizen's perception of a sudden event and its importance is different. The more important a netizen views an event, the easier it is to accept and disseminate information regarding that event. This paper assumes that a given emergency has the same importance for netizens, the government, and the media with $I_a(t)$ indicating the importance of moment t , with values randomly selected between 0 and 1.

Event ambiguity: This refers to the uncertainty of an event. If an event is more uncertain and less specific, then netizens are more likely to discuss and voice grievances. $I_b(t)$ indicates the fuzzy value of the event: $I_b(t) \in (0, 1)$.

Timeliness of event propagation: Due to information on emergencies and the short attention span of netizens, the spread of information on emergencies varies over time, and the effects of transmission change with time. Eq. 6 is used to indicate the timeliness of emergencies:

$$I_c(t) = a^* \frac{\lambda^T}{T!} e^{-\lambda T} \quad (6)$$

where $I_c(t)$ is the time-effect value of the sudden event at time t , λ is the time-dependent feature scale factor of the target information, and a is a constant that can be adjusted in the iterative process in the simulation model. Programming a values in the Netlogo software show that Internet users' desire to spread information declines over time, as duration (time since the occurrence of the event) changes netizens' desire to spread information.

Event propagation intensity: This is derived according to Alport's formula (Wang & Yu, 2017) for propagating the intensity of rumors. $R = I_a * I_b$, in which I_a refers to an event's importance, I_b refers to the event's degree of ambiguity, and the event intensity can be expressed as:

$$CI(t) = \beta_1 I_a(t) I_b(t) + \beta_2 v(T) \quad (7)$$

In the above formula, $T = \beta$ -t and β_1, β_2 are constants, and $I(t)$ is the subject attribute, which can be adjusted according to the actual situation. The transmission intensity of public opinion is directly influenced by netizens' and the media's attention to an event.

2.6. Interactions between netizens and the media

The influence of media n on a netizen i at time t can be expressed by:

$$f(n, i, t) = b_1 U_n(t) M_{d_n}(t) + b_2 Y_i(t) Z_i(t) \quad (8)$$

In the above formula, $U_n(t)$ is the media's credibility, $M_{d_n}(t)$ is the media's authority, $Y_i(t)$ equals the rate of dissemination, $Z_i(t)$ refers to netizen dissemination, and $b_1 + b_2 = 1$.

When media n communicates an unexpected incident to netizen i , i will react in one of two ways:

- 1 If $A_j(t) = 0$, then netizen i is the event receiver.
- 2 If $A_j(t) = 1$, then netizen j is the event communicator.

In addition, when netizen i is the recipient of event information, they will react in one of three ways, given that:

- 1 If $A_i(t) = -1$, then netizen j is not interested in the event and withdraws from consuming and disseminating information on it.
- 2 If $A_i(t) = 0$, then netizen j is interested in the event and will continue to pay attention to messages on the topic.
- 3 If $A_i(t) = 1$, then netizen j is very interested in the event and actively spreads information regarding it.

2.7. Interactions between netizens and the government

The influence of government G on netizen i at time t can be expressed by:

$$f(G, i, t) = c_1 Y_i(t) Z_i(t) + c_2 [1 - G_c(t)] + c_3 [1 - G_d(t) G_c(t)] \quad (9)$$

where $Y_i(t)$ represents the rate of dissemination, $Z_i(t)$ is the netizens' desire to disseminate information, $G_c(t)$ represents the government's credibility, $G_d(t)$ is the government's speed of publication, $G_c(t)$ represents government transparency, and $c_1 + c_2 + c_3 = 1$.

When government G spreads information about an emergency to netizen i , then i will react in one of two ways:

- 1 If $A_i(t) = 0$, then netizen i is the recipient of an event.
- 2 If $A_i(t) = 1$, then netizen j becomes the communicator of an event.

2.8. Interactions among all three parties

The interactions among netizens, government, and the media are led by the government and the media. However, the government is influenced by the opinions generated by the media and netizens, and netizens (i) also interact with other netizens (j). The influence function of netizens i on netizens j at time t is as follows:

$$f(i, j, t) = a_1 X_i(t) + a_2 Y_i(t) Z_i(t) + a_3 C_i(t) \quad (10)$$

where $X_i(t)$ is the netizens' credibility, $Y_i(t)$ represents the rate of dissemination, $Z_i(t)$ is the netizens' desire to disseminate information, $C_i(t)$ is the intensity of communication, and $a_1 + a_2 + a_3 = 1$.

