

Research Article

Spread of Misinformation in Social Networks: Analysis Based on Weibo Tweets

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Social networks are filled with a large amount of misinformation, which often misleads the public to make wrong decisions, stimulates negative public emotions, and poses serious threats to public safety and social order. The spread of misinformation in social networks has also become a widespread concern among scholars. In the study, we took the misinformation spread on social media as the research object and compared it with true information to better understand the characteristics of the spread of misinformation in social networks. This study adopts a deep learning method to perform content analysis and emotion analysis on misinformation dataset and true information dataset and adopts an analytic network process to analyze the differences between misinformation and true information in terms of network diffusion characteristics. The research findings reveal that the spread of misinformation on social media is influenced by content features and different emotions and consequently produces different changes. The related research findings enrich the existing research and make a certain contribution to the governance of misinformation and the maintenance of network order.

1. Introduction

Misinformation is an objective social phenomenon that appears in the social operation environment. It usually refers to the information that is widely circulated intentionally or unintentionally without a factual basis and confirmation or clarification [1]. It has been a concern not only in the social sciences such as sociology and journalism [2] but also in computer science and other research fields [3]. With the development of Internet technology and social media platforms, the misinformation spread by word-of-mouth is rapidly spread through social media platforms and has the characteristics of fission diffusion, fast propagation speed, a wide range of influence, and deep impact. A large amount of false information and the spread of rumors and misleading information on social media platforms not only cause public concern and pose a threat to the public's physical and psychological health but also bring serious challenges to the governance and stability of social order [4].

The destructive nature of misinformation has also made the concept of "information epidemic" known to the

public. "Information epidemic" refers to a series of physical and psychological reactions formed by the public when they are faced with misinformation because it is difficult to identify the veracity of the information, and the spread of misinformation infiltrates into everyone's life [5]. For example, during the COVID-19 outbreak, the World Health Organization considered fighting against the "information epidemic" as an important part of its work [6]. With the influence of social media, the "information epidemic" expanded in scope and magnified the threat posed by misinformation. For example, when faced with misinformation, the uncertainty of the future and the lack of access to information will increase the psychological pressure of the public, causing anxiety and panic among the public [7]. At this time, under the influence of rumors and misleading information, the public is very likely to be trapped by the group, amplifying mass panic, triggering collective social crisis, and even leading to various social tragedies [8]. It has been shown that the harm caused by misinformation spread on social media is more serious due to the characteristics of social media such

as fast propagation speed, a wide range of influence, and deep impact. On this basis, it is urgent to understand the propagation process of misinformation on social media and to govern misinformation [9].

In addition, with the convenience of communication and the timeliness of information dissemination, social media often becomes an important communication channel for two-way information exchange. On the one hand, considering the influence of "information cocoon," weak ties can provide us with more diverse information, based on which social media becomes a better choice for people to communicate. With the help of social media, we can get in touch with people from different regions and industries more easily, and communicate more frequently with people who different from us. Therefore, the public can also learn about relevant situations and specific information about different events in different regions from social media [10]. On the other hand, influenced by the interaction and fusion of massive true information and misinformation on social media platforms, the public is often prone to emotional fluctuations and tends to publish their views and emotions on social media platforms and receive different responses depending on the type, progress, and content of events [11]. At the same time, social networks formed on social media will spread public opinions or emotions and form new communication networks [12].

In recent years, the spread of misinformation on social media platforms has caused public concern, not only because misinformation can easily confuse people, causing them to make wrong decisions, resulting in economic and material losses, but also because misinformation can have an impact on health, medical, and other fields, spreading wrong treatments which even further damages the public's physical and mental health. At the same time, unconstrained misinformation will lead to social disorder and the prevalence of negative emotions, ultimately causing a huge impact on society. Therefore, it is especially important to understand the spread process and diffusion characteristics of misinformation on social media platforms [13]. Considering this, the study is based on large-scale social media datasets, takes true information and misinformation as the research objects, and conducts correlation analysis on the content and emotion of true information and misinformation for their dissemination. In addition, we use the social network analysis method to further compare the network structure of true information and misinformation in the process of dissemination, expecting to reveal the evolution law of false information to realize the public opinion governance of misinformation and reduce the negative impact brought by misinformation.

The results for the rest of this article are as follows. In the second part, we introduce relevant studies. In the third part, we present the methodology used in the study. In the fourth part, we show the analysis results and discussions, mainly involving the analysis of the content and emotions spread by true information and misinformation on social media. In the fifth part, we present the conclusion of the research and further put forward future ideas for the research.

2. Related Research

2.1. Misinformation in Social Network. Unverified or unclarified messages are very common on social media, and studies have attempted to conceptualize unverified messages from different perspectives. Common names include "misinformation," "disinformation," "fake news," and "rumor" [14]. Among them, misinformation, disinformation, and fake news all emphasize the false nature of information and describe the object of information that has been falsified. The difference lies in the fact that misinformation often appears in a random form with unknown intention and motivation, and is often used by researchers to describe false information in a broad sense [15]. Disinformation is usually the deliberate tampering of correct information to obtain benefits or advantages and then spread [16]. Similar to disinformation, fake news is used to disseminate false information and stories in the guise of reliable sources for economic or political gain [17]. Rumor is quite different from the previous three concepts. Although a rumor is also unconfirmed information, it need not always be false information, as it can also be correct information in some cases, and the dissemination motivations and intentions of rumor are often unknown [18].

The spread of misinformation on social media has always been an important research topic. But before we can understand why misinformation can spread on social media, we need to have a clearer understanding of the misinformation. One of the reasons why misinformation is concerned as important by researchers lies in the misleading nature of misinformation. Misinformation often misleads the public to make decisions, causes them to form corresponding actions, and generates emotional and psychological fluctuations [19]. At this time, the public forms an adaptive response under the stimulus and influence of misinformation, and tends to interact with the outside world, and then magnifies the scope and degree of the influence of misinformation [20]. On the one hand, misinformation, as an adaptive form of stimulus-response, has a warning function, indicating that the public's emotions are dictated by external forces in a tense situation. On the other hand, misinformation also reflects the psychological state behind public emotions in the social environment. For example, when a social crisis occurs, the public is more susceptible to the influence of other public emotions under the misdirection of misinformation, forming a large-scale emotion cluster phenomenon, which will then impact the social order and easily cause a negative effect on society [21].

In addition, some studies have analyzed factors that influence the spread of misinformation on social media. Studies have pointed out that true information and misinformation are often mixed and difficult to identify, and misperception of misinformation as true information is the main reason for the public to share and spread misinformation on social media [22]. Social media users tend to support the spread of unverified information on social media but generally do not spread information that has been proven to be false. The problem is that social media users often lack the ability to recognize misinformation before

sharing it [23]. Studies have been conducted to explain the public's deficiency in misinformation recognition on this basis, with related studies mainly focusing on political, psychological, and media literacy perspectives. For example, from the political perspective, it has been argued that the public's political orientation affects the human brain's processing of information, and an identity-based model of political orientation has been proposed to explain how political orientation causes the public to form information bias and thus choose to trust false information [24]. Other studies have combined web browsing data and online survey data to analyze how people share fake news in political elections. The study found that the public's behavioral preferences have a significant impact on the trust in misinformation and that the public is more willing to believe stories about politicians they support, even if the stories are false and full of implausible elements [25]. In the field of psychology, some studies measured the accuracy of respondents' perception of misinformation by conducting the Cognitive Reflection Test (CRT) for the respondents, and it was found that the better the respondents performed in the CRT test, the more likely they were to detect misinformation and the more accurate they were. The findings of the study prove the importance of psychological factors. When the public is more inclined to use analytical thinking rather than lazy thinking when identifying information, they are more likely to recognize the difference between true and false information [26]. Studies have also paired Twitter data with public accounts during elections to analyze the process of spreading fake news, and they found that psychologically conservative people are more likely to be exposed to fake news and less able to spot it. Related studies have confirmed the influence of psychological factors on the identification of misinformation [27]. In the field of media literacy, some scholars believe that the public's general trust in the misinformation spread on social media mainly stems from the lack of digital media literacy. The study has used survey data from the US and India during elections to assess the effectiveness of media literacy campaign interventions, and the findings confirm that digital media literacy plays an important role in the identification of misinformation [28]. Some scholars have conducted empirical studies to evaluate whether individuals with higher media literacy are more capable of identifying fake news and compared different media literacy aspects such as information literacy and news literacy. The results verified the effectiveness of information literacy, which can effectively enhance the public's ability to identify misinformation [29]. These studies also provide references for us to understand the spread of misinformation on social media from multiple perspectives, and help us further understand the reasons why Internet users share and spread misinformation on social media.

2.2. Misinformation and Content Analysis. Social media has become an important mode for the public to communicate and obtain relevant information by virtue of its unlimited access. However, due to the lack of online supervision and user anonymity, the line between true information and

misinformation is not always easy to distinguish, which makes the public often face the risk of being misled when accessing relevant information. And, the unique echo chamber design of social media platforms allows people with a common need for information to gather together. Although this facilitates communication among people in the same situation and increases the possibility that the public will have access to the true information they need, it also amplifies the negative impact of misinformation [30]. Moreover, the interaction and fusion of true information and misinformation on social media platforms have also attracted many scholars to study the dissemination of misinformation and conduct quantitative research on it. For example, some scholars extracted Ebola-related tweets from social media and coded them by using professionals with knowledge background to evaluate the proportion of the extracted tweets that contained specific content. It was found that ten percent of the relevant tweets contained misinformation [31]. Another study conducted a content analysis on the misinformation about COVID-19 and found that only thirty-eight percent of the misinformation about COVID-19 on social media platforms was completely fabricated, and most of the misinformation was formed by distorting and falsifying the true information [32]. The relevant findings confirm the current situation of integration and fusion of misinformation and true information on social media, which can help us understand the evolution and diffusion pattern of misinformation on social media.

In addition to using content analysis to distinguish true information from misinformation, relevant studies have also focused on the characteristics of the spread of misinformation on social media, especially how misinformation spreads relative to true information [33]. For example, by examining the differential distribution of large-scale true information and misinformation on social media platforms, a study found that misinformation had the characteristics of faster propagation speed, longer propagation path, and wider propagation range than true information. Moreover, the information content of misinformation was often more novel than true information, so it was more likely to be shared by the public on social media. It was also found that the content of misinformation was more likely to stimulate emotions such as fear, surprise, and disgust than the emotions such as anticipation, sadness, and joy evoked by true information [34]. Some studies also pointed out that the misinformation can be spread more quickly when the content of misinformation was related to major public crisis events. For example, during COVID-19 in 2019, the amount of misinformation exploded and spread worldwide in a very short spread. According to relevant agencies, during the spread of the epidemic, about 46,000 instances of epidemic-related misinformation were spread on social media every day and spread rapidly with retweets from Internet users [35]. In addition to these studies, some scholars have also tried to understand the sources and evolutionary patterns of misinformation by means of content analysis. Based on the analysis of massive amounts of Twitter data, it was found that most of the misinformation on social media was generated by general accounts, but the content often contained

links to websites that lacked credible sources. It was also found that the spread of misinformation on social media was a **dynamic process** in which the content undergoes dynamic changes, i.e., it was constantly modified by network users to spread at the next step in the process of spreading [36].

