Original Paper

Research on Emotion Analysis Based on a Topic Emotion Fusion Model: The Case of the "Post-holiday Symptoms of Pharyngitis" Event on the Weibo Platform

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Abstract

[Objective] From early 2023 to 2024, multiple public health incidents related to "post-holiday pharyngitis" erupted in china, impacting public health and education among other areas. This study analyzes the data dissemination trends and the emotional development of these incidents. The insights are aimed at enhancing the government and disease control agencies' mechanisms for guiding and responding to such public sentiment incidents, thereby improving preparedness and response capabilities for potential future public health events. [Methods] The methodology employed involves using three instances of "post-holiday pharyngitis" events on the Weibo platform as data samples. The study applies the LDA model integrated with TD-IDF weighted Word2vec algorithm for thematic organization across different periods. The DUTIR sentiment dictionary is used to analyze public sentiment, and data visualization techniques are employed to present the thematic-emotional evolution within the incidents. [Results] The results suggest that the proposed thematic-emotional fusion model effectively extracts and analyzes the dissemination trends and emotional evolution of the event, providing actionable suggestions for government and public health agencies in managing such public sentiment incidents.

Keywords

Post-holiday pharyngitis, public opinion analysis, theme-sentiment integration, LDA model, DUTIR dictionary

1. Introduction

With the rapid expansion of social media, social platforms have emerged as an important medium for the public to discuss hot subjects in society. The public shares personal ideas, forwards others'

comments, and produces articles using social media to enhance information sharing and dissemination while also contributing to the development of public opinion information. According to the Weibo data report, the average monthly active users of Weibo reached 598 million in the fourth quarter of 2023, and based on the information dissemination mode of "hotspot+social", Weibo has become one of the main platforms for the discussion of hot social topics and the generation of social opinions. Emotion analysis of topics based on text information is an essential method of public opinion analysis and early warning since it may not only reveal the deep emotional orientation of social hot topics, but also the public's ideas and attitudes concerning public opinion events.

Text topic extraction aims to identify the main concepts and topic information in the text, and researchers usually use word frequency-inverse document frequency (TF-IDF), latent Delicacy Allocation (LDA), text clustering, and deep learning algorithms (e.g., Transformer, BERTopic) to accomplish topic extraction (Xie & Zhao, 2016). Emotion analysis can be performed using emotion dictionaries to determine the emotion orientation of public beliefs (Lu, Song et al., 2021). Dictionary-based emotion analysis methods are typically used for emotion discrimination at the word-level granularity, using the semantic attributes, hierarchical structure, and emotion intensity of words in the emotion dictionary to determine the semantic emotion of words after weighted calculation. By utilizing deep learning techniques in text topic-emotion analysis, researchers can enhance their results by training the algorithm with a limited number of manually labeled samples. This involves extracting contextual semantic features from the sample data and accurately identifying the topic and emotion orientation of the text. When faced with various application circumstances, researchers can utilize a combination of numerous methodologies based on their computational capabilities, data scale, and data characteristics to complete the task successfully and precisely (Hua, Wu et al., 2023).

In 2023, due to a combination of factors, including the increased spread of toxins and other pathogens (Zhao, Yu, et al., 2021), there were many outbreaks of "post-holiday symptoms of pharyngitis" in the domestic situation, which had a serious impact on the public's daily life, health care, social security, education, and other aspects. In the social media environment, reports, rumors, and other information about the event are widely disseminated, triggering public opinion events on hot topics. Based on Weibo data, this study utilizes LDA model fused with TD-IDF weighted Word2vec algorithm to sort out the themes of "post-holiday symptoms of pharyngitis" public opinion events in different periods. The DUTIR emotion dictionary was used to examine the emotion orientation of public comments, the dissemination trend of public opinion data, and the process of producing and changing topic emotions for this event. It contributes to the strengthening of the reaction system for guiding and disseminating these types of public opinion events, as well as improving the planning and response capabilities for future public health events.

2. Related Research

2.1 Text Topic Extraction

Text topic extraction is an important research area in natural language processing, as well as the primary method for public information analysis, such as public topic refinement and public opinion topic clustering. It aims to automatically identify potential topics or topic sets from a large amount of text data (Wang & Chen, 2018). With the continuous development of natural language processing technology, the word frequency-inverse text computation model (TF-IDF), latent semantic analysis model (LSA), and LDA topic clustering model can be used for topic discovery, document classification, and text clustering of large-scale text for text data in different scenarios, respectively. Zhai Shanshan and other researchers have built upon the LDA model, integrating the cosine similarity algorithm to reduce the sparsity of clustering results, thereby analyzing the emotional evolution of the public during sudden public health events (Zhai, Wang, et al., 2022). Zhang Xiuhua and other researchers have utilized TF-IDF to quantitatively represent text and employed the K-means clustering method to predict the themes of news content (Zhang, Yun et al., 2020).

