Analyzing Emergency News Comments to Assess Online Public Opinions: A Case Study of COVID-19

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Abstract. For the purpose of enhancing the online public opinion intervention mechanism, fostering a positive public opinion environment, it is crucial to examine the rules and traits of online public opinion dissemination from multiple perspectives. The paper proposes a fresh approach to measuring network public opinion by analyzing emergency news comments. In order to develop risk assessment indicators, we first employ the multi-round Delphi method. Then, we organize the "COVID-19" news comments using natural language processing and text clustering techniques, correlating the risk assessment indicators with the risk evolution of emergency events. Finally, we analyze the time evolution trend of users' participation in network public opinion. Results show that the use of news commentary can effectively predict the tendency of social risk. Therefore, the risk assessment method in this paper can judge and warn the network public opinion in time, which is of great value in assisting major emergency management decisions.

1.Introduction

Network emergencies are inextricably linked to public safety, in part because the content of online media affects users' cognitive and emotional reactions [1], and network public opinion driven by them easily triggers the accumulation of negative emotions among Internet users and constituting an undesirable social psychological state. As a result, developing a risk assessment system for online public opinion is of tremendous scientific value in order to assess and control public opinion as early as possible. The online public opinion index system is the basis for constructing a monitoring system. Su et al. introduced dynamic seasonal factors and Bernoulli equation to establish a seasonally corrected exponential gray Bernoulli model [2]. Liu et al. combined the Analytic Hierarchy Process Ranking II method with the Stochastic Multi-Criteria Acceptability Analysis method to assess the level of online opinion risk in social media during the COVID-19 local outbreak [3]. The existing findings give a solid theoretical framework as well as methodological advice.

However, due to the complexity of the network environment and the variety of contingencies, there are still issues with the evaluation of online public opinions, including the evaluation index system's poor adaptability, low attention to the online opinion audience, and its lack of empirical research [4]. Since different risk assessment systems are established for various emergencies, it is difficult to integrate public opinion assessment systems at the theoretical level.

To address the aforementioned concerns, this paper crawls real online news comments and reconstructs the risk assessment index system by merging the characteristics of online emergency comments. The Delphi method is utilized first to produce risk assessment indicators, and then natural language processing and text clustering is employed to connect the indicator system with risk prediction. Similar to previous studies, this paper also verifies the validity of the proposed model with the help of specific scenarios [5]. The results show that the characteristics and development rules of emergency news commentary revealed in this paper not only provide new ideas for the research of risk assessment, but also provide decision-making references for the control of relevant departments.

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2.Risk assessment indicator system

2.1. Establishment of the indicator framework

New media play an indispensable role in the evolution of emergencies because of their speed of communication and interactivity. The public can participate in the discussion and further dissemination of news commentary and, in some cases, even influence the evolution of emergencies. Accordingly, this paper adheres to the principles of comprehensiveness and independence and uses the Delphi method to construct a risk assessment index system. The specific steps are as follows: selecting experts, designing questionnaires, and organizing experts to answer questions. Three rounds of expert surveys are conducted, and the indicators for risk assessment are finalized after the expert opinions are stabilized. The results are shown in Table 1.

Table 1. Hierarchical indicator construction.

Overall indicator	Classification indicator	Single indicator
Risk Assessment of Online Public Opinion on Emergency A_1	Attention level B_{11}	The number of news comments C_{11}
		The number of participating netizens C_{12}
		The length of comment text C_{13}
	Audience information B_{12}	The regional diffusion degree C_{21}
		The emotional tendency C_{22}
		The amount of praise C_{23}

2.2.Single Indicator Interpretation

The first-level indicators in this study consist of attention level and audience information. Among them, the attention level is used to reflect the emotional intensity of Internet users; the audience information is used to measure the geographical distribution and emotional tendency. The contents of the statistical indicators and the assignment methods are explained below.

C_{11}: The total number of news comments about an emergency news within a certain period of time. The fundamental motivation of netizens to write news comments is the attention to the events being commented on.

C_{12}: Calculate the number of clicks on news about an urgent event in a certain period of time (remove duplicate user Id).

C_{13}: Calculate the total character number of news comments for the relevant emergency. Cao, Duan and Gan [6] point out that the length of the comment text is positively correlated with the significance of news comments.

Table 2. Weights of each province.

