Original Research Article

DIGITAL HEALTH

DIGITAL HEALTH
Volume 10: 1–14

DOI: 10.1177/20552076241234619
journals.sagepub.com/home/dhj
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Opinion leaders and crisis communication during the COVID-19 pandemic: A study of theme evolution and emotional impact on Twitter

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Abstract

This study uses Twitter data from the early stages of the pandemic to analyze the evolution of topics during different time periods and attempts to investigate the content and emotional impact of opinion leaders on public opinion evolution under different themes, in order to understand their role in shaping public discourse and emotions. Divide the life cycle into three stages; NLTK emotional analysis and dynamic topic models (DTMs) are employed to extract and analyze topic words. The results showed that there were significant differences between opinion leaders and followers in terms of hot topics and their evolution trends: (1) In terms of hot topics, opinion leaders have always been paying attention to measures and methods aimed at the public, while followers usually have persist in seeking information and dissatisfaction. (2) In terms of identifying and evolving hot topics, opinion leaders have shifted from the impact of the epidemic on individuals and resources to government responses and policies, while followers are more inclined to express people's growing concerns and dissatisfaction with crisis management. The content of opinion leaders has a significant relationship with evolving public opinion, highlighting the importance of understanding their role in crisis communication. Opinion leaders are also categorized into five types, each with different audience sizes, contents, emotions, and network structures, and they impact public opinion differently. This study identifies and analyzes the characteristics and impact mechanisms of opinion leaders in crisis communication. It hopes to contribute to understanding crisis communication dynamics in the digital era and provide insights into effective communication strategies during crises.

Keywords

Crisis communication, opinion leaders, theme evolution, COVID-19

Submission date: 1 June 2023; Acceptance date: 25 January 2024

Introduction

In the era of social media, crisis communication has become increasingly important as real-time information dissemination can rapidly shift and evolve public opinion. Effective management of communication strategies and maintaining trust with stakeholders is crucial for governments and organizations, and understanding the factors that influence public opinion during crises is key.[1] In crisis communication, opinion leaders play an important intermediary or filtering role in the formation of the effectiveness of mass communication, spreading information to the audience and forming a two-level dissemination of information.[2] Opinion leaders in online environments are particularly persuasive, to some extent, it can guide social opinion.[3] This content is rapidly and widely disseminated and shared on social platforms in a viral manner, significantly broadening the scope of information dissemination

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and reception, and the influence of these opinion leaders is thereby magnified and strengthened.[4]

In the field of political science, online opinion leaders can leverage their strong ability to mobilize and guide public opinion to foster positive consensus. This contributes to consolidate the public opinion foundation necessary for governance and decision-making, promote political socialization, and enhance the capacity and efficiency of public governance in the whole society. Government opinion leaders play a pivotal role in shaping public discourse and sentiment; they can either facilitate or hinder communication efforts of governments and organizations by endorsing or challenging official narratives during crises, such as natural disasters[3], public health emergencies, and political crises[5]. In this study, the chosen opinion leaders are government Twitter accounts. Government accounts on Twitter are authoritative sources of information, especially during crises such as the COVID-19 pandemic.

Some researchers have found that applying natural language methods to Twitter data contributes to study public discussion and sentiment and improve the efficiency of information dissemination during the COVID-19 pandemic.[1,5] Twitter has emerged as an alternative medium for scholars, health experts, journalists, government authorities, and other credible sources worldwide to disseminate the latest information on COVID-19.[6] Government Twitter accounts play a pivotal role in disseminating official policies, updates, and responses to public concerns. By analyzing these accounts, the study can effectively assess how government communication strategies impact public opinion and influence the social media narrative during critical times.[7]

In crisis communication, these accounts have become trusted sources of information and guidance in times of crisis through professional experience and official certification, underscoring their role in shaping public discourse. Government opinion leaders have an impact on both network media and netizens.[8] Government opinion leaders impact both network online media and netizens. As catalysts for event transmission, network media can promote the government's crisis response by cultivating network public opinion as the final recipient.[9,10] The strategic behavior of netizens is influenced by the government and online media, and its evolution may lead to a positive outcome, but for skeptics, it may also backfire.[11,12] Furthermore, the development and changes in public health emergencies exert a driving influence on the cross-evolution of netizens' risk perception levels. Not only may their risk perception levels gradually increase as external factors exacerbate public health emergencies.[13,14] At present, with the rapid changes in media technology and consumption, social changes, and the emergence of global issues, there is a demand for new analysis in the field of public opinion, all of which require updated frameworks and methods to be fully understood. The traditional model of public opinion formation may not fully capture the complexity of how public opinion is formed in this new environment.[15] As mentioned earlier, the emergence of WEB2.0 has resulted in increased social media influence on government and public interactions.[16,17] Scholars have analyzed opinion leaders and their followers in the context of political environments such as the French and US elections, asserting that the public opinion is crucial for decision-makers, media organizations, and society as a whole. Accurate and updated analysis can provide information for better decision-making and help the public be more informed and engaged. Some scholars have also found that emotional expression is crucial for the role of opinion leaders in the media.[10,18,19]

Through literature research, it is found the analysis and construction of opinion leaders' public sentiment communication mechanism models during the COVID-19 public health emergency. On the one hand, as massive public opinion data on public health emergencies continuously appears on various social media platforms, studying communication and evolutionary laws through social network analysis, statistical analysis, and text mining becomes exceedingly challenging. On the other hand, there is limited research on the analysis and construction of opinion leaders' public sentiment communication mechanism models during the COVID-19 public health emergency.

Objectives

This study aims to explore the content and emotional influence of opinion leaders on the development of public opinion across various themes, with the goal of comprehending their role in molding public discussions and emotions, by using Twitter data from the early stages of the COVID-19 pandemic to analyze the evolution of topics during different time periods. It also seeks to examine the content and emotional impact of opinion leaders on the evolution of public opinion under different topics. By investigating the transformation of public discourse and the role of opinion leaders in shaping these transformations, we hope to contribute to the understanding of crisis communication dynamics in the digital age and provide insights for effective communication strategies during crises.

Methods

This study collected and analyzed tweets and reposts from 50 states in the United States through data mining, allowing for comparative analysis of regional differences in public opinion formation. This study used the Natural Language Toolkit (NLTK) and Valence Aware Dictionary and sEntiment Reasoner (VADER) sentiment analysis tools to evaluate emotional responses in the data. It uses a Dynamic Topic Model (DTM) to track the changes of theme words over time, providing a comprehensive view of the evolution of themes during the epidemic. Use descriptive analysis, cluster analysis, and other methods to express the results.