2.2 Text Emotion Analysis

In the field of text emotion analysis, researchers usually apply emotion dictionaries and deep learning algorithms to discriminate the emotion of text data. The construction method of emotion dictionary is mainly to use web crawlers and data interfaces to obtain raw data of public comments from social media, and after data pre-processing operations such as data cleansing, word segmentation, and lexical annotation, it is handed over to manually annotate the emotional polarity or intensity of words, so as to construct an emotion dictionary (Wang, Chen et al., 2020). With the application of semantic networks, word co-occurrence and other technologies, the coverage of emotion dictionary words is expanded and the granularity of emotion words is refined (Wang, Zeng et al., 2024). HowNet is a knowledge base of language resources developed by the Computer Language Information Center of the Chinese Academy of Sciences. The knowledge base depicts the relationship between real-word concepts by constructing a semantic network in which the meanings of all words are expressed as smaller semantic units. In terms of emotion expression, HowNet categorizes words that express emotions (e.g., angry, sad, happy) into positive and negative words (Pan, 2015). Hu and other researchers utilize an open semantic relations library to explore the relationships of word context, synonym and antonym, positive and negative, and form a collection of words with the same attribute, and gradually expand the scale of emotion dictionary through cyclic iteration and manual screening (Hu & Liu, 2004).

With the application of artificial intelligence technology in text mining, researchers have applied deep learning algorithms to conduct research on text emotion analysis. Liu Tiantian and other researchers improved the Stacking algorithm for text emotion analysis based on the entropy method, evaluating different base learner combinations through an index weight comprehensive assessment. The learning prediction results are assigned different weights and output to a secondary learner, thus determining the emotion classification results (Liu, Gu et al., 2023).

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2.3 Evolutionary Analysis of Public Opinion

Public opinion evolution is the process of utilizing different perspectives to explore the evolution of the life cycle of public opinion events in the process of public opinion event dissemination. Currently, based on the three stages of the life cycle of public opinion events, namely, generation, spreading, and fading, academics have expanded it into four to six stages according to the corresponding criteria (Lan, Xia et al., 2018). The goal of public opinion evolution analysis is to assess and anticipate the trend of public emotion as well as the evolution of public opinion events over time utilizing data mining, machine learning, social network analysis, and other technologies. Jia Ruonan and other researchers use the spatio-temporal evolution model to complete the clustering of temporal and geographical characteristics of public opinion events, analyze the differences and characteristics of spatio-temporal distribution in public emergencies, and provide a reference for public opinion management of public emergencies (Jia, Wang et al., 2023).

3. Research Design

3.1 Research Framework

This article is based on text data and dissemination data from the "post-holiday symptoms of pharyngitis" public emotion event on the Sina Weibo platform during 2023-2024. It utilizes public emotion keyword information monitored by the "Medical Health Public emotion Platform" set up by the Institute of Medical Information, Chinese Academy of Medical Sciences (Hou, Tong et al., 2021). After obtaining the public opinion data by using the platform interface, and cleaning the data by deactivating words and splitting words, we analyzed the theme and emotion evolution of the public opinion event by using the public opinion theme-emotion analysis model. The research framework is shown in Figure 1.
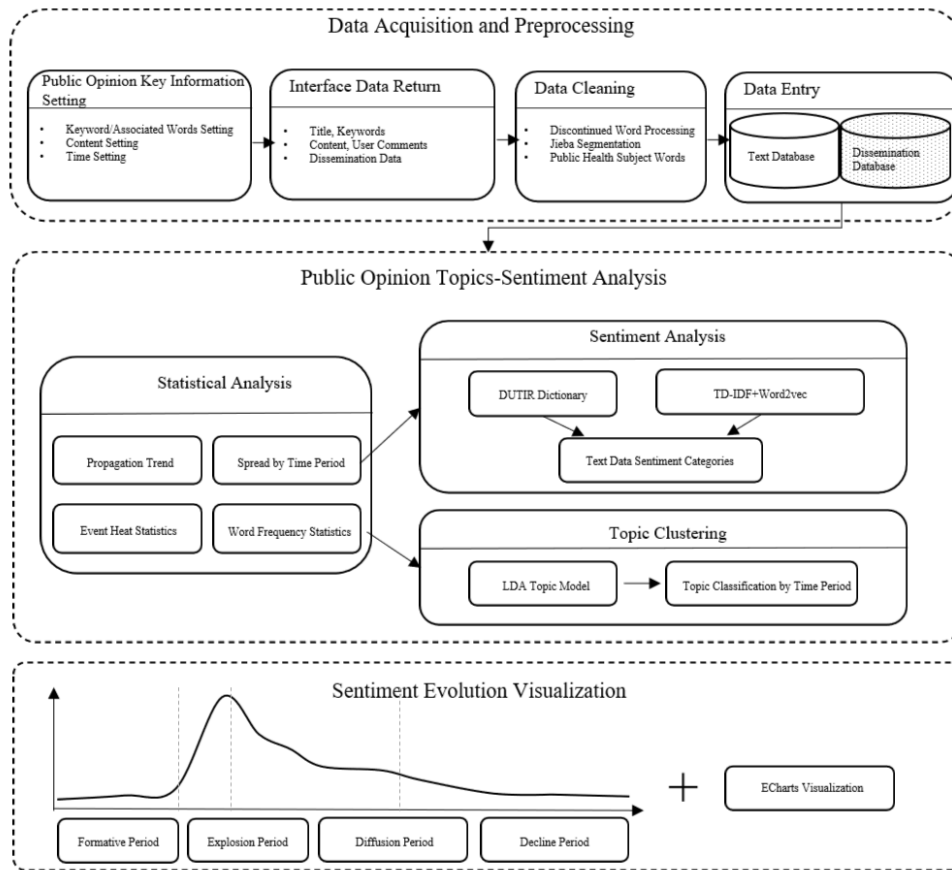
Figure 1. Research Framework for Public Opinion Topic Emotion Analysis