Provinces	No.
Guangdong, Shandong, Jiangsu, Henan, Hebei	1
Zhejiang, Hunan, Hubei, Sichuan, Liaoning	2
Anhui, Guangxi, Fujian, Jiangxi, Shanxi	3
Shanghai, Beijing, Shaanxi, Heilongjiang, Yunnan	4
Jilin, Chongqing, Inner Mongolia, Guizhou, Tianjin	5
Xinjiang, Gansu, Tibet, Hainan, Ningxia, Qinghai	6

Note: Due to data reasons, the provinces involved in the survey only cover mainland China, excluding Taiwan. The data of the number of netizens in each province is referenced from the 44th Statistical Report on Internet Development in China [7].

C_{21}: Calculate the geographical distribution of participating netizens involved. The wider the spread of breaking news, the greater its impact, the greater its ability to spread, and the greater the potential social risk. Thus, the extent of the impact is judged by analyzing the area where the outbreak spreads. For areas where an emergency was infiltrated, the smaller the number of netizens in the area, the worse their ability to transmit. Based on this idea, we assign corresponding weights to each province, and provinces with a relatively large number of netizens are given lower weights, and vice versa. The region in which a participating netizen's location is confirmed by the IP address which is displayed when the news comments is posted. The rankings of the weight assignments of each province are shown in Table 2.

C_{22}: We will assign values by using the grid method [8]. The classification system used in this paper is a unified five-point system, in which 1, 2, 3, 4, and 5 correspond to emotional tendencies that are excellent, good, average, poor, and worst respectively.

C_{23}: Calculate the number of likes of breaking news and its comments, which is also a reflection of the emotional response of Internet users.

2.3.Determination of Indicator Weights

This study used hierarchical analysis to determine the index weights. Specifically, after constructing the hierarchical model, we calculated the weight vector for consistency test. Based on the calculated combination vector, we performed the combination consistency test. The final indicator weights of online public opinion risk assessment are shown in Table 3. It should be pointed out that after several interviews with experts, indicator C_{23} (the amount of praise) was used only to calculate the emotional tendency (C_{22}) and thus it was not weighted.

Table 3. Grading indicator weights.

Classification indicator	B_{11}	B_{12}	A_1
	0.6132	0.3868	
C_{11}	0.3287		0.2016
C_{12}	0.4351		0.2668
C_{13}	0.2362		0.1448
C_{21}		0.5738	0.2219
C_{22}		0.4262	0.1649
C_{23}		/	/

Based on the above indicators, we derive the formula for calculating the risk value in equation (1).

$$\begin{aligned} R=&0.2016*C_{11}+0.2668*C_{12}+0.1448*C_{13} \\ &+0.2219*C_{21}+0.1694*C_{22} \end{aligned} \tag{1}$$

3.Empirical analysis and results

3.1.Data acquisition and processing

Reference to previous studies, this paper also uses the global public health emergency "COVID-19" as a study case [9]. The main processes of data acquisition and processing are as follows: firstly, according to a certain chronological order, select the top 25 news under the topic of "COVID-19" from Netease. Second, set up a crawler to crawl the comments under the corresponding news. The collected data includes comment number, user number, user name, comment time, the amount of praise, comment content, total number of news comments, number of participants, news source, news title, etc. About 2,200,000 news comments were obtained. Thirdly, data cleaning is needed to reduce the interference of noise. For example, news comments with advertisements are identified and eliminated using keyword matching.

3.2.Topic Clustering

This study calculates the similarity between review texts based on k-Means text clustering method using cosine similarity. To measure word values, we used a vector space model to assign corresponding weights to each word in terms of importance. Then the word frequency statistics of TF-IDF was used to analyze the news comments.

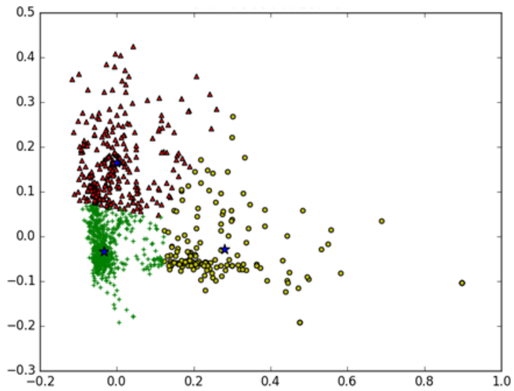

Fig. 1. Visualization of news comments clustering.

The results of topic clustering for all news comments are shown in Fig. 1. After comparing the silhouette coefficients, we can define three clusters (categories), marked with different colours.

In category 1, the high frequency words are: Wuhan(F=54), number of infections(F=59), number of newly increased(F=105), etc, which is mainly focused on the current status of the epidemic. The high frequency words in category 2: United States(F=77), seafood market(F=35) and expert(F=75), show that Internet users are mainly exploring the causes of the outbreak. Category 3, with subject lines such as: disinfection (F=186), protection(F=123), and alcohol(F=87), is discussed around daily protection.

