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Exploring the impact of sentiment on multi-dimensional information dissemination using COVID-19 data in China

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ABSTRACT

The outbreak of information epidemic in crisis events, with the channel effect of social media, has brought severe challenges to global public health. Combining information, users and environment, understanding how emotional information spreads on social media plays a vital role in public opinion governance and affective comfort, preventing mass incidents and stabilizing the network order. Therefore, from the perspective of the information ecology and elaboration likelihood model (ELM), this study conducted a comparative analysis based on two large-scale datasets related to COVID-19 to explore the influence mechanism of sentiment on the forwarding volume, spreading depth and network influence of information dissemination. Based on machine learning and social network methods, topics, sentiments, and network variables are extracted from large-scale text data, and the dissemination characteristics and evolution rules of online public opinions in crisis events are further analyzed. The results show that negative sentiment positively affects the volume, depth, and influence compared with positive sentiment. In addition, information characteristics such as richness, authority, and topic influence moderate the relationship between sentiment and information dissemination. Therefore, the research can build a more comprehensive connection between the emotional reaction of network users and information dissemination and analyze the internal characteristics and evolution trend of online public opinion. Then it can help sentiment management and information release strategy when emergencies occur.

1. Introduction

With the development of information technology and communication technology, social media has penetrated people's daily life and gradually replaced the original communication mode, becoming the primary communication mode today. Through the creation of online communities, users can share information and ideas on social media platforms and facilitate the electronic exchange of personal information with other users (Gottlieb & Dyer, 2020). For example, social media represented by Twitter, Weibo, and Facebook have become an important information center through convenient instant messaging, and powerful interactive communication services, and have successfully attracted a large number of individuals or organizations to seek or share information and express their opinions and sentiments on various topics in daily life (Saroj & Pal, 2020). Furthermore, during a crisis, emergency management departments often use social media to improve risk communication, reduce the public's worry and uncertainty and weaken the adverse impact of the crisis (Gui et al., 2017). At this time, the use of social media by the public increased significantly, confirming the important role of social media during crisis communication (Niles, Emery, Reagan, Dodds, & Danforth, 2019). Meanwhile, social media has a specific promotion effect on information dissemination, which not only has a good publicity effect, but also can promote multi-level information dissemination through social networks. In addition, it can also get better attention through the amplification and focusing effect of public opinion. Therefore, social media has become the preferred channel for crisis communication and has been widely accepted and recognized as an essential platform for public information exchange and crisis management communication (Reuter, Kaufhold, Schmid, Spielhofer, & Hahne, 2019). With the support of social media platforms, the public can share ideas and information in real-time, keeping abreast of crisis information and disaster situations during the crisis (Jin, 2020; Sadri, Hasan, Ukkusuri, & Cebrian, 2017).

The spread of information on social media is affected by many

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factors. However, it can be roughly considered from multiple perspectives, such as information itself, information users, and the information environment. From the information perspective, the characteristics include the richness of content and emotional tendency (Chua & Chen, 2019). Among them, the richness of information content is usually related to the presentation form, and information with videos and pictures is often richer than pure text content. The richer the content, the more likely it is to attract the attention of users, to have a better dissemination effect (Chen et al., 2020; Zhou, Xiu, Wang, & Yu, 2021). At the same time, sentiment is also an essential factor affecting the effect of information dissemination. Information with decadent emotional tendencies tends to arouse the emotions of other users more quickly, forming empathy among users, and having a better dissemination effect on social media (Lee & Hong, 2016; L. Li, Liu, & Li, 2020). Information users are closely related to the influence of users involved in information formation and dissemination. The stronger the authority and influence of users, the more profound the impact on information dissemination. For example, posts published by institutional users often have a better dissemination effect than ordinary users, and users with a high number of followers and high activity have more advantages in communication ability (Cai, Luo, Meng, Cui, & Wang, 2022; L. Li, Liu, & Li, 2020). The interpretation of the information environment is more extensive and is often studied from the perspective of network structure or dissemination environment. For example, the network structure of topics on social media has a significant and direct impact on information dissemination, and topics with a high degree of aggregation are more likely to have better dissemination effects (An et al., 2021; Cai, Luo, Meng, & Cui, 2021).

As one of the most popular persuasion models in social psychology and user behavior research, the elaboration likelihood mode (ELM) (Petty & Cacioppo, 1986a) uses two basic approaches to explain the motivation and ability of users to process problem-related information on social media (Saini, Liang, Yang, Le, & Wu, 2022). Specifically, based on differentiated information content and different information processing ability of individuals, the ELM divides the influence mechanism into two possible paths, namely the central and peripheral routes. The former mainly deals with clues related to information quality, which is suitable for users with high cognitive ability and motivation to evaluate information, and requires users to have a complete understanding of information. When the ability or motivation is low and the user is satisfied with the current knowledge of the information, the user is more inclined to make judgments based on the overall impression and intuition, and take the peripheral route (Lee & Theokary, 2021; O'Keefe, 2013). With the effective explanation of users' behavioral motivation and ability, the ELM is also widely used in information dissemination, health information, false comments, and other related fields, and through the mining of central clues and peripheral clues to achieve multidimensional in-depth research in the field of social media (Munzel, 2016; Shi, Hu, Lai, & Chen, 2018; Song, Li, Guo, Shen, & Ju, 2022). On the other hand, ELM also assumes that people's information processing capacity is limited, and when people encounter information overload, they will have the incentive to resort to peripheral cues (Petty & Cacioppo, 1986a). During the crisis, sentiment, as a peripheral clue, can meet the psychological needs of users and is found to be associated with users' information behavior (Xu & Zhang, 2018). Therefore, based on the ELM, the research can take the sentiment type as the independent variable to investigate the main effect of the influence of sentiment type on the dissemination effect.

In addition, existing studies have tried to explore the influencing factors of information dissemination in social networks from the perspectives of information, information users, or information environment and have made some interesting findings (Zhang, Dong, & Mu, 2018). However, most studies in this field are from a single perspective, and it is not easy to estimate the effect of information dissemination in all aspects. The theory of information ecology holds that information ecology is a system of people and tools with solid interrelationships and dependencies (Nardi & O'Day, 2000), which provides a more comprehensive perspective for the analysis of information dissemination. Therefore, it is valuable to integrate the above influencing factors from the perspective of information ecology and explore the effect of information dissemination from multiple perspectives. At the same time, except for a few studies, there needs to be more research on the effect of information dissemination at the intersection of theories (Chua & Chen, 2019). Although the combination of information characteristics, user characteristics, and environmental characteristics can evaluate the dissemination effect of information on social media from multiple perspectives (Wang, Chen, Shi, & Peng., 2019a; Xing, He, Cao, & Li, 2021), it is easy to ignore the specific effect of interaction on the social media, and it is difficult to explain a series of factors affecting the dissemination effect from the perspective of subjective and objective combination. The view of information ecology theory on the interdependence of multiple clues can enrich ELM, so the situation in which the cues act can be discovered. Therefore, from the perspective of theoretical fusion, this paper intends to combine the information ecology theory and ELM to explain the dissemination effect of information on social media from the perspective of combining subjectivity and objectivity.

Based on the above analysis, the research tries to explore the dissemination effect of information in social networks from the perspectives of information characteristics, user characteristics, and environmental characteristics from the perspective of information ecology and the elaboration likelihood model. The specific steps are as follows. First, since previous studies have confirmed that sentiment is the direct factor affecting the dissemination effect, there are significant differences in the dissemination effect of information containing different sentiment types during crisis events (Alamoodi et al., 2021; L. Li, Liu, & Li, 2020). Therefore, the primary model is constructed around the influence of sentiment types on the dissemination effect. Secondly, considering that the dissemination effect of information in social networks is hierarchical, it is not comprehensive enough to measure the dissemination effect only by the scale of forwarding, and there are specific biases (Chua & Chen, 2019; Sharma & Kapoor, 2021). Therefore, with the support of the theory, we divided the dissemination effect into two levels: diffusion ability and contagion ability, and the contagion ability was further divided into spreading depth and network influence. Specifically, the forwarding volume is used to represent the horizontal diffusion ability, and the spreading depth and the proportion of nodes with the same topic and sentiment as the original post in the network are used to represent the vertical contagion ability. Finally, it is taken into account that the difference in the dissemination effect of the information under different sentiments is not all caused by direct factors, but by indirect factors (Jin & Oh, 2021; Zhang, Wang, & Zhu, 2020). Combined with the existing research, we further included the important variables of information characteristics, user characteristics, and environmental characteristics into the analysis under the theoretical support, and explored the moderating effects of important variables such as information richness, information authority, and topic influence in the process of emotional information transmission (An et al., 2021; Cai et al., 2022; Zhou, Xiu, et al., 2021).

Based on the previous research, this paper extends the existing work from the following aspects. Firstly, based on the perspective of information ecology, we integrate the influencing factors of information dissemination and analyze the dissemination effect from the perspectives of information characteristics, user characteristics, and environmental characteristics, which provides a comprehensive research perspective for the relevant research on information dissemination and avoids the possible selection bias caused by omitted variables as much as possible (G. Wang, Chen, et al., 2019; Yan, You, Wang, & Sheng, 2021). Secondly, the information ecology theory and elaboration likelihood model are combined to explain the direct and indirect effects of information dissemination from the perspective of combining subjectivity and objectivity. This verifies the important value of the perspective of information ecology in crisis events and provides a more comprehensive theoretical horizon for subsequent research from the perspective of theoretical fusion. Thirdly, the research not only investigates the differences in the dissemination effects of different emotional information from the perspective of direct effects, but also explores the possible indirect effects in the communication process. By constructing a more explanatory propagation model, we can dig out the influence mechanism of the dissemination effect more deeply (Cai et al., 2022; Zhou, Li, & Lu, 2021). Finally, the comparative analysis is conducted based on the COVID-19 cases of the two cities, which helped to eliminate the particularity of a single case and clarify the scope of application of the research conclusions.

The rest of this paper is shown below. In the second section, we review the existing literature and propose the research hypotheses of this paper. In the third section, we introduce the specific methods used in the research, including data collection and variable measurement. In the fourth section, we verify the research hypotheses and introduce the research results of this paper. In the fifth section, we discuss the research results, put forward the theoretical and practical significance of the research, and further reveal the current problems and future research directions. Finally, we review the whole paper and summarize the research conclusions in the sixth section.

2. Literature review

2.1. Sentiment type and dissemination effect

During crisis events, various social sentiments interweave and jointly construct the sharing and communication network of sentiments. As an internal psychological state, user sentiment is an evaluation or effective response formed in the face of different events and objects. It can not only arouse the strong willingness of other users to spread information, so that the information with sentiment tendency can spread quickly on social media, but also have an important influence on the individual's behavioral tendency and cognitive tendency, so that the dissemination characteristics of the information under different sentiment types show differences (Jin & Oh, 2021; R. Wang et al., 2020a). According to ELM, considering the limited clues available to users on social media, posts with rich sentiments, as content features of information, can provide users with richer clues, deepen their understanding, and attract their attention (Saini et al., 2022; Zheng, Goh, Lee, Lee, & Theng, 2022). In addition, when crises occur, unrestrained negative sentiment will aggravate the interest differences and conflicts between groups, making crisis management more complicated. This will also weaken social cohesion, destroy social order, and often make public opinion derivative, evolving into a second crisis (Cai, Luo, & Cui, 2021). Therefore, it is necessary to take the dissemination of emotional information in social networks as the research topic, build a research framework based on information characteristics, user characteristics, and environmental characteristics, and explore the differential dissemination mechanism on social media under different sentiment types. It can effectively promote the scientific analysis of the law of sentiment spread, and then realize public opinion guidance and information management during crisis events (Zhang et al., 2020).

As an important characteristic of information content, sentiments can interact with information systems and thus play an important role in information behavior research. Therefore, this study uses the perspective of information ecology to analyze the sentiment paradigm in information behavior research and theory, and further investigates the different dissemination effects of information with different sentiments in social networks (Nahl & Bilal, 2007). For example, from the perspective of structural attributes of information, some studies believe that the differences in sentiment types of information are caused by different social environments, and thus form differentiated structural attributes. Specifically, the information between positive sentiment is more similar, while the information under the negative sentiment is more diverse (Alves, Koch, & Unkelbach, 2017), and the positive information with a higher degree of similarity is more likely to be forwarded by the public (Unkelbach, Koch, & Alves, 2019). However, some studies, from the perspective of sentiment induction, believe that although positive information is more densely clustered in the information ecosystem, the intensity is different from that of negative information (Koch, Alves, Krüger, & Unkelbach, 2016). Meanwhile, negative sentiment tends to have higher affective stimulation and attract more attention from users. Therefore, compared with positive information, negative information is easier to be remembered by users and brings better dissemination effects (Alves, Koch, & Unkelbach, 2018).

Although previous studies have verified the important role of sentiments in information dissemination from various aspects, there is no consensus on the difference in the dissemination effect of information with different sentiment types in the research on crisis events. On the one hand, previous studies have suggested that negative sentiment has a more vital contagion ability during the crisis and has more advantages in the effect of information dissemination (Steinert, 2020; Tsugawa & Ohsaki, 2015; Yeo, Pang, Cheong, & Yeo, 2020). On the other hand, considering that posts with positive sentiment in crisis events can bring optimism and are more likely to be publicized by media and organizations, some studies have empirically confirmed that positive sentiment has a better dissemination effect during the crisis and are more likely to be transmitted than negative sentiment (Ferrara & Yang, 2015; Li, Liu, & Li, 2020b). Therefore, combined with existing research and theoretical support, we propose a set of competing hypotheses based on the example of COVID-19, a typical and long-lasting crisis event.