This study uses multiple methods to conduct descriptive analysis, clustering analysis, and visualization of data, combining quantitative data analysis with qualitative insights, with the aim of comprehensively understanding the dynamics of public opinion leaders and public opinion in the early stages of the epidemic.

Related definitions

This study selected data from tweets and retweets from followers of US state government Twitter accounts at the beginning of the new crown epidemic in 2020.

Relevance: The New Crown Pneumonia pandemic was one of the most important events of the 21st century, with a major impact on public opinion and discourse. By focusing on the early stages of the pandemic, which is the period when public opinion is still forming and evolving, it can provide unique insights into the dynamics of public opinion.

Availability of data: With the widespread use of social media platforms such as Twitter, there is a wealth of data on public opinion and sentiment. By collecting tweets and retweets from US state government Twitter accounts to create a large dataset; this dataset provides insight into the evolution of public opinion at that time.

Opinion leader selection: This study first identified the scope of opinion leaders as official government Twitter accounts. These opinion leaders have the characteristics of high influence, strong attention, and meeting the standards of opinion leaders.

Subject word analysis and evolution

After pre-processing and topic extraction using the NLTK and spaCy libraries, each text is analyzed for relevant topics and classified. If multiple topics emerge, they are categorized under the most relevant main topic. Based on this, use DTM[20] to reflect the change of subject words over time. DTM is an unsupervised machine learning model for documenting topic generation based on the LDA model proposed by D.M. Blei et al.[21] and consists of a three-layer structure of documents, topics, and words,[22] where K denotes the number of topics, A denotes the number of documents in each time segment, N denotes the number of words in the documents, and z and ω denote the final generated topics and topic words. ∂ with β denotes the Dirichlet prior distribution parameters, ∂ is the possible topic distribution for each document, and β is the possible word distribution for each topic, and when ∂ is implemented to a document, θ is the topic model of that document, denoting a multinomial distribution, and ∂ is really a conjugate prior distribution of θ. For the words in a document N, the topic z determined by a multinomial distribution θ is selected, and the word ω associated with the topic is selected by a multinomial distribution of z and β. At each time segment t under the document topic distribution a_t and the distribution of topic-related words β_t, k are dependent on the previous time slice in $\partial_{t-1},\ \beta_{t-1}$. k, the previous time segment $t-1$ generates this time segment t $\beta_{t,k}$. The formula is as follows:

$$\beta_{t,k}|\beta_{t-1,k}, k \sim N\left(\beta_{t-1,k}, \theta^2\ |\right) \tag{1}$$

where N represents the Gaussian distribution, the mean is the Dirichlet distribution of the previous time period, and the variance needs to be obtained by training. Similarly, from the previous time period $t-1$, generate this time period t a_t, and the equation is:

$$\alpha_t|\alpha_{t-1} \sim N(\alpha_{t-1}, \delta^2|) \tag{2}$$

The DTM generates continuous document topics in time segment t as follows:

1. Generation of subject word distribution:

$$\beta_{t,k}|\beta_{t-1,k} \sim N\left(\beta_{t-1,k}, \sigma^2\ |\right) \tag{3}$$

2. Generate theme distribution:

$$\alpha_t|\alpha_{t-1} \sim N(\alpha_{t-1}, \delta^2|) \tag{4}$$

where the function $\pi(x)$ is the parameter of the Gaussian distribution mapped to the polynomial distribution normalized by the equation

$$\pi(\beta_{t,k})_\omega = \frac{exp(\beta_{t,k,\omega})}{\sum \omega exp(\beta_{t,k,\omega})} \tag{5}$$

Sentiment analysis

NLTK is used to perform sentiment analysis on the Twitter data collected. The VADER sentiment analysis tool is used to calculate a sentiment score for each tweet in our dataset. The SentimentIntensityAnalyzer class initializes the sentiment analyzer, and the polarity_scores method calculates the sentiment scores for the input text. The sentiment scores are returned as a dictionary containing four scores: a positive score, a negative score, a neutral score, and a compound score, which is a normalized weighted composite score that ranges from −1 (most negative) to +1 (most positive). This study uses dictionary-based word sense disambiguation.

Finally, opinion leaders are classified according to their sentiment scores, the use of subject words, and the characteristics of social networks, and the impact of different types of opinion leaders and the measures that can be taken are judged.

Statistical analysis

In order to classify opinion leaders into different types, clustering analysis techniques are applied to identify groups with similar characteristics and behaviors. Use descriptive statistics to summarize the characteristics of opinion leaders, followers, and discussion topics.

Evolution and visualization of public opinion

Based on the obtained data on emotional responses and topic evolution, this study will conduct an analysis and visualization of the evolution of public opinion under different topics and time periods. This study lies in its comprehensive analysis of emotional responses and topic evolution during the early stages of the COVID-19 pandemic, using Twitter data to uncover the dynamics of public opinion. By examining different topics and time periods, the study aims to identify which topics garner more attention and have a greater impact during crisis communication.

Results

Emotional analysis showed that, during the initial stage, there were more positive sentiment tweets than negative sentiment tweets, but the number of negative sentiment tweets gradually increased in the fluctuation and peak stages. However, positive sentiment tweets remained more numerous. In terms of comments, neutral sentiment tweets outnumbered positive sentiment tweets across all three stages.

Data collection and life cycle partitioning

This study selected relevant data from the largest social media platform, Twitter, as the data source for public health emergencies and corresponding sentiment outbreaks. Based on preliminary research, the number of new cases remained relatively stable in April and May.

Twitter data from various state governments and the White House were extracted using Python, collecting a total of 7128 tweets from April 1, 2020, to May 1, 2020. After deduplication and screening, 6369 tweets were included in the study, including 2008 COVID-related tweets, which were retweeted 1,226,855 times, liked 5,102,986 times, replied to 774,719 times, and quoted 164,380 times. The tweet comments totaled 550,381, and after natural language processing segmentation, lemmatization, and frequency statistics, 510,992 valid comments were retained after excluding irrelevant content and advertisements, including 137,150 COVID-related comments. The segmentation and natural language processing were performed using a Python code, and the results were saved in a CSV file.

Use the combination of tweet volume and participation indicators (retweet, favorite, reply, quote) to divide the life cycle. The frequency of dissemination and the level of participation in that dissemination are also taken into account, allowing for a more comprehensive understanding of how public opinion changes over time. Assign equal weight to each type of engagement weight, i.e. 0.01. This approach assumes that all types of engagement are equally important. Consolidated data is generated by comprehensive data calculation. The life cycle of the data is divided into three stages: the initial stage (April 1–3), the fluctuation stage (April 4–16), and the peak stage (April 17–30), based on the development of the data (see Figure 1).