The content analysis method based on misinformation is important. On the one hand, misinformation content conveys **bias and misunderstanding** which may affect the public's trust in experts, institutions, and governments, leading to the spread of unnecessary fear and suspicion. For example, studies have pointed out that the majority of the public relies on online comments to evaluate and judge enterprises and institutions, and maintains their trust in relevant institutions under the influence of online comments. ~~However, online comments containing misinformation can exacerbate public prejudice and misunderstanding [37]. On the other hand, misinformation can also reverse the public's behavioral response to natural disasters, accidents, public health, and social security emergencies. For example, studies have pointed out that with the development of the Internet, social media has become an important channel for the public to seek health information. However, the authenticity of health information will significantly affect the treatment of patients and threaten their lives [38]. Therefore, the content analysis method is used to analyze the misinformation on social media to understand the content characteristics of the misinformation. It is not only beneficial to identify misinformation on social media, but it also can contribute to the governance of misinformation and the maintenance of network security.~~

2.3. Misinformation and Emotion Analysis. The spread of misinformation on social media implies **different emotions** of the public, and the emotions also change with the spread of misinformation. On the one hand, in addition to the influence of specific social conditions, the **psychological state** is an important factor in the production of misinformation, which is formed as an additional product of public events under the adaptive condition of public emotions [39]. On the other hand, emotions also play an important role in spreading misinformation on social media. It is because they can meet some psychological needs of the public that misinformation keeps forming and spreading on social media. Related studies point out that the spread of misinformation is inseparable from emotions, and misinformation can spread rapidly when a group falls into negative emotions such as anxiety [40]. Therefore, it is particularly important to analyze the misinformation on social media based on emotion analysis.

Among the research on misinformation using the emotion analysis method, **exploring the influencing factors of emotion changes in misinformation** is an important object of research. For example, some researchers explored the factors influencing the emotional dynamics in misinformation by quantitatively analyzing the emotional behaviors of Internet users on social media. Studies have found that misinformation contains far more negative emotions

than other kinds of information, while factors such as user engagement, number of comments, and time of discussion all had an impact on the change of emotions in misinformation. Generally, the more active the users are, the more comments they make, the longer the discussion takes, and the more dominant negative emotions become [41]. ~~Studies have also been conducted to study misinformation active on social media during public crises as the research object and to identify emotions of Internet users in relation to comments under the misinformation.~~ It was found that both the gender of Internet users and the subject category of the content had an impact on the change in emotions [42]. Some studies conducted **sentiment analysis** on popular misinformation on social media based on content analysis methods and found that as the content, form, and linguistics of misinformation changed, so did the public's sentiment. In general, the more conflicting the content of the misinformation, the more attractive the font (e.g., colorful fonts are more attractive than regular fonts), and the more exaggerated and extreme the use of language, the more intense the change in public sentiment would be [43].

In addition to analyzing the influencing factors of emotions, it is also an important topic to understand the evolution pattern of emotions triggered by misinformation on social media. On the one hand, social media exists as a disseminator of misinformation, and when the public has emotional fluctuations under the influence of misinformation, social media often magnifies the impact of emotions and makes emotions spread rapidly in social networks. On the other hand, the spread of emotions on social media often exists in some regular form. By analyzing a certain amount of text data, we can try to reveal the **evolution law of emotions** on social media. For example, a study combined with network science to analyze the sentiment of misinformation about the political election in Twitter, and found that posts with negative sentiments last longer than those with positive or neutral sentiments. At the same time, misinformation about the election winners had a broader diffusion network in the social media, and more positive sentiments representing likes and support among them [44]. Some studies used big data-driven approaches to conduct sentiment analysis on the "viral" spread of false and true information about natural disasters on social media based on massive data. The study found that **tweets with negative emotions spread faster than tweets with positive or neutral emotions**. It was also found that emotions had an opposite effect on the "viral" spread of true and false information on social media [45]. Based on data from social media chat platforms, some studies have also attempted to map the trends in public sentiments over time related to misinformation. The study not only confirmed that the proportion of negative emotions triggered by misinformation was more than positive emotions but also found that negative emotions were affected by event information in an inverted U-shaped curve over time. When event information was further revealed, when handling measures and coping methods were introduced or falsified information appears, the proportion of negative emotions caused by misinformation would decrease and the negative emotions brought by misinformation would be weakened [46].

To sum up, the active misinformation on social media brings mainly negative emotions, which not only affects the public's psychology and behavior and increases the difficulty of network public opinion governance but also has an impact on the stability of social order and the maintenance of social security. Therefore, combining with network analysis methods, and analyzing the law of spreading emotions of misinformation in social networks is not only beneficial to provide suggestions for emotion management when online public opinions occur but also to better achieve guidance and prevention and control of online public opinions, and thus eliminate the negative effects brought about by the changes in group emotions.

3. Research Methods

This paper selects misinformation as the research object and compares the network structure of misinformation and true information on social media to better reveal the diffusion and evolution law of misinformation on social media, and provides a reference for the public opinion management of misinformation. The frame structure diagram of the study is shown in Figure 1. Firstly, we obtained misinformation, true information, and the corresponding public opinion datasets on social media, and completed the data pretreatment. Secondly, we combined deep learning methods to conduct content analysis and emotion analysis on misinformation and true information data and tried to compare the diffusion patterns of misinformation and true information on social media using network analysis methods. Finally, we drew a correlation graph to show the disturbance of misinformation and true information on the network structure and revealed the evolution pattern of misinformation and true information in the network.

3.1. Network Analysis Method. ~~As a research method for analyzing interpersonal relationships, the network analysis method has been widely used in various disciplines.~~ One of the most typical and well-known network analysis methods belongs to the social network analysis method, which is a combination of methods and tools for studying interpersonal relationships, interactions, and communication, and has been adopted by a large number of researchers and research fields [47]. In the social network analysis method, we describe the relationships between people in the social network through the concepts of nodes and edges. Nodes which are defined as individuals or groups are connected in a certain direction by the edge representing the relationship to form a social network graph [48]. With the social network analysis method, we can understand the sparse relationship between participants in social networks. At the same time, we are able to analyze the importance of the location of participants in the social network by measuring network centrality and identifying important and isolated participants in the network [49]. In short, the social network analysis method is able to analyze not only the breadth (scope) but also the depth of the relationship between participants, providing support for exploring the interpersonal interaction and the degree of communication.

With the development of network technology, the online social network formed on the basis of social media has become an important part of interpersonal activities. Compared with traditional social networks, online social networks are characterized by higher participation, larger network scale, faster changes in network structure, and wider network influence [50]. At the same time, the online social network has a rapid growth rate, and has penetrated people's daily lives, and provides everyone with a convenient way to communicate. Unlike traditional social network analysis methods, online social network analysis methods mainly focus on the flow and dissemination of information on social media and have become an important research method in the field of machine learning, data mining, and complex network systems with the support of massive social media data [51, 52]. In the analysis process of online social network analysis methods, on the one hand, social media users act as individual nodes of the network, and the forwarding of information among users constitutes a propagation relationship, and the network structure is shown by visual methods. On the other hand, relevant information continues to evolve and spread in social networks through user interactions such as comments, favorites, and reposts. Through the online social network analysis method, we can not only analyze the structure of communication and interaction among network users but also explore the propagation evolution pattern of a certain event with the support of social media data. Therefore, we use the network analysis method to analyze the propagation pattern of misinformation on social media.

In this paper, we used the network users involved in the spread of misinformation as nodes and the forwarding relationship between users as edges to map out the network structure of misinformation. In addition, in combination with the content analysis method and emotion analysis method, we analyzed the network diffusion characteristics of misinformation, such as the number of reposts, favorites, and comments of misinformation, and then explored the evolution pattern of misinformation in social networks. At the same time, considering that only misinformation was not enough to investigate the evolution of misinformation on social media, we also selected the corresponding true information as the comparison object. Through the comparison of the spread of misinformation and true information on social media, we can gain an insight into the evolutionary diffusion characteristics of misinformation on social media.

3.2. Content Analysis Method. In this paper, we used the content analysis method to analyze the data and summarize the topics of misinformation and true information. Firstly, after data preprocessing, to reduce noise interference and the need for further filtering the data in this paper, we used the TF-IDF method to extract text keywords based on the importance of the words. According to the frequency of words in the text and corpus, we extracted 20 keywords most important in the text using the TF-IDF method based on the weighted processing.

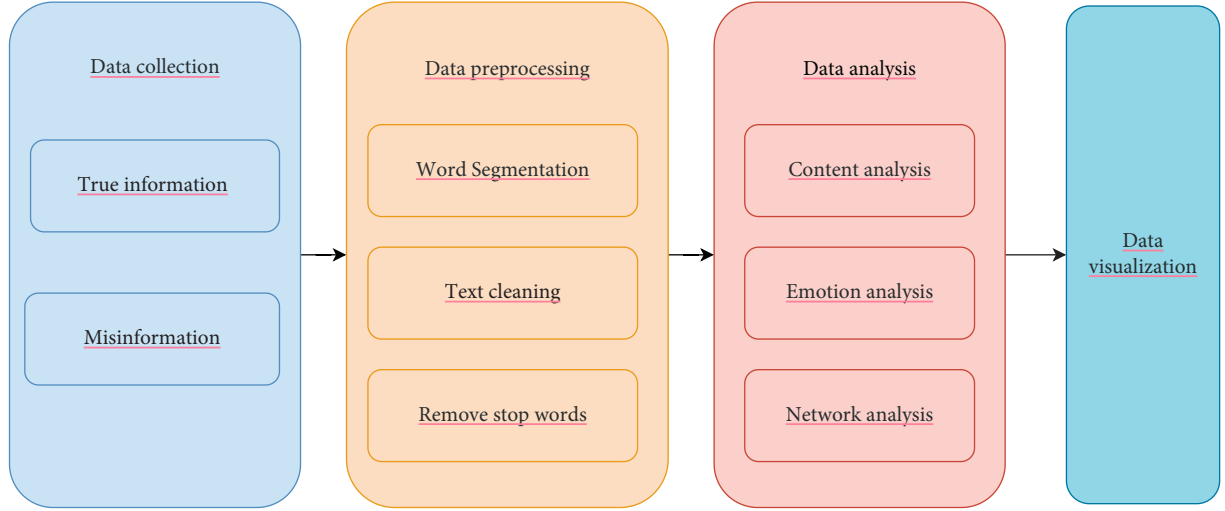


FIGURE 1: Research frame diagram.

Secondly, we need to **extract semantic features** according to the meaning of words in the language environment and the relationship with other words and then **transform semantic features into feature vectors**. In general, **discrete representation and distributed representation are commonly used for word representation in the computer**. The difference is that the former represents each word as a long vector, while the latter represents each word as a dense continuous vector of fixed length. Compared with the former, the latter can not only save the vector space but also better represent the relationship between words. Therefore, in existing studies, distributed representation has often been adopted by researchers to represent word vectors [53]. In this study, we used the **Word2vec** method introduced by Google to convert text data into word vectors and mapped text content into vector space to **calculate the similarity between words** [54]. The Word2vec model is mainly composed of the **Continuous Bag-of-Words model**, which predicts the current word based on the upper and lower words, and the **Continuous Skip-gram model**, which predicts the context word based on the current word. In the analysis of large sample datasets, the effectiveness of the CBOW model in text analysis has been confirmed by previous studies. Compared with the Skip-gram model, the CBOW model has greater advantages in analysis efficiency and analysis speed [55]. Therefore, we used the CBOW model to complete the training of word vectors and convert text data into word vectors.