In addition, in the information ecosystem, forwarding behavior is the core mechanism for information dissemination in social networks, and it is also common to use the forwarding volume to measure the dissemination effect. Generally, the more the volume, the better the dissemination effect (Brubaker & Wilson, 2018; L. Li, Liu, & Li, 2020). However, the forwarding volume represents the dissemination effect more from the diffusion ability of information on the horizontal network, and it is difficult to analyze the dissemination effect in social networks from a more comprehensive perspective (Chua & Chen, 2019). Especially during public health emergencies, the process of social media information dissemination is more complicated due to the uncertain information environment and panic psychology, which can cause emotional contagion and viral spread. Relevant studies often measure the dissemination effect of information with a single index such as the forwarding volume or network centrality, while ignoring the influencing factors from other dimensions (Cai et al., 2022; Zhou, Xiu, et al., 2021). Therefore, to better measure the dissemination effect in social networks during public health emergencies, the research further divides the dissemination effect into two levels: horizontal diffusion and vertical contagion, and analyzes it from three perspectives: volume, depth, and influence. This can not only enrich the existing research from the perspective of information dissemination and emotional response, but also provide a reference for exploratory research on the effect of sentiment on information dissemination in multiple dimensions. In addition, it can also provide targeted suggestions and measures for effective public opinion governance during the crisis from a realistic perspective. Hypotheses 1 and 2 are broken down as follows.

H1a. When public health emergencies occur, the information with negative sentiment is more likely to be forwarded.

H1b. When public health emergencies occur, the information with negative sentiment has greater spreading depth.

H1c. When public health emergencies occur, the information with negative sentiment is more influential than information with positive sentiment.

H2a. When public health emergencies occur, the information with positive sentiment is more likely to be forwarded.

H2b. When public health emergencies occur, the information with positive sentiment has greater spreading depth.

H2c. When public health emergencies occur, the information with positive sentiment is more influential than information with negative sentiment.

2.2. Information attributes and dissemination effects

As another feature of information content, information richness is instructive for us to understand the spread of emotional information. Typically, information richness is defined as the amount of information in a post that allows users to make a decision (Chen & Tseng, 2011). However, considering the limitation of the number of words in social media posts, the information richness also includes content such as pictures and videos provided by users in posts. The richer the form provided in the posts, the more information it contains, and the higher the level of information richness it provides (Chen et al., 2020; Zhou, Li, & Lu, 2021). In dissemination behavior, the important role of information richness is also highlighted. The higher the information richness, the better the needs of users can be met, the easier it is for users to share information, and the better the dissemination effect will be (Shi et al., 2018; Yan & Huang, 2014). Therefore, incorporating information richness into the research framework of affective information dissemination is not only a further improvement of the information ecosystem, but also an important decision to broaden the perspective of information dissemination and deeply analyze the influencing factors of dissemination effect.

In the information ecosystem, considering the mixture of cognitive and affective features in information, the information on social media is typically characterized by ambiguity (Oh, Kwon, & Rao, 2010), and it is difficult for users to make the most rational choice according to the limited information content. At this time, information quality becomes an essential factor affecting users to share information, and information richness is one of the most compelling dimensions for evaluating high-quality information (Shi et al., 2018). When the information richness is low, users seek clues heuristically and are less willing to share information. However, when the information richness is at a high level, users have a complete understanding of the information content and are more likely to share the information with other users, so the information has a better dissemination effect (Chua & Chen, 2019). In previous studies, information richness is also regarded as an important central factor affecting individuals to promote information dissemination, which has also been tested in empirical studies. Related studies have found through the analysis of social media data that posts with pictures and links are more likely to be shared, and visual content such as pictures and videos are more attractive and have better dissemination effects than plain text (Guidry et al., 2020; Shi et al., 2018; Yin & Zhang, 2020). However, whether information richness positively affects affective information transmission remains controversial. When the dissemination effect is divided into horizontal diffusion ability and vertical contagion ability, the specific effect of information richness still needs to be clarified. Based on the ELM and existing studies, we propose the following hypotheses.

H3a. Information richness can moderate the effect of sentiment type on forwarding volume.

H3b. Information richness can moderate the effect of sentiment type on spreading depth.

H3c. Information richness can moderate the effect of sentiment type on network influence.

In addition, as an important component of user characteristics, information authority also plays an important role in the dissemination of information with different sentiments. When faced with crisis events, the urgent need for information prompts the public to use social media as much as possible, and to obtain information from highly authoritative users first, to reduce the inauthenticity of information (Chua & Chen, 2019). In the explanatory framework of the ELM, the peripheral route tends to influence individual attitudes and behavioral tendencies through simple decision criteria and cues, such as whether the information comes from celebrities and whether the information sender is highly attractive (Angst & Agarwal, 2009; Petty & Cacioppo, 1986a). Compared with information sources with low authority levels, when receiving information provided by highly authoritative users, the public tends to ignore the authenticity of the information and have a high trust attitude towards the information sources to understand the specific information of crisis events. At the same time, when the public receives authoritative information, it is more likely to forward it to other users, which promotes the diffusion and contagion of information in social networks (Xu & Zhang, 2018; Zha, Li, Yan, Wang, & Wang, 2016; Zhang, Peng, Zhang, Wang, & Zhu, 2014).

Firstly, the authority of information mainly refers to the credibility of the information source. Specifically, the receiver of information determines whether the information is credible based on the characteristics of the information source, which essentially represents the trust degree of the information sender (Sussman & Siegal, 2003). Generally, the more authoritative the source, the more trustworthy the information will be. Authority in the traditional sense is often determined by the identity of experts or non-experts (Petty & Cacioppo, 1986b), and in online communication composed of social networks, the identity attribute in the traditional sense is difficult to play an influential role in information dissemination (Xu, Sang, Blasiola, & Park, 2014). On the contrary, the authentication type of the user is the first choice to judge the user's authority, and the difference in user types has a significant impact on the effect of information dissemination (An et al., 2021; Xie & Rong, 2019). For example, compared with ordinary users, the information published by government users or media users is more likely to encourage other users to share, to have a better dissemination effect (Cai et al., 2022). In addition, source attractiveness is also an important criterion for judging the authority of information. In social networks, source attractiveness represents the degree to which a user is liked and welcomed by others, usually measured by the number of followers that the user has. The larger the number of followers and the more attractive the source is, the more likely the user is to approach the position of opinion leader in social networks (Shi et al., 2018). At this point, the user is more authoritative than the user with fewer followers, and the information released by the user is easier to be shared by other users, which has a better dissemination effect on social media (Jin, 2020; Song, Dai, & Wang, 2016). Although the promotion effect of information authority on individuals' willingness to share and the effect of information dissemination has been found, the specific effect of information authority in the process of information dissemination containing different sentiments remains to be determined (Rufai & Bunce, 2020; Wang, Zhang, Fan, & Zhao, 2022). In addition, in the exploration of information authority, existing studies often define the influence of information authority on the dissemination effect as the influence of information authority on the forwarding volume (L. Li, Liu, & Li, 2020; Xu & Zhang, 2018), and the investigation of the vertical contagion ability of information is still unclear. Therefore, the following hypotheses are proposed to comprehensively verify the possible mechanism of information authority in the relationship between sentiment types and dissemination effect.

H4a. Information authority can moderate the effect of sentiment type on forwarding volume.

H4b. Information authority can moderate the effect of sentiment type on spreading depth.

H4c. Information authority can moderate the effect of sentiment type on network influence.

2.3. Topic influence and dissemination effect

As a macroscopic factor in the information ecosystem, network or environmental characteristics also affect information dissemination. Network characteristics such as centrality, density, and clustering coefficient are commonly used in existing studies to analyze the interaction behavior among users and explore the network factors affecting information dissemination (X. Wang et al., 2020b; Xu, Su, Xu, Fang, & Han, 2017). For example, information dissemination in social networks is divided into different modes according to network attributes such as network centrality and clustering coefficient, and the differential effects of information dissemination under different modes are further compared (G. Wang, Chen, et al., 2019). Some studies establish dissemination models based on social networks and consider how information can be transmitted virally in social networks according to network characteristics and user characteristics (Alamsyah & Putra, 2019). In addition, in the public opinion interaction caused by crisis events, users have significant differences in social background and personal demands. Therefore, around the same crisis event, posts published by different users often have significant differences in content and form different discussion topics (G. Wang, Chen, et al., 2019). At the same time, the differentiation effect of different topics or information types on information dissemination has also been verified in existing studies (Cai et al., 2022). For example, during the crisis, information related to the crisis response and recovery phase is more likely to be shared by other users, which has a better dissemination effect (Imran & Castillo, 2015; Yu, Huang, Qin, Scheele, & Yang, 2019). During the public health emergency represented by COVID-19, topics such as the transmission of cases, suggestions on prevention and rehabilitation, or the economy under the influence of the epidemic have been influential in social networks, showing a dominant position in the dissemination effect (Chandrasekaran, Mehta, Valkunde, & Moustakas, 2020; Wahbeh, Nasralah, Al-Ramahi, & El-Gayar, 2020). In addition, although the role of the topic in information dissemination has been verified, previous studies tend to regard topic types as a separate variable affecting information dissemination, ignoring the differential role played by different topics in different information environments (Cai et al., 2022; Han, Wang, Zhang, & Wang, 2020). Therefore, to better evaluate the influencing factors of dissemination effect from the perspective of the information ecosystem, this study combines network structure with topic types, and incorporates the influence of different topics in social networks into the information ecological framework. In addition, topic influence reflects which topic information is easier to spread in crisis events, reveals the nature and background of crisis events, and helps explain the influence relationship between information environment and dissemination effect.

As a typical persuasion theory, the ELM reveals how the information that individuals have been exposed to influences attitude formation and behavioral tendency (Petty & Cacioppo, 1986a). More social network users pay more attention to topics with high influence, so they have higher importance and relevance and are more likely to impact individual attitudes. Considering that topics with high influence in social networks represent the main content of events, users will pay more attention to understanding the information of topics with high influence. Therefore, this study incorporates topic influence into the analytical framework of the central path (Shi et al., 2018; Teng, Khong, & Goh, 2014). Previous studies have also confirmed the mechanism of topic influence on information dissemination from many aspects. For example, some studies have compared the differences in topic influence among different types of users, and explored the differentiated effects of user types and topic influence in the process of information dissemination (An et al., 2021). Meanwhile, some studies have linked the influence of topics with the dissemination effect of information with different sentiments, confirming the correlation between the topic influence and sentiment contagion in the process of information dissemination (Cai, Luo, Meng, & Cui, 2021). In addition, considering the exponential distribution of attention to tweets on social media, only a small number of tweets are followed and forwarded by users in the long tail (Orellana-Rodriguez, Greene, & Keane, 2016). Therefore, if a post wants higher attention and forwarding, the influence of topics is the key factor. The more influential the topic is, the more likely the information is to attract users' attention, and then cause other users to share, which has a better dissemination effect. However, information with low topic influence is often difficult to be found by other users under limited attention, and it is less likely to be shared by other users (Fan et al., 2021; Orellana-Rodriguez & Keane, 2018). Therefore, to further investigate the possible mechanism of topic influence in the relationship between sentiment types and information dissemination, and analyze the possible commonalities of topic influence in the process of information diffusion and contagion, the research incorporates topic influence into the analysis model and puts forward the following hypotheses.

H5a. Topic influence can moderate the effect of sentiment type on forwarding volume.

H5b. Topic influence can moderate the effect of sentiment type on spreading depth.

H5c. Topic influence can moderate the effect of sentiment type on network influence.

Finally, combined with the above analysis, the overall analysis framework is drawn (Fig. 1).

3. Method

To answer the above hypotheses, specific research methods were developed based on the research model. Firstly, the relevant data was obtained from the Weibo platform and preprocessed. Secondly, natural language processing tools represented by deep learning algorithms were used to extract topic and sentiment features from the text. On this basis, relevant variables such as sentiment, topic influence, and dissemination influence were constructed. In addition, each variable was also defined and operationalized in this section. Finally, the descriptive analysis of each variable was carried out to show the relevant results, and on this basis, the regression method was used to explore the causal mechanism between variables.

3.1. Data collection

As one of the most influential Chinese social media, Weibo has reached 582 million monthly active users as of June 2022. Weibo attracted a large number of users to share life and interact on the platform. With the help of the publishing and sharing functions of social media platforms, we can learn the views and opinions of network users during the epidemic from Weibo and then analyze the behavioral tendencies and affective trends of users during crisis events, which provides rich data support for research. In order to collect epidemic-related data conveniently and accurately, this study selected representative epidemic events as research cases and obtained relevant data by searching keywords within a limited time. In order to ensure the comprehensiveness and representativeness of the data, the epidemic in X city and the epidemic in J city was selected as the study cases. On the one hand, the two cities selected in this study are located in the west and east of China, and both of them have adopted lockdown measures and static management decisions during the outbreak of the epidemic, which can reflect the views and affective attitudes of network users on the epidemic in different regional cities. On the other hand, the outbreaks in the two cities belong to the same virus type, with the same degree of harm and dissemination speed at the source. In addition, the outbreak time and duration of the epidemic in the two cities are not only close, but also the heat caused by the network and the attention of users are consistent, so social media data of the same scale can be obtained.