3.2 LDA-Based Topic Clustering

LDA topic clustering model is a clustering and keyword extraction method for text data proposed by BleiBM in 2003, which can identify potential topic information in large-scale text data by unsupervised learning. The core idea of the method is that a document contains multiple topic distributions, with each topic comprised of multiple words. By iteratively simulating the document's generation process, the probability of each topic being generated within the document is calculated (Wang, Deng et al., 2023). Therefore, the LDA topic clustering model can assist in the extraction of topics in opinion text data and help researchers to mine the deep-rooted topic content in opinion texts. Figure 2 shows the LDA topic generation model.
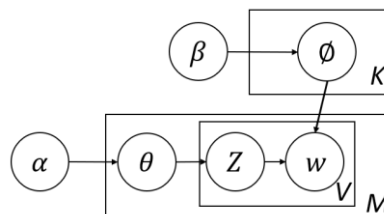

Figure 2. LDA Topic Generation Model

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Where M is the number of texts in a document; V is the number of words in a document; K is the number of topics; Z is the topic distribution of words; W denotes words; θ and Φ are the probability of topic distribution in a document and the probability of word distribution in a topic, respectively; α and β are the hyperparameters of θ and Φ, respectively.

Gibbs sampling algorithm can provide learning parameters for the LDA topic model, which is completed by the sampling algorithm to obtain the text-topic distribution matrix θ and topic-word distribution matrix Φ, computational formulas as shown in equations (1) and (2).

$$\theta_{m,k} = \frac{n_m^{(k)}+\alpha}{\sum_{k=1}^{K}(n_m^{(k)}+\alpha)} \qquad (1)$$

$$\Phi_{k,t} = \frac{n_k^{(t)}+\beta}{\sum_{t=1}^{|V|} n_k^{(t)}+\beta} \qquad (2)$$

In the formula V is the number of words in a document; K is the number of topics; n is the number of samples; $\theta_{m,k}$ is the probability of topic k in document m; $\Phi_{k,t}$ is the probability of word t in topic k. After the word vector matrix is constructed, it is filled using the Word2vec fusion TD-IDF technique to address the issue of sparse feature dimensions in the word vector matrix caused by the varied lengths of datasets in Weibo texts. Finally, the matrix is output to the convolutional neural network model for topic classification.

3.3 DUTIR-based Emotion Similarity Calculation

DUTIR (Chinese emotion Phrase Ontology Repository) is a Chinese ontology resource organized and annotated by the Information Retrieval Research Office of Dalian University of Technology (Yang, Kevin et al., 2007). The ontology database depicts Chinese words or phrases from multiple perspectives, such as word lexicality, emotion category, and emotion intensity. The emotion categorization system of the Chinese emotion vocabulary ontology is based on Ekman's six categories of emotions with the addition of the emotion category "good". The emotions in this lexical ontology are divided into 7 categories and 21 subcategories, namely: good, happy, sad, angry, fearful, wicked, and scared, and contain a total of 27466 emotion words, as shown in Table 1. DUTIR contributes to the resolution of multi-category emotion categorization and emotion tendency issues in Chinese text sentiment analysis. In this study, data from public opinion events is collected, cleaned, and segmented, and then each piece of data is split into phrases, with the emotion polarity of the phrases calculated separately, and the overall emotion tendency of the data calculated after the data is weighted. Since emotional phrases in the DUTIR emotional classification dictionary may have multiple emotional categories and intensities, it is first necessary to calculate the emotional intensity of the phrase, as shown in formula (3) (Dun, Zhang et al., 2017).

$$P_i = \sum_{k=1}^{n} a_k b_k \ (1 \le k \le n, n \in 1,2) \qquad (3)$$

Where P_i is the intensity value of the emotion word, a is the intensity value of the emotion word in the DUTIR library; b is its emotion polarity value; and since the emotion word may belong to more than one emotion classification, n is the number of classifications to which the emotion word belongs

to, $n = 1$ when the emotion word belongs to one class of emotion classifications only, and $n = 2$ when the emotion word has more than one class of emotion classifications. In this study, in order to facilitate the analysis of emotion orientation of Weibo data and the presentation of data visualization, phrase emotion is classified based on the 8 emotion grand classifications of DUTIR, and the classification method is as follows as shown in formula (4).

$$E_{pi} = \begin{cases} M, |a_{k1}b_{k1}| \\ N_1, |a_{k1}b_{k1}| \geq |a_{k2}b_{k2}| \\ N_2, |a_{k1}b_{k1}| < |a_{k2}b_{k2}| \end{cases} \quad (4)$$

When the emotion word belongs to only one class of emotion categorization, M is the classification of the emotion word, and $a_{k1}b_{k1}$ is the emotion intensity of the word; when the emotion word belongs to more than one class of emotion categorization, if $a_{k1}b_{k1}$ is greater than or equal to $a_{k2}b_{k2}$, N_1 is the classification of its emotion, and if $a_{k1}b_{k1}$ is less than $a_{k2}b_{k2}$, N_2 is the classification of its emotion. M, N_1, N_2 is mapped by the DUTIR emotion categorization dictionary data to get the emotion categorization E_{pi}.