Finally, we analyzed the topics of misinformation and true information based on **the K-means clustering method**. By using the K-means method, the study divided the processed sample set into K categories and tried to minimize the distance between samples in each category and maximize the distance between categories, which in turn could be achieved based on setting the clustering category as $\omega_1, \omega_2, \omega_3, \dots, \omega_k$. The calculation process of the least square error is shown in equation (1). **The minimum squared error is denoted by β** , and the different clustering categories are denoted by ω_n . The documents and mean vectors in the clustering category are represented by w and φ_n , respectively.

$$\beta = \sum_{n=1}^k \sum_{w \in \omega_n} \|w - \varphi_n\|^2. \quad (1)$$

As a common **unsupervised clustering method**, K-means mainly achieves the classification of different categories through similarity, where K and means, respectively, represent the **number of clustering categories** and the **mean value of clustering vectors**. A common method used to measure the size of K is the Elbow method, and the distance is measured by the cosine distance or Euclidean distance formula [56]. Using the Elbow method, we selected different K values to cluster the sample set and calculated the square sum of the error between the document vector and the clustering mean vector, based on which the curve of the sum of the square error is plotted. By observing the comprehensive curve of the square error, we could find that the square error varies with the value of K. Accordingly, we could infer the appropriate value size of K, and then classify the misinformation and true information topics into K categories.

3.3. Sentiment Analysis Methods. With the expansion of social network corpora built on social media platforms, sentiment analysis has become an important research field in natural language processing and text mining. Sentiment identification and analysis of comments, opinions, and other texts in the social network corpus through sentiment analysis not only provide data support for our understanding of the dissemination pattern of information on social media and the change of public sentiment but also enable further explanation of the behavior logic behind social networks of Internet users [57]. At present, common sentiment analysis methods are mainly divided into two categories. **One is by building sentiment dictionaries and combining semantics to compare the similarity between the text keywords in the sample data and the sentiment words in the dictionary and then calculating the sentiment intensity of the text keywords to assign the corresponding sentiment**

labels to the text [58]. The other is to use machine learning methods such as SVM, Naive Bayes, or deep learning methods based on neural networks to conduct bias analysis of sentiments in a supervised way and assign corresponding sentiment labels to texts [59]. However, in the sentiment analysis based on the sentence types of social media platforms, the approach based on sentiment dictionaries often has an impact on the final sentiment classification results due to the neglect of context. Therefore, machine learning and deep learning methods are often used in sentiment analysis of social network data. However, taking sentiment analysis as an example, SVM, CRF, and other machine learning methods excessively rely on manual labeling data and have limitations in processing natural data in the original form. Deep learning methods combine simple but nonlinear modules to learn complex functions and the self-learning feature of deep learning greatly improves its application ability in the field of natural language and shows better effect in sentiment analysis [60, 61].

In sentiment analysis of sentence-level objects, long- and short-term memory models that can learn word vectors of different lengths have shown better performance in sentiment classification and have been widely used by researchers [62]. As a result of the further development of the recurrent neural network, the LSTM model retains the flexibility of recurrent neural networks in learning contextual information of text sequences and addresses the difficulty of traditional recurrent neural networks in storing information for long periods of time. Similarly, the LSTM model remains structurally consistent with recurrent neural networks, but the internal structure is composed of the cell circulation state C , input gate I , forgetting gate F , output gate O , and hidden state output θ , which differs from that of the recurrent neural network. Among them, the final output of the model is completed by tan transformation of the current state. The calculation process is shown in Equation 2, where θ_T represents the output of the hidden state at time T , and O_T and C_T , respectively, represent the state of the model output gate cell unit at time T .

$$\theta_T = O_T * \tan\theta(C_T). \quad (2)$$

The output gate of the model determines what should be output by calculating the sigmoid layer, and the calculation process is shown in equation (3), where O_T denotes the state of the output gate at the moment of T , θ_{T-1} denotes the output state at the previous moment, φ_T denotes the input state of the information at the current moment, ω_O and b_O denote the weight and deviation of the output gate, and the activation function is denoted by σ .

$$O_T = \sigma(\omega_O \theta_{T-1} + \omega_O \varphi_T + b_O). \quad (3)$$

As an important stage of model operation, the cell renewal is an intermediate stage in which input information passes through the input gate, the forgetting gate, and finally enters the output gate. The cell state update is updated as shown in equation (4), C_T , F_T , and I_T denote the state of the cell unit, the forgetting gate, and the output gate at the moment of T , respectively, and the weights and deviations are denoted by ω_C and b_C .

$$C_T = F_T * C_{T-1} + I_T * \tan\theta(\omega_C \theta_{T-1} + \omega_C \varphi_T + b_C). \quad (4)$$

The forgetting gate determines what information should be discarded and the calculation process is shown in equation (5), where σ denotes the activation function, ω_F and b_F denote the weights and biases of the forgetting gate, respectively.

$$F_T = \sigma(\omega_F \theta_{T-1} + \omega_F \varphi_T + b_F). \quad (5)$$

The main work of the input gate in the model structure is to decide which information should be input, as shown in equation (6). In this case, the weight and deviation of the input gate are denoted by ω_I and b_I , respectively.

$$I_T = \sigma(\omega_I \theta_{T-1} + \omega_I \varphi_T + b_I). \quad (6)$$

Although the LSTM model performs well in processing the input context sequence in this paper, the model also has some shortcomings in that it cannot consider the direction of input and can only process text sequence context in one direction. Therefore, we adopted a bidirectional long- and short-term memory model, which can process text sequences from left to right and from right to left by two parallel long- and short-term memory models. Compared with the long- and short-term memory model, the bidirectional long- and short-term memory model can obtain past and future information and concatenate the hidden states in the backward and backward directions, and output contextual information through the same output layer. It not only improves the scope of text processing but also improves the efficiency of text processing. The calculation process of the final output Z of the model is shown in the following equation:

$$Z_T = \omega_Z \theta_T + b_Z. \quad (7)$$

In this paper, we used the training and test sets from the NLP&CC dataset, and the emotion labels in the dataset were "like," "surprise," "disgust," "sadness," "happiness," "anger," and "fear," respectively [63, 64]. In our study, we used a bidirectional LSTM model to assign emotion labels to text data. The test accuracy of the model met our research needs and was expressed as 0.71. Meanwhile, to further improve the accuracy and efficiency of the model emotion, we randomly grabbed 200,000 Weibo tweets for pre-training. Based on the pre-training, we implemented the analysis of both misinformation and true information datasets. Finally, we assigned emotion tags to each Weibo tweet in the misinformation dataset and the true information dataset to study the pattern of emotional evolution in social networks.

4. Results and Discussion

4.1. Data Collection and Preprocessing. In this paper, we chose the large open-source dataset of the Sina Weibo platform as our analysis object [65]. As one of the most popular social media platforms in China, Sina Weibo has about 530 million active users and has established a huge online social network, which also provides rich data sources to investigate the spread of misinformation in social

networks. Datasets are open-source datasets from 2015 and 2016, mainly composed of misinformation and true information datasets. We obtained the relevant content and forwarding information of each original microblog in the dataset and constructed the dissemination network of misinformation and true information on social media. Among them, the misinformation in the microblog dataset came from the information that has been falsified by the Sina Community Management Center. At the same time, the dataset also collected a similar amount of true information for comparative studies. True information and misinformation were present at the same time, which attracted extensive public attention and the content had been proved to be true. The details of the misinformation dataset and the true information dataset are shown in Table 1.

Table 1 shows the statistics of the dataset. Among them, there were 2351 true information tweets and 1717154 retweets. The original Weibo tweets were retweeted 52,158 times at most and 12 times at least, with an average of 730 retweets. The number of misinformation tweets was 2313, and the number of retweets was 2093056. The original Weibo tweets were retweeted 59,319 times at most, 11 times at least, and 905 times on average.

4.2. Network Structure of Misinformation. Through the microblog ID and forwarding relationship in the dataset, we can understand the diffusion of true information and misinformation in the social network. Meanwhile, based on the Mid of microblog, we obtained the secondary and tertiary forwarding information of some true information and misinformation in the process of forwarding, so as to construct the dissemination network of true information and misinformation on social media. Based on this, we used the Fruchterman Reingold layout to draw the graph of the forwarding network. The spread graph of true information and misinformation on social media is shown in Figure 2.

In Figure 2, we can observe the network built by true information and misinformation on social media. Considering the limitation of space, we randomly selected and showed the spread of some true information and misinformation on social media. Among them, Figure 2(a) shows the forwarding network built by true information and misinformation on social media, with the purple node representing misinformation events and network users who forward misinformation, and the green node representing true information events and network users who forward true information. Figures 2(b) and 2(c) show the network diffusion structures of misinformation and true information, respectively.

Firstly, in the network graph composed of misinformation and true information, the network structure of true information or misinformation is sparse, the number of edges is much smaller than the number of nodes, and there are many isolated nodes. This may be related to the nature of the content of the dataset. The dataset we adopted consists of different misinformation events and true information events, and the connection between the events is not very close. Although there are crossover relationships between

some events, most of them are differentiated and exist in an isolated form during the forwarding process. Combined with text materials, most of the related events in the original data collected were related to the topic. For example, when referring to food safety events, users often enumerate previous similar events for comparative analysis, which was also an important reason for the network connection between different events. Secondly, in the dataset adopted in this paper, although the number of events of misinformation is smaller than that of true information, the forwarding relationship of misinformation is much more than that of true information. It can also be intuitively observed from Figure 2 that the network graph of misinformation is denser and the nodes are more closely connected to each other than the network graph of true information. Compared with true information, misinformation has more advantages in both the scope and depth of diffusion and is more likely to attract the attention of the public and be spread by the public in social networks. Combined with text materials, misinformation in social networks often exists with exaggerated titles and contents, which are more likely to be noticed and retweeted by the public. This also tentatively confirms the conclusion of existing studies that misinformation is more likely to be disseminated on social media than true information.

4.3. Topic Categories of Misinformation and True Information. Based on the obtained dataset of misinformation and true information, we divided the data into seven categories by using the clustering method and determined the topic tag and interpretation content of each category in conjunction with the information content. However, considering the information content embedded in the event microblog was not always easy to distinguish, there are often situations involving multiple topics. Therefore, researchers extracted the top keywords of each topic and matched the extracted keywords with the text information of the event microblog. If the text information of the event microblog conforms to multiple keywords, the Weibo tweet would be given the corresponding topic tag, while the microblog that did not match the keyword would be given the corresponding topic tag according to the content by manual annotation. The topic categories for true information and misinformation are shown in Table 2.

It can be observed from Table 2 that the distribution of the number of microblogs is in an unbalanced state among the seven topics divided into true information and misinformation. Firstly, both true information and misinformation microblog posts are distributed in the largest number in the field of food and product safety. Food and product safety involves everyone's daily life, so it is most likely to breed misinformation and true information. Existing studies have also revealed the causes of misinformation and true information related to food and product safety from multiple perspectives such as education level, gender, age, and media reports [66].