Specifically, the study searched with the keyword "Epidemic in X

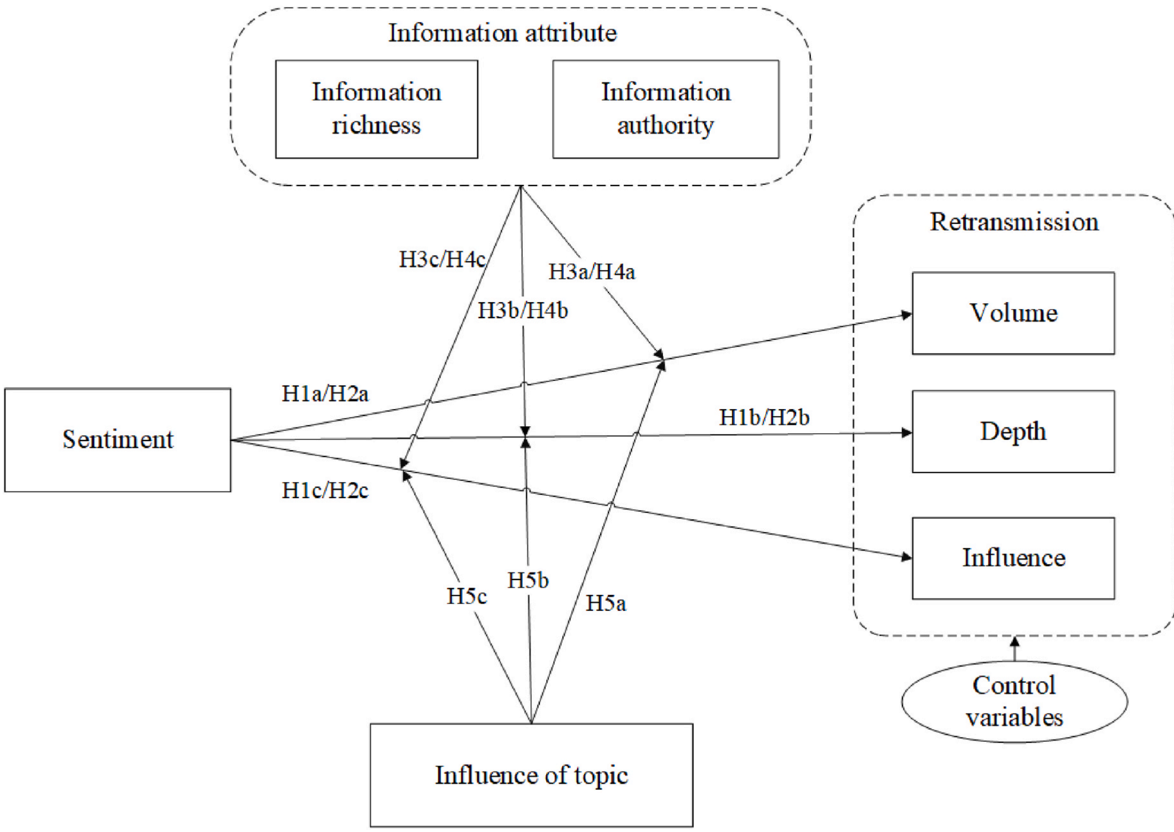

Fig. 1. Research model.

City " in the limited period from December 9, 2021 to January 10, 2022. Among them, December 9 is the time when the first confirmed case appeared in X city, and January 10 is the specific time when the epidemic in X city was cleared. A total of 185,782 microblogs were obtained, including 61,404 original posts and 124,378 forwarded posts. Similarly, the study also takes a limited time from March 1 to April 18, 2022, and used "Epidemic in J City" as the keyword to obtain relevant data. Among them, April 18 was the specific time when the infected people in high-risk areas of J city cleared. Finally, 144,314 microblog posts related to the epidemic in J city were obtained, including 36,184 original posts and 108,130 forwarded posts. In addition, to further enrich the data content, this study also obtained a series of public information of users who publish posts, including user gender, type, number of followers, and Posting frequency as supplementary data. Finally, the obtained microblog data was preprocessed. For example, the Chinese text is segmented by Jieba, the stop words are removed by the stop words list, and the text content is filtered by regular expressions.

3.2. Variable definition and operationalization

3.2.1. Dependent variable: volume, depth, and influence

In this paper, the dissemination effect was divided into two levels: diffusion ability and contagion ability. The horizontal diffusion ability of information was measured by the volume of forwarding, and the vertical contagion ability was measured by the spreading depth and network influence. Taking the forwarding volume as an example, previous studies have measured the virality ability of common information and its spreading trend in social networks by the number of common information being forwarded on social media platforms. Referring to existing studies, in this paper, we measured the forwarding volume of information by using the number of posts forwarded by other users for each post (Chen et al., 2020; L. Li, Liu, & Li, 2020; Zhou, Xiu, et al., 2021). In addition, considering that users who participate in information forwarding on social media may be forwarded by other users, the amount of reposting is often not equivalent to the scale of posts involved in information dissemination (Zhao, Zeng, Qin, Si, & Liu, 2021). This also indicates that although the volume of forwarding is an important indicator to measure the impact of information on social media, the dissemination effect of single-dimension measurement is insufficient (Chua & Chen, 2019).

Then, in order to further explore the dissemination effect of information on social media, the research adopted the dissemination distance of posts in social networks to measure the depth of information dissemination (Wang et al., 2022; Zhao et al., 2022). Specifically, the information sent by information source A is forwarded by user B, and the dissemination depth of the information is defined as 1. The message sent by information source A is forwarded by user B, and the content forwarded by user B is forwarded by user C. In this case, the spreading depth of this message is defined as 2. Based on the analysis of forwarding volume and spreading depth, relevant studies can understand the dissemination mode of the information during crisis events. For example, Liang et al. (2019) compared the spreading scale and depth of Ebola virus-related information on Twitter, and found that compared with the virus spread mode of individual-to-individual dissemination, crisis information with smaller depth but larger spread scale followed the one-to-many broadcast mode on social media, etc. (Liang et al., 2019).

Finally, in addition to considering the forwarding volume and spreading depth, the research also measured the dissemination effect from the perspective of network structure. Considering the important role played by network structure in information dissemination, relevant studies focus on information dissemination and carry out a series of studies from the perspectives of network information channels, node structure of public opinion dissemination, dissemination routes and dynamic relationships in the network (Jiang, Wang, & Liu, 2019; G. Wang, Chen, et al., 2019; X. Wang, He, et al., 2020). Drawing on existing studies, in this paper, we used the dissemination influence of network characteristics to measure the dissemination effect (An et al., 2021). In the process of information dissemination, the dissemination influence of node *N* was defined as the proportion of the number of nodes with the same sentiment type as node *N* in all connected nodes in the forwarding network. Combined with the above analysis, this paper adopts three indicators of forwarding volume, spreading depth and network influence to analyze the diffusion and contagion ability of information on social media, so as to have a more comprehensive understanding of the dissemination effect of affective information in social networks.

3.2.2. Sentiment type

The dissemination of information on social media is often sentiment-oriented, and the sharing of information is accompanied by the sharing of sentiment (Gallotti, Valle, Castaldo, Sacco, & De Domenico, 2020; Wang, Zhou, Jin, Fang, & Lee, 2017). In this paper, sentiment type is used as an independent variable to explore whether there are differences in the dissemination of crisis information with different sentiments on social media. This not only helps to understand the information dissemination mechanism in social networks, but also provides an important reference for reducing the social influence of negative sentiments, so as to realize public opinion governance under crisis events.

Reviewing existing research, traditional sentiment classification calculation mainly focuses on two methods: unsupervised sentiment lexicon-based classification and supervised classifier learning, etc. (Zhang et al., 2020) However, in recent years, with the further development of machine learning and deep learning methods (Li et al., 2020a), deep learning models represented by BERT et al., have been significantly improved in efficiency and accuracy in sentiment classification, and have been widely adopted in the field of public opinion (Devlin, Chang, Lee, & Toutanova, 2018; Gao, Feng, Song, & Wu, 2019). Therefore, this paper applied the BERT model to sentiment analysis. Firstly, more than 100,000 posts from January 1, 2020 to February 20, 2020 published by data. beijing.gov.cn were selected to complete the training of the model. The posts in this dataset are all closely related to COVID-19 and come from Weibo. The sentiment of each post in the dataset was labeled as positive, neutral or negative. The study selected 80% of the data as the training dataset and 20% as the testing dataset. The accuracy, recall, and F1 values of the final BERT model on the test set were 0.76, 0.72 and 0.72, respectively. The research applied the model to classify the research data as positive, negative, and neutral, represented by numbers 1,0, and -1, respectively. In order to confirm whether the model was reliable, we manually checked the classified data, and the results show that the microblog sentiment is classified accurately.

3.2.3. Information richness

As a common index to measure the ability of information dissemination, information richness is expressed by measuring the complexity of common information presentation forms in existing studies. Specifically, according to the presentation form of information in posts, relevant studies divide it into three levels. The information richness from low to high is respectively text, text + picture and text + video, which are encoded in numbers (Chen et al., 2020; Ji, Chen, Tao, & Li, 2019; Zhou, Xiu, et al., 2021). Referring to existing studies, considering that videos and pictures have richer information content than the basic posting format of plain text, users can have a clearer and more comprehensive understanding of the information content, which can affect the dissemination effect of information (Li, Zhou, Luo, Benitez, & Liao, 2022; Zhou, Li, & Lu, 2021). Therefore, the information richness was defined as a categorical variable. The three categories of text combined with video, text combined with picture and plain text are assigned corresponding numeric codes from high to low. For example, 1 means plain text content, 2 means text combined with pictures, 3 means text posts combined with videos.

3.2.4. Information authority

The degree of authority of information determines whether users trust information and further promotes individual information dissemination behavior. In this paper, two methods were used to measure information authority. The first measure was the type of authentication a user has on social media. As a component standard to judge whether the information is authoritative, existing studies often choose whether users are authenticated and what type of authentication they have as important features that affect information dissemination (Cai et al., 2022; Shi et al., 2018). In the Weibo platform, the authentication mechanism is also used to ensure the authenticity of users. After authentication, a “V" logo will appear on the right of the username. Typically, individual verification users on the Weibo platform are represented by yellow “V" marks, while government, enterprise, and media users are represented by blue “V" marks. Therefore, in this paper, we encoded different authentication types. 1 indicates ordinary user, 2 indicates celebrity user, 3 indicates a government user, 4 indicates an organization or enterprise user, and 5 indicates a media user. In addition, the second metric of the information authority is the number of users’ followers. Related studies have verified the important role played by the number of user followers in judging information authority and influencing information dissemination based on theoretical and empirical studies (Dong, Li, Zhang, & Cai, 2018; L. Li, Liu, & Li, 2020; Xu & Zhang, 2018). Therefore, the study directly extracted the number of followers from user characteristics to measure the authority of information. The higher the number of followers, the higher the authority of information.

3.2.5. Topic influence

Before obtaining the variable of topic influence, the research first needs to extract the different topic types of posts by machine learning methods. In this paper, the Top2vec method was used to model text topics and classify the text into different topic types (Angelov, 2020). Firstly, combined with the Transformer language model, text features in posts are obtained through the encoder-decoder structure of the BERT model, and word vectors are created to aggregate semantically similar texts in vector space (Devlin et al., 2018). Secondly, the dimension reduction method UMAP and density clustering method HDBSCAN are combined to study the ability to create corresponding document vectors in low-dimensional space and further obtain dense regions of document vectors ((McInnes, Healy, & Melville, 2018; McInnes & Healy, 2017). Thirdly, by combining the dense regions of different document vectors, the study can calculate the center of document vectors to obtain the topic vectors of each dense region, and obtain each topic vocabulary based on the distance from the topic vector (Angelov, 2020). Finally, through the development of appropriate topic classification criteria, the study gives each post a corresponding topic label based on different topic vocabulary and then classifies the post into different topic types. After finishing the classification of topics, the study combined the topic type with the network structure to further explore the impact of the topic influence on information dissemination (An et al., 2021). The topic influence of node *N* was defined as the proportion of the number of nodes with the same topic type among all the nodes directly connected to node *N* in the forwarding network.

3.2.6. Control variables

In addition to the above variables, the dissemination of information in social networks is also affected by other factors, such as user gender, user level, user credit, content length, the existence of URLs and the number of hashtags (Cai et al., 2022; L. Li, Liu, & Li, 2020; Lin & Wang, 2020). For example, as an important influencing factor of information dissemination, gender differences may lead to inequality in information dissemination, resulting in significant differences in the popularity of information (Vásárhelyi, Zakhlebin, Milojević, & Horvát, 2021; Zhang, Takanashi, Si, Zhang, & Wang, 2019). Therefore, in order to reduce the possible interference caused by omitted variables and ensure the robustness of the results, the above variables were included as control variables in the regression equation for analysis. In addition, considering that the data used in this study were related to the COVID-19 epidemic, the number of daily confirmed cases was also included in the analysis as a control variable to reduce the possible influence of environmental factors (Gallotti et al., 2020). The definitions of each variable are shown in Table 1.

3.3. Descriptive analysis

Table 2 shows the descriptive statistical results of each variable. As shown in Table 2, among the discussions caused by the epidemic in J city, the proportion of posts with positive sentiments (27.41%) was higher than that of posts with negative sentiments (11.90%). Ordinary users (71.46%), celebrity users (17.02%) and government users (6.45%) ranked the top among user types. The number of users with good credit ratings was the largest (74.01%), higher than those with very good credit ratings (15.43%) and ordinary credit ratings (10.57%). In addition, despite the differences in the number of confirmed cases, the social media data caused by the epidemic in X city and the social media data caused by the epidemic in J city showed similar characteristics. Compared with the negative sentiment in J city, which accounted for 11.9%, the public opinion in X city was more negative (17.8%).