When netizen i communicates a given incident to netizen j , then j will react in one of two ways:

- 1 If $A_j(t) = 0$, then netizen j is the recipient of the event.
- 2 If $A_j(t) = 1$, then netizen j becomes the event communicator.

If netizen j receives information from netizen i , they will have one of three attitudes:

- 1 If $A_j(t) = -1$, then netizen j is not interested in the event and withdraws from consuming and disseminating information on it.
- 2 If $A_j(t) = 0$, then netizen j is interested in the event and will continue to pay attention messages on the topic.
- 3 If $A_j(t) = 1$, then netizen j is very interested in the event and actively spreads information regarding it.

2.9. Spatial analysis of online public sentiment on emergencies

The key to SNA is to identify and measure the relationships between actors to capture the interactions between people (Yousefi-Nooraie, Dobbins, Brouwers, & Wakefield, 2012). By using graphs and matrices to measure density and centrality in social network data, researchers can depict the overall shape of the network in terms of a hierarchy, which identifies the center of the network and influential people to determine how change happens over time.

Density is used to measure the degree of interaction between actors in a social network. A density measurement of 0–1.0 indicates that there is no connection between actors, while a measurement of 1 means that there is a direct connection between all actors. The higher the density, the faster the flow of information about an event. The higher the degree of contact between objects, the quicker public opinion develops; the lower the density, the slower information disseminates.

The connections in a self-centered network are measured according to the directed binary; density (D) is equal to the dual

relationship between all objects (L) divided by the most probable number of such relationships (Kim & Kim, Baek, & Kim, 2015). The centrality algorithm is shown in Eq. (11).

Network density refers to the ratio of the number of connections actually existing in the social relationship network diagram to the maximum number of possible connections. It reflects the degree of information interaction among network members. In a directed graph containing n network nodes, the maximum number of possible connections is $n(n-1)$. If the number of connections that actually exists is m , the density (D) of the directed graph is calculated as follows:

$$D = \frac{m}{n \times (n - 1)} \quad (11)$$

An important role of centrality in SNA is to identify prominent individuals and groups by synthesizing the structural relationships between all points. To this end, an actor's intermediate center value represents how much the actor controls other actors and is measured between 0 and 1. If an individual's median center value is 0, then he/she does not have the ability to influence the behavior of other individuals and is located at the edge of the network. If an actor's median center value is 1, then the actor has direct influence over all other actors and is at the center of the network.

In the undirected binary graph, the behavioral degree measures the extent to which an object in a social network is associated with all other objects. For a network graph with g objects, the degree of centrality of actor i is measured by the total number of direct contacts between i and other actors ($g - 1$), as represented by the matrix in Eq. 12 (Hegselmann & Krause, 2002):

$$C_B = \frac{\sum_{j < k} g_{jk}(n_i)}{g_{jk}} \quad (12)$$

Where g_{jk} is the number of shortest lines between points j and k , and $g_{jk}(n_i)$ is the number of shortest lines between the two nodes containing node n_i .

The *degree of centrality* measures the degree to which an object in a social network is associated with all other objects. The *degree of outwardness* indicates the degree to which an object focuses on other objects, whereas the *degree of intrinsic centrality* indicates the degree to which the object is concerned.

From the perspective of spatial structure, nodes at different locations possess different resources and play different roles in the development of public opinion. Some nodes are in relatively central positions and play the role of "opinion leaders." Their views expressed during emergencies can often influence the development of public opinions and have a greater impact on network information dissemination. Other nodes are on the outside edges of the network and only play a role in transmitting information rather than influencing opinion.

2.10. Case studies

We then applied our model to real-life data taken from the list of popular annual events of the "China Online Public Opinion Annual Report" in the "Letter about the Internet" published by the Humanities and Social Sciences Research Report Cultivation Project of the Ministry of Education of the People's Republic of China and [Shanghai Jiaotong University's Public Opinion Research Laboratory \(2017\)](#). From this list, we selected 101 emergencies with responses that were considerably influenced by public opinion between 2010 and 2017. We then divided these into four groups according to the provisions of the Law of the People's Republic of China on Emergency Response: natural disasters, accidents, public health events, and social security events. This allowed us to compare and analyze the characteristics of online public sentiment for different types of emergencies.