Secondly, true information and misinformation are distributed in public safety and crime topics only second to

TABLE 1: Descriptive analysis of the dataset.

Descriptive analysis	True information	Misinformation
Tweets (i.e., original posts by Sina Weibo users)	2351	2313
Retweets (i.e., reposted messaged by Sina Weibo users)	1717264	2093056
Maximum forwarding relationship	52158	59319
Minimum forwarding relationship	12	11
Average forwarding relationship	730	905

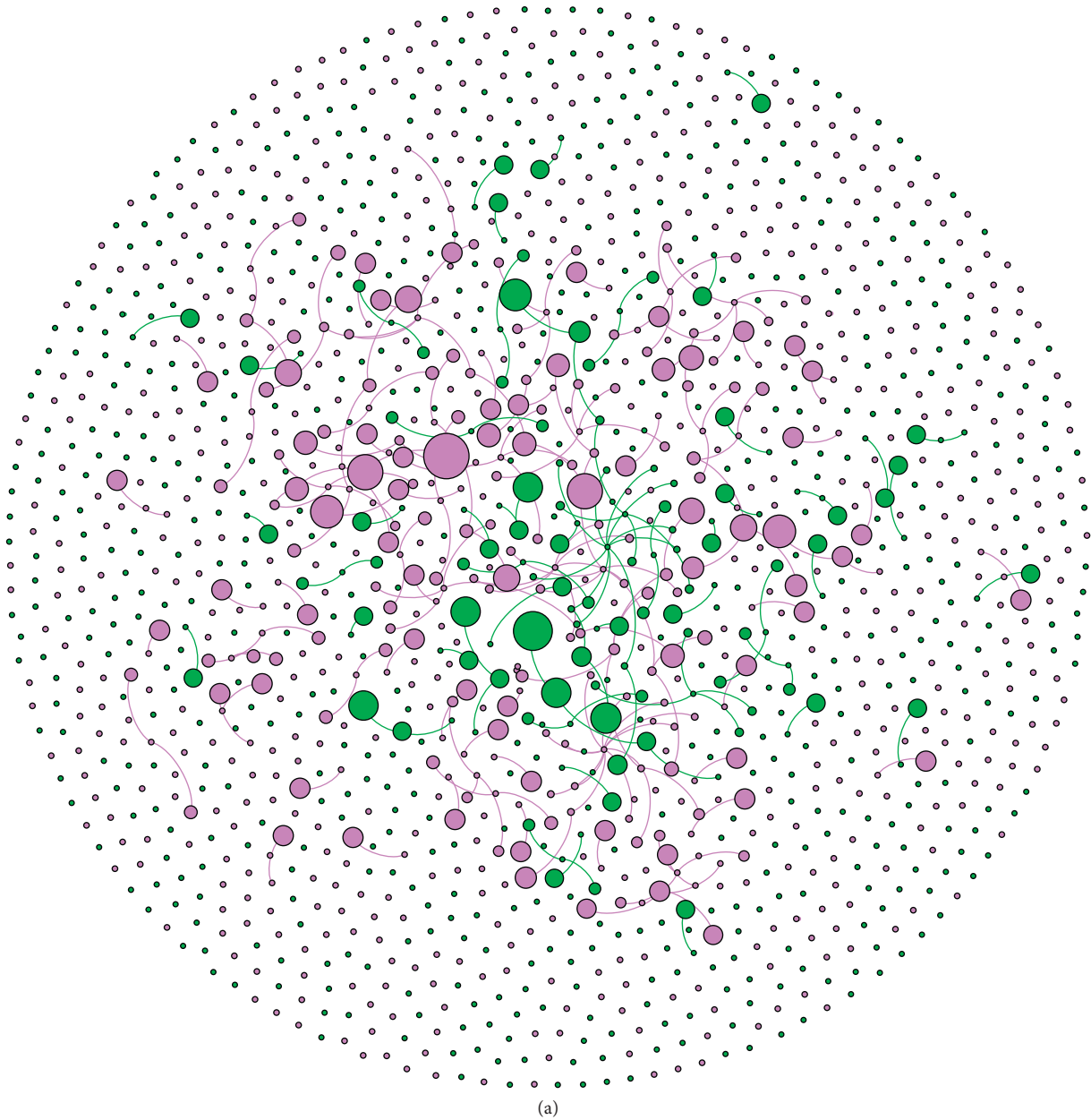
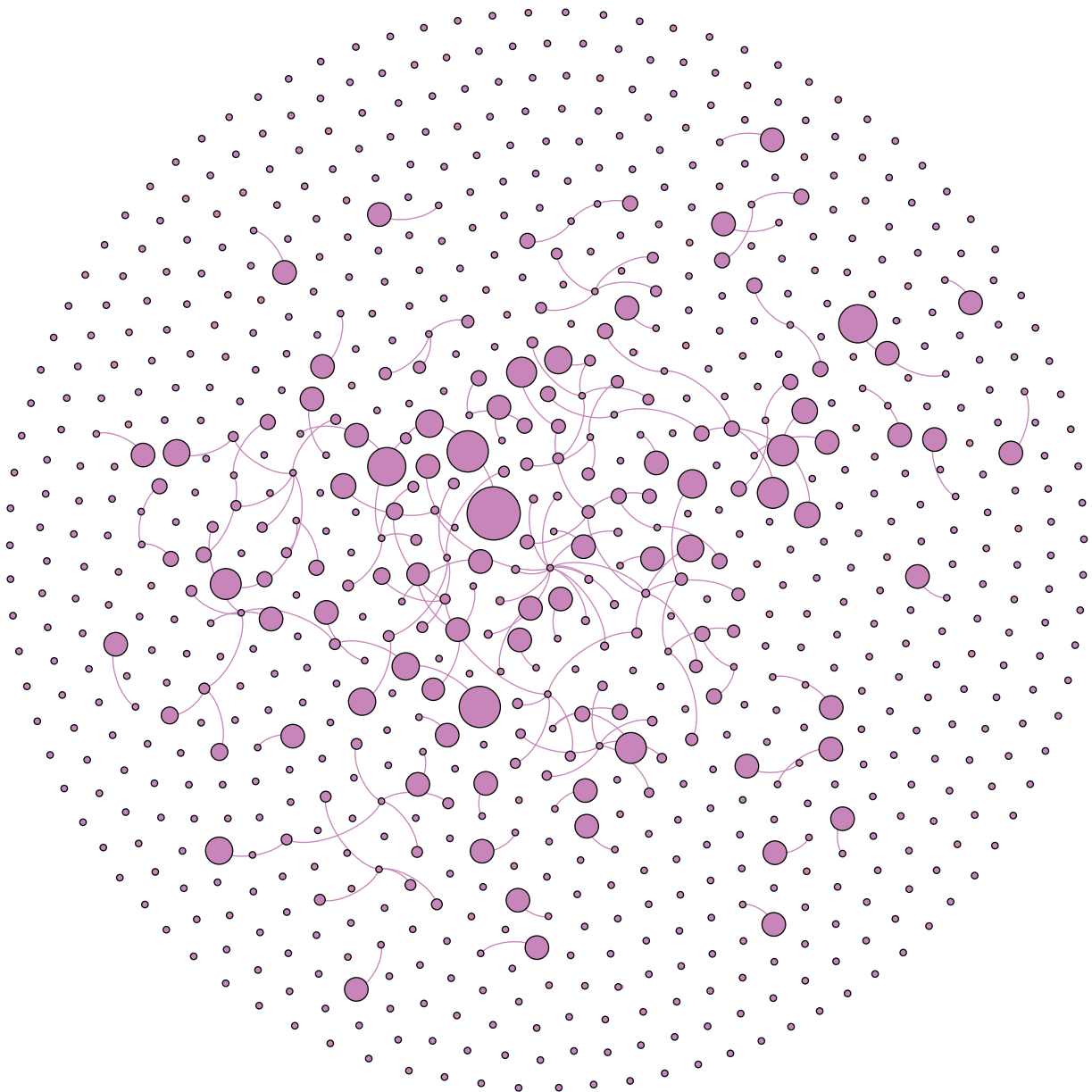


FIGURE 2: Continued.



(b)

FIGURE 2: Continued.

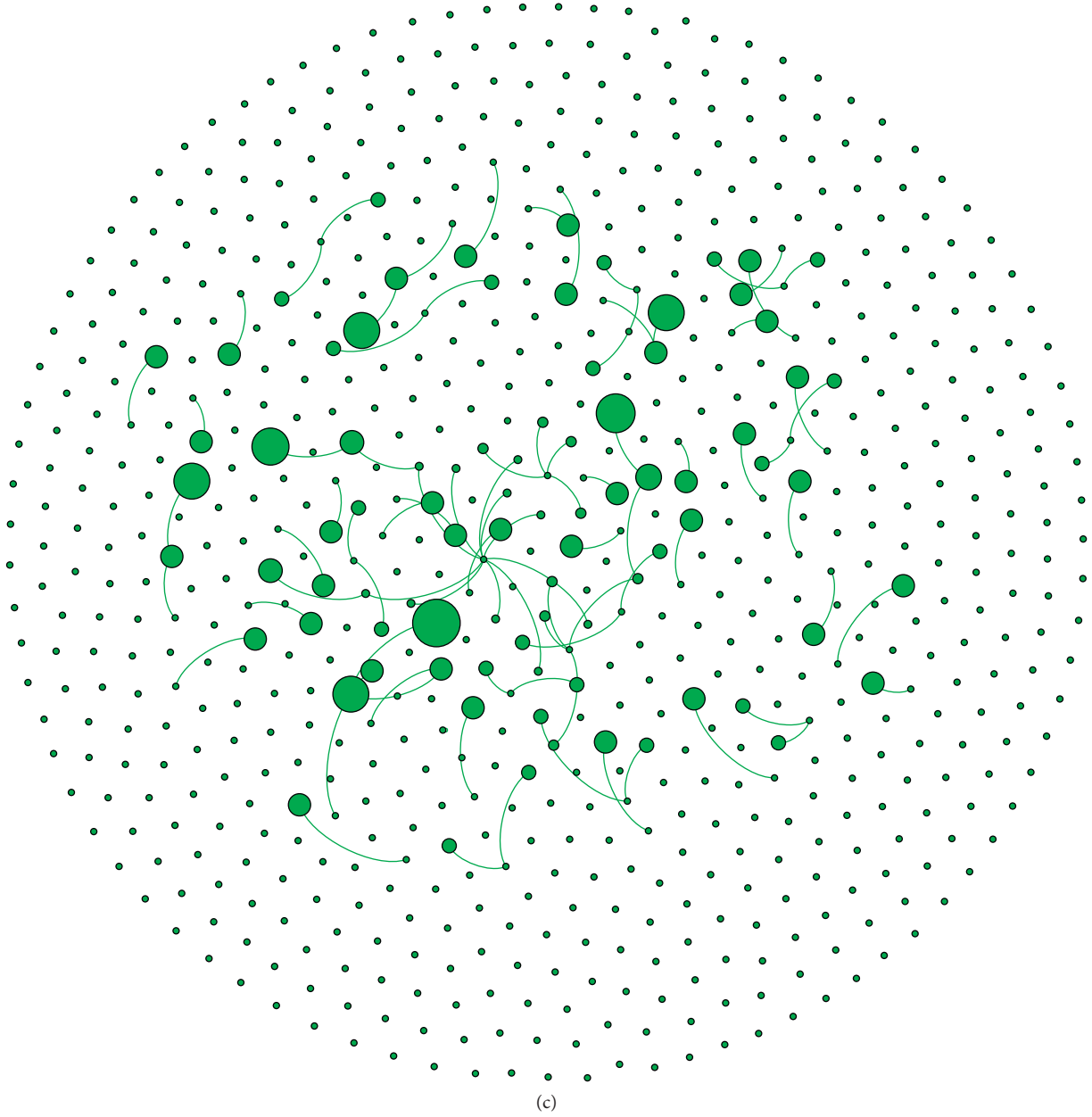


FIGURE 2: An illustration of the forwarding network. In the figure, the node represents the microblog ID and the edge represents the forwarding relationship between the microblogs. (a) True information and misinformation. (b) Misinformation. (c) True information.