4. Research results

Considering a series of factors that may bias the results, such as omitted variables and conditional mechanisms, it is necessary to further conduct causal inference through regression analysis. Therefore, the study included a series of control variables in the model, and empirically tested the influence of the sentiment type based on controlling the user attributes, post attributes and the number of confirmed cases. We further analyzed the conditional mechanism of the information attributes and topic influence. In addition, before the regression analysis of the research model, considering the possible multicollinearity problem among variables, the study conducted a collinearity test for each regression model with volume, depth and influence as the dependent variables. The test results show that the variance inflation factor (VIF) values of all variables in the model were less than 4, and there was no obvious multicollinearity problem, which can be carried out for subsequent analysis.

Table 1
Measurement of variables.

Variable name	Measure item	Description
Dependent variables		
dissemination effect		
Volume	Volume	The number of reposts of every post
Depth	Depth	The depth at which posts are reposted
Influence	Influence	The spread of sentiment in the network
Independent variable		
Sentiment types	Sentiment	Categorical variables for different sentiment types
Moderate variables		
Information richness	Richness	The complexity of how posts are presented
Information authority		
User types	User types	Users are authenticated to different types
Number of followers	Fans	The number of followers of different users
Topic influence	Top_inf	The spread of the topic in the network
Control variables		
Male	Male	Whether the gender of the user is male
User rank	Urank	The different levels of activity that users show
Sunshine credit level	Credit	The credit footprint left by the user
Content length	Length	The content length of each post
URLs	URL	Whether the post has a URLs
Hashtags	Hash	The number of hashtags a post contains
Number of cases	Cases	The number of confirmed cases per day

Table 2
Descriptive analysis.

Variable	Percentage (%)/Mean (S.D.)	
	J city	X city
Volume	1.609(48.829)	1.817(65.160)
Depth	.095(.418)	.119(.476)
Influence	.051(.214)	.063(.235)
Sentiment		
Positive sentiment	27.41	23.42
Neutral sentiment	60.69	58.78
Negative sentiment	11.90	17.80
Richness	1.174(.485)	1.295(.612)
User types		
Ordinary users	71.46	67.16
Celebrities	17.02	18.50
Government	6.45	6.96
Institutions and Enterprises	1.81	2.39
Media	3.27	4.99
Fans	271511.8(3,345,220)	332960.8(3,240,815)
Top_inf	.010(.095)	.011(.098)
Male	.454(.498)	.492(.500)
Urank	17.850(16.537)	20.599(16.726)
Credit		
ordinary	10.57	6.21
good	74.01	75.13
very good	15.43	18.67
Length	60.380(78.390)	68.950(86.064)
URL	.014(.116)	.008(.088)
Hash	.310(.602)	.366(.640)
Cases	949.487(657.546)	89.383(58.235)

4.1. Baseline regression

First, the study established a benchmark regression model with sentiment type as the independent variable and dissemination effect as the dependent variable. The regression results are shown in Table 3. The first three columns were analyzed with the epidemic in J city, and the volume, depth and influence were used as dependent variables, respectively. Model 1 shows that both positive sentiment ($\beta = 0.012$, $p < 0.001$) and negative sentiment ($\beta = 0.029$, $p < 0.001$) had a significant positive effect on the volume when the reference group was set to neutral sentiment, and the regression coefficient of negative sentiment was larger than that of positive sentiment. Considering the same magnitude, messages embedded with negative sentiment are more likely to be forwarded by other users on social media during a crisis compared to positive sentiment, in line with the theoretical expectation of negative sentiment bias. H1a was supported. Model 2 explores how depth is characterized differently by different sentiment types. Specifically, it was found that negative sentiment ($\beta = 0.034$, $p < 0.001$) had a positive and significant effect on depth, while positive sentiment did not have a significant positive effect on depth. To further discuss the difference between negative and positive sentiment in terms of depth, a regression analysis was conducted using positive sentiment as the reference group and found that negative sentiment ($\beta = 0.030$, $p < 0.001$) had a positive and significant effect on the depth. Compared with positive sentiment, information with negative sentiment was more likely to be cascaded on social media and have stronger penetration in the network. H1b was supported. Model 3, with the influence as the dependent variable, found that both negative sentiment ($\beta = -0.015$, $p < 0.001$) and positive sentiment ($\beta = -0.021$, $p < 0.001$) had negative and significant effects on the influence compared to neutral sentiment. This is consistent with the reality that institutional and media accounts, which mainly explain factual information, are at the core of social networks, and most node users also forward factual information with a neutral sentiment. Moreover, most users only forward posts without expressing positive or negative sentiments, which made posts with positive and negative

Table 3
Main effect regression.

	(1)	(2)	(3)	(4)	(5)	(6)
	volume	depth	influence	volume	depth	influence
Negative	0.029***	0.034***	−0.015***	0.034***	0.047***	−0.010***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)
Positive	0.012***	0.004	−0.021***	−0.008**	0.005+	−0.031***
	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)
Male	0.065***	0.038***	0.018***	0.044***	0.033***	0.015***
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Length	0.107***	0.076***	0.041***	0.108***	0.076***	0.044***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Good	−0.008+	−0.006+	−0.004*	−0.021***	−0.010*	−0.004*
	(0.005)	(0.004)	(0.002)	(0.005)	(0.005)	(0.002)
Very good	0.115***	0.085***	0.038***	0.103***	0.088***	0.035***
	(0.006)	(0.005)	(0.003)	(0.007)	(0.006)	(0.003)
Urank	0.003***	0.003***	0.001***	0.004***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
URL	−0.041***	−0.024**	−0.008+	−0.033*	−0.002	−0.009
	(0.011)	(0.009)	(0.005)	(0.014)	(0.012)	(0.006)
Hash	0.062***	0.038***	0.022***	0.049***	0.028***	0.018***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Cases	−0.000	−0.000	−0.000**	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−0.402***	−0.276***	−0.133***	−0.408***	−0.295***	−0.152***
	(0.008)	(0.006)	(0.003)	(0.008)	(0.007)	(0.003)
Observations	143,348	143,348	143,348	185,133	185,133	185,133
Adjusted R^2	0.098	0.078	0.079	0.099	0.076	0.086

Note. Standard errors in parentheses; $+ p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

sentiments less influential than neutral sentiments. Further, the effect of positive sentiment on influence was significantly negative ($\beta = -0.004$, $p < 0.001$) in the regression with negative sentiment as the reference. This suggests that negative affect was more influential and more contagious in the network structure compared to positive affect. H1c was supported.

In addition, the analysis results of the X city epidemic are shown in the last three columns. Models 4, 5, and 6 examine the differential effects of communicative ability under the influence of different sentiment types, using volume, depth, and influence as dependent variables, respectively. The analysis results of the epidemic in X city were similar to that in J city. The findings verify that during a crisis, information with negative sentiment had an advantage in terms of volume, depth, and influence compared to positive sentiment, which better supports the

Table 4
Moderating effect of information richness.

	(1)	(2)	(3)	(4)	(5)	(6)
	volume	depth	influence	volume	depth	influence
Negative	−0.024+	0.005	0.090***	0.017	0.036***	0.094***
	(0.014)	(0.012)	(0.006)	(0.011)	(0.009)	(0.005)
Positive	−0.049***	−0.007	0.071***	0.023***	0.030***	0.089***
	(0.008)	(0.006)	(0.003)	(0.007)	(0.006)	(0.003)
Richness	0.105***	0.057***	0.058***	0.068***	0.038***	0.049***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)
Negative* Richness	0.058***	0.031**	−0.091***	0.024**	0.014+	−0.087***
	(0.013)	(0.010)	(0.005)	(0.009)	(0.008)	(0.004)
Positive * Richness	0.049***	0.008+	−0.076***	−0.027***	−0.020***	−0.086***
	(0.006)	(0.005)	(0.002)	(0.004)	(0.004)	(0.002)
Male	0.055***	0.033***	0.017***	0.043***	0.033***	0.016***
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Length	0.086***	0.065***	0.034***	0.097***	0.070***	0.039***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Good	−0.012**	−0.007*	−0.003	−0.022***	−0.011*	−0.005*
	(0.005)	(0.004)	(0.002)	(0.005)	(0.005)	(0.002)
Very good	0.117***	0.086***	0.040***	0.104***	0.089***	0.034***
	(0.006)	(0.005)	(0.003)	(0.007)	(0.006)	(0.003)
Urank	0.003***	0.003***	0.001***	0.004***	0.003***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
URL	−0.008	−0.009	−0.004	−0.020	0.005	−0.009
	(0.011)	(0.009)	(0.005)	(0.014)	(0.012)	(0.006)
Hash	0.030***	0.022***	0.013***	0.024***	0.014***	0.012***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Cases	−0.000+	−0.000	−0.000**	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−0.425***	−0.292***	−0.173***	−0.438***	−0.313***	−0.193***
	(0.008)	(0.007)	(0.003)	(0.008)	(0.007)	(0.003)
Observations	143,348	143,348	143,348	185,133	185,133	185,133
Adjusted R^2	0.108	0.081	0.089	0.101	0.078	0.098

Note. Standard errors in parentheses;$+p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

above research hypothesis and verifies the robustness of the findings.

4.2. Moderating effects of information richness

To explore whether there is heterogeneity in the relationship between sentiment type and dissemination, the study included information richness as a central path in the analysis framework to further examine how information richness moderates the effects of sentiment on dissemination effect. The results are shown in Table 4. Model 1 represents how information richness moderates the effect of sentiment type on the volume with the epidemic in J city as the study target. It was found that the interaction term between negative sentiment and information richness ($\beta = 0.058, p < 0.001$) and the interaction term between positive sentiment and information richness ($\beta = 0.049, p < 0.001$) had a positive and significant effect on volume. This suggests that information richness moderates the relationship between sentiment type and volume. H3a was supported. Model 2 represents how information richness moderates the effect of sentiment type on the depth of dissemination. It was found that the interaction terms of negative sentiment and information richness ($\beta = 0.031$, $p < 0.01$), and the interaction terms of positive sentiment and information richness ($\beta = 0.008$, $p < 0.1$) maintained a positive and significant effect on the depth. This suggests that information richness moderates the relationship between sentiment type and spreading depth. H3b was supported. Model 3 represents how information richness exerts a moderating effect when network influence is the dependent variable. It was found that the interaction term between negative sentiment and information richness ($\beta = -0.091$, $p < 0.001$) and the interaction term between positive sentiment and information richness ($\beta = -0.076$, $p < 0.001$) both had a negative and significant effect on network influence at this time. The study confirms that information richness moderates the effect of sentiment type on influence. H3c was supported.

The analysis results of the X city epidemic are shown in the last three columns. Models 4, 5, and 6 examine how information richness moderate the effect of sentiment type on volume, depth, and influence, respectively. Specifically, the interaction terms of negative sentiment and information richness ($\beta = 0.024$, $p < 0.01$), and the interaction terms of positive sentiment and information richness in model 4 had significant effects on volume ($\beta = -0.027$, $p < 0.001$). H3a was again supported. Meanwhile, model 5 found a significant effect of the interaction term of positive affect and information richness ($\beta = 0.014$, $p < 0.1$), and the interaction term of positive affect and information richness ($\beta = -0.020$, $p < 0.01$) on depth. H3b was supported. Model 6, with similar results to model 3, again confirmed that information richness moderates the effect of positive affect ($\beta = -0.086$, $p < 0.001$) and negative affect ($\beta = -0.087$, $p < 0.001$) on influence. H3c was again supported.

In order to more intuitively show how information richness moderates the influence of sentiment type on dissemination effect, we draw the moderating effect diagram of information richness, as shown in Fig. 2. The data of J city and X city reveal similar conclusions: with the enhancement of information richness, taking neutral sentiment as the reference, the promoting effect of negative sentiment on the volume and depth of information dissemination is enhanced. Meanwhile, the effect of negative and positive sentiment on influence changed from positive to negative. However, the impact of information richness on the relationship between positive sentiment, volume and depth were different in J city and X city data. In the epidemic situation of J city, with the enhancement of information richness, the effect of positive sentiment on volume and depth changed to positive with neutral sentiment as the reference. In the epidemic situation in X city, with the enhancement of information richness, the effect of positive sentiment on the volume and