2.11. Time evolution simulation

This study uses MATLAB (R2016b version) simulation software and the Baidu index data of the 101 emergency network public opinion transmissions. Our model is applied to determine the overall effect of network public opinion and the interactions between all three subjects. Through continuous iteration, the weight of each subject attribute is constantly adjusted and compared with data that is consistent with the real-time evolution of the incidents. Fig. 1 includes screenshots taken directly from the Netlogo.

2.12. Analysis of spatial effects

To analyze the spatial distribution of online public sentiment, we used data from Sina Weibo, one of China's four major online portals, to search for keywords relating to the 101 events in our dataset. We then selected the 50 individuals with the most forwarded content on each event based on a search of microblogging platforms using relevant keywords. These 50 bloggers were randomly selected as nodes from among the bloggers who posted early evaluations. We then randomly selected five nodes as initial information publishing sources. Then, five individuals who forwarded or commented on events from each of those five nodes were randomly selected, giving us a 75*75 propagation matrix model. This allowed us to analyze the spatial propagation effect between 75 nodes for each of the 101 emergencies studied. If one node forwards or comments content to another node, the relationship value between those two nodes is 1. If the two nodes have no forwarded comments, then the relationship value is 0. The relationship between a node and itself is 1. We used UCINET software to calculate the density of each event.