TABLE 2: Topic categories of true information and misinformation.

Topic type	Topic content	True information	Misinformation
Public security	Information related to public safety and social security incidents	145	259
Food and product	Related to the safety of the diet or certain type of product	1618	1430
Politics	Information related to political events, politicians, or major policies	74	87
Celebrity	Celebrity information such as anecdotes	26	9
Crime	Information related to criminal events and people	269	358
Disaster	Information related to natural disasters or accidents	79	49
Social events	Involving a strong social response, biased towards folk tales	78	84

food and product safety areas. The difference between the public safety theme and the crime theme lies in that the former has a wider scope, involving national security, social

security, and personal security, while the latter is mainly for acts that violate the law generated by individuals or small groups. The reason why the two topics rank high in terms of

the number of topic distribution is not only because such incidents are most likely to trigger public anger, sympathy, and other emotions but also because related events are easy to be favored and extensively reported by the media. Therefore, both true information and misinformation have a large number of microblogs in public safety and crime topics.

The political topic mainly involves information about political events, politicians, and major policies. On the one hand, the public tends to pay more attention to politics and is keen on discussing and paying attention to events and information related to politics. On the other hand, it is also because the major policies issued by the government often affect every field of society and everyone's life. However, there are also some individuals or groups who misinterpret policies for personal gain, allowing misinformation to spread.

The disaster topic mainly involves natural disasters and accidents that cause economic and property losses to the public and threaten the safety of the public. When natural disasters or accidents occur, social media, as a convenient way of communication, becomes an important platform for the public to share disaster information and seek help. Therefore, there often is a wide public discussion under related topics. However, social media's weak falsification capabilities have also led to the widespread dissemination of misinformation about events such as natural disasters and accidents. For example, disaster-related information is often distorted on social media by exaggerating the number of people, distorting the real situation of events, conspiracy theories, and other ways.

Social events and celebrity topics are more targeted, with the former mainly targeting events that arouse social responses and discussions and concerns about the public, and the latter mainly responding to celebrities and other celebrity-related events. However, these two types of events tend to cover only some groups; for example, the former is more geographically differentiated, the latter is more distinguished by demographic attributes such as fans. The distribution of true information and misinformation is less compared to other topics.

4.4. Diffusion Characteristics of Misinformation and True Information. To further compare the evolution pattern of misinformation and true information in social networks and understand the diffusion characteristics of misinformation and true information, we tracked the forwarding relationship of each original microblog and measured the diffusion characteristics of datasets of misinformation events and true information events by using the three indicators: the number of retweets, number of comments, and number of favorites of microblog. The number of retweets mainly refers to the accumulation of the diffusion index of posts in social networks constructed by social media, which measures the diffusion degree of microblog posts. The number of comments refers to the accumulation of user interaction index for posts in the social network, which measures user engagement of microblog posts. The number of favorites

mainly refers to the accumulation of the number of times that posts are collected by users in social networks and measures the user acceptance and recognition degree of microblog posts. The three indicators involve several diffusion characteristics, such as the diffusion range, diffusion participation, user acceptance, etc., which can give us a more comprehensive understanding of the diffusion patterns of misinformation and true information in social networks. Table 3 shows the difference between true information and misinformation in the number of retweets, favorites, and comments on the microblog.

It can be observed from Table 3 that each true information event is forwarded about 924 times (SD 2706.101). Among them, a maximum of one true information was forwarded 81,776 times, and at least one true information was forwarded 30 times. From the point of view of the number of favorites, the average of each true information was about 648 times (SD 1961.269), true information was saved 40,873 times at most, and at least one was not saved. In terms of the number of comments, there were about 387 comments (SD 1061.163) on average for each true information event on Weibo, with a maximum number of 26,275 comments and a minimum number of no comments. Skewness and kurtosis represent the asymmetry and steepness of variables, respectively. Through the observation of skewness and kurtosis, we found that the number of retweets, favorites, and comments of true information was all rightward and steeper, with a sharp peak. Among them, the rightward deviation and peak degree of the forwarding number was the deepest.

Based on the data in Table 3, we also found that each misinformation was forwarded about 2138 times (SD 6299.091), with the maximum number of forwards being 103682 and the minimum number of forwards being 88. In terms of the number of favorites, each misinformation was saved 521 times (SD 2308.874) on average, with the maximum number of favorites being 48889 times and the minimum number of favorites being 0 times. In terms of the number of comments, there were about 540 comments (SD 2261.956) for each misinformation on average, with the maximum number of comments being 38,103, and the minimum number of comments being 0. In terms of skewness and kurtosis, the number of forwards, favorites, and comments of misinformation all showed rightward deviation and peak state. Among them, the spikes of the number of collections were the most obvious, and the right skew of the number of comments was deeper.

At the same time, we also took the independent sample *T*-test to further compare the difference in diffusion characteristics between true information and the misinformation. The results showed that there were significant differences between true information and misinformation in the number of retweets, favorites, and comments ($P < 0.01$), and the mean value of the number of retweets and comments of misinformation was greater than the mean value of the true information, which means that the spread feature of misinformation would have been easier to be spread on social media had it been further verified. Compared with the true information, the public was more inclined to interact

TABLE 3: Diffusion characteristics of true information and misinformation.

	Retweets		Favorites		Comments	
	<i>T</i>	<i>M</i>	<i>T</i>	<i>M</i>	<i>T</i>	<i>M</i>
Mean	923.78	2138.09	648.23	521.28	386.97	540.36
Std. deviation	2706.101	6299.091	1961.269	2308.874	1061.163	2261.956
Maximum	81776	103682	40873	48889	26275	38103
Minimum	30	88	0	0	0	0
Skewness	17.022	7.913	8.716	10.581	10.751	11.033
Kurtosis	421.234	86.120	113.224	153.908	188.846	145.921
<i>T</i> value	−9.750**		16.139**		−1.816**	

Note. ** $P < 0.01$, *T* denotes true information, and *M* denotes misinformation.

and communicate around the misinformation in the social network, and it was more likely to forward and spread the misinformation, which makes the misinformation spread rapidly in the social network. At the same time, we also found that the number of true information events was greater than that of misinformation, which means that despite the rapid spread of misinformation on social media, people had higher levels of recognition and support for true information. Combined with text materials, this was related to the content characteristics of true information. True information usually contained more knowledge and had more detailed arguments, and was more likely to be collected by network users. As for misinformation, on the one hand, it often attracted users' attention through exaggerated titles, and then was retweeted by Internet users. On the other hand, with the help of misleading and controversial content, users often argued with each other, resulting in a large number of comments under misinformation posts. However, as misinformation can be easily proved to be forged and the polarizing debate also made users tend not to collect posts, the number of misinformation collected was smaller than that of true information.

In addition, we used the General Linear Model (GLM) to examine the differences in diffusion characteristics between different categories of topics in true information and misinformation based on setting the number of original Weibo users' followers as the control variable. GLM allows for multivariate analysis of variance and is often used to compare differences in means between two or more variables. First of all, we established the model according to the research needs and decided the model to be a univariate or multivariate analysis of variance. The difference between the two lies in the number of dependent variables. Secondly, we estimated the model through the test and got the value of the model test. And, we used statistical inference to calculate significance and values. Finally, after obtaining significant values, the meaning of the relationship needed to be explained. GLM statistics showed a significant interaction between information veracity and topic category ($F = 2.264$, Wilks' Lambda = 0.991, $P < 0.01$). The marginal estimates and confidence intervals on the number of retweets for true information and misinformation on different topic categories are shown in Figure 3. The marginal estimates and confidence intervals on the number of favorites are shown in Figure 4. The marginal estimates and confidence intervals for the number of comments are shown in Figure 5. At the same

time, to further conform to the normal distribution hypothesis, we carried out the logarithmic transformation on the number of retweets, the number of favorites, and the number of comments.

Combining marginal estimates and significance tests, we analyzed the diffusion characteristics of true information and misinformation in each topic category. For the topic categories of public security and politics, the estimated mean value showed that the diffusion index of misinformation in retweets and comments was higher than those of true information, and the diffusion index in favorites was lower than that of true information. However, there was a significant difference between misinformation and true information only for favorites. For the topic category of food and product, the diffusion index of misinformation in retweets and comments was also higher than that of true information, and smaller than that of true information in favorites, and there was a significant difference between misinformation and true information in all the three aspects. For the topic category of celebrity, there was no significant difference between misinformation and true information in the number of retweets, favorites, and comments, which may be related to the small sample size of the topic category of celebrity. For the topic category of crime, there was a significant difference between misinformation and true information in the number of retweets and favorites, and in the diffusion index of retweets, misinformation was larger than true information. In the diffusion index of the favorites, misinformation was less than true information. For the topic category of disaster, misinformation was larger than true information in the diffusion indexes of retweets and favorites, and there was a significant difference, which may be related to the occurrence of disaster information often accompanied by information of first aid measures. As for the topic category of social events, contrary to the previous topic categories, the diffusion index of misinformation was smaller than that of true information in both retweets and favorites, and there was a significant difference, which may be related to the fact that the true information of social events was easier to be identified, and it was more likely to arouse the emotions of Internet users.