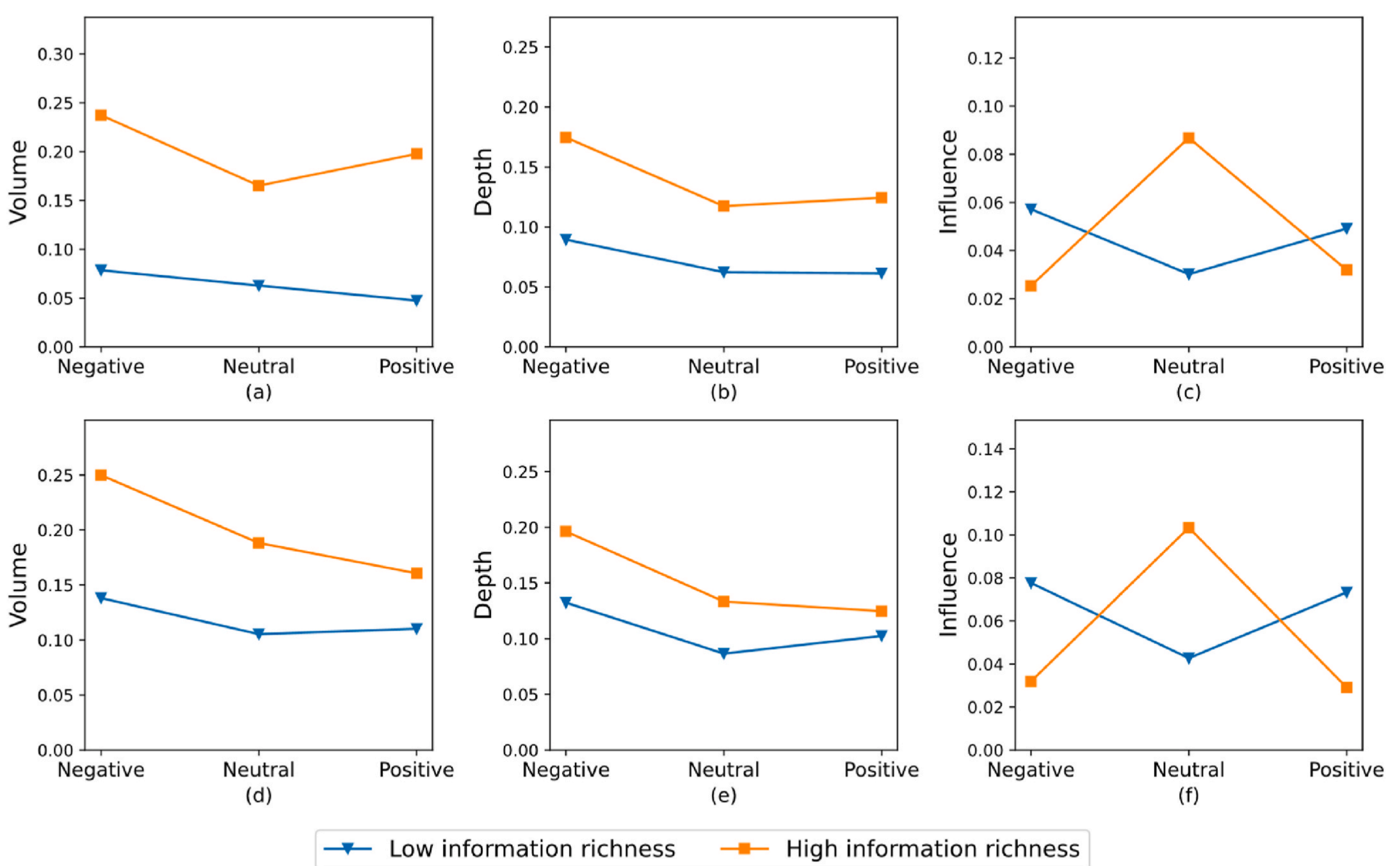

Fig. 2. Moderating effect of information richness. *Note*. The slope of the line reflects the strength and direction of the influence. **a-c** shows the moderating effect of information richness in the data of J city. ***d-f*** shows the moderating effect of information richness in the data of X city.

depth of dissemination changed from positive to negative.

4.3. Moderating effect of information authority

In addition to including information richness as a central path in the analysis framework, the study also included information authority, a common information characteristic in information dissemination research, as a peripheral path in the research model to further explore the conditional mechanism of information authority in the process of sentiment type influence on dissemination effect. Furthermore, concerning existing studies, in order to comprehensively and deeply explore the mechanism of the role of information authority in information dissemination, the study analyzed the moderating effect of information authority in two dimensions: user type and the number of user followers, respectively (Cai et al., 2022; L. Li, Liu, & Li, 2020; Shi et al., 2018).

First, considering that both sentiment type and user type are categorical variables, the study used a multivariate ANOVA model to verify the moderating effect of user type. The effects of sentiment type ($F = 213.86$, $p < 0.001$), user type ($F = 169.18$, $p < 0.001$), and the interaction term between sentiment type and user type ($F = 77.91$, $p < 0.001$) in the main effects model on volume are significant, confirming the moderating effect of user type in the relationship between sentiment type and volume. H4a was preliminarily supported. The effects of sentiment type ($F = 52.83$, $p < 0.001$), user type ($F = 98.45$, $p < 0.001$) and the interaction term ($F = 23.52$, $p < 0.001$) on depth are also significant, confirming the moderating effect of user type in the relationship between sentiment type and depth. H4b was preliminarily supported. Then, the effects of sentiment type ($F = 164.59$, $p < 0.001$), user type ($F = 35.77$, $p < 0.001$), and the interaction term ($F = 110.32$, $p < 0.001$) were significant on the influence, confirming the moderating effect of user type in the relationship between sentiment type and influence. H4c was preliminarily supported. In addition, the study analyzed the social media data of X city, and found that the effects of user type, sentiment type and the interaction term on volume, depth and influence were all significant, further confirming the moderating effect possessed by user type in the relationship between sentiment type and dissemination effect. H4 was further supported.

Although the above analysis proves that user type plays a moderating role in the relationship between sentiment type and information dissemination, and preliminarily verifies hypothesis 4, it is not clear whether the influence effect of sentiment type on dissemination effect changes with different levels of information authority. Therefore, in order to further clarify the specific differences in the moderating effect of different user types, the study draws the moderating effect diagram of user types (Fig. 3).

In the epidemic situation of J city and X city, the role of user types has a common character. Compared with ordinary users, media can significantly enhance the positive impact of negative sentiment on volume and depth but increase the negative effect of positive and negative sentiment on influence. This indicates that media is more conducive to the dissemination of negative sentiment, and it is difficult for media to arouse similar sentiments of information recipients. Similar to the media, celebrities can enhance the positive impact of negative and positive sentiment on the volume and depth, but the negative impact of celebrities on the relationship between sentiment and influence is weak. Therefore, compared with other types of users, celebrities have an advantage in evoking similar sentiments in message recipients. Institutional users and enterprises can inhibit the positive impact of negative sentiments on volume of forwarding, and promote the positive impact of positive sentiments on volume, depth and influence. The government can promote the positive influence of positive sentiment on volume and depth. This means that governments, institutional users and businesses

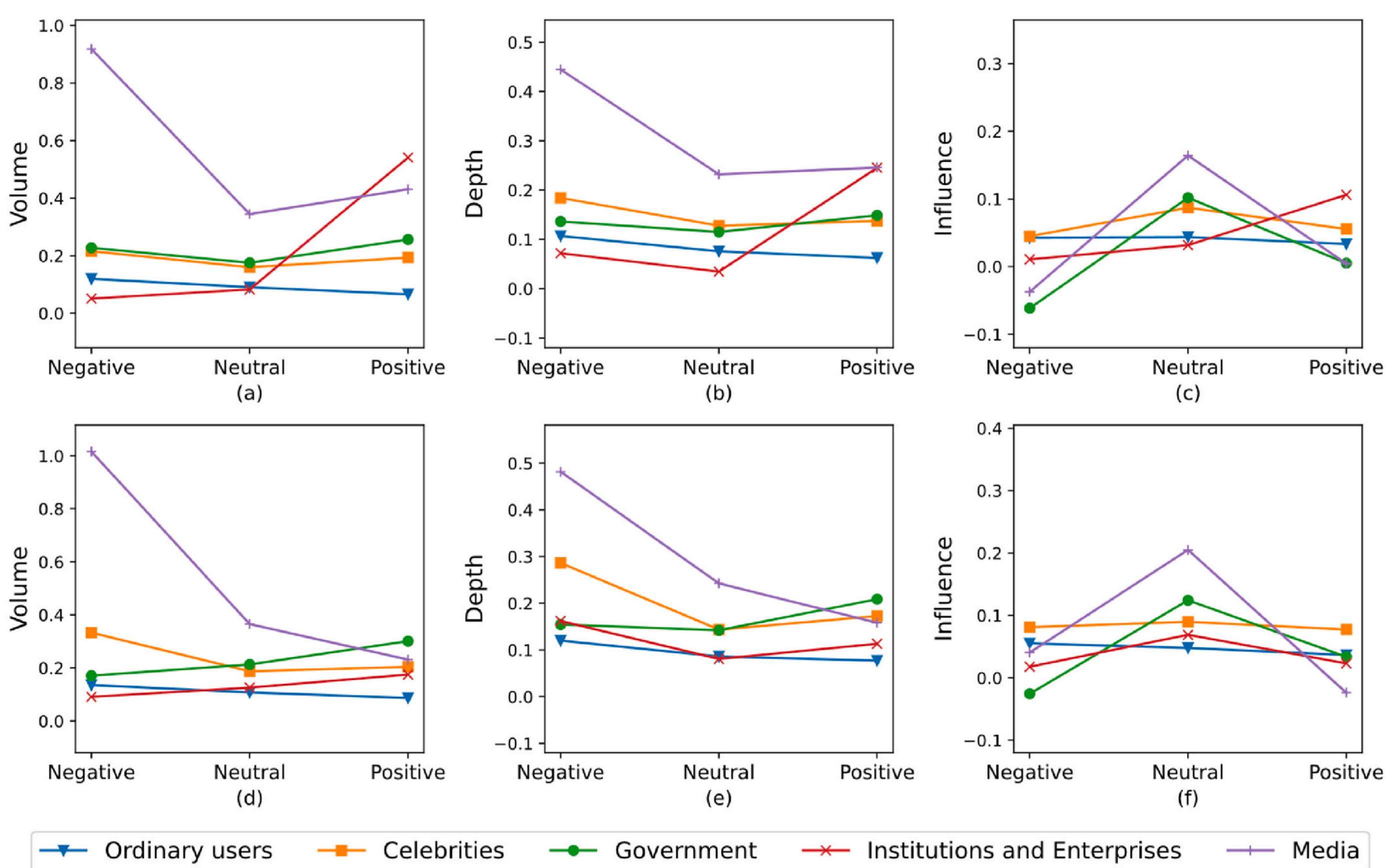

Fig. 3. Moderating effect of user type. *Note.* The slope of the line reflects the strength and direction of the influence. **a-c** shows the moderating effect of user type in the data of J city. ***d-f*** shows the moderating effect of user type in the data of X city.

have the potential to spread positive sentiment.

The study also used the number of user followers to measure the moderating effect of information authority on the relationship between sentiment type and information dissemination. The results are shown in Table 5. The results of public opinion analysis in J city are shown in models 1, 2 and 3. Model 1 found that the interaction term between negative sentiment and the number of user followers ($\beta = 0.021$, $p < 0.001$), the interaction term between positive sentiment and the number of user followers ($\beta = 0.019$, $p < 0.001$) had a positive and significant impact on volume. This indicates that the number of user followers can positively moderate the relationship between sentiment type and volume. H4a was supported. The results of model 2 and model 1 were similar. The interaction term between negative sentiment and the number of user followers ($\beta = 0.021$, $p < 0.001$), the interaction term between positive sentiment and the number of user followers ($\beta = 0.008$, $p < 0.001$) had a positive and significant impact on the spreading depth. This suggests that the number of user followers can moderate the relationship between sentiment type and depth. H4b was supported. The results of model 3 show that the interaction term between negative sentiment and the number of user followers ($\beta = -0.007$, $p < 0.001$), the interaction term between positive sentiment and the number of user followers ($\beta = -0.009$, $p < 0.001$) had a negative and significant impact on the influence. This indicates that the number of user followers can moderate the relationship between sentiment type and influence. H4c was supported.

The results of public opinion analysis in X city are shown in models 4, 5 and 6. Model 4 found that the interaction term between negative sentiment and the number of user followers positively and significantly impacted volume ($\beta = 0.041$, $p < 0.001$). However, the interaction term between positive sentiment and the number of user followers had no significant impact on volume. The moderating effect of the number of user followers on the relationship between sentiment type and volume was partially confirmed. H4a was partially supported. Similar to model 4, model 5 only found that the interaction term between negative sentiment and the number of user followers had a positive and significant impact on depth ($\beta = 0.036$, $p < 0.001$). The moderating effect of the number of user followers on the relationship between sentiment type and depth was partially confirmed. H4b was partially supported. Model 6 shows that the interaction term between negative sentiment and the number of user followers ($\beta = -0.004$, $p < 0.001$), the interaction term between positive sentiment and the number of user followers ($\beta =$ -0.014, $p < 0.001$) had a negative and significant impact on influence. This indicates that the number of user followers can moderate the relationship between sentiment type and influence. H4c was further supported.

The moderating effect of the number of user followers is shown in Fig. 4. Fig. 4(a) and (b) show the results based on the data of J city, when the number of users' followers is higher, compared with the neutral sentiment, positive and negative sentiment have a stronger positive effect on the forwarding volume and spreading depth. Compared with positive sentiment, the number of followers has a stronger influence on the relationship between negative sentiment, volume, and depth. Fig. 4 (c) shows that the effect of sentiment on influence changes from positive to negative with the increase in the number of followers. Fig. 4(d) and (e) show the results based on the data of X city. When the number of users' followers is higher, compared with the neutral sentiment, negative sentiment has a stronger positive effect on volume and depth. Fig. 4 (f) shows that the effects of sentiment on influence change from positive to negative with the increase in the number of fans, and the negative effect of positive sentiment on influence is stronger. The moderating effect of information authority on the relationship between sentiment and dissemination effect was further confirmed.

4.4. Moderating effect of topic influence

Topic clustering was conducted based on Top2Vec method, and 181 subjects about epidemic in J City and 196 subjects about epidemic in X city were obtained. The topics were described according to topic

Table 5
Moderating effect of the number of user followers.