Using Gephi to build a social network analysis matrix, we can create a social network structure of Twitter opinion leaders based on the relationships between Twitter retweets,

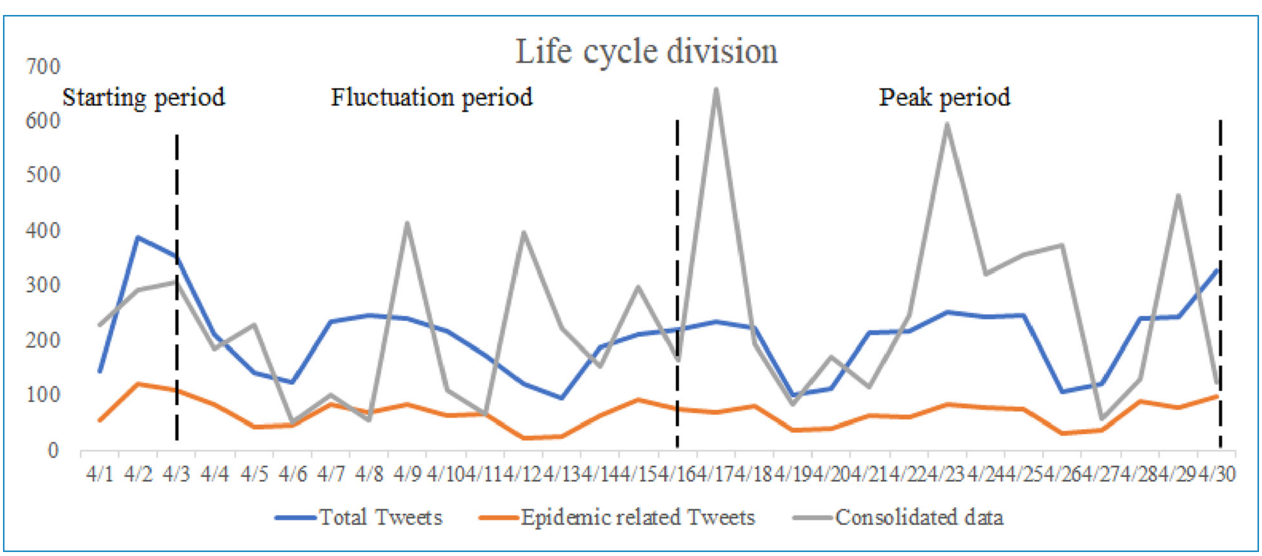

Figure 1. Tweets' comment changes and life cycle division.

comments, and likes. The analysis consists of 63,526 nodes and 120,189 edges, with an average weighted degree of 1.892 and a point degree centrality of 1.056. There are 20 nodes with a degree greater than 1000. The most central nodes include the White House, Donald Trump, and the state of Ohio.

Emotional analysis and clustering results

Analysis of opinion leader sentiment and their level of attention across different stages of the life cycle reveals that in the initial stage, there were more positive sentiment tweets than negative sentiment tweets (see Figure 2). However, as time passed, the number of negative sentiment

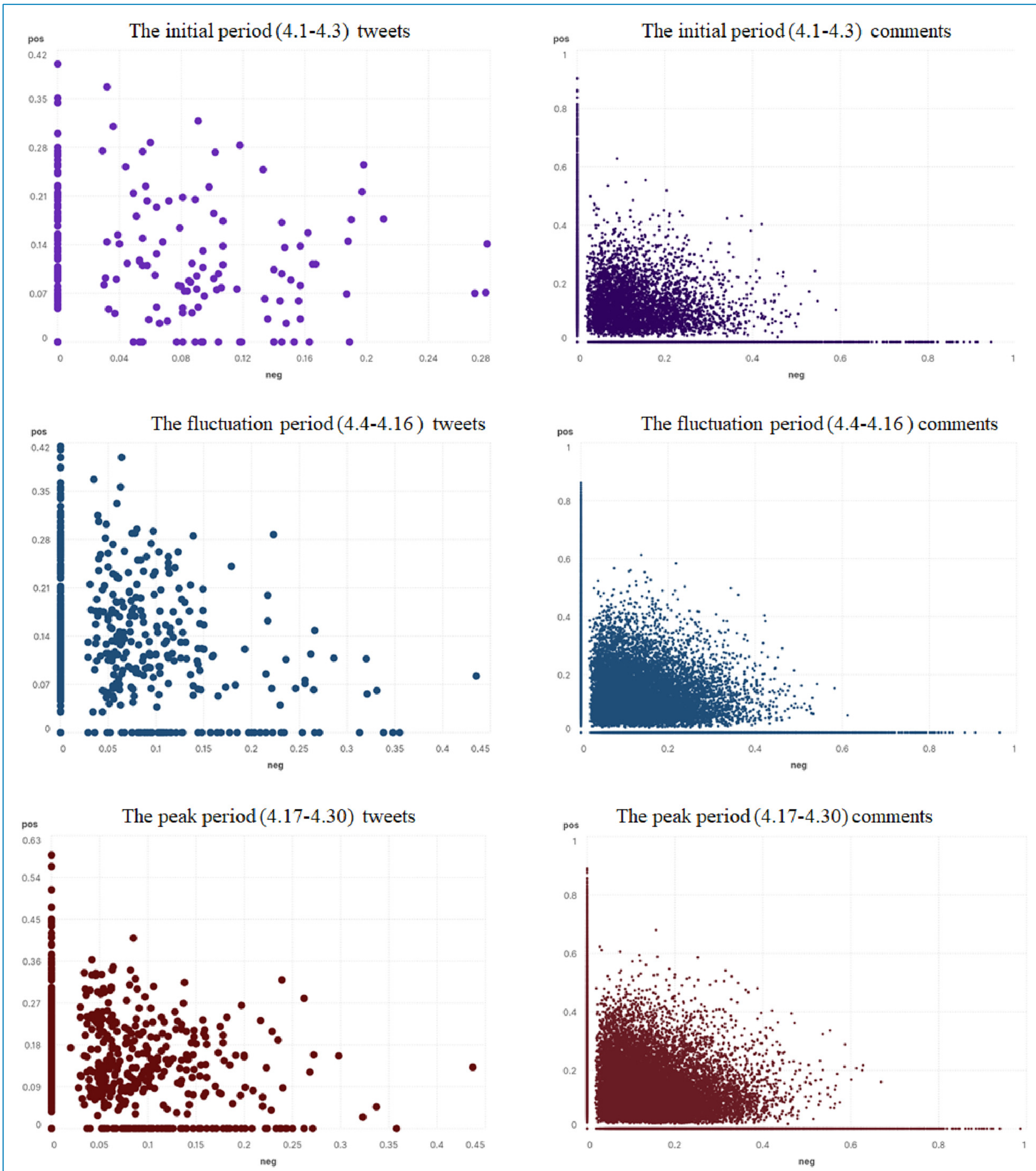

Figure 2. The distribution of sentiment in tweets and comments varies across different stages of the life cycle.

tweets gradually increased in the fluctuation and peak stages, but the number of positive sentiment tweets was always higher. In terms of comments, the number of neutral sentiment tweets was higher than the number of positive sentiment tweets in all three stages.