To sum up, we further confirmed that in social networks, misinformation spread faster than true information in most cases, and was more likely to be forwarded and spread by network users. In terms of user participation represented by comments, misinformation was also in an advantageous

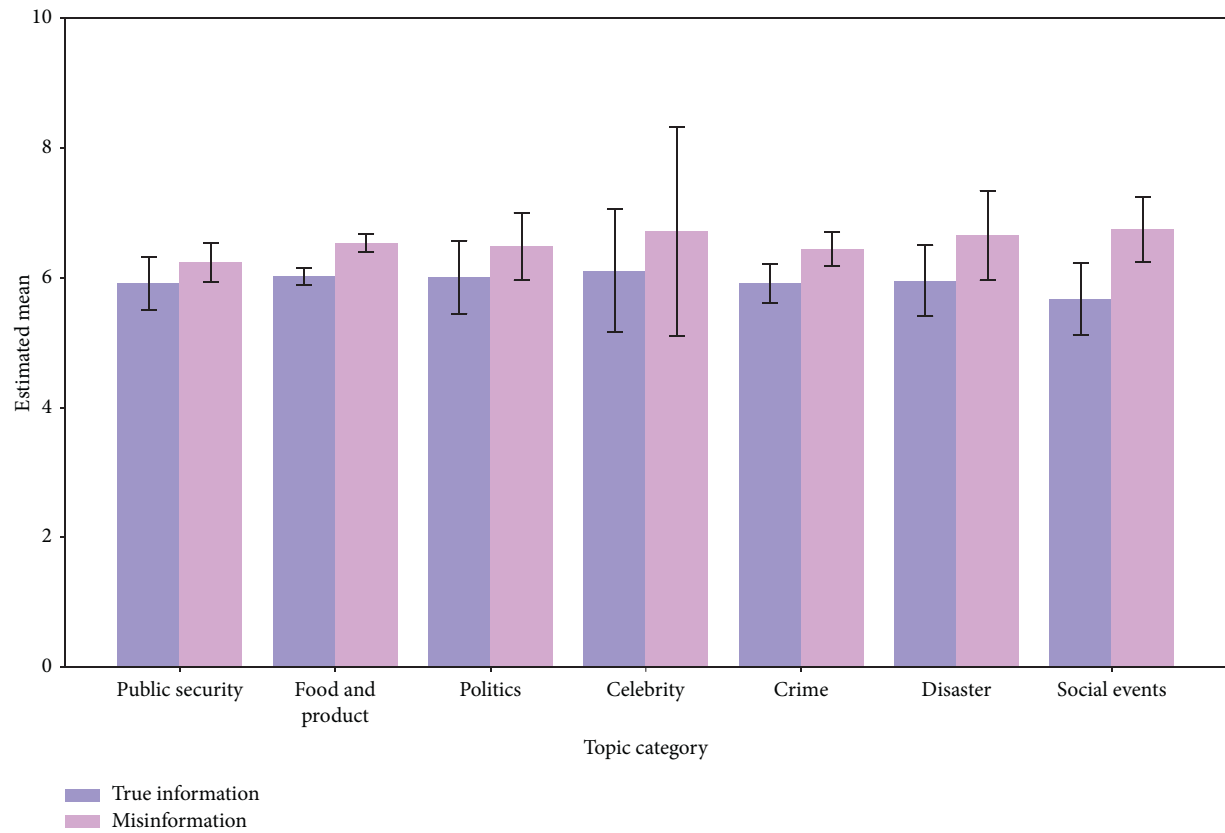


FIGURE 3: Estimated diffusion characteristics of true information and misinformation based on the topic category by the number of retweets.

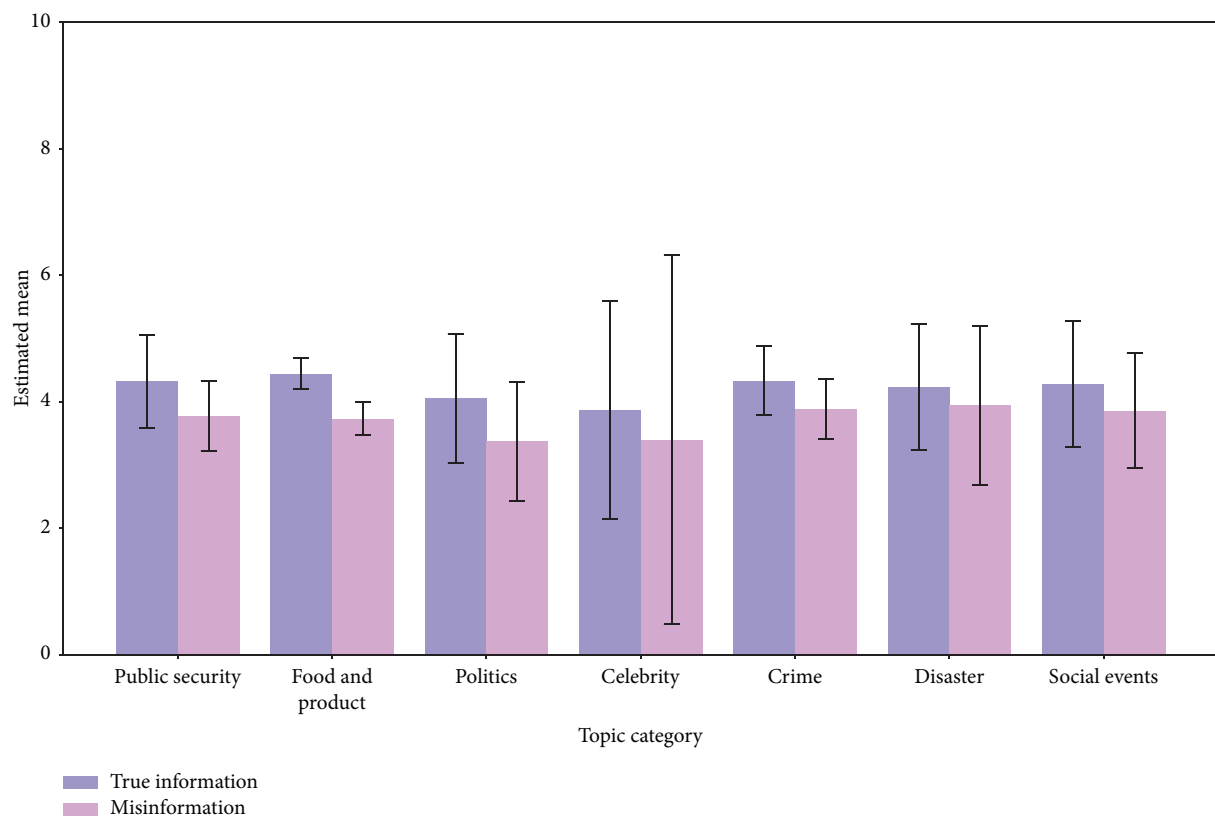


FIGURE 4: Estimated diffusion characteristics of true information and misinformation based on the topic category by the number of favorites.

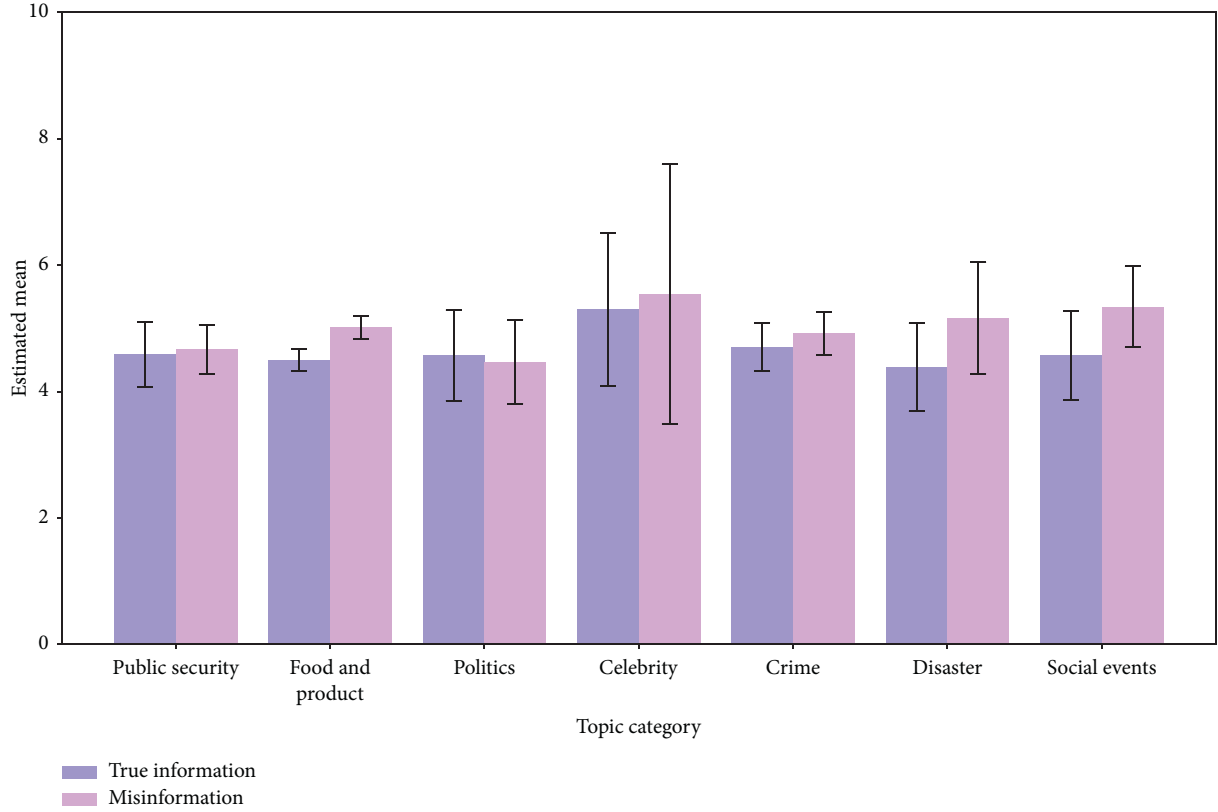


FIGURE 5: Estimated diffusion characteristics of true information and misinformation based on the topic category by the number of comments.

position compared with true information. However, in terms of the number of favorites, misinformation was generally less than true information, and true information was more likely to be recognized by the public for its more detailed content characteristics, and thus showed an advantage in terms of the number of favorites.

4.5. Emotion Changes of Misinformation in Topic Classification. After assigning emotion labels corresponding to misinformation and true information events, we first used the Chi-square test to analyze whether there was a significant difference in emotion distribution between misinformation and true information. The results confirmed the existence of significant differences in the distribution of information veracity across emotions (Pearson Chi-Square = 17.705, $P < 0.01$). Second, we compared specific differences in the distribution of emotions between misinformation and true information. The details are shown in Table 4.

It can be observed from Table 4 that “like” emotion dominates both true information and misinformation, which was also the reason why both true information and misinformation can get many retweets. Combined with text materials, both true information and misinformation contained information that the public wanted to obtain, such as diet collocation, health knowledge, anecdotes, etc., which attracted the interest of the public. Therefore, in the distribution of emotions between true information and

TABLE 4: Distribution of information veracity in different emotions.

Emotion type	Information veracity	
	True information	Misinformation
Like	1715	1729
Disgust	300	277
Surprise	31	21
Happiness	29	56
Fear	24	23
Sadness	241	203
Anger	11	4

misinformation, the “like” emotion became the dominant emotion.

Secondly, in contrast, in addition to the emotion of “like,” negative emotions dominated by “disgust” and “sadness” occupied the mainstream in both misinformation and true information, and the number was much larger than other emotion types. The analysis of textual materials showed that the public tended to form emotions of “disgust” and “sadness” in the face of disasters, crimes, and other kinds of news. This finding was also in line with our expectations that when faced with natural disasters, accidents, or other similar events, in reality, we are more likely to form “disgust” and “sadness” emotions under the influence of factors such as compassion and sense of justice.

At the same time, we also divided true information and misinformation into different topic categories and compared

the distribution of true information and misinformation on emotions under different topic categories. The specific distribution information of information veracity on emotion under different topic categories is shown in Table 5.