	(1)	(2)	(3)	(4)	(5)	(6)
	volume	depth	influence	volume	depth	influence
Negative	−0.036***	−0.046***	0.041***	−0.135***	−0.119***	0.038***
	(0.009)	(0.008)	(0.004)	(0.008)	(0.007)	(0.003)
Positive	−0.093***	−0.040***	0.035***	−0.004	0.003	0.065***
	(0.006)	(0.005)	(0.003)	(0.006)	(0.006)	(0.003)
Fans	0.052***	0.033***	0.020***	0.060***	0.038***	0.025***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Negative * Fans	0.021***	0.021***	−0.007***	0.041***	0.036***	−0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Positive * Fans	0.019***	0.008***	−0.009***	−0.001	−0.000	−0.014***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Male	0.022***	0.011***	0.005***	−0.005*	0.001	0.000
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Length	0.046***	0.038***	0.020***	0.041***	0.033***	0.019***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Good	−0.114***	−0.072***	−0.031***	−0.135***	−0.085***	−0.042***
	(0.004)	(0.004)	(0.002)	(0.005)	(0.005)	(0.002)
Very good	−0.020**	−0.000	0.005*	−0.069***	−0.027***	−0.018***
	(0.006)	(0.005)	(0.003)	(0.007)	(0.006)	(0.003)
Urank	−0.002***	−0.001***	−0.000***	−0.001***	−0.000**	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urls	−0.037***	−0.021*	−0.003	−0.000	0.020+	0.003
	(0.011)	(0.009)	(0.005)	(0.014)	(0.012)	(0.006)
Hash	0.006*	0.004*	0.004***	−0.009***	−0.009***	−0.003***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Cases	−0.000***	−0.000***	−0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−0.252***	−0.186***	−0.113***	−0.276***	−0.204***	−0.135***
	(0.008)	(0.006)	(0.003)	(0.008)	(0.007)	(0.003)
Observations	143,348	143,348	143,348	185,133	185,133	185,133
Adjusted R^2	0.158	0.114	0.112	0.162	0.117	0.129

Note. Standard errors in parentheses,$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

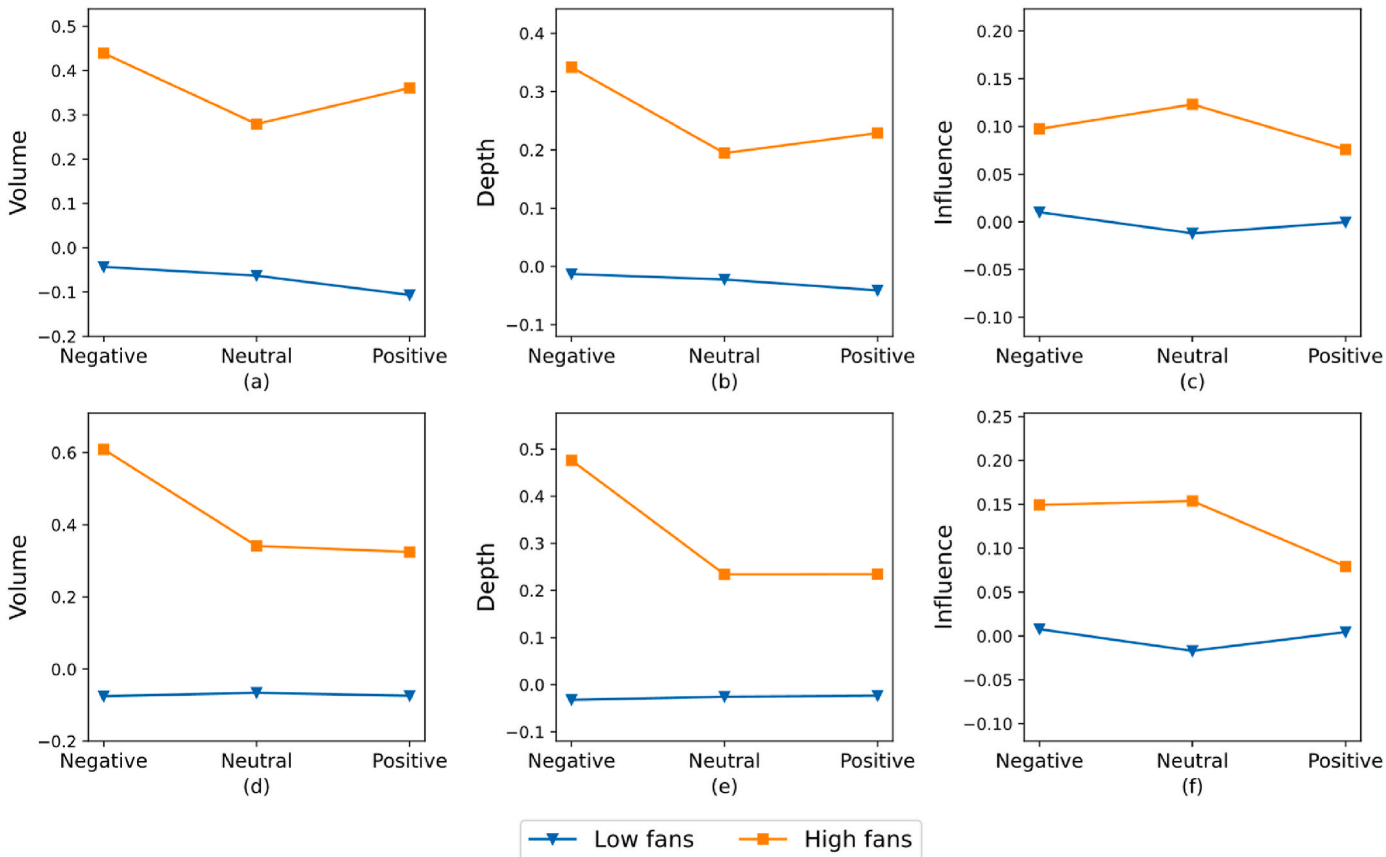

Fig. 4. Moderating effect of the number of user followers. *Note*. The slope of the line reflects the strength and direction of the influence. **a-c** shows the moderating effect of the number of user followers in the data of J city. ***d-f*** shows the moderating effect of the number of user followers in the data of X city.

keywords. Table 6 shows the top 10 topics containing the most microblogs. During the outbreak in J city, "Forwarding microblogs" was the topic with the highest number of microblogs, which indicates most users forwarded without saying anything. And then, positive publicity topics such as "Central enterprises fight against the epidemic", "Cheer for J city" and "Refueling the fight against the epidemic" got a lot of attention. In addition, because there was an outbreak in Shanghai during the outbreak in J city, some netizens compared the outbreak between the two cities, so the "Shanghai outbreak" attracted attention. "Forwarding microblogs" was also the topic with the largest number of posts during the epidemic in X city. Topics such as "Discussion of protest policy", "Management problems" and "The difficulty of buying vegetables" have received high attention, which expressed doubts about the local government's epidemic prevention policies. Positive publicity voices such as "News in support of fighting against COVID-19", "Cheer for fighting against COVID-19" and "Cheer for X city" also gained attention.

Table 6
Top 10 topics by number of microblogs in J city and X city.

ID	Topic (J city)	Num	ID	Topic (X city)	Num
0	Forwarding microblogs	41,688	0	Forwarding microblogs	45,178
1	Central enterprises fight against the epidemic	16,262	1	Discussion of protest policy	23,378
2	The plight of life caused by the pandemic	6762	2	Expressing pessimism	6522
3	Looking forward to the end of the epidemic	3965	4	X city's epidemic prevention management problems	5531
4	Cheer for J city	2493	9	The impact of the pandemic on life	4581
5	Shanghai outbreak	2470	7	The difficulty of buying vegetables	3802
8	Watch and show attitude	1879	5	News in support of fighting against COVID-19	3175
9	Refueling the fight against the epidemic	1680	3	Cheer for X city	3015
6	Social news during the pandemic	1575	6	Cheer for fighting against COVID-19	2395
19	Problems in epidemic prevention at the grassroots level	1484	16	The pain of isolation	2258

Fig. 5(a) and (b) show the evolution trend of the top 10 popular topics in J city and X city, respectively. In the early period of the epidemic in J city (around March 9), "Looking forward to the end of the epidemic" and "The plight of life caused by the pandemic" gained more attention. These topics expressed negative and panicky feelings. Then, positive official publicity kicked in, and "Central enterprises fight against the epidemic" began to take on significant weight. "Cheer for J city" peaked on March 19. Around April 6, there was an outbreak in Shanghai, and the topic "Shanghai outbreak" dominated the discussion. During the pandemic in X city, during the early pandemic period (before December 19), the discussion among netizens mainly centered on the topics of "Expressing pessimism" and "The pain of isolation". However, due to the emerging problems of the government's epidemic prevention policy, the topics "Discussion of protest policy" and "Management problems" began to take up a large proportion after December 19. Around December 29, the topic "The difficulty of buying vegetables" got much attention. Although the authorities tried to guide them through more positive topics, such as "News in support of fighting against COVID-19" and "Cheer for X city", netizens still focused on more negative topics.

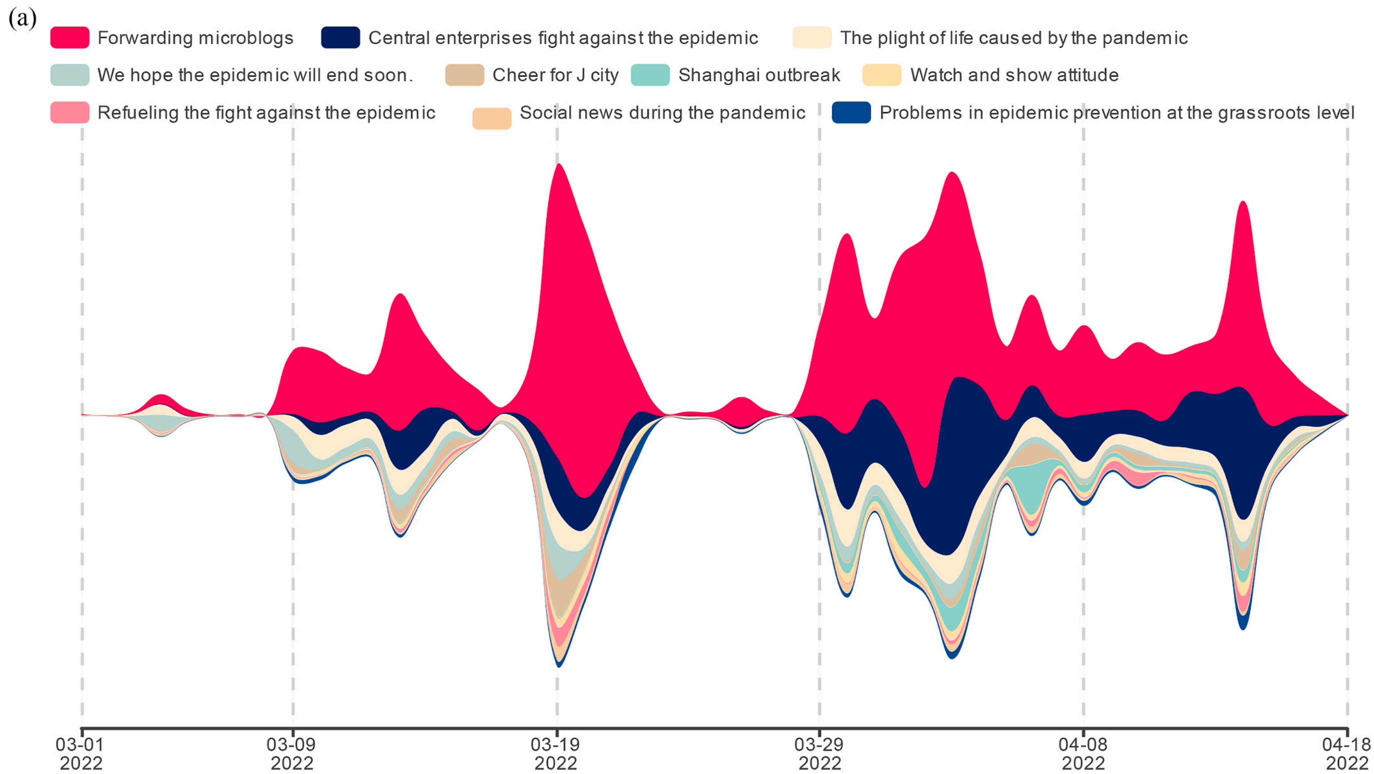

Fig. 5(a). Topic river map of the top 10 topics in J city.