The sentiment of the initial period tweets has a correlation with their engagement metrics (see Table 1), while the sentiment of comments has no correlation with their engagement metrics (Pearson correlation analysis $P > 0.05$). The correlation between the sentiment of tweets and comments during the fluctuation period was analyzed, and it was found that negative tweets and negative comments have a correlation of 0.019 ($P = 0.000$). The correlation between the sentiment of tweets and comments during the peak period was also analyzed, and it was found that negative tweets and negative comments have a correlation of 0.011 ($P = 0.003$), while positive tweets and negative comments have a correlation of −0.012 ($P = 0.001$).

The sentiment scores of tweets are significantly correlated with retweets, favorites, replies, and quotes. During the initial phase, tweets with a positive sentiment are more likely to be shared, liked, replied to, and quoted, while those with a negative sentiment are relatively less popular. In the fluctuation period, tweets with a negative sentiment are more likely to be shared and liked, whereas those with a positive sentiment are more likely to be replied to and quoted. In the peak period, tweets with a negative sentiment are more likely to be shared, liked, replied to, and quoted. Other factors such as comment data and comment sentiment score do not show any correlation with Twitter and sentiment scores.

Subject word analysis and clustering

Using the DTM, extract the topic words of each day's tweets and comments as a new column and divide them into time slices, manually screen related content, remove irrelevant topic words such as "@users," use text similarity calculations to determine content relevance, and use sentiment scores to determine emotional relevance.

Based on the overall word cloud (see Figure 3), Twitter's word cloud is more focused on certain topics than the word cloud of comments. To perform topic analysis and clustering, it is necessary to distinguish between the two. There seems to be a disconnect between the topics that the US government Twitter tweets are focusing on, such as leading the people, and the concerns expressed by the people in their comments, which tend to express dissatisfaction with government measures and fear of viruses. This indicates that there may be a gap between the government's communication strategy and the concerns of the public. It could be due to differences in perspective between the government and the public, or a lack of effective communication and engagement strategies by the government.

Table 1. The correlation analysis results between the sentiment scores of tweets and the numbers of retweets, favorites, replies, and quotes.

	The initial stage			The fluctuation stage			The peak stage		
	Negative	Neutral	Positive	Negative	Neutral	Positive	Negative	Neutral	Positive
Retweet	−0.119 (0.000)	−0.135 (0.000)	0.216 (0.000)	0.077 (0.000)	−0.095 (0.000)	0.059 (0.000)	0.067 (0.000)	0.001 (0.820)	−0.044 (0.000)
Favorite	−0.202 (0.000)	−0.15 (0.000)	0.279 (0.000)	0.12 (0.000)	−0.13 (0.000)	0.07 (0.000)	0.043 (0.000)	0.002 (0.666)	−0.029 (0.000)
Reply	−0.073 (0.000)	−0.193 (0.000)	0.255 (0.000)	0.013 (0.003)	0.057 (0.000)	−0.074 (0.000)	−0.12 (0.000)	0.031 (0.000)	0.042 (0.000)
Quote	−0.078 (0.000)	−0.091 (0.000)	0.144 (0.000)	0.022 (0.000)	0.019 (0.000)	−0.037 (0.000)	−0.044 (0.000)	0.056 (0.000)	−0.036 (0.000)

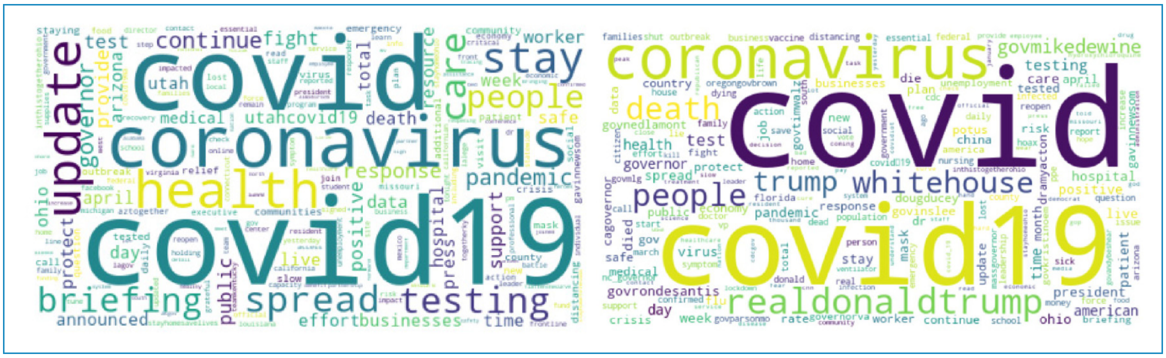

Figure 3. The word cloud diagrams of tweets and comments.