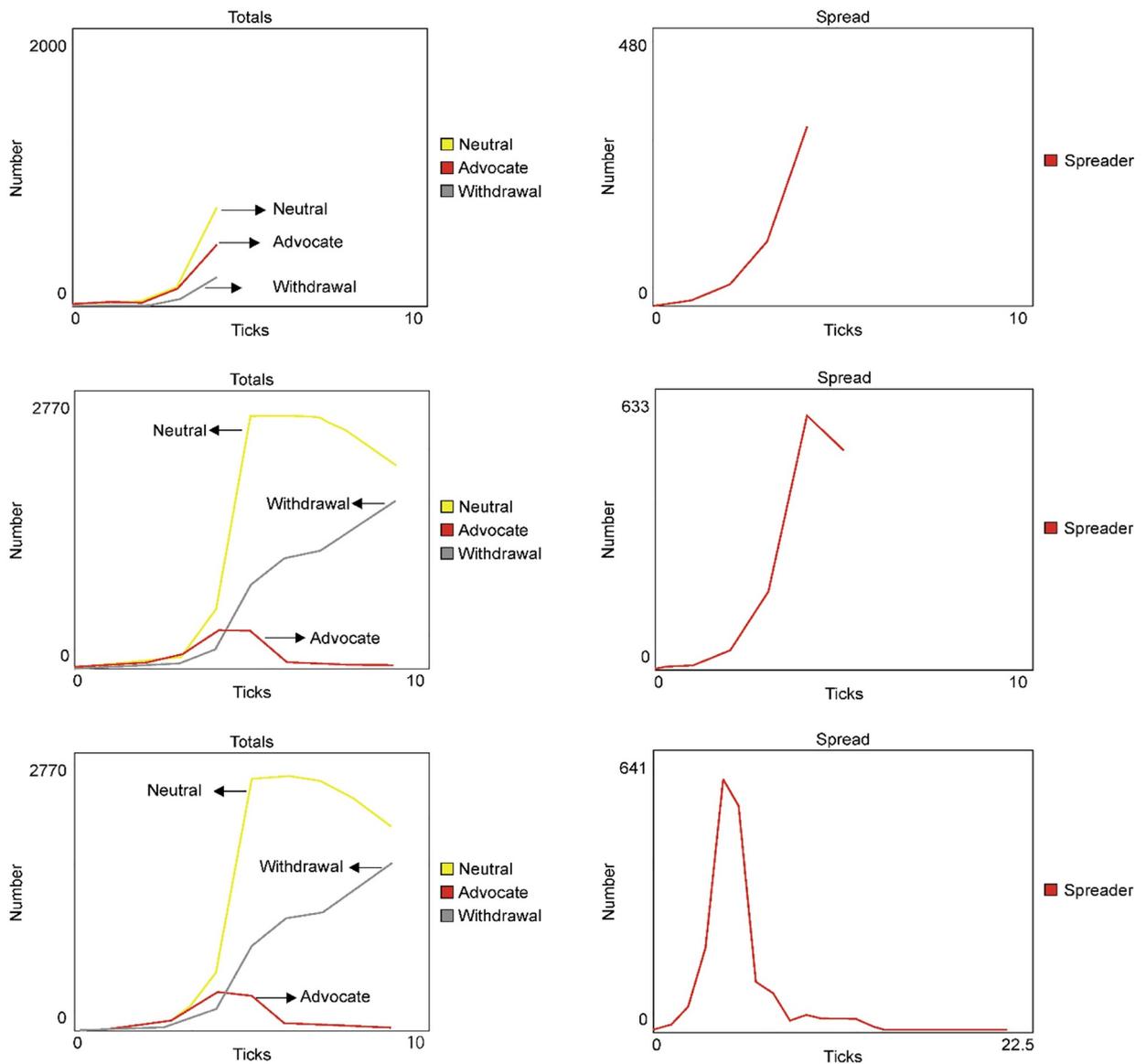


Fig. 1. The three periods of emergency incident spreading (spread period, control period, and stable period).

Neutral: the potential communicator or the recipient of the information.

Advocate: the recipient of public sentiment regarding the incident.

Withdrawal: withdraw from the spreading of public sentiment by netizens.

3. Results

Fig. 1 shows that information on emergencies begins with network communication. The media publishes information, which attracts netizens, who begin to participate in disseminating the information. During this dissemination period, the emergency is still developing, and information increases geometrically through an increase in media coverage. Over time, as shown in the figures, an increasing number of netizens become concerned about the emergency and the available information, and media communication reaches its peak. At this stage, the government then takes emergency measures that take into consideration the public interest, thereby effectively controlling the evolution of the emergency.

At this point, the government's emergency response has a controlling effect on the dissemination of information, including the elimination of rumors and communication of the truth. Fig. 1 shows that government response controls the speed with which emergency information propagates through media, and information on an event enters a second stage: the control period. The online popularity of the event and the number of netizens who are concerned decrease sharply, as does the speed of transmission.

As the government and netizens continue to interact, the following four steps repeat: (1) government interpretation (official release of news), (2) netizen questioning, (3) government reinterpretation (official release of news), and (4) netizen re-questioning. At

the same time, the government also takes measures to restore social trust. Netizens' emotions will gradually converge, and the emergency will subside, both of which entail that the event will receive less attention. Fig. 1 demonstrates that the speed with which emergency information propagates gradually becomes very slow and stabilizes after a point. This marks the beginning of a third stage—the stable stage—during which time netizens almost entirely lose interest.

Considered together, Fig. 1 demonstrates a consistent trend in online public sentiment during an emergency: It grows rapidly for a time and then gradually disappears in a manner consistent with true lyrical spikes and thick tail data. This indicates that the simulation has high credibility and is consistent with reality. In addition, the weight of each subject attribute is credible and, therefore, reflects the transmission of public opinion networks in China.

We further analyzed the media attribute weights at each stage (Fig. 1) and found that when the level of trust remains low, netizens have a strong desire for information dissemination and seriously overestimate information, resulting in a state of “high weight.” This means that Internet users may be convinced of network rumors and even spread undisclosed information at random. At this point, Internet users over interpret existing event information. Meanwhile, if the government speedily intervenes in supervising and controlling online public sentiment, then official media can guide the direction of public opinion, thereby reducing the risk of information spreading throughout the network without control.

Because of the openness and freedom of network media, opinion leaders exist who have a larger influence and can attract more attention; these leaders play an important role in mediating public opinion communication. When netizens are in a semi-closed state, it is easier to spread unproven information at random and in a limited rational situation, thus accelerating the speed of transmission of public opinion across the network. In a worst-case scenario, this triggers a mass network public opinion event: When netizens are in a semi-closed state, in the case of bounded rationality, they may randomly spread unconfirmed information and criticize network rumors, thus speeding up the spread of events and increasing the amount of online public opinion. This will, in turn, trigger a discussion among netizens, induce negative emotions among the people, trigger violations and excessive behavior among the masses, and threaten social stability. We adjusted the relevant parameter settings of the media, strengthened the media influence and credibility, kept the other subject parameter attributes unchanged, and examined the role of opinion leaders in network public opinion communication.