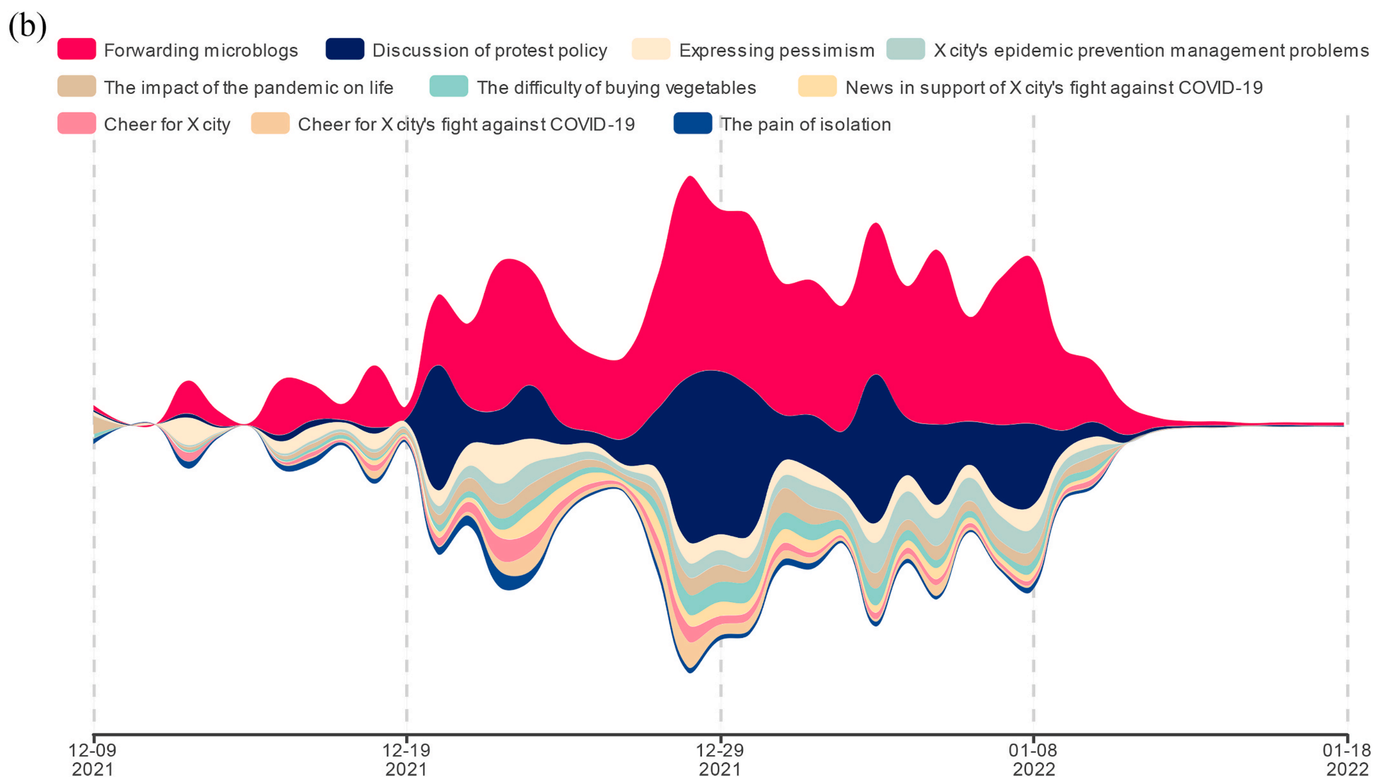

Fig. 5(b). Topic river map of the top 10 topics in X city.

In order to further explore how the topic influence plays a role in the dissemination of affective information, the research also constructs the moderating model of topic influence based on the public opinion in J city and X city, respectively. The results are shown in Table 7. Model 1 found that when neutral sentiment was used as the reference group, the interaction term between positive sentiment and topic influence ($\beta = 0.035$, $p < 0.001$) had a positive and significant impact on volume, but the interaction term between negative sentiment and topic influence had

Table 7
Moderating effect of topic influence.

	(1)	(2)	(3)	(4)	(5)	(6)
	volume	depth	influence	volume	depth	influence
Negative	0.022***	0.026***	−0.017***	0.019***	0.025***	−0.017***
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)
Positive	0.012***	0.005*	−0.020***	−0.007*	0.004+	−0.030***
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Top_inf	0.298***	0.301***	0.191***	0.322***	0.304***	0.186***
	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)
Negative * Top_inf	0.008	0.028***	−0.021***	0.022***	0.098***	−0.006**
	(0.007)	(0.006)	(0.003)	(0.005)	(0.005)	(0.002)
Positive * Top_inf	0.035***	0.006	0.007**	−0.031***	−0.007	−0.009***
	(0.006)	(0.005)	(0.002)	(0.006)	(0.005)	(0.003)
Male	0.064***	0.037***	0.017***	0.043***	0.031***	0.014***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Length	0.098***	0.066***	0.035***	0.098***	0.065***	0.039***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Good	−0.008+	−0.005	−0.004*	−0.019***	−0.009*	−0.004+
	(0.004)	(0.003)	(0.002)	(0.005)	(0.004)	(0.002)
Very good	0.101***	0.072***	0.030***	0.094***	0.079***	0.030***
	(0.006)	(0.005)	(0.002)	(0.006)	(0.005)	(0.003)
Urank	0.003***	0.002***	0.001***	0.003***	0.003***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
URL	−0.055***	−0.039***	−0.017***	−0.047***	−0.015	−0.017**
	(0.011)	(0.009)	(0.004)	(0.013)	(0.011)	(0.005)
Hash	0.064***	0.041***	0.023***	0.060***	0.040***	0.024***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Cases	−0.000	−0.000	−0.000**	0.000***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	−0.375***	−0.248***	−0.116***	−0.373***	−0.258***	−0.133***
	(0.007)	(0.006)	(0.003)	(0.007)	(0.006)	(0.003)
Observations	143,348	143,348	143,348	185,133	185,133	185,133
Adjusted R^2	0.179	0.202	0.258	0.182	0.200	0.238

Note. Standard errors in parentheses, + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

no significant impact on volume. H5a was partially supported. Model 2 found that the interaction term between negative sentiment and topic influence ($\beta = 0.028, p < 0.001$) had a positive and significant impact on depth, but the interaction term between positive sentiment and topic influence was not significant. H5b was partially supported. Model 3 found that the interaction term between negative sentiment and topic influence ($\beta = -0.021$, $p < 0.001$), and the interaction term between positive sentiment and topic influence ($\beta = 0.007$, $p < 0.001$) had a negative and positive impact on the network influence respectively. H5c was supported.

The analysis results of X city are shown in models 4, 5, and 6. Model 4 took volume as the dependent variable, and found that the interaction term between negative sentiment and topic influence ($\beta = 0.022$, $p < 0.001$), the interaction term between positive sentiment and topic influence ($\beta = -0.031$, $p < 0.001$) had a significant impact on the forwarding volume. H5a was supported. Model 5 took depth as the dependent variable, and found that only the interaction term between negative sentiment and topic influence ($\beta = 0.098$, $p < 0.001$) had a positive and significant impact on the spreading depth. H5b was partially supported. Model 6 took influence as the dependent variable, and found that the interaction term between negative sentiment and topic influence ($\beta = -0.006$, $p < 0.001$), the interaction term between positive sentiment and topic influence ($\beta = -0.009$, $p < 0.001$) had a negative and significant impact on the influence. H5c was supported. These findings confirm that topic influence can effectively moderate the relationship between sentiment type and dissemination effect.

In order to show more comprehensively how topic influence plays a moderating role, this study draws a moderating effect diagram of topic influence (Fig. 6). For J city, as shown in Fig. 6(a)-(c), when the topic influence is high, the positive effect of positive sentiment on volume is strengthened. The promotion effect of negative sentiment on depth was enhanced. The negative effect of negative sentiment on influence is strengthened. The negative effect of positive sentiment on influence is weakened. For X city, as shown in Fig. 6(d)-(f), when the topic influence is high, positive sentiment negatively influences volume. The positive effect of negative sentiment on volume is enhanced. The positive effect of negative sentiment on depth is strengthened. The negative effects of negative and positive sentiments on influence are slightly enhanced. Compared with X city, high topic influence strengthens the influence of positive sentiment on information dissemination in J city. The particularity of the two events can explain the difference in the moderating effect of topic influence in the epidemic situation of J city and X city. The public opinion topic of the epidemic in J city is more positive. Due to the outbreak of negative public opinion related to epidemic prevention policies in X city, users have more negative feelings towards the epidemic situation in X city. When users are exposed to positive sentiment information, even if they agree with the importance of the information topic, the information would be interpreted negatively, reducing the influence of positive sentiment. This reflects that the information environment may guide the user's bias for specific affective information.

4.5. Summary of the findings

In order to make the results more intuitive, the research summarized the support of each hypothesis and map them to the respective concepts in which they were grounded. The results are shown in Table 8. Among them, hypothesis 1 and hypothesis 2 are competitive hypotheses. When hypothesis 1 is supported by research, hypothesis 2 must be rejected by research. The results show that when a public health emergency occurs, the volume, depth, and influence of negative sentiment are stronger than those of positive sentiment. This is also consistent with the theoretical expectation of negative bias. That is, posts with negative sentiments are more likely to be spread after a crisis (L. Li, Liu, & Li, 2020). Previous studies have mainly confirmed the effect of negative sentiments on volume. This study further found that negative sentiments were more likely to trigger viral forwarding, and more likely to produce emotional contagion, and wake up other users' negative sentiments. This is due, on the one hand, to the potential of negative sentiments to cause conflicts

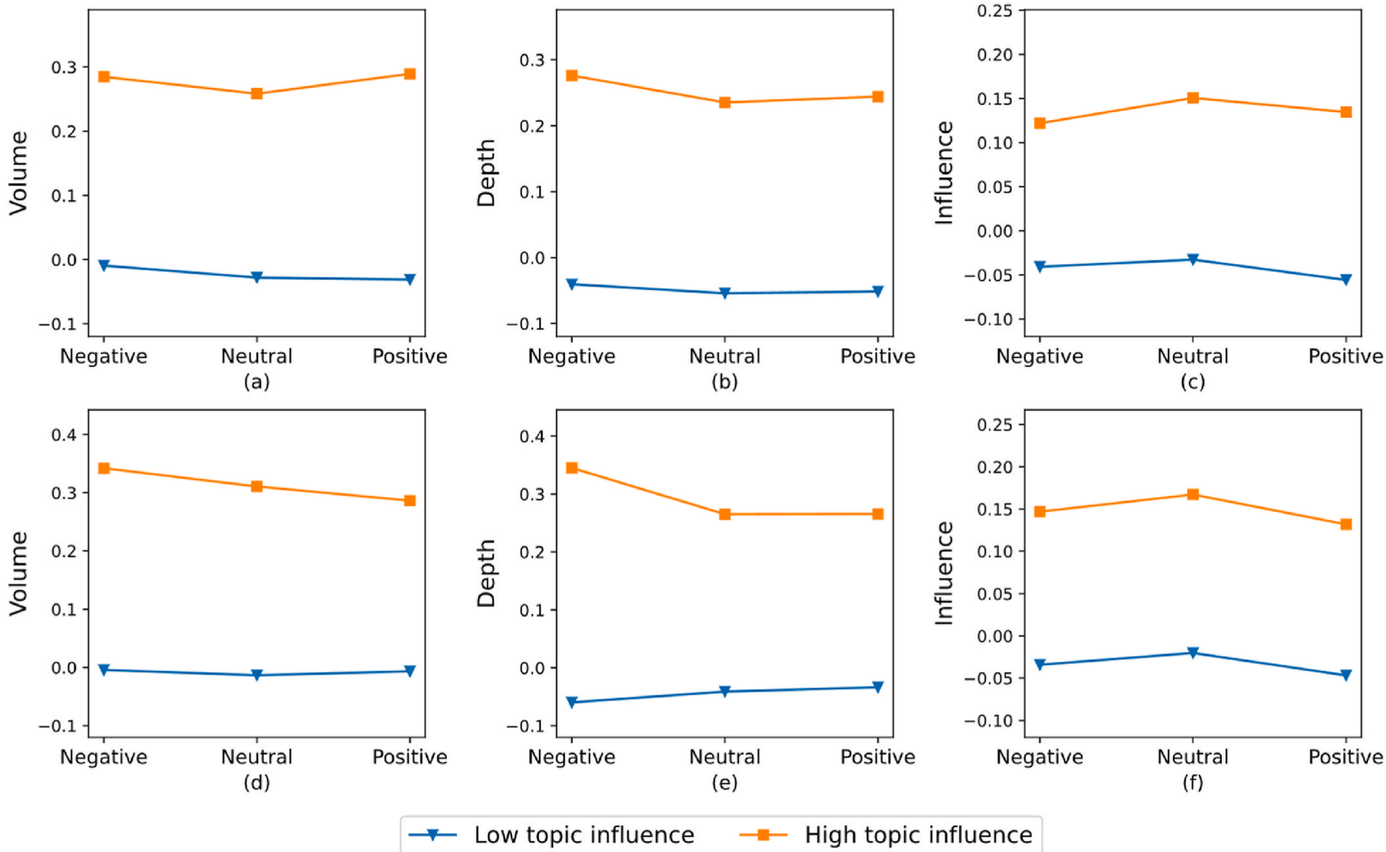

Fig. 6. Moderating effect of topic influence. *Note*. The slope of the line reflects the strength and direction of the influence. **a-c** shows the moderating effect of topic influence in the data of J city. ***d-f*** shows the moderating effect of topic influence in the data of X city.

Table 8
Summary of hypotheses supportiveness.

Concept	Hypothesis	Independent variable	Dependent variable	Supportiveness	
				J city	X city
Sentiment	H1a	Negative	Volume	Fully supported	Fully supported
	H2a	Positive	Volume	Rejected	Rejected
	H1b	Negative	Depth	Fully supported	Fully supported
	H2b	Positive	Depth	Rejected	Rejected
	H1c	Negative	Influence	Fully supported	Fully supported
	H2c	Positive	Influence	Rejected	Rejected
Information richness	H3a	Sentiment*Richness	Volume	Fully supported	Fully supported
	H3b	Sentiment*Richness	Depth	Fully supported	Fully supported
	H3c	Sentiment*Richness	Influence	Fully supported	Fully supported
Information authority	H4a	Sentiment*User	Volume	Fully supported	Fully supported
	H4b	Sentiment*User	Depth	Fully supported	Fully supported
	H4c	Sentiment*User	Influence	Fully supported	Fully supported
	H4a	Sentiment*Fans	Volume	Fully supported	Partially supported
	H4b	Sentiment*Fans	Depth	Fully supported	Partially supported
	H4c	Sentiment *Fans	Influence	Fully supported	Fully supported
Topic influence	H5a	Sentiment*Top_inf	Volume	Partially supported	Fully supported
	H5b	Sentiment*Top_inf	Depth	Partially supported	Partially supported
	H5c	Sentiment*Top_inf	Influence	Fully supported	Fully supported

and quarrels, and on the other hand, to the nature of crisis events. The real-world roots of a crisis tend to trigger panic, and people turn to social media for information to reduce uncertainty. However, social media discussions tend to cause affective polarization and further aggravate the spread of negative information. The negative bias in crisis events makes government departments face great resistance in defusing public sentiment. In addition, we also need to recognize that negative sentiment has more than just a negative effect on society during crises. When a crisis occurs, users may also post messages with negative sentiment to warn others of danger, or inform the government of existing problems, thus helping to deal with the crisis more targeted and effectively.