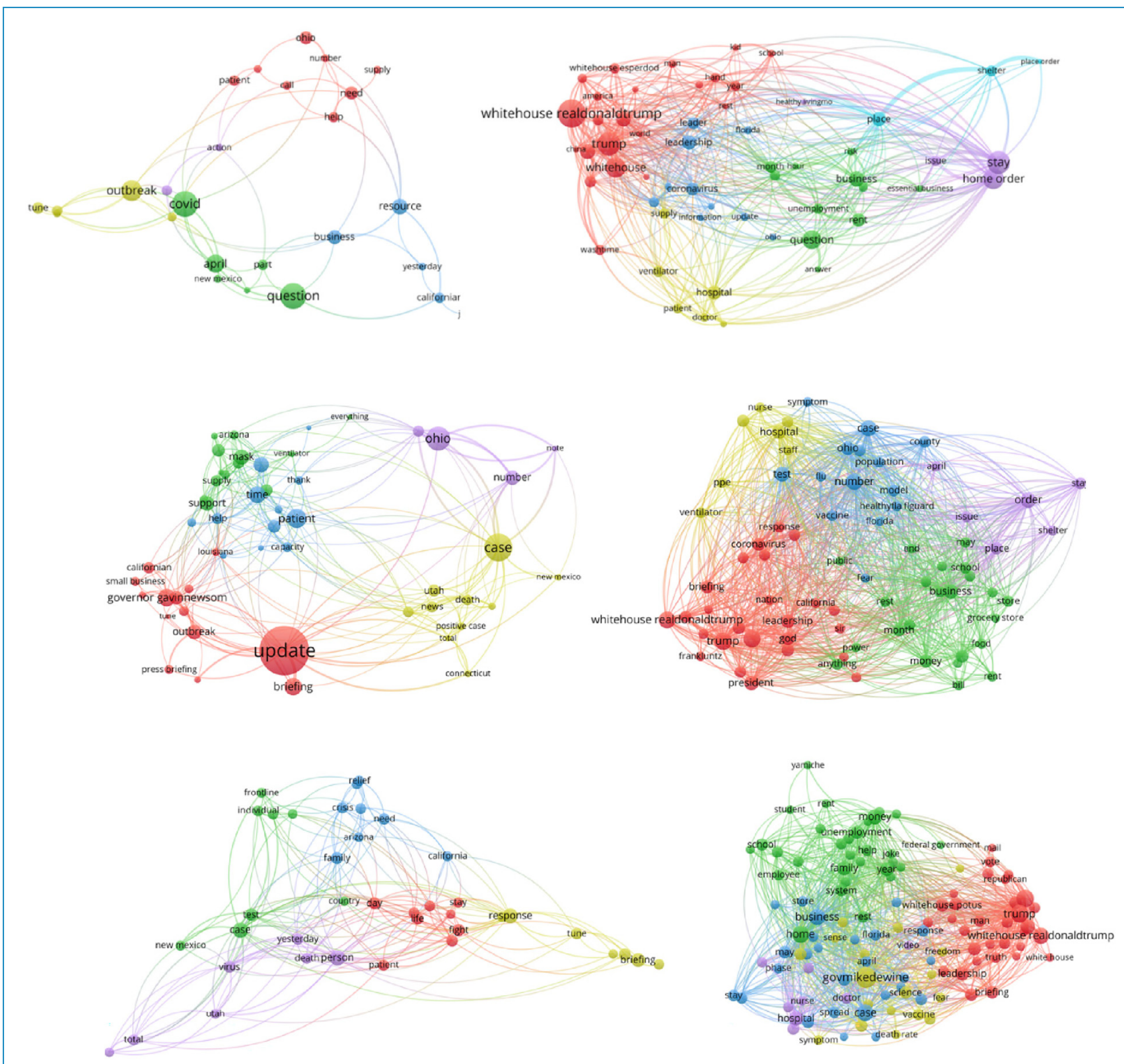

Figure 4. Clustering of theme words at different stages.

Analysis on the evolution of subject words

In order to analyze dynamic changes in more detail, thematic terms from different periods were clustered (see Figure 4). It has been observed that themes change at different stages. Through word frequency analysis and clustering of the overall content, the focus of government tweets is mainly on the virus itself and related policies, while the focus of comments is mainly on the virus, people's lives, and allegations against the President and White House officials.

Word frequency analysis and overall content clustering: The focus of government tweets is mainly on the virus itself and related policies, while the focus of comments is mainly on the virus, people's lives, and accusations against the President and White House officials. The overall thematic terminology of tweets can be divided into two categories: "epidemic focus" and "assistance and resources." The overall thematic terms of the review can be divided into three categories: "epidemic information," "request for assistance," and "political criticism."

After analyzing the topic of all tweet data, it is found that the topic words are mainly divided into five topics, which are extracted and summarized as follows: healthcare, prevention measures, government response, impact on society and individuals, and request for supplies. Analyze and summarize the topic of followers' comments from different tweets; it is found that the topic words are mainly divided into five topics, which are extracted and summarized as follows: help seeking, concerns, criticism, ask for help, discussion, and the results are shown in Table 2.

The use of Sankey diagrams can provide a clearer description of the evolution process of themes. In this study, themes were divided into several themes, more than five. After conducting a thematic analysis, the themes were further divided according to their respective categories. Thematic analysis was conducted on tweet data and comment data from various states, and themes that appeared only once were assigned a weight of one. The overall theme evolution Sankey diagram was then created by summing up the weights of different states. The thickness of the lines in the diagram represents the weight multiplied by the number of tweets published by each state, indicating how many different states have this type of evolution. For the different tweet data (see Figure 5), calculate the evolution process of tweet topics in different states, and the thickness of the lines represents the weight multiplied by the number of tweets published by each state, which was used to calculate the degree of evolution.

1. The initial stage: The themes in this stage mainly focus on emergency medical response and care, various stakeholders involved in responding to the pandemic, the current state of business and employment resources, and announcing and communicating actions or plans.

Table 2. Classification and quantity of subject words.

Tweets' theme	Detailed information	Number of tweets	Comments Theme	Detailed information	Number of comments
Topic 1: Healthcare	Healthcare workers and their efforts to fight coronavirus	408	Topic a: Help seeking	Medical and supplies assistance	33,292
Topic 2: Prevention measures	Public response to coronavirus, including social distancing and testing	314	Topic b: Concerns	Different views and concerns about the COVID-19 and the government's response measures	22,610
Topic 3: Government response	Political decisions and actions related to coronavirus management	408	Topic c: Criticism	Criticism of Trump's response to the pandemic and media	33,362
Topic 4: Impact on society and individuals	Coronavirus outbreak and its impact on individuals and communities	314	Topic d: Ask for help	Call for economic and medical assistance for openness	24,654
Topic 5: Request for supplies	Request for COVID-19 supplies and economic impact of coronavirus and financial aid	63	Topic e: Discussion	Discussion on wearing masks, disease surveillance, and cases	4795
Others	Other related topics	502	Others	Other related topics	18,437

This stage is characterized by uncertainty, confusion, and a sense of urgency as the pandemic rapidly spreads and governments and healthcare systems struggle to respond.

2. The fluctuation stage: The themes in this stage are more diverse and reflect the ongoing impact of the pandemic on communities, healthcare workers, businesses, and governments. The themes in this stage include updates on the number of cases, deaths, and positive tests, community support, policy updates and announcements, and public response and feedback. This stage is marked by a sense of unease and a desire for clear and effective leadership and communication from government officials.
3. The peak stage: The themes in this stage largely reflect the ongoing efforts to manage and respond to the pandemic. The themes in this stage include providing