While keeping the other subjects' attributes unchanged in order to analyze the influence of these so-called opinion leaders. As shown in Fig. 1, these leaders rapidly promote the spread of public opinion and play an active role in their evolution. The number of people actively spreading news has grown rapidly, thereby increasing the official media activity by expanding the relevant attributes of the media. Fig. 2 shows how the model changes after shifting the media attributes. In this situation, changing media attributes have doubled the number of Internet users participating in discussions, increasing the number of netizens who trust and receive media information. At the same time, the number of netizens creating and spreading rumors has decreased, thus pushing public sentiment into a stable stage.

Finally, we adjusted the government's credibility to 0.9 and government information disclosure speed and transparency to 0.6, while keeping all other subject attributes unchanged (Fig. 3). A shift is noticeable after government intervention in an emergency: When the government's credibility, openness, and transparency are stronger, netizens' emotions gradually stabilize, and their fears are eliminated. The presence of official information entails that netizens will not arbitrarily spread news. The overall number of discussions drops significantly, and the sensational nature of an emergency quickly dissipates. This controls the risk in the transmission of online public sentiment.

- 1 The sooner the government releases information, the higher the rate of acceptance by the media and netizens.
- 2 Increased government guidance releases positive signals to netizens and the media and makes it easier to control information.
- 3 The spread of public opinion throughout a network is nonlinear. Therefore, the more authority a government has to release information, the faster it can obtain the convergence of the media and netizens and reach equilibrium.
- 4 Government credibility also has an important impact on the evolution of online public sentiments. The higher the credibility, the higher the support of the media and netizens.
- 5 Government guidance and supervision impacts both netizens and the media. Stronger guidance and supervision make a greater impact on the media, which enhances the government's ability to guide the network.

3.1. Density analysis

Tables 1–4 show the densities of the networks for each of the four types of emergencies in this study. Values varied from 0.0041 to 0.0341; the highest density is eight times greater than the lowest, indicating that the popularity of public opinion on an event varies greatly. The highest density for accidents and social security events is about 0.02 higher than for natural disasters and public health events. In other words, accidents and social security events are more likely to attract the attention of netizens and elicit public opinion.

We also found that the density of communication on natural disasters was three times greater in 2017 than in 2010. Likewise, the density of opinion on accident disasters grew 2.3 times between 2010 and 2015, public health events grew 2.1 times between 2010 and 2016, and social security events grew 1.2 times between 2010 and 2017. As online media has grown over time, so has media coverage of crisis events and network enthusiasm for public opinion on these incidents. However, even today, the density of all 101 emergencies is very low, indicating that communication between users about emergencies remains low, and the dissemination of information is still slow. This may be because microblogs are mostly used for entertainment; user participation behavior is relatively random, unlike that of communication subjects with limited information dissemination capabilities.

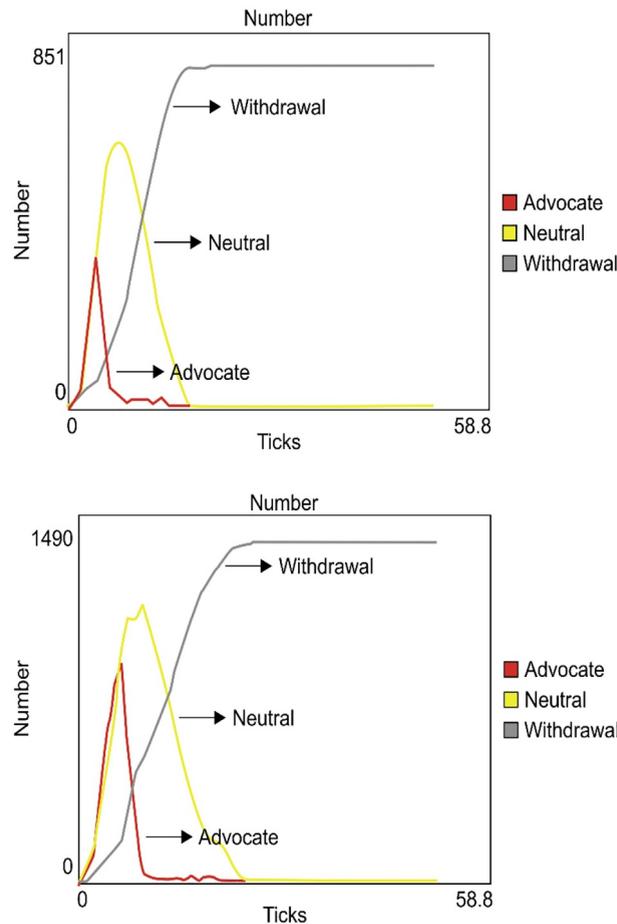


Fig. 2. Simulation result, displaying changed media attributes
 Neural: the potential communicator or recipient of the information
 Advocate: the recipient of the public sentiment regarding the incident
 Withdrawal: withdraw from the spreading of public sentiment by netizens.