Table 1. DUTIR Dictionary of Emotion Categories

No.	Emotion Classification (major category)	Emotion Classification (small category)	Example
1	Happy	Happy (PA)	Pleasure, honor, good day, glow
2		Peace of mind (PE)	Reassurance, comfort, confidence, peace and security
3		Respect (PD)	Honorable, noble, worthy, gentlemanly
4		Praise (PH)	Celebrate, honor, wise, respect for teachers
5	Good	Believe (PG)	Belief, trust, friendliness, integrity
6		Favorite (PB)	Admiring, beautiful, doubly awesome, graceful
7		Wish (PK)	Advice, congratulations, promise, respect for the elderly
8	Anger	Anger (NA)	Wrongful indignation, cursing, swearing at the top of one's lungs, relying on force bully others
9	Sadness (NB)	Sorrow (NB)	Sorrowful thoughts, cold heartedness, compassionate, fail utterly
10		Disappointment (NJ)	Deplorable, unworthy, to have talent but no opportunity, irredeemable

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11		Guilt (NH)	Shame, disgrace, now and gone different, brooding
12		Think (PF)	Mourning, sadness, depression, parting feelings
13	Fear	Panic (NI)	Panicked, busy, terrified and uneasy, terrified and fearful
14		Fear (NC)	Panicked, Violent, Terrified, Overly Cautious
15		Shame (NG)	Restrained, Timid, Unable to refuse due to politeness, Ashamed of oneself
16		Boredom (NE)	Resentful, depressed, regretful, self-inflicted annoyance
17	Wicked	Abomination (ND)	Vanity, slander, confusion of right and wrong, moral turpitude
18		Derogatory (NN)	Misinterpretation, scolding, killing for money, running away in terror
19		Jealousy (NK)	Jealous and hateful, irrational, uninteresting
20		Skeptical (NL)	Speculation, indecision, apprehension, lose one's head out of fear
21	Surprise	Amazing (PC)	Surprised, shocked, both shocked and surprised, marveled in admiration

On the basis of calculating the emotion classification and emotion intensity of the participial phrase, the emotion of the phrase is calculated according to the negative words, adverbs and their combination forms occurring in the contextual semantics of the phrase. The emotion words, negative words, adverbs and combination forms are shown in Table 2.

Table 2. Combination Modes of Containing Emotion Words

Serial Number	Type	Example
1	Emotional words only	Satisfied
2	Negative words + Emotion words	Not Satisfied
3	Adverbs of degree + Emotion words	Too Satisfied
4	Negative words + Adverbs of degree + Emotion words	Not Too Satisfied
5	Adverbs of degree + Negative words + Emotion words	Too Not Satisfied
6	Negative words + Negative words + Emotion words	No Not Satisfied

The formula for combining emotion words, negatives, and adverbs is shown in formula (5) (Zheng, Yang et al., 2014).

$$E_i = (-1)^{O_i} a_i p_i m \quad (5)$$

Where E_i is the emotion value of the emotion phrase; O_i is the number of negative words; a_i is the strength of adverbs in the emotion phrase; p_i is the weights of the emotion words and the emoticons appearing in the emotion words; and m is the combination weights, $m = 0.4$ in the combination of category 4, which is used for correcting the role of degree adverbs, and $m = 1$ in the other combinations, which has no effect on the emotion analysis. The final calculation of the integrated emotion orientation of the Weibo data, the formula is shown in equation (6), where n is the number of emotion words in the Weibo comments.

$$\overline{E} = \frac{\sum_{i=1}^{n} E_i}{n} \quad (6)$$

4. Experiment and Data Analysis

4.1 Experimental Data Acquisition

After the Labor Day in May 2023, National Day in October 2023, and Chinese New Year holidays in 2024, some of the public indicated on Weibo, Small Red Book, and other social media that after the holidays, they or most of the relatives and co-workers around them had symptoms of pharyngitis such as swelling and pain in the throat, frequent coughing, and hoarseness of voice, and that the public suspected a new round of COVID-19 virus, influenza viruses, and other infections. On social media, topics such as "the whole country is suffering from symptoms of pharyngitis", "patients with symptoms of pharyngitis continue to increase?" and "Experts answer why symptoms of pharyngitis is so common after the holidays" have become hot topics of public discussion. This study cleaned and evaluated data from Weibo platforms within 15 days of the end of the aforementioned holidays, collecting a total of 184,201 valid data.

This study evaluates the emotion-topic development process at various stages of a public opinion event from the standpoints of emotion evolution and event subject evolution, as well as the changes in public emotion and focus of attention on the event.

4.2 Analysis of Trends in the Dissemination of Public Opinion Events

The dissemination trend analysis of the collected data reveals that there are 83,131 pieces of public opinion event data related to post-holiday symptoms of pharyngitis in May 2023, the event dissemination from May 4 to May 19, 2023, with an evolution cycle of 15 days, and the related public opinion topics have been included in Weibo hot search list 5 times; 70,861 pieces of public opinion data related to post-holiday symptoms of pharyngitis in October 2023, the event spreads from October 9 to October 18, 2023, with an evolution cycle of 15 days, and the related public opinion topics were included in Weibo hot search list for 2 times; 30,209 pieces of public opinion data related to