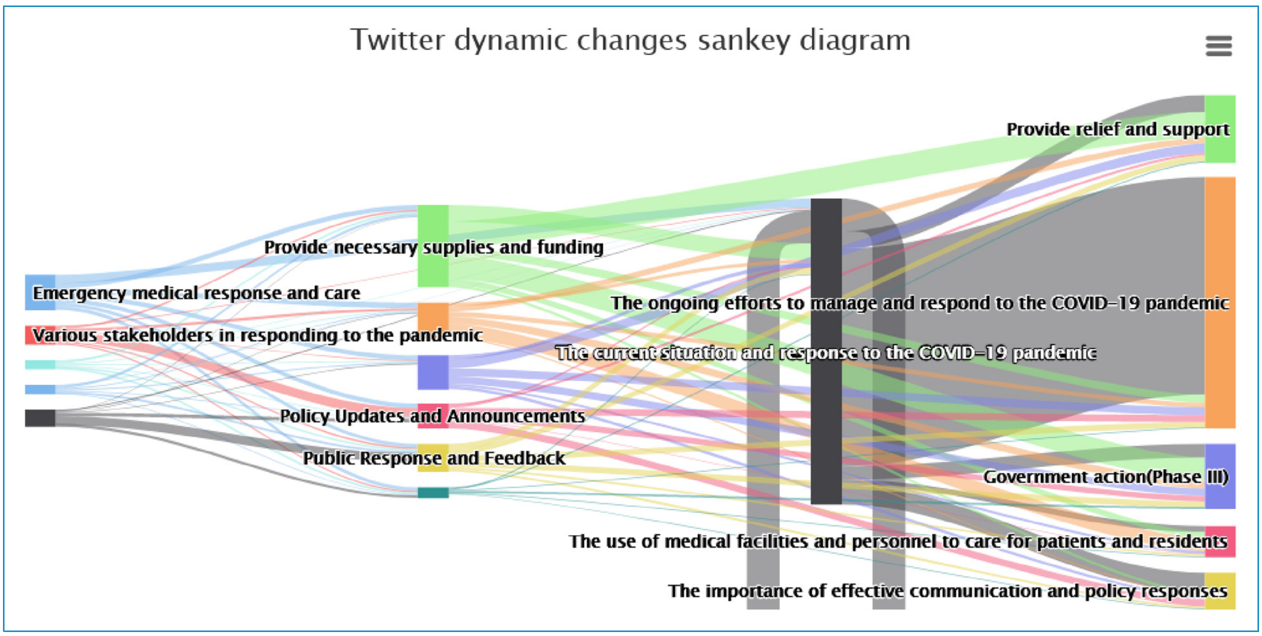

Figure 5. Clustering of tweets' theme words at different stages.

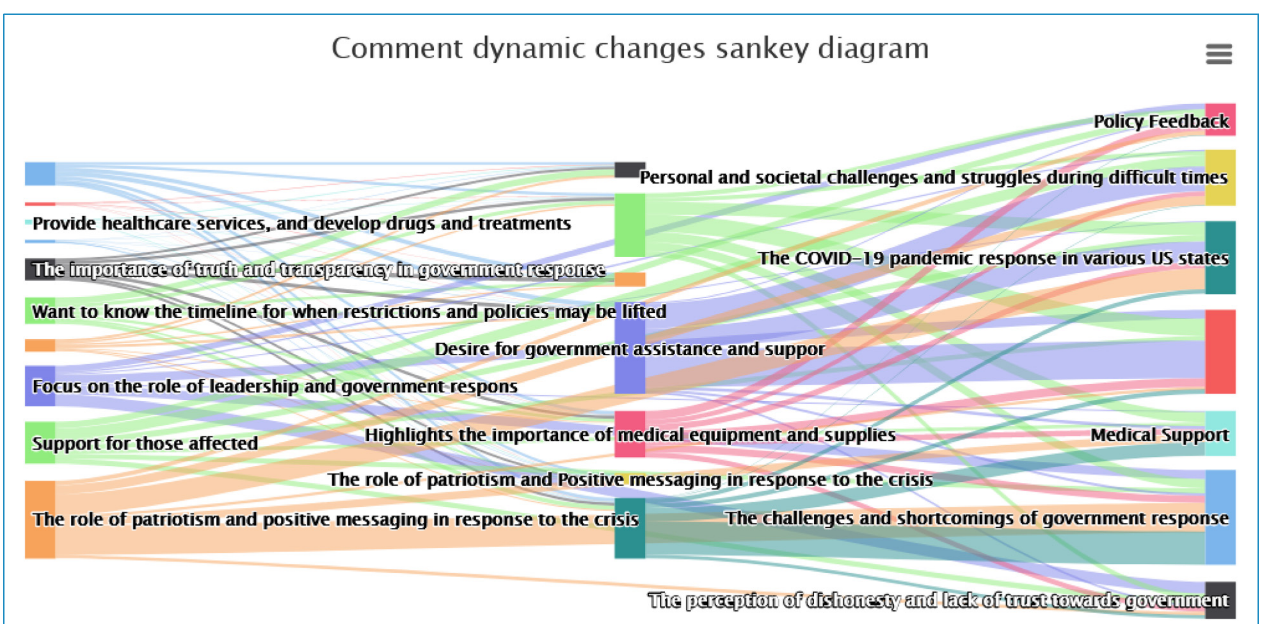

Figure 6. Clustering of comments' theme words at different stages.