3.3.Calculation of Indicator Values

Next, the metrics of the news comments need to be calculated and normalized based on the cleaned dataset.

C_{11}: direct access from the dataset.

C_{12}: the sum of the number of Internet users participating in news under various online media.

C_{13}: aggregate the number of characters of all comments.

C_{21}: the weight of the region*the number of users from that region participating in the comment.

C_{22}: We take the average of the emotional tendency values of all comments under a news as the emotional tendency value of this news. The emotional tendency of each comment is the product of the amount of praise and the emotional tendency value of the comment text itself.

Normalizing the obtained values and based on the equation (1), we calculate the risk value of the online public opinion corresponding to each news of "COVID-19" (shown in Table 4). The results can be used for emergency response and public opinion management, helping relevant departments to quickly determine news that is highly likely to explode negative sentiment among netizens.

Table 4. Risk calculation values.

News number	Risk values	News number	Risk values	News number	Risk values
1	0.697	10	0.270	18	0.057
2	0.988	11	0.141	19	0.016
3	0.325	12	0.161	20	0.036
4	0.308	13	0.129	21	0.070
5	0.258	14	0.113	22	0.037
6	0.252	15	0.093	23	0.062
7	0.213	16	0.036	24	0.092
8	0.132	17	0.085	25	0.165
9	0.324				

3.4.Risk analysis

We analyzed the evolution of the netizen's participation level and online public opinion's risk level with time series (as show in Fig. 2). The data is mainly from Netease's news comments on "COVID-19" from January 10, 2020 to February 10, 2020. Online public opinion's risk level is positively correlated with netizen's participation level. As a result, the higher the level of netizen's participation and online public opinion's risk, the greater the social risks.

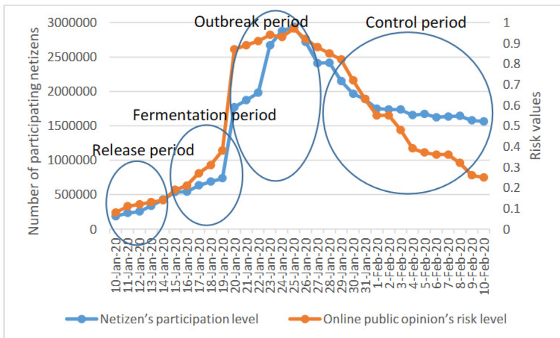

Fig. 2. Time evolution of netizen's participation level and opinion risk level.

Similar to previous research findings, user behavior is closely related to time [10]. There is a life cycle for the risk of online public opinion, which includes release period, fermentation period, outbreak period and control period. During the release and fermentation periods, although the number of involved netizens and the risk value were gradually increasing, the social risk was not high, probably because the initial reports of the "COVID-19" outbreak were relatively mild and netizens were not aware of the potential crisis.

During the outbreak, the number of participating netizens exploded and the risk of online public opinion skyrocketed to its peak, with a high potential for information cascades and panic. Key events during this period were the media broadcast of the extremely contagious nature of "COVID-19" and the sudden announcement of the government's closure of Wuhan.

During the control period, although the number of involved Internet users remained high, the risk value of online public opinion continued to decline. This result indicates that the government has achieved some success in responding to the COVID-19 outbreak and reassuring the public. Moreover, the risk assessment system in this paper is consistent with the evolution of the COVID-19 outbreak, demonstrating the validity of our proposed risk assessment system and thus can provide assistance in risk prediction and response.

4.Discussions and conclusions

This paper investigates the relationship between the characteristics of online news comments and the risk values of emergencies, and the results show that news comments can reflect the degree of involvement of Internet users and the temporal evolution of risk values. That is, targeted measures can be designed to pacify netizens at the four stages of online opinion dissemination. It should be noted that the model constructed in this paper can also be applied to other fields. In addition, this paper has several theoretical and practical implications.

In terms of theoretical significance, firstly, this paper innovatively uses news commentaries as the basis for constructing risk indicators, which is a novel perspective. Secondly, this study confirms that it is feasible to assess risk by analyzing news commentaries on mainstream social media. The risk assessment model in this paper not only accurately reflects the risk level of emergencies, but also reduces the complexity of model construction.

In terms of practical significance, on the one hand, the risk assessment system can help relevant organizations predict the development trend of emergencies so that timely intervention measures can be taken to maintain social stability. On the other hand, the model has a high degree of general applicability.

However, although the use of social media news comments to assess and predict social risk is innovative, the indicators used may not be sufficient. In the follow-up study, we will add more dimensions and build a more comprehensive indicator system.

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