3.2. Centrality analysis

We also analyzed each of the 101 incidents from the perspective of spatial density. Fig. 4 provides an example of our analysis: For each of the four types of events, we selected three at different levels of network strength—high heat, medium heat, and low heat.

In cyberspace, as described above, the location and power of a node are unequal, as are the ways it develops and trends during emergencies. Some nodes are in a core position while others transmit information, and still others are only bystanders. For example, in Fig. 4, official media—such as *Vista World*, *Financial Network*, *Pear Video*, and the *People's Daily*—are at the center of the networks, indicating that these nodes are active in public opinion transmission. They are more vocal and can influence a wider range of people. These are also regulation nodes that are important for the propagation of public opinion during an emergency and that are more able to intervene and control communication between and transmission to other nodes.

Fig. 4 and Tables 1 through 4 illustrate that the centrality of natural disasters and public health events do not change drastically with an increase of public opinion heat. Rather, the media has a significant role in guiding nodes during these two types of emergencies: Netizens obtain news on an event directly from official media, such as the *People's Daily*, in the early stages of an incident. Since they trust this media source, they then quickly spread public opinion by forwarding, commenting upon, and paying attention to official media sources. There are not many intermediate links in the network. As a result, public opinion does not fluctuate very much. After accidents and social security incidents, however, media is not always at the center of a network. Instead, netizens are active in the communication process, and individuals are likely to be the center of networks. This suggests that in these two types of emergencies, netizens are vulnerable to misinformation.

4. Conclusions

Our simulations show that the spread of online public sentiment conforms to the scale-free and small-world characteristics of

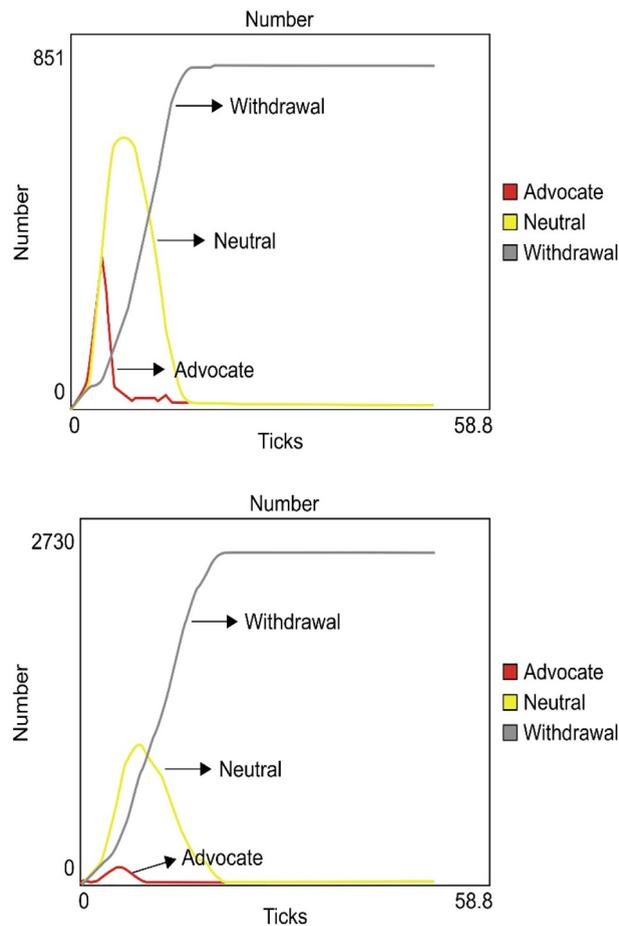


Fig. 3. Simulation results, displaying changed government properties
 Neural: the potential communicator or recipient of the information
 Advocate: the recipient of public sentiment regarding the incident
 Withdrawal: withdraw from the spreading of public sentiment by netizens
 Our analysis demonstrates the following.