Based on the observation in Table 5, we found that there was a relationship between misinformation and true information in terms of the content type and sentiment type. In the topics of public security, the most common expressions of emotion in true information and misinformation were the emotions of like, disgust, and sadness. Among them, the emotion of like came from the emergency management measures embodied in information and timely response to events; the emotion of disgust came from the harm brought about by public safety events to the country, society, and individuals; and the emotion of sadness mainly came from sympathy for victims. In the topic category of food and product, emotions in true information and misinformation were most reflected as like and disgust. Combined with the text materials, the emotion of like lied in the knowledge of food safety and products contained in the microblog information, and the emotion of disgust lied in the conflict and hatred of fake and shoddy food and products. In the topic category of politics, like and disgust were often reflected in true information, while like and happy were usually reflected in misinformation. In combination with the text materials, the emotion of like was reflected in the information that satisfies the public's curiosity about the political field, the emotion of disgust was reflected in the dissatisfaction with some political events and policies, and the emotion of happiness was often reflected in the support for political figures and the approval of some policies. In the topic category of celebrity, the emotions of like and disgust became the mainstream in true information and misinformation. The emotion of like came from the public's love for some stars and celebrities, while the emotion of disgust also came from the public's resistance to some stars and celebrities. In the topic category of crime, emotions were mainly embodied in two types of emotions: like and disgust. As the most direct source of information, the public's emotion of like is more obvious when they see images of criminals being arrested and punished in media reports, while the emotion of disgust was mainly from the resistance to the crime. In the topic category of disaster, the emotions of like and sadness were often reflected. Among them, the emotion of like came from the solidarity and common support of the public in the face of disaster, while the emotion of sadness was mainly reflected in the loss of personnel and property. In the topic category of social events, like and disgust often occupied the dominant position. Among them, the emotion of like came from the public's curiosity about strange and usual stories, while the emotion of disgust came from the fact that some social events often contained contents that go against the social conscience.

In addition, we also verified whether there was a significant difference in the effect of subject category on emotion between true information and misinformation. The results showed that compared with true information (Pearson Chi-Square = 38.707, $P > 0.05$), the topic category

of misinformation had a more significant impact on the emotion types (Pearson Chi-Square = 178.625, $P < 0.01$), and there were significant differences in the emotional distribution of different topics in misinformation. Therefore, it is important to divide misinformation into different topics and understand the emotional distribution of misinformation from different topic categories for us to better understand the diffusion pattern of misinformation in social networks.

4.6. Emotion Analysis of Network Diffusion Characteristics of Misinformation. Related studies have confirmed that emotion plays an important role in the spread of misinformation. On the one hand, under the influence of emotion, the public will interact and communicate with each other about different events, which will cause heated discussions. On the other hand, information is also embedded with public emotions in the process of information sharing and spreading, and the spread of misinformation in social networks is often promoted by different emotions. Therefore, this paper compares the network diffusion characteristics of misinformation and true information through emotion analysis to further reveal the network diffusion pattern of misinformation. Combined with the available data, to further determine the specific correlation of each topic in different emotions, we used Pearson's Point Biserial correlation coefficient to analyze the correlation between information veracity and the corresponding network diffusion characteristics. Among them, the direction of correlation represents whether it had a dominant position in network diffusion. Positive correlation meant that misinformation was more likely to be retweeted, favored, and commented by network users in social networks than true information, and negative correlation meant that true information was more likely to be retweeted, favored, and commented by network users in social networks than misinformation. The stronger the correlation, the closer the relationship between information veracity and network diffusion. The correlation between information veracity and the number of retweets is shown in Figure 6. The correlation between information veracity and the number of favorites is shown in Figure 7. The correlation between information veracity and the number of comments is shown in Figure 8.

From the perspective of topics, in the topic of public security, misinformation containing like and sadness was more likely to be retweeted by Internet users, while misinformation containing disgust and fear was more difficult to be retweeted by Internet users. Among them, the information containing the emotion of like had statistical significance in the correlation between veracity and the number of retweets ($P = 0.073 < 0.1$). In terms of the number of favorites, misinformation with sadness was more likely to be collected by Internet users, while misinformation with like, disgust, and fear was less likely to be collected by Internet users. Among them, the information containing the emotion of disgust had statistical significance in the correlation between veracity and the number of favorites ($P = 0.066 < 0.1$). In terms of the number of comments, misinformation with emotions of like and sadness was more likely to be

TABLE 5: Distribution of topic types of information veracity in different emotions.

Topic type	Emotion type						
	Like	Disgust	Surprise	Happiness	Fear	Sadness	Anger
<i>True information</i>							
Public security	107	16	2	1	4	15	0
Food and product	1144	218	27	20	18	185	6
Politics	56	11	0	1	0	5	1
Celebrity	20	4	0	0	0	2	0
Crime	215	30	1	6	1	14	2
Disaster	61	6	1	0	1	10	0
Social events	54	14	0	1	0	9	0
<i>Misinformation</i>							
Public security	207	25	0	1	1	24	1
Food and product	1035	194	16	29	16	137	3
Politics	58	6	0	19	1	3	0
Celebrity	7	2	0	0	0	0	0
Crime	292	32	3	5	4	22	0
Disaster	36	5	2	1	0	5	0
Social events	70	11	0	1	1	11	0



FIGURE 6: Correlation between information veracity and retweets' volume.

commented on by Internet users, while misinformation with emotions of fear and disgust was more difficult to be commented on by Internet users.

In the topic of food and product, the veracity of information under different emotional types was positively

correlated with the number of retweets, and misinformation was more likely to be retweeted in social networks. Among them, the information containing the emotions of like ($P = 0.000 < 0.001$), disgust ($P = 0.001 < 0.01$), and sadness ($P = 0.02 < 0.05$) had statistical significance in the

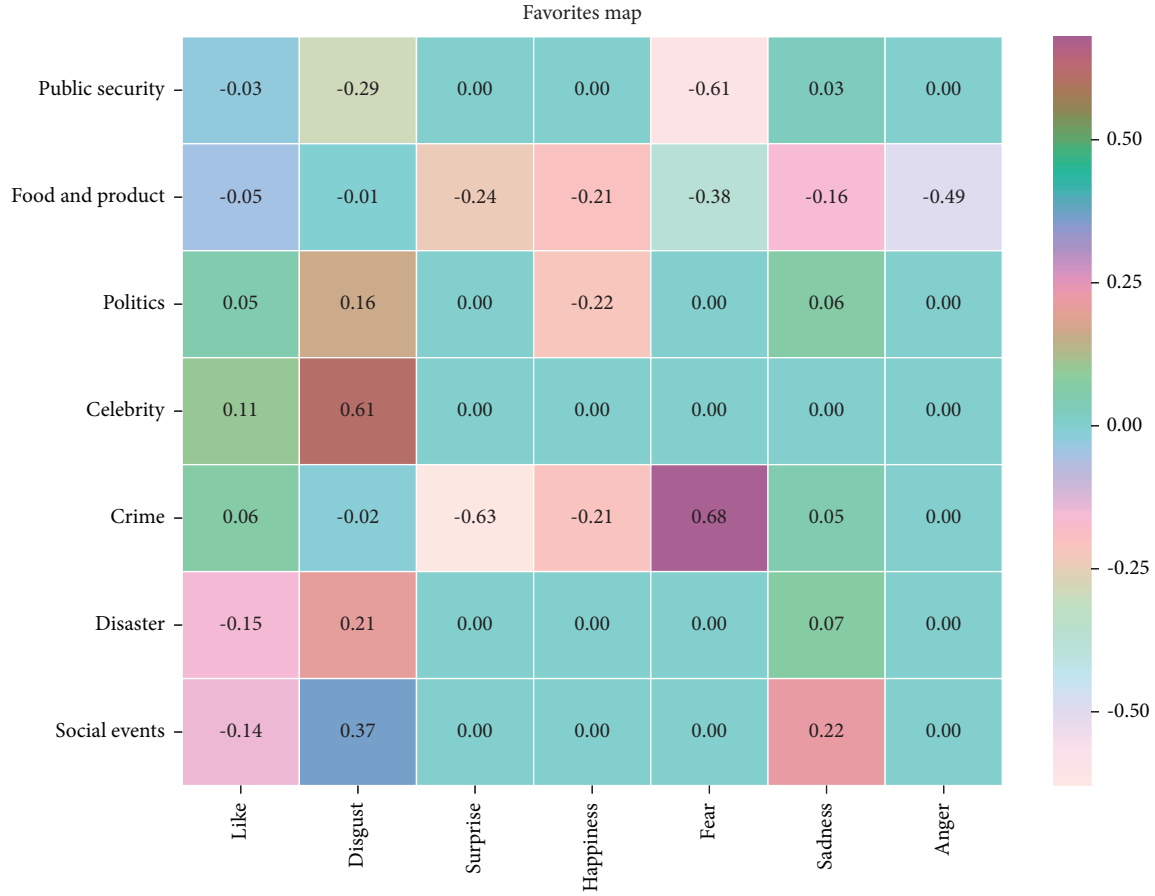


FIGURE 7: Correlation between information veracity and favorites' volume.

correlation between veracity and the number of retweets. In terms of the number of favorites, the veracity of information under different emotional types was negatively correlated with the number of favorites, and true information was more likely to be collected by network users. Among them, the information containing the emotions of like ($P = 0.024 < 0.05$), fear ($P = 0.03 < 0.05$), and sadness ($P = 0.004 < 0.01$) had statistical significance in the correlation between veracity and the number of favorites. In terms of the number of comments, the veracity of information under different emotional types was positively correlated with Internet users, and misinformation was more likely to be commented on by Internet users. Among them, the information containing the emotions of like ($P = 0.000 < 0.001$) and disgust ($P = 0.04 < 0.05$) had statistical significance in the correlation between veracity and the number of comments.

In the topic of politics, misinformation in the emotions of like, disgust, and sadness was more likely to be retweeted by Internet users, while true information with happy emotion was more likely to be retweeted by Internet users. Among them, the information containing the emotions of like ($P = 0.09 < 0.1$) and disgust ($P = 0.082 < 0.1$) had statistical significance in the correlation between veracity and the number of retweets. In terms of the number of favorites, misinformation with the emotions of like, disgust, and sadness were more likely to be collected by Internet users,

while true information with happy emotion was more likely to be collected by Internet users. In terms of the number of comments, misinformation with like, disgust, happiness, and sadness was more likely to elicit comments from Internet users.

In the topic of celebrity, misinformation containing the emotion of like was more difficult to be retweeted by Internet users, and misinformation in the emotion of disgust was more likely to be retweeted by Internet users. In the number of favorites, misinformation in the emotions of like and disgust was easier to be collected by Internet users. In terms of the number of comments, the misinformation in the emotion of like was less likely to be commented by users, while the misinformation in the emotion of disgust was more likely to be discussed by users.