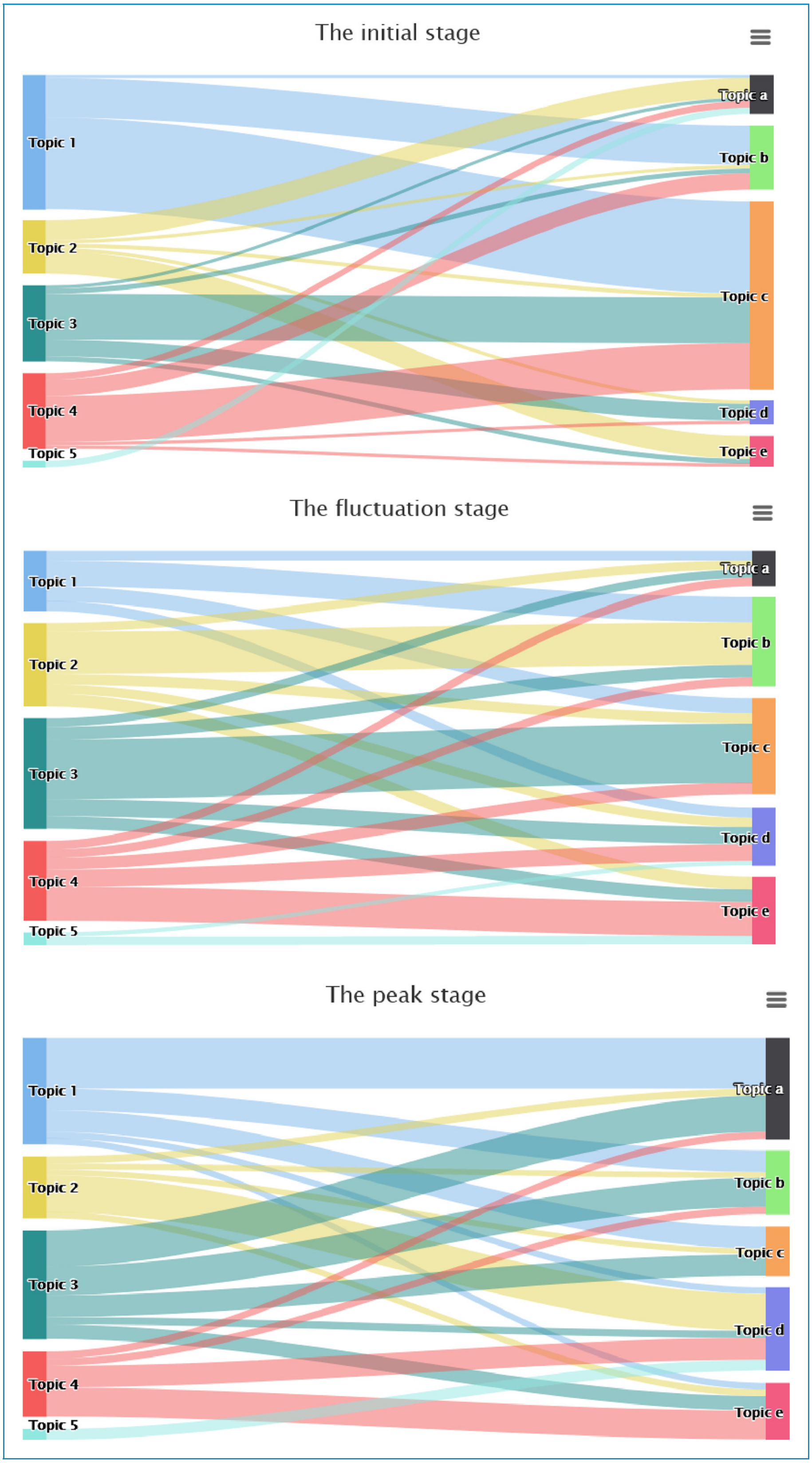

Figure 7. Clustering of comments' theme words at different stages.

relief and support, government action, the use of medical facilities and personnel to care for patients and residents, and the importance of effective communication and policy responses. This stage is characterized by a sense of urgency and a need for immediate action to address the ongoing crisis.

The themes appear that there is a general shift in focus from emergency medical response and care in the initial stage to the current situation and response to the pandemic in the fluctuation and peak stages. Additionally, the themes of community support and the efforts of healthcare workers appear in both the fluctuation and peak stages, indicating a growing awareness of the importance of these topics. There is also a consistent focus on government action throughout all three stages, highlighting the crucial role of policy and leadership in managing the crisis. Finally, there is a shift in focus from the impact of the crisis on small businesses in the initial stage to providing relief and support in the peak stage, reflecting the evolving needs and priorities of communities as the pandemic continues to unfold.

Regarding the comment data, the weight of the frequency of theme evolution is set to 1, and the thickness of the Sankey diagram line is multiplied by the weight and the number of comments under tweets in a certain state (see Figure 6).

On this basis, this study investigated the changes of Twitter themes and followers' participation in different stages of the COVID-19. By analyzing these changes, three Sangi diagrams at different stages were constructed to visualize the evolution of Twitter theme words and their comments on different topics at each stage. Each topic is represented by a unique topic number, which can clearly and concisely represent changes in public discourse. This visualization helps identify trends, patterns, and key shifts in the thematic pattern of crisis communication, providing valuable insights into how public opinion and emotions respond to opinion leaders and key events during a crisis (see Figure 7).

Calculate the topic relevance (text similarity) between a certain tweet and its comments over different time periods, and find that there is a large gap. Therefore, this study uses the frequency of comment topics generated by different topic tweets as the line thickness to determine the changes in tweets and comments over different time periods.

In the initial stage, no matter what kind of tweets, their comments tended to be critical of the government's response to thne epidemic and the media. In the fluctuation stage, comments tend to have different views and concerns about COVID-19 and the government's response measures. At the peak stage, comments tend to focus on medical and supplies assistance and call for economic and medical assistance to promote openness. Through the transformation of different themes, it can be found that there are significant differences between tweets and their comments (see Figure 8).

By analyzing emotional changes, it was found that there was a significant difference between comments and tweets under different topics, with comments generally having lower emotional scores than tweets. In particular, there is a significant difference in the emotional scores of comments and tweets on topics 2, 4, and 5 during the initial and fluctuation periods. Overall, the comment themes shifted from a

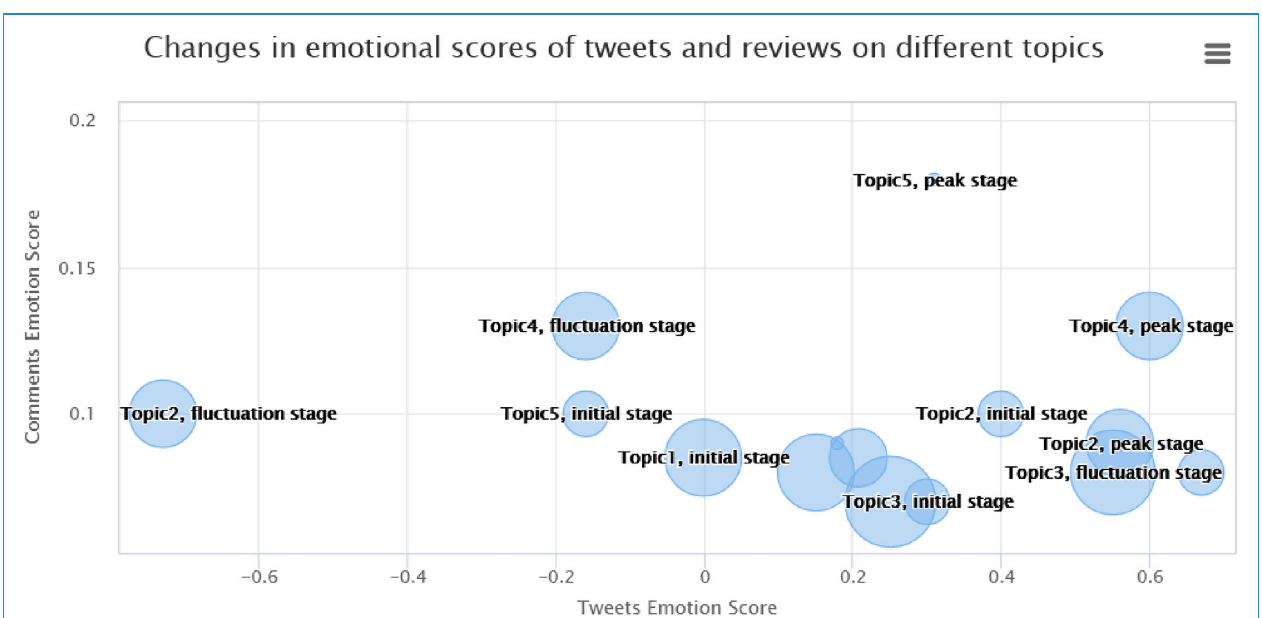

Figure 8. Distribution map of emotional scores in tweets.

focus on the pandemic's impact on individuals and resources to a greater emphasis on government response and policy. The themes also reflect a growing concern and frustration toward government response and a need for more support and transparency.