Table 1
 Density and centrality statistics of China's natural disasters, 2010–2017.

Year	Natural disaster	Density	Center degree	Year	Natural disaster	Density	Center degree
2010	Yushu Earthquake, Qinghai	0.0067	13.98%	2014	Xinjiang Yutian Earthquake	0.0103	21.60%
	Zhouqu Mudslide	0.0185	9.13%		Yunnan Jinggu Earthquake	0.0159	24.55%
	Shanxi Earthquake Rumors	0.0071	5.98%	2015	Nepal Earthquake	0.011	11.74%
2011	Japan Earthquake	0.0241	12.85%		Shenzhen Landslide	0.0254	32.60%
	Yunnan Yingjiang Earthquake	0.0341	15.35%	2016	Japan Ms 8.5 Earthquake	0.0056	9.96%
2012	Beijing Heavy Rain	0.024	12.85%	2016	Flood Disaster in Hebei	0.0315	27.84%
2013	Earthquake in Ya'an	0.0205	22.71%	2017	Heavy Rain in Hunan	0.0236	27.42%
	Yunnan Ludian Earthquake	1.59%	24.12%		Mao County Landslide	1.44%	51.22%

complex networks. At the beginning of an emergency, mainstream media play a crucial role in rapid reporting of real information on an emergency, especially accidents and social security incidents. In the early stages of public sentiment evolution, the influence of the media is insufficient, and it is, therefore, necessary for the government to give relevant information to the public. The government also needs to strengthen the public's judgment of information and reduce misinformation. Such methods will reduce the value of information dissemination by individuals and maximize the effectiveness of media communication.

4.1. Strengthen media guidance

Media are one of the main actors in an emergency and connect the government and the public. On the one hand, the media should

Table 2

Density and centrality statistics of China's accident disaster, 2010–2016.

Year	Accident disaster	Density	center degree	Year	Accident disaster	Density	Center degree
2010	Shanghai Fire	0.0086	13.50%	2013	Taishan Fire	0.0045	6.02%
	Sino-Japanese Collision Incident	0.0098	17.48%		Qingdao Oil Pipeline Explosion	0.0079	9.48%
	Yichun Passenger Plane Crash	0.0078	13.72%	2014	Sunken Korean Passenger Ship	0.0081	19.16%
Nanjing Chemical Plant Explosion	0.0076	13.72%	Malaysia Airlines Flight Lost Contact		0.0178	29.73%	
2011	Yongwen High-speed Railway Accident	0.0077	9.51%	2015	Tianjin Bombings	0.0187	26.77%
	Qian Yunhui Event	0.005	7.29%		Oriental Star	0.02	19.60%
2012	Tianjin Jixian Fire	0.0056	7.18%	2016	Hubei Dangyang Electric Heating Factory Explosion	0.0088	7.94%
	Harbin Bridge Collapse	0.63%	12.59%		Fengcheng Power Plant Accident	0.72%	9.63%

Table 3

Density and centrality statistics of China's Public health event, 2010–2016.

Years	Public health event	Density	Center degree	Year	Public health event	Density	Center degree
2010	Gutter Oil Incident	0.0056	8.57%	2013	Avian Influenza	0.0044	6.09%
	Overlord Cancer	0.0048	5.98%		Weifang Groundwater Pollution	0.0072	15.22%
2011	Clenbuterol event	0.0067	11.13%		KFC Crash Chicken Incident	0.0067	6.96%
2012	Poison Capsule	0.0052	7.26%	2014	Ebola Virus Outbreak	0.0142	22.14%
	Shifang Accident	0.0251			Korea Middle East Respiratory Syndrome	0.0117	19.81%
2012	Liquor Plasticizer	0.0079	8.13%	2015	MERS Virus	0.0172	17.60%
	Golden Rice Event	0.0086	12.11%		Chaijing Smog	0.0054	7.22%
	Old Yogurt Shoes	0.0054	7.22%	2016	Changzhou Foreign Language School Poisonous Land	0.0119	19.81%
					Nanjing Crayfish Event	0.65%	11.16%

Table 4

Density and centrality statistics of China's Social security incident, 2010–2017.