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post-holiday symptoms of pharyngitis in 2024, the event spreads from February 20 to February 25, 2024, with an evolution period of 6 days, and the related public opinion topics were not included in the Weibo hot search 100 list; Comparing the dissemination data of the post-holiday symptoms of pharyngitis event in the three periods, it is found that the public opinion data related to the event has gradually decreased, and the evolution cycle of the event from its creation to its decline has gradually shortened. The public attention and discussion of the event gradually decreased, as shown in Figure 3.
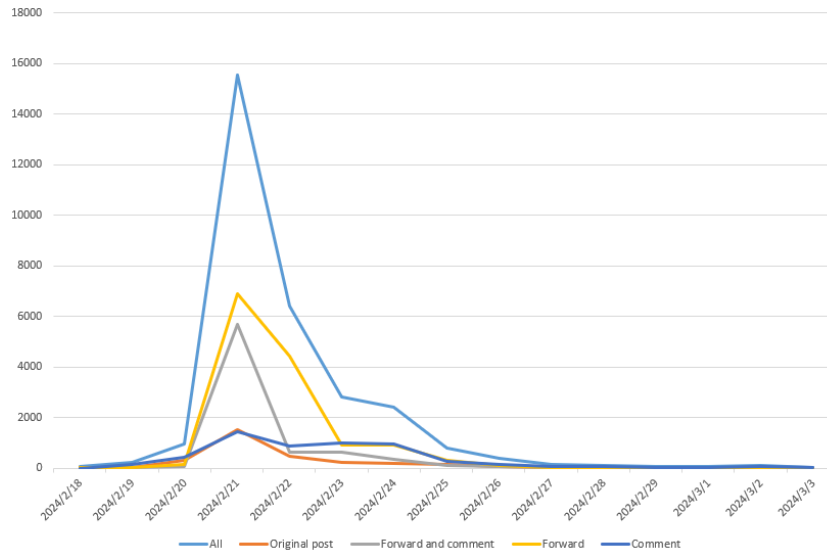

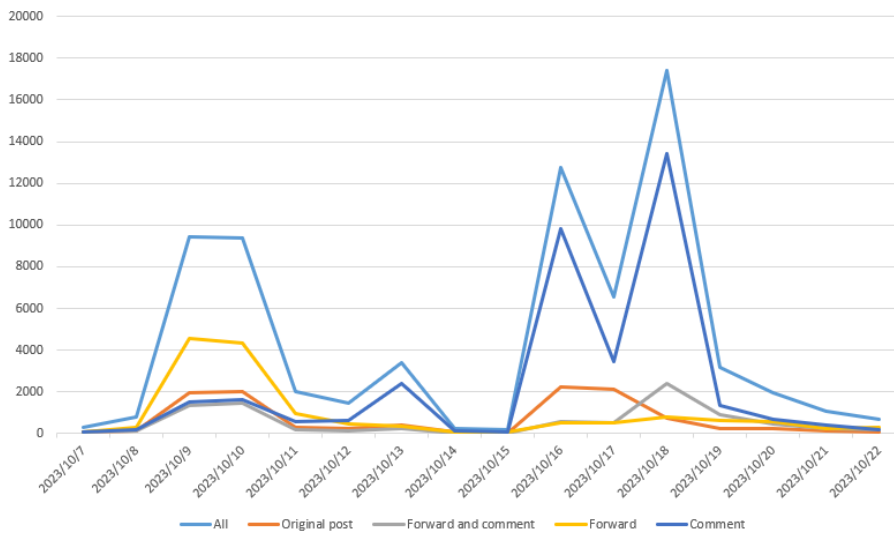**Figure 3-1. Trend of Dissemination of Symptoms of Pharyngitis Events after May 2023**

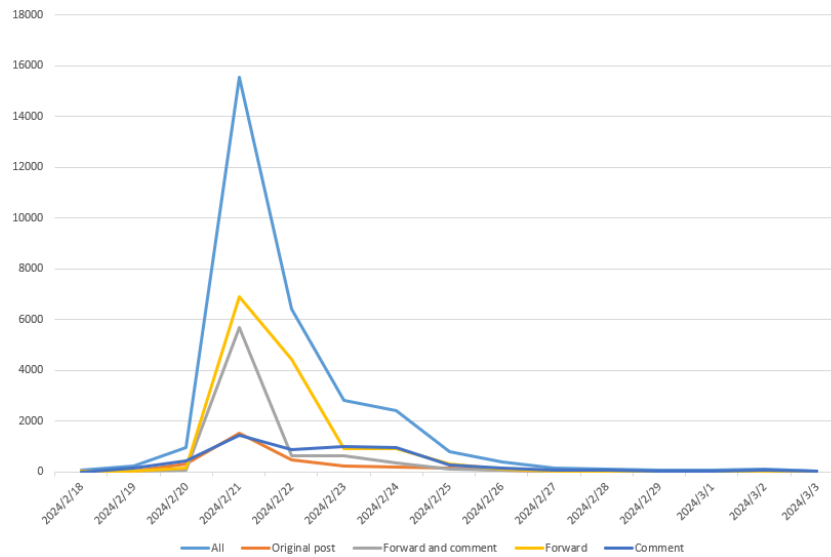**Figure 3-2. Trend of Dissemination of Symptoms of Pharyngitis Events after October 2023**

Figure 3-3. Trend of Dissemination of Symptoms of Pharyngitis Events after February 2024

During the event's dissemination, at the early stage of dissemination, the public tended to share information through the behavior of retweeting or re-commenting rather than directly posting comments due to the authenticity and uncertainty of the topics related to the event, as evidenced by data showing that the data of retweeting and re-commenting was significantly higher than the data of other types of dissemination. As the incident progressed and more associated information was disseminated, public opinion of the occurrence entered a period of dissemination and diffusion, and the public gained a more in-depth understanding and view of the incident. At that stage, the general public is more likely to express their opinions and emotions through comments. Meanwhile, the interactivity of information dissemination on the Weibo platform encourages public engagement, and the public's ongoing debate of the topic prompts more responses, and public comment data dominates event distribution at that point.