The analysis revealed a significant disconnect between the content of US government Twitter tweets and the comments made by the public. Specifically, the focus of government tweets was primarily on the virus itself and related policies, while the focus of comments was mainly on the virus, people's lives, and making claims against the President and White House officials. We conducted word frequency analysis and clustering of the overall content to identify these differences. Our findings suggest that the government's messaging strategy may not be fully aligned with the concerns and priorities of the public, highlighting the importance of considering public sentiment and feedback in crisis communication.

Research on the classification and influence mechanism of opinion leaders

By distinguishing the content of different opinion leaders' posts and using the DTM topic classification method, they were divided into five categories. For each category of opinion leaders, their research findings were synthesized by examining changes in topic coherence and sentiment.

Table 3. Classification of opinion leaders.

Types of opinion leaders	Interpretation	Topic coherence	Specific location	Emotional tendency of tweets			Emotional tendency of comments		
				Negative	Neutral	Positive	Negative	Neutral	Positive
Health experts	Including opinion leaders who primarily focus on public health issues related to the pandemic, such as public health officials	0.064	Ohio Utah Alabama	0.045	0.841	0.114	0.077	0.819	0104
Political leaders	Including government officials and political figures who are responsible for making and implementing pandemic-related policies	0.032	Alabama Utah	0.038	0.865	0.097	0.067	0.798	0.135
Community activists	Including opinion leaders who work at the grassroots level to mobilize communities and provide support to vulnerable populations during the pandemic	0.055	Alabama Arizona	0.046	0.834	0.120	0.101	0.818	0.098
Advocates and critics	Including opinion leaders who use their platform to advocate for or criticize government policies and actions related to the pandemic	0.013	Arizona Ohio Kentucky	0.041	0.835	0.123	0.207	0.718	0.061
Information providers	Including opinion leaders who provide the public with accurate and up-to-date information about the pandemic	0.068	Michigan Utah West Virginia	0.050	0..775	0.164	0.206	0.718	0.074

The impact of different types of opinion leaders varies (see Table 3).

Based on the results, it was found that by classifying opinion leaders' content using topic keywords, different opinion leaders with varying intersections were identified in the classified categories. Health experts and information providers were found to have higher topic coherence between their comments and tweets, with little variation in sentiment. On the other hand, community activists and advocates and critics had lower topic coherence between their comments and tweets, with greater variation in sentiment. Notably, advocates and critics had more positive sentiment in their tweets but more negative sentiment in their comments. By combining with social network results, Advocates and critics have a large following and be well-connected within the Twitter community, which can amplify their influence and reach.

By using these categories, we can identify the opinion leaders who are most influential in shaping public opinion and the strategies they use to achieve their goals. These revised categories seem appropriate for analyzing the influence of opinion leaders during the pandemic and can provide valuable insights for policymakers and public health officials.

The evolution of the study's theme uncovered a disconnect between government tweets and public comments, suggesting that the government's messaging strategy may not fully align with public concerns and priorities. Factors that could contribute to this disconnect include differences in viewpoints, priorities, and communication methods between government officials and the public. It is crucial to emphasize the importance of considering public sentiment and feedback in crisis communication and the necessity of effective communication strategies that consider the concerns and priorities of all relevant stakeholders.

Discussion

The study reveals four major findings. Firstly, we analyzed the changing trends in public attention to the COVID-19 pandemic during crisis situations, dividing it into three stages: the initial period, fluctuation period, and peak period. Secondly, the focus of opinion leaders and public comments on topics differed in each stage and changed as the situation evolved. Thirdly, over time, the public's emotional tendencies toward pandemic-related topics in crisis communication changed from positive to neutral, and then to negative, with an overall decrease in positive emotions and an increase in negative ones. Fourthly, divide tweets and reviews into five themes, and conduct evolutionary analysis based on different themes. It is found that the evolution process of topics is different in different time periods. In the early days, followers and the public were more inclined to express their dissatisfaction and needs generally in tweets such as fighting against the COVID-19 government's decision-making efforts. In the middle and later stages, discussions will gradually shift to discussing different perspectives on the epidemic and the use and assistance of medical supplies. Finally, we classified opinion leaders who played a significant role in the crisis communication process into five categories, calculating their topic coherence, Twitter and comment sentiment scores, and specific cases. The main shortcomings of this study are that there are still ambiguities when using dictionary-based sentiment analysis, which is also the main problem faced in the semantic processing of public opinion. At the same time, the inclusion period of this study is only 1 month, and there may be situations where the identification of opinion leaders is unclear.

Conclusions

This research has found that social media can be used to measure public attention to emergencies and show the content and emotional changes of leaders with different opinions during crisis communication. During the COVID-19, we found that there were differences in the content of opinion leaders and their followers, and the theme and opinion leaders were effectively classified to provide practical evidence for the evolution of different theme content and explore better communication time and content of different opinion leaders and their followers. These findings can help the government solve the problem of crisis transmission. More specifically, they can help health departments communicate with the public on health issues, and translate public health needs into practice, so as to develop targeted measures to prevent and control the spread of COVID-19.

Finally, we found that Twitter leaders may have influence in shaping public opinion through their messaging and communication strategies. Some factors that may affect their effectiveness as opinion leaders include their influence on social media, the content and topics they focus on, the emotions they convey in communication, and the structure of their social network connections. The effectiveness of government information delivery may be limited by a lack of consistency with public sentiment and feedback. This highlights the importance of considering public opinion and feedback in crisis communication strategies, as well as the potential role that opinion leaders can play in bridging the gap between the government and the public. In summary, this study provides valuable insights into the mechanisms by which opinion leaders influence public opinion on social media during crises. The research results have implications for understanding the formation of public opinion and the importance of considering public emotions in crisis communication.

Acknowledgments: Weijie Wang provided assistance in data collection for the paper.

Contributorship: XYA and YW researched literature and conceived the study. YW and SY wrote the first draft of the manuscript. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

Consent statement: No personal identifiers or sensitive information from Twitter users are used or published in this study. All data has been anonymized, ensuring user privacy.

Declaration of conflicting interests: The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding: The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the "Biomedical Literature Information Security and Integration Service Platform" **(2021-I2M-1-033)** under Grant medical and health science and technology innovation project.

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