Further, the moderating effects of information richness, information authority, and topic influence were tested. As shown in Table 8, hypothesis 3 focuses on the moderating effect of information richness, and the results verified the moderating effect of information richness. Information richness promoted the impact of negative sentiments on the volume and depth of information dissemination. However, the effect of information richness on the relationship between positive sentiment and volume and depth differed in the two cases. In addition, the higher the information richness, the higher the influence of neutral sentiment in social networks. This may be because when the objective information of neutral sentiment is presented in the form of pictures and videos, it often has high usefulness, which means that the information can reduce users' uncertainty and stimulate users to forward. In addition, based on the ELM, when information is scarce, people use peripheral route cues to evaluate posts, then when information is more abundant, users may switch to the central route. At this point, users have a complete understanding of the information content and are more likely to share the information with other users, so the information has a better dissemination effect (Chua & Chen, 2019).

To demonstrate the role of authority, hypothesis 4 measures the moderating effect of information authority by taking user type and user follower number as variables, respectively. The research results confirmed that the number of user followers could effectively enhance the effect of sentiment, especially negative sentiment, on the volume and depth. This further confirmed the negativity bias in crisis events. However, the effect of sentiment on influence changes from positive to negative with the increase in followers. This is because when a high-influence user posts a microblog with a neutral sentiment, most of the user's followers only repost the microblog without expressing their opinions, which increases the proportion of neutral sentiment in the network. The results of the topic analysis provide evidence for this, with the most popular topic in both events being reposts. However, when the number of users' followers is low, compared with positive and negative sentiments, microblogs with neutral sentiments is difficult to attract users' attention and resonance due to the lack of sentiment and drama. At the same time, different types of users have different effects on disseminating affective information. The potential of the media and celebrities to promote the spread of negative sentiments was discovered. Celebrities have a greater ability to evoke affective resonance. Governments, institutions, and enterprises have an advantage in facilitating the impact of positive sentiments on information diffusion. This may be related to the differences in functions undertaken by different user types in information dissemination. The primary function of governments and businesses is to spread hope and trust to support emergency governance in crisis events. However, the function of media is more likely to alert people, explain various aspects of the crisis, and act as a social corrective mechanism.

To demonstrate the role of topic influence, hypothesis 5 takes topic influence as the moderating variable to investigate how topic influence affects the dissemination of affective information. The results partially confirmed the moderating effect of topic influence. At the same time, the moderating effect of topic influence shows differences between J city and X city, which may be related to the particularity of the event. In more negative crisis events, the promotion effect of topic influence on positive sentiment dissemination was inhibited, and the promotion effect on negative sentiment dissemination was enhanced.

5. Discussion

Based on social media data related to COVID-19 in two Chinese cities, this study combines the perspective of information ecology and ELM to investigate the influence of sentiment on information dissemination from multiple dimensions, as well as the interaction between sentiment and information richness, information authority and topic influence. It is found that under the background of a crisis, information with negative sentiment has more advantages in volume, depth, and influence. In addition, information attributes and network characteristics can further moderate the influence of sentiment type on the dissemination effect. These findings not only promote our understanding of the evolution trend of public opinion in the context of COVID-19 but also provide a tool for emergency management to further systematically deal with the network public opinion in the context of an emergency. The specific implications are discussed further below.

5.1. Theoretical implications

First of all, this study incorporated multi-dimensional dissemination ability into the analysis model, which is helpful to enrich the related research on public affective reaction to information dissemination during crisis events. For a long time, the management of public opinion has been a complex problem for emergency management departments. Research on the influencing factors of information dissemination has always been the critical content of public opinion research. Among them, as an important influencing factor, the influence of sentiment on information-sharing behavior during the crisis has been verified in many aspects (Grabe & Kamhawi, 2006; Hornik, Satchi, Cesareo, & Pastore, 2015; Wu & Shen, 2015). The negative bias theory or Pollyanna hypothesis has provided a classical explanation for the influence of negative or positive sentiments on information-sharing behavior (Ferrara & Yang, 2015; Li, Liu, & Li, 2020b; Steinert, 2020; Tsugawa & Ohsaki, 2015; Yeo et al., 2020). However, considering that most studies replaced information-sharing behavior with volume or degree centrality, it can only show the horizontal dissemination ability of information(Cai et al., 2022; Chen et al., 2020; Zhou, Xiu, et al., 2021), our study further extended this by combining horizontal and vertical dissemination to enrich the relevant literature in this field, and further found the differential influence of sentiment types on the dissemination effect of different dimensions.

Secondly, this study combined machine learning methods with causal statistical methods, extracted variables from big data texts of machine learning models, and built statistical models on causal mechanisms, enriching the relevant applications of machine learning in social sciences. In recent years, with the rise of computational social science and the emerging demand for large-scale data analysis, more and more social science research began to gradually incorporate machine learning or deep learning methods to promote the further progress of research work (Lazer et al., 2020). However, the existing research mainly used machine learning as a tool for descriptive analysis, while lacking more exploratory and causal studies. In this paper, we adopted deep learning models represented by Top2Vec and BERT to extract topic and sentiment variables from the mass of public opinion text corpus, which promotes the realization of the causal model. The use of machine learning could better explain the social problem, enriching the applications of machine learning methods in the causal mechanism.

Finally, from the perspective of information ecology, the paper included information characteristics, user characteristics, and environment characteristics in the analysis, and combined information ecology theory with the ELM to explain the direct and indirect effects of information dissemination from the perspective of subjective and objective. Specifically, the combination of information characteristics, information users, and information environment can more comprehensively reveal the specific mechanism of emotional information dissemination in social networks (Wang, Chen, Shi & Peng, 2019a; Xing et al., 2021), but there are theoretical deficiencies in the specific explanation. Therefore, based on the perspective of information ecology, the ELM was included in the paper, and information attributes were divided into the central path and peripheral path, so as to explain the conditional mechanism in emotional information dissemination (Angst & Agarwal, 2009; Fan et al., 2021; Orellana-Rodriguez & Keane, 2018; Petty & Cacioppo, 1986a; Shi et al., 2018). Finally, the paper can provide persuasive explanations for the model from the perspective of theoretical integration, further enrich the relevant literature in this field, and also provide a reference for the subsequent research on public opinion governance.

5.2. Practical implications

This paper took the COVID-19 outbreak as the research background, integrated information characteristics, information users, and information environment characteristics into the analysis framework, and investigated the impact of sentiment types on multidimensional dissemination effect, which has certain practical significance for public opinion governance and public affective support during the crisis.

First of all, in the online public opinion caused by the COVID-19 outbreak in different cities, the public's affective state was similar. As the crisis has natural advantages and a practical basis to arouse negative sentiments, it is easier for negative sentiments to spread than positive sentiments. Therefore, the government should formulate guidance strategies to enhance the volume of information with positive sentiment. The distribution of public sentiment in negative sentiment and positive sentiment can help us predict the public sentiment reaction at the beginning of the crisis, and provide the preparation basis for the public opinion emergency department to realize the topic guidance in advance and evacuate the public negative sentiment. Considering the differences in the specific impact of different sentiment types on volume, depth, and influence, the public opinion management department should implement differentiated management measures according to different goals, so as to provide more targeted governance measures for the diffusion ability of information in social networks and the contagion ability of negative sentiment.

Secondly, according to the results of this paper, information characteristics play an important role in the process of emotional information dissemination. Specifically, both information richness and information authority can enhance the influence of emotional information on dissemination effect. Meanwhile, the posts with high-richness content and posts published by highly authoritative users have better dissemination effect in social networks. Therefore, emergency management departments can formulate different information publicity strategies to achieve favorable guidance of public opinion. Such as releasing more information with videos and pictures of events to reduce the impact of rumors and misinformation on the public. Or pay close attention to users with high authority in social networks, which can achieve better publicity effects while reducing publicity costs. At the same time, through the guidance of information richness and authoritative users, the dissemination rate of posts with negative sentiments in social networks can also be reduced, and the proportion of posts with positive sentiments in the network can be promoted to increase, so as to realize the prevention of network collective behavior.

In addition, by combining topic type and network structure, the paper constructed a topic influence variable to measure the influence of information environment on emotional information dissemination ability. It was found that topic influence plays a moderating role in sentiment type and dissemination ability. This provides new governance means for emergency management departments to guide public opinion and alleviate public pessimism in crisis. Specifically, in the face of an emergency, the emergency management department shall timely pay attention to the evolution of the public opinion environment, dissemination with the public relations department, strengthen the forwarding and publicity of posts with positive sentiment, promote the transmission of blessing and encouraging information in the deep space of the network. And give play to the power of the media and institutions in the network publicity, so that the relevant information of crisis-fighting events can occupy a high influence in cyberspace. In addition, government media should keep in touch with the public, timely release crisis-specific information, such as progress in crisis management, crisis prevention and crisis after the compensation and other related information, to divert public negative sentiments, and play a good topic influence the positive role, promote positive mood spread in social networks.

5.3. Research limitations and future research directions

From the perspective of information ecology and elaboration likelihood model, this study combined machine learning methods to explore the specific impact of sentiment types, especially negative sentiments, on dissemination ability from multiple dimensions, and further investigated the conditional role played by information characteristics, user characteristics and environment characteristics. But the study still had some limitations.

First, the two social media data sets used in the research are both from Weibo, the same social media platform. The geographical area of data collection is only limited to China, and the users involved are mostly from mainland China, which lacks generalization and universality. In addition, given the differences between different regional cultures, users from different countries may have different perspectives and attitudes when faced with the same public health emergency. Therefore, in future research, we will consider obtaining more epidemic-related data sets from different social media platforms, such as WeChat and Twitter, to make up for the data deviation caused by region and culture, and make the research more comprehensive.

Secondly, the inherent black box technology of machine learning forces us to further improve the prediction performance, and select more accurate and innovative models to complete the classification and prediction of topics and sentiments. In addition, the study only analyzes the topic and sentiment reflected in the text and lacks further analysis of images and videos. Therefore, considering the possible differences between images, videos, and text, it is also necessary for future research to adopt computer vision methods to identify user sentiments in images and videos.

Finally, the data collected during the same period were used to verify the model. Given the long duration of the COVID-19 pandemic, negative and positive sentiment may be perceived and processed differently at different times. Therefore, in the future, the research would collect data from different periods to explore the evolution of public sentiment from the longitudinal timeline, so as to better discover the law of public opinion development.

6. Conclusion

Based on the information ecology theory and elaboration likelihood model, this study presented the affective reactions of social media users during the crisis, and compared and analyzed the impact of affective factors on the dissemination ability of social media information after the outbreak of COVID-19 in J city and X city. In addition, the study further incorporated information characteristics and network characteristics into the analysis model to consider how emotional information is affected by the conditional mechanism, and then had a differential impact on horizontal diffusion ability (forwarding volume) and vertical contagion ability (spreading depth and network influence). Specifically, machine learning methods represented by Top2Vec and BERT are first used to train the topic recognition model and sentiment classification model, and the topic variables and sentiment variables were extracted from the large-scale text data set. Secondly, combined with the network analysis method, this paper investigated the combination of topic, sentiment variables, and network characteristics, and extracted topic influence and network influence variables. Thirdly, the research took the sentiment type as the independent variable and the volume, depth, and influence as the dependent variable to investigate the difference between different sentiment types in information dissemination ability. Finally, the study put information features represented by information richness and authority and network features represented by topic influence into the model to explore how information features and network features play a conditional role in the relationship between sentiment and dissemination effect.

The specific findings of the study are as follows. First, the study found that negative sentiments are more likely to be forwarded by other users on social media, and are more likely to be spread in depth. Therefore, negative sentiments are more influential, which means they resonate more easily. This conclusion is the validation and extension of the negative bias theory. Secondly, in the two social media data sets, the moderating effects of information richness, information authority, and topic influence are confirmed. Both information richness and the number of followers enhance the influence of sentiment, especially negative sentiment, on the volume and depth. The user type could effectively moderate the relationship between sentiment type and information dissemination. The potential of media and celebrities to spread negative sentiments was discovered. Governments, institutions, and enterprises have an advantage in facilitating the impact of positive sentiment on information diffusion. The moderating effect of topic influence in the two events data is different, which may be related to the event characteristics. Therefore, combined with the findings of this study, emergency management departments can formulate more appropriate publicity strategies when an emergency comes, provide better emotional support for network users, and better realize the intervention and guidance of online public opinions.

Credit author statement

Han Luo: Conceptualization, Methodology, Project administration, Software, Writing - Original Draft, Writing - Review & Editing, Visualization. Xiao Meng: Conceptualization, Methodology, Software, Writing - Original Draft, Writing - Review & Editing, Visualization. Yifei Zhao: Conceptualization, Writing - Review & Editing, Visualization. Meng Cai: Conceptualization, Supervision, Funding acquisition, Writing - Review & Editing.

Declaration of competing interest

The authors declare no competing interests.

Data availability

The data can be found at OSF (https://osf.io/3hmgb/).

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