During the rest day of the event's dissemination, the public's attention was more focused on real-life communication and interaction, resulting in less attention devoted to the event on social media, as indicated in the dissemination data: on the rest day after the outbreak of the May 2023 post-holiday symptoms of pharyngitis public opinion event (May 7), and on the rest day after the outbreak of the October 2023 post-holiday symptoms of pharyngitis public opinion event (October 14-October 15), the trend of the event's dissemination appeared to have dropped significantly.

4.3 Topic-emotion Analysis of Public Opinion Events

In this study, topics were extracted from the data of post-holiday symptoms of pharyngitis events in different periods based on the emotion-topic model. Seven, seven and five interpretable topics were extracted for the three periods of post-holiday symptoms of pharyngitis events, respectively. When the post-holiday symptoms of pharyngitis incident first appeared in May 2023, the topics of public discussion were more diversified. As new COVID-19 variants appeared in the country one after another

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during that period, the focus of public discussion was on elaborating that they themselves and their family members also experienced the symptoms of pharyngitis, thus worrying about the outbreak of a new type of virus or a new COVID-19 virus; In October 2023, when the post-holiday symptoms of pharyngitis incident appeared for the second time, the main topic of public opinion, in addition to elaborating that they and people around them had once again developed symptoms of pharyngitis, was the emergence of negative attitudes toward future expectations for the life of some members of the public and their family members due to their having experienced multiple infections with COVID-19 viruses, influenza viruses, and mycoplasma during the current year; When the public experienced a third post-holiday symptoms of pharyngitis event in February 2024, the number of valid topics extracted decreased to five. During this period, as the public had already experienced a number of post-holiday symptoms of pharyngitis incidents, the public's reaction to the incident had changed from the initial topics with strong emotional tendencies, such as fear of re-infection by COVID-19 virus and pessimism about the future of life, to more neutral topics, such as calls for better protection and suspicion of problems with one's own immunity. The post-holiday symptoms of pharyngitis event topics for the three time periods are shown in Tables 3-5.

Table 3. Post-holiday Symptoms of Pharyngitis Event Topics after May 2023

Post-holiday symptoms of pharyngitis event topics after May 2023	Keywords represent
New COVID-19 virus re-infection	COVID-19, re-positive, di-positive, nucleic acid positive
Symptoms of pharyngitis in ourselves or someone close to us	Symptoms of pharyngitis, sore throat, phlegm, pharyngitis, unpleasant, me too
Critics of experts downplay the risk of a massive symptoms of pharyngitis situation in the nation	Experts, bullshit, indifference
Calls for national CDC authorities to pay close attention to the event	Health Commission, CDC, large number of patients, symptoms of pharyngitis
Calls for a rational view of the event	Relaxed, normal, seasonal changes
Call for increased protection	Masks, rest, avoid gathering
Worry about outbreaks caused by new viruses	Variant viruses, new outbreaks, mass infections

Table 4. Post-holiday Symptoms of Pharyngitis Event Topics after October 2023

2023/10 Public Opinion Topics	Keywords represent
Mycoplasma viral infection	Mycoplasma, fever, positive, children
COVID-19 and influenza A co-endemic	COVID-19, influenza A, co-endemic, positive
Symptoms of pharyngitis in ourselves or someone	Symptoms of pharyngitis, sore throat, phlegm,

close to us	pharyngitis, unpleasant, me too
Lamenting the gradual deterioration of the immune system	Fever, immunity, deterioration, recurrence
Hoping for a quick turnaround for ourselves and those around us	Get better, improve, recover
Call for increased protection	Masks, rest, avoid gathering
Pessimistic about the future of life	Death, destruction, doom

Table 5. Post-holiday Symptoms of Pharyngitis Event Topics after February 2024

2024 Chinese New Year Public Opinion Topics	Keywords represent
Symptoms of pharyngitis happened again when returning to work after Chinese New Year	Returning to work, sore throat, coughing
Lamenting that avoided COVID-19 but did not avoid this symptoms of pharyngitis	Symptoms of pharyngitis, upper respiratory tract infection, COVID-19
Are recurrent infections a sign of low immunity	Immunocompromised, immune system, recurrent infections
The recent high incidence of sore throats could be the result of this emergency	EBV, cross infection, respiratory viruses
Call for increased protection	Masks, reduced gathering, increased self-exercise