In the topic of crime, misinformation containing emotions of like, disgust, happiness, fear, and sadness was more easily retweeted by Internet users, while misinformation under the emotion of surprise was more difficult to be retweeted by Internet users. Among them, the information containing the emotion of like ($P = 0.023 < 0.1$) had statistical significance in the correlation between veracity and the number of retweets. In terms of the number of favorites, misinformation under the emotions of like, fear, and sadness was more likely to be collected by Internet users, while misinformation under the emotions of disgust, surprise, happiness, and sadness was more difficult to be

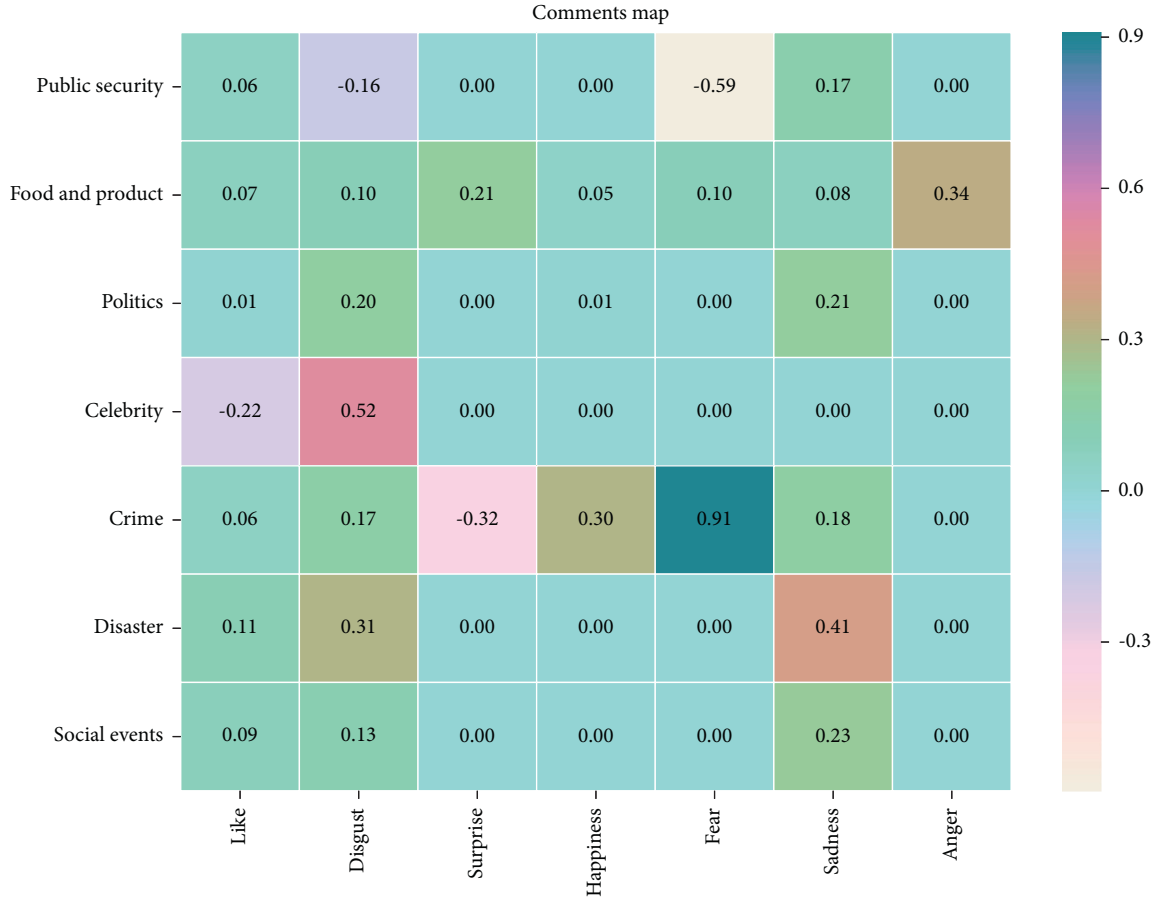


FIGURE 8: Correlation between information veracity and comments' volume.

collected by Internet users. In terms of the number of comments, the misinformation containing emotions of like, disgust, happiness, fear, and sadness was more likely to be commented on by Internet users, while the misinformation containing the emotions of surprise was more difficult to be discussed and communicated by Internet users.

Among the topics of disaster and social events, misinformation containing the emotions of like, disgust, and sadness was more likely to be retweeted by Internet users. In terms of the number of favorites, misinformation containing the emotion of like was more difficult to be collected by network users, and misinformation containing the emotions of disgust and sadness was more likely to be collected by network users. Among the topic of social events, information containing the emotion of disgust ($P = 0.078 < 0.1$) had statistical significance in the correlation between veracity and the number of favorites. In terms of the number of comments, misinformation containing the emotions of like, disgust, and sadness was more likely to be discussed and communicated by Internet users.

From the perspective of emotion, in the topic category under the like emotion, misinformation under the topic of celebrity was more difficult to be retweeted by Internet users, and misinformation under the rest of the topic categories was more likely to be retweeted by Internet users than true information. Among them, the information containing the

topics of public security ($P = 0.073 < 0.1$), food and product ($P = 0.000 < 0.001$), politics ($P = 0.09 < 0.1$), and crime ($P = 0.023 < 0.05$) had statistical significance in the correlation between veracity and the number of retweets. In terms of the number of favorites, true information under the topics of public security, food and product, disaster, and social events were more likely to be collected by network users. Misinformation under the topics of politics, celebrity, and crime was more likely to be collected by Internet users. Among them, the information containing the topic of food and product ($P = 0.024 < 0.05$) had statistical significance in the correlation between veracity and the number of favorites. In terms of the number of comments, misinformation under the topic of celebrity was more difficult to be discussed by online users, and misinformation under the remaining topic categories was more likely to be discussed by online users than true information. Among them, the information containing the topic of food and product ($P = 0.000 < 0.001$) had statistical significance in the correlation between veracity and the number of comments.

In the topic category under disgust emotion, true information under the topic of public security was more likely to be retweeted by Internet users than misinformation. Misinformation under the other types of topic categories was more likely to be retweeted by network users. Among them, information containing the topics of food and product

($P = 0.001 < 0.05$) and politics ($P = 0.082 < 0.1$) had statistical significance in the correlation between veracity and the number of retweets. In terms of the number of favorites, true information under the topics of food and product, public security, and crime were more likely to be collected by Internet users, while misinformation under the topics of politics, celebrity, disaster, and social events was more likely to be collected by Internet users. Among them, information containing the topics of public security ($P = 0.066 < 0.1$) and social events ($P = 0.078 < 0.1$) had statistical significance in the correlation between veracity and the number of favorites. In terms of the number of comments, misinformation under the topic categories of food and product, politics, celebrity, crime, disaster, and social events was more likely to be discussed by Internet users. Compared with misinformation, true information containing the topic of public security is more likely to be commented on by network users. Among them, the information containing the topic of food and product ($P = 0.04 < 0.05$) had statistical significance in the correlation between veracity and the number of comments.

In the topic category under surprise emotion, misinformation under the topic of food and product was more likely to be retweeted by Internet users. In the topic category of crime, true information was more likely to be retweeted by network users than misinformation. In terms of the number of favorites, true information under the topics of food and product, and crime was more likely to be collected by Internet users. In terms of the number of comments, misinformation under the topic of food and product was more likely to be discussed by Internet users. In the topic category of crime, true information was more likely to be discussed by Internet users than misinformation.

In the topic category under happiness emotion, misinformation under the topics of food and product, and crime was more likely to be retweeted in social networks. In the topic category of politics, true information was more likely to be retweeted on the network than misinformation. In terms of the number of favorites, true information under the topics of food and product, politics, and crime was more likely to be collected by Internet users. In terms of the number of comments, misinformation under the topics of food and product, politics, and crime was more likely to be discussed by Internet users.

In the topic category under fear emotion, misinformation in the topic categories of food and product, and crime was more likely to be retweeted in social networks than true information. In the topic category of public security, true information was more likely to be retweeted over the network than misinformation. In terms of the number of favorites, true information under the topics of public security and food and product was more likely to be collected by Internet users, while misinformation under crime was more likely to be collected by Internet users. Among them, the information containing the topic of food and product ($P = 0.03 < 0.05$) had statistical significance in the correlation between veracity and the number of favorites. In terms of the number of comments, misinformation was more likely to arouse users' discussion in social networks in the topic categories of food and product, and crime. In the topic

category of public security, true information was more likely to be discussed by users on the network.

In the topic category under sadness, except for the topic category of celebrity where there was no significant correlation, misinformation in the rest of the topic categories was more likely to be retweeted on the network than true information. Among them, information containing the topic of food and product ($P = 0.02 < 0.05$) had statistical significance in the correlation between veracity and the number of retweets. In terms of the number of favorites, true information under the topic of food and product was more likely to be collected by network users, while misinformation under the topics of public security, politics, crime, disaster, and social events was more likely to be collected by network users. Among them, information containing the topic of food and product ($P = 0.004 < 0.01$) had statistical significance in the correlation between veracity and the number of favorites. In terms of the number of comments, except for the topic of celebrity where there was no obvious correlation, misinformation under other topics was more likely to be discussed by users on the Internet than true information.

In the topic category under anger, misinformation in the topic of food and product was more likely to be retweeted and commented on the network than true information. True information on the topic of food and product was more likely to be collected by Internet users. There was no significant correlation among the rest of the topic categories.

To sum up, by comparing the correlation between information veracity and network diffusion characteristics of each topic under different emotions, we can further provide corresponding suggestions for public opinion governance and prevention assessment of misinformation. When misinformation spreads in social networks, its threat can be effectively reduced by guiding the discussion content and emotions, and the governance goal of maintaining network order and social stability can be achieved.

5. Conclusions

As an important channel of information dissemination, social media has not only become an important platform for the communication of true information but has also contributed to the spread of misinformation in social networks. On the one hand, the spread of misinformation on social media misleads the public and prompts them to make wrong decisions. On the other hand, it also brings about great threats to the public's physical and mental health and economic properties. Therefore, it is important to understand the diffusion characteristics of misinformation on social media. It can not only provide reference and basis for the governance of misinformation in social media but also maintain the order of network security. And, it is also possible to prevent and control misinformation in advance by understanding the diffusion rules of misinformation, to reduce the spread of misinformation on social media more effectively, and thereby reduce the harm caused by misinformation from the source. In this paper, we took the misinformation spread on social media as the research object, used the deep learning method to analyze the content

characteristics and emotional characteristics of misinformation, and combined it with the network analysis method to make a targeted analysis of the network diffusion characteristics of misinformation in the social network. In addition, the study also introduced corresponding true information for comparative study on the basis of the analysis of misinformation to further reveal the propagation law of misinformation in social networks.

Related studies have found different characteristics of misinformation and true information dissemination in social networks. In content analysis, there were differences in the network distribution and diffusion characteristics of misinformation and true information of different topics. In emotion analysis, we also found that emotion was an important factor influencing the spread of misinformation, and the process of spread of misinformation in social networks showed different changes due to the influence of different emotions. On the one hand, these findings supplement the research content with misinformation as the object and broaden the research boundary of misinformation. On the other hand, they also provide a reference for the public opinion management of misinformation. By guiding the public to discuss different topics and contents, and guiding the public to generate corresponding emotions, it helps to achieve the management of misinformation, reduce the harm caused by misinformation, and maintain the stability of social order. In addition, with the help of the distribution of topics and emotions of misinformation on social media, we also have a deeper understanding of the propagation rules of misinformation on social media. And, it also makes a deeper analysis of the evolution characteristics of misinformation on social media and the driving factors of the social network to misinformation. This provides a basis for us to further explore the propagation mechanism of misinformation on social media. Meanwhile, in the future, we will further deepen the research based on this paper and adopt different datasets and methods to better reveal the propagation pattern of misinformation in social networks.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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