Year	Social security incident	Density	Center degree	Year	Social security incident	Density	Center degree
2010	Filipino Hostage Incident	0.0077	10.90%	2014	Kunming Railway Station Terrorist Attack	0.0079	9.51%
2011	Salt Grab	0.0052	7.26%		2015	Shanghai Bund Stampede	0.0178
	2012	Zhongfei Huangyan Island Apocalypse	0.0049	7.33%		Wendeng Incident	0.0051
Wukan Event		0.0072	5.46%	Yemen Evacuates	0.0159	24.55%	
2013	Qidong Incident	0.0063	8.42%	Qingdao High Price Shrimp	0.0082	6.16%	
	Xinjiang Hetian Hijacking	0.0054	15.60%	Hebei Suning Shooting Case	0.0097	10.53%	
	The Prism	0.0054	7.26%	2016	Wei Zexi Incident	0.0045	6.02%
	Fudan Poisoning Case	0.0067	8.35%		South Korean President	0.0067	8.35%
Yan'an City Management Violence Enforcement	0.54%	0.0726	Luo Yixiao Incident	0.0268	30.93%		
				2017	Campus Loan	0.0045	6.02%
					Xuzhou Kindergarten Explosion	0.0094	9.18%

pursue their own value standards: to report incidents fairly and truthfully and to communicate real-time information on emergencies. On the other hand, strengthening the media's relationship with the government can allow the media to report on government decisions and plans for responding to emergencies to the public in real-time. This allows the public to quickly determine the evolution of emergencies and guide the trend of online public sentiment.

4.2. Strengthen supervision of public opinion

In the early days of many emergencies, official information is not publicized, which often arouses public suspicion and deepens distrust of the government. Through online rumors, netizens' distrust of the government ferments, eventually triggering an online public opinion event. In the era of big data, the government must handle public opinion incidents quickly, promptly, and efficiently in order to fulfill the public's need to receive information promptly. Otherwise, they may risk the expansion of public opinion networks, which will increase the difficulty in guiding public sentiment as the emergency continues to evolve. Especially in major emergencies involving national security and the safety of lives and property, the government should decisively intervene in publicity control and information dissemination. Moreover, the use of fast and effective media should be maximized to communicate the "voice" of the government, conduct quick and positive online guidance, and strengthen communication with the public and the media to ensure the smooth spread of online public sentiment.

excessive grievances. Meanwhile, it is necessary to clarify facts, eliminate rumors, communicate scientifically, control knowledge, and implement tools to control and block false and maliciously misleading information.

4.5. Strengths and limitations

This paper analyzes the characteristics of the evolution of online public sentiment during emergencies from the perspective of time and space. First, a multi-agent modeling and simulation method is used to simulate interactions between netizens and netizens, between the media and netizens, and between the media and government. This is done to illuminate the evolution of public opinion and the effects of governance over time. Second, an SNA method is used to analyze the characteristics of key node structures and the important actors in the network of public opinion communication during an emergency. Because of the complex factors affecting emergencies and the difficulty in obtaining data, the construction of the model is inaccurate, and the four types of emergencies are analyzed from a time perspective. By enriching the data, we hope to find, through the model, the distribution characteristics of the four types of emergencies and find the root causes of the evolution of public sentiment during emergencies.

The advantage of this study is that the simulation of the model and its main parameters enable the government to control and guide a response to an accident at the initial stage by understanding how public opinion evolves. It can enable the media to strengthen cooperation with the government, enhance its credibility, affect most netizens, actively evade rumors, and understand, promptly, the rules that determine netizen activity. This would be beneficial to netizens as it would reduce loss of interest and improve the comprehensive management of online public sentiment. However, because of the limited ability to acquire data, this paper extracted 75 individuals in the study of the spatial structure of public sentiment evolution, and the data is relatively poor. Moreover, the time evolution model assumed many parameters to be linear, rather than actual changes, which are nonlinear. The accuracy and depth of the research need to be improved.

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Data availability statement

The datasets generated and analyzed during the current study are available in the Baidu Index and Sina Weibo repository at the following URLs: <http://index.baidu.com/baidu-index-mobile/?from=pinzhuan#/> <https://m.weibo.cn/>

CRedit authorship contribution statement

Shiyue Li: Conceptualization, Data curation, Formal analysis, Software, Writing - review & editing. **Zixuan Liu:** Methodology, Resources, Visualization, Writing - original draft. **Yanling Li:** Funding acquisition, Investigation, Project administration, Supervision, Validation.

Declarations of Competing Interest

None.

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