Based on the aforementioned theme extraction results, this study uses emotion analysis to examine the distribution of public emotion and the proportion of emotion distribution in each period of post-holiday symptoms of pharyngitis events, as illustrated in Figures 4-6. When the post-holiday symptoms of pharyngitis event first appeared in May 2023, most members of the public had just experienced their first new coronavirus infection, and when confronted with the symptoms of pharyngitis caused by unknown causes, the public was fearful of the lack of information on the cause of the disease, the scope of transmission, and preventive measures, resulting in the emergence of negative emotions. At the same time, social media, particularly Weibo, facilitated the event's rapid spread, and the proportion of negative messages such as dread, gloomy, and anger that appeared in public comments during that period was significantly higher than that of positive messages such as happiness and positivity, as shown in Table 6.
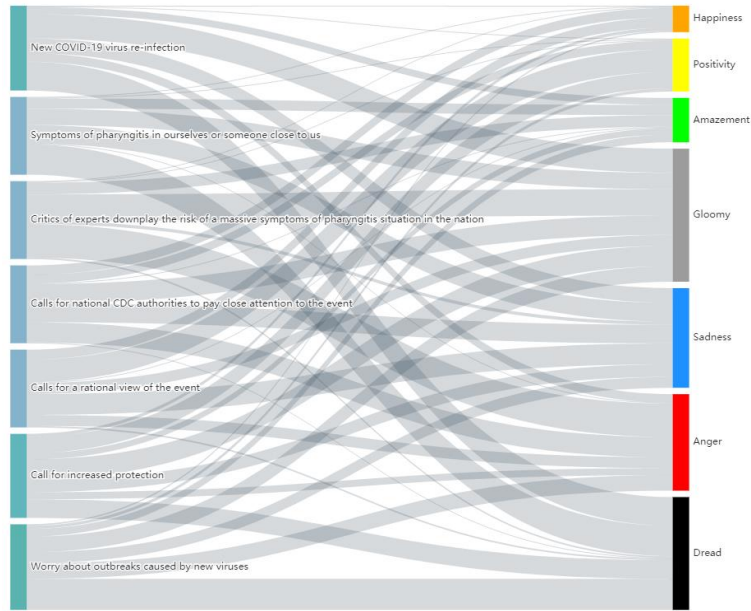
Figure 4. Trend of Dissemination of Post-holiday Symptoms of Pharyngitis Events after May 2023

When the public was exposed to the post-holiday symptoms of pharyngitis event again in October 2023 and February 2024, the majority of them experienced information fatigue as a result of multiple reports and discussions of similar events over a short period of time, reducing their attention and information sensitivity to the event. The emotion-topic analysis reveals that the number of extracted topics gradually decreases; secondly, with the recurrence of the "post-holiday symptoms of pharyngitis" event, the public, government, and medical institutions have gained more knowledge and experience in responding to and managing this type of health crisis. This better coping capacity and knowledge can help people overcome their fears and uncertainties, as well as minimize negative emotions. More importantly, the public faced numerous challenges and crises during the event, which increased inner resilience, i.e., the ability to maintain a positive attitude in the face of stress and adversity, as evidenced by the gradual decrease of negative types of information and the gradual increase of positive types of comments and information in the data analysis.
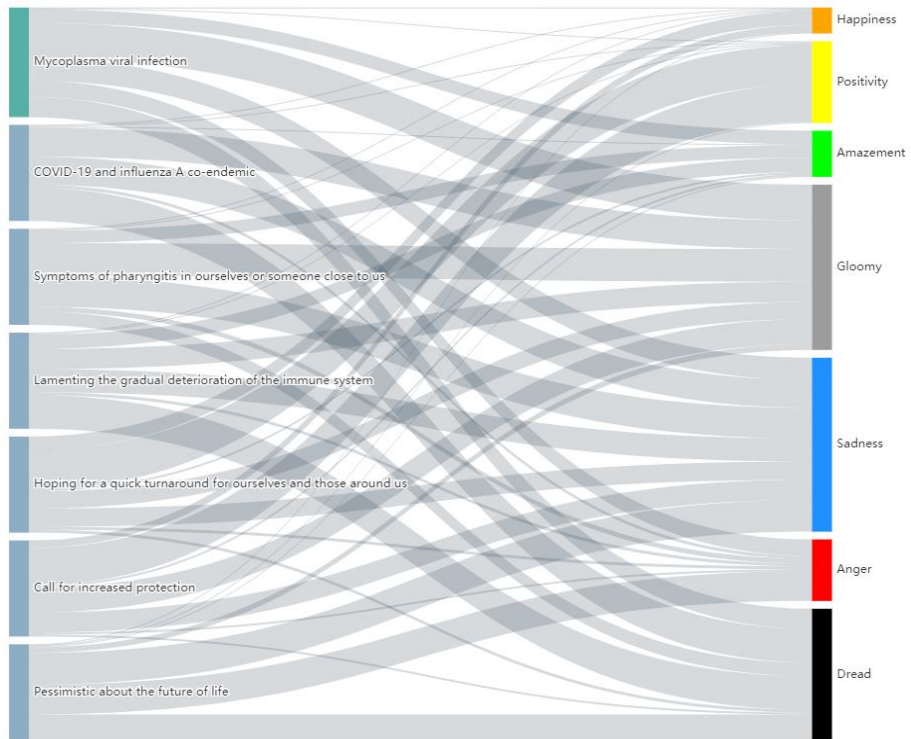
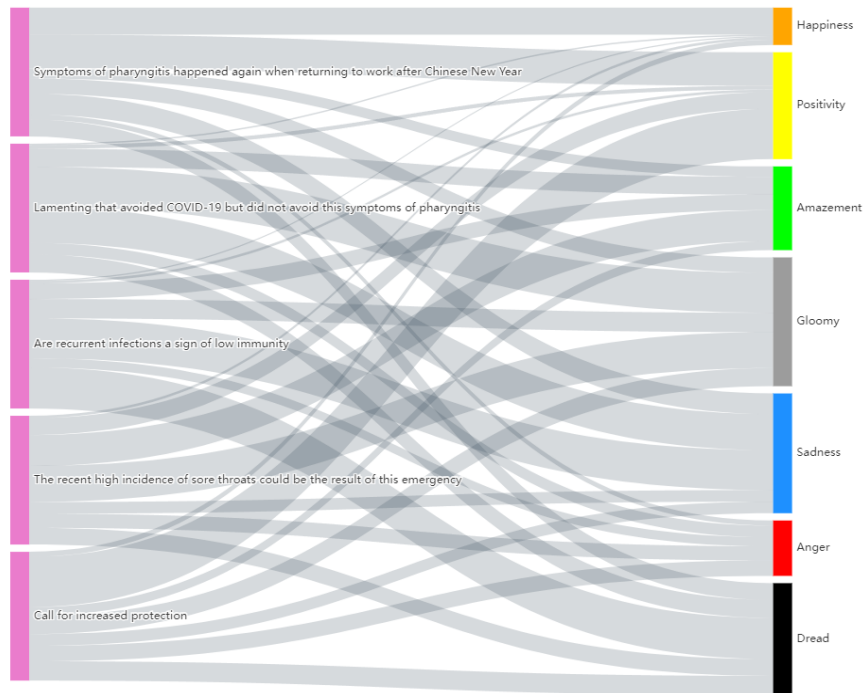**Figure 5. Trend of Dissemination of Post-holiday Symptoms of Pharyngitis Events after October 2023**

Figure 6. Trend of Dissemination of Post-holiday Symptoms of Pharyngitis Events after February 2024

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Table 6. Distribution of Emotion of Post-holiday Symptoms of Pharyngitis Events in Different Time Periods

	May 2023	October 2023	February 2024
Happiness	4.68%	3.78%	5.8%
Positivity	9.35%	11.9%	16.6%
Anger	17.06%	8.96%	8.6%
Sadness	17.61%	23.35%	18.6%
Dread	19.94%	19.19%	17.4%
Gloomy	23.52%	24.09%	20%
Amazement	7.84%	6.72%	13%

4.4 Results and Public Opinion Response

Comparing the communication data of the three post-holiday symptoms of pharyngitis events, it is discovered that the public's concern about the event steadily declines with the number of events. In the early stages of event communication, the public's communication behavior was mostly dependent on retweeting or re-commenting, which was heavily affected by opinion leaders such as celebrities and authoritative media outlets. During rest days, the public tends to focus on offline activities, which greatly reduces their attention to events.

This study uses the topic-emotion model to mine post-holiday symptoms of pharyngitis event from various time periods. Comparing the number of topics extracted from the post-holiday symptoms of pharyngitis event in the three periods, the number of interpretable topics gradually decreases over time, and the public's concern for the event decreases as well. Reactions to the event have changed from initial topics with strong emotion, such as fear of disease outbreaks caused by new viruses and pessimism about the future, to more neutral topics, such as calls for better protection and suspicion of problems with one's own immunity.

Based on the above theme extraction results, this study conducts emotion analysis. When the post-holiday symptoms of pharyngitis event first appeared in May 2023, due to the public's uncertainty about the causes of the disease, accompanied by the dissemination of related rumors and inaccurate information, the public's emotion was dominated by negative information at that stage. As the second and third post-holiday symptoms of pharyngitis events occurred, public concern about the event decreased, while the public, government, and medical institutions gained knowledge and experience in responding to and managing this health event. Although negative information continued to account for a large proportion, positive and positive information from the public gradually increased.

Using the topic-emotion model, this study collects data on the post-holiday symptoms of pharyngitis event on the Weibo platform over various time periods, analyzes the event's communication and topic-emotion evolution characteristics, and makes the following recommendations for public opinion

response based on the study's results:

(1) In the early stages of the dissemination of this type of event, the public primarily shares information by forwarding or re-commenting, taking into account the authenticity and uncertainty of the event's topics, and is influenced by opinion leaders such as celebrities and authoritative media sources. As a result, propaganda departments should ensure that official news is provided in a timely manner based on reliable and authoritative information in order to steer public opinion and prevent the spread of public confusion and bad emotions. The propaganda department's timely voice can also successfully restrict the propagation of misinformation and rumors on social media, thereby stabilizing social opinion.

(2) During the rest days of the event, the public's attention to the event decreases significantly, and the publicity department should take advantage of this buffer period by sorting out the public's main opinions using the topic-emotion model and responding to the public's concerns in a targeted manner. The interactivity of information exchange on the new media platform is used to achieve two-way communication in information dissemination, while the government's communication and participation in public opinion events reflects the government's openness and responsibility.

(3) During the multiple dissemination of this event, although the public concern continues to decline, negative information still accounts for a relatively large proportion. As a result, the publicity department must continue to release new information and actively respond to media and public inquiries. The publicity department can use simple, easy-to-understand expressions to release, update, and respond to disease-related information on a regular basis, to maintain public attention and participation while spreading disease prevention and control knowledge, and to raise disease prevention and control awareness among individuals and families.

5. Conclusion

This study takes Weibo data as research samples, and utilizes the LDA model fused with TD-IDF weighted Word2vec algorithm to acquire, clean and sort out the themes of the three "post-holiday symptoms of pharyngitis" public opinion events from 2023 to February 2024. The DUTIR emotion dictionary was used to analyze the emotion orientation of public comments, and to analyze the propagation trend of the public opinion data, and the process of generating and evolving the theme emotion of the event. In response to the study's findings, suggestions for directing and publicizing the handling of this sort of public opinion event are made, which will aid in the handling and guiding of public opinion in future such public health events.

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