



# Differences in Behavioral Characteristics and Diffusion Mechanisms: A Comparative Analysis Based on Social Bots and Human Users

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In the field of social media, the systematic impact that bot users bring to the dissemination of public opinion has been a key concern of the research. To achieve more effective opinion management, it is important to understand how and why behavior differs between bot users and human users. The study compares the differences in behavioral characteristics and diffusion mechanisms between bot users and human users during public opinion dissemination, using public health emergencies as the research target, and further provides specific explanations for the differences. First, the study classified users with bot characteristics and human users by establishing the relevant formulas of user indicator characteristics. Secondly, the study used deep learning methods such as Top2Vec and BERT to extract topics and sentiments, and used social network analysis methods to construct network graphs and compare network attribute features. Finally, the study further compared the differences in information dissemination between posts published by bot users and human users through multi-factor ANOVA. It was found that there were significant differences in behavioral characteristics and diffusion mechanisms between bot users and human users. The findings can help guide the public to pay attention to topic shifting and promote the diffusion of positive emotions in social networks, which in turn can better achieve emergency management of emergencies and the maintenance of online orders.

**Keywords:** social networks, bot users, behavioral characteristics, diffusion mechanism, comparative analysis

## 1 INTRODUCTION

With the formation and development of Internet technology, online social networks (OSNs) have also been developed rapidly. And various social media with online social functions have gradually penetrated everyone's daily life and occupied an important position in interpersonal communication and interaction. With the help of different social media platforms, people share and receive information and interact with each other [1]. The popularity of social media has not only brought about close social ties and easier access to information, but also exposed individuals to massive amounts of fragmented information [2], which puts pressure on their information processing abilities [3]. In recent years, public and scientific discussions about the Internet and

social media have begun to focus on the possible negative effects of social media. Social media is often seen as a nexus for spreading misinformation, fake news, and hate speech during the breaking of major events [4]. The negative effects of social media make online users vulnerable to irrational or malicious users. Web users may ignore or avoid information or even reduce the use of social media platforms in several ways [5]. On the other hand, social bots often play an important role in the mass dissemination of misinformation. Users are easily misled by misinformation, which further intensifies group pressure and negative emotions and may escalate the situation, which may lead to mass incidents [6].

Social bots active in social media, manipulated by automated algorithms and driven by human interests and purposes, have attracted considerable attention from researchers in recent years. Social bots create a large amount of social media content and occupy an important role in online communication and interaction. For example, Pew Research Center examined about 1.2 million tweets linked to the most popular news and current affairs sites on Twitter and found that 66% of the tweets were likely shared by bot accounts [7]. From the perspective of social media accounts, related studies have also found that between 9 and 15% of social accounts on Twitter are manipulated by bots [8]. In other social media, social bots have similarly high activity. For example, Facebook has also shown that about 100,000 bots interact in this social media every month [9]. The large number of bots that populate social media, interacting with human users in the media environment and using them to spread news and information, is an important factor influencing the dissemination of information in social networks.

Social bots are also active in various types of emergencies. When emergencies occur, social media becomes an important channel for public communication and exchange. The public uses social media to seek information about events, share opinion strategies, and gain emotional support [10]. However, the problems caused by social bots and related rumors, and fake news cannot be ignored [11]. During breaking events, social bots imitate human users and deliver false news and fake information, and even carry out malicious activities such as spreading conspiracies and publishing hate speech, which in turn disrupt the normal network order and network ecology and cause network users to form negative emotions such as panic, causing great hindrance and difficulties in network governance [12]. Meanwhile, social bots can create false popularity [13] and make the complex social media environment more uncertain through group pressure and network contagion. Therefore, it is necessary to study social bots to compare the differences in information dissemination between bots and human users in emergent events, and thus contribute to the maintenance of online order.

In this paper, we explore the systematic impact of social bots on the social media environment and compare the differential impact brought by social bots and human users. Social media researchers have explored the information diffusion and human-computer interaction behaviors involving bots in various event scenarios. Bot detection techniques and recognition methods

have been iterated to support and inform the classification of social bots and human users [14]. After distinguishing social bots and human users, we conducted a correlation analysis for the emergent event-related dataset. First, we conducted text analysis on the contents of posts under emergencies and compared whether bot users and human users differed in behavioral characteristics during the dissemination of information. Second, we used social network analysis methods to construct the propagation network of posts in social networks, and further compared the attributes and features in the networks constructed by social bots and human users. Finally, we further explored the effects of text features on information dissemination behavior using multi-factor ANOVA and compared the differences in the effects between bot users and human users. Because the group behavior of social bots is uncertain and difficult to measure and control accurately through experiments and questionnaires, this study will verify the differential influence mechanism between social bots and human users through individual user behavior data in real social media scenarios.

The structure of the remaining part of the article is shown below. In the second section, we review the related research on social bots and introduce the concept, characteristics, and influence of social bots. In the third section, we introduce the research methodology and operationalization of this paper, including topic modeling, sentiment analysis, and social network analysis methods used. In the fourth section, we conduct a comparative analysis of social bots and human users, and present our findings. In the fifth section, we present the discussion and conclusions of this paper, and present the shortcomings of the current study, as well as the outlook for future research.

## 2 RELATED WORK

### 2.1 Concept and Behavioral Characteristics of Social Bots

Social bots are computer algorithms in social media that automatically generate content and interact with humans in an attempt to mimic and possibly change them (15). As code-built computer programs, social bots manipulate social accounts, post tweets in social media, and enable interactive communication with other social media users with the help of artificial intelligence and other technologies [15]. As the popularity of social media has increased, programs controlling the social bot to mimic human behavior have been able to grow in social media platforms [16]. With different penetration strategies, social bots form interactions in human users to influence or even change their behavior [17]. At the same time, related studies have found a tendency for humans to extend real-life psychological dynamics to artificial entities [18]. For example, one researcher analyzed the ability of humans to distinguish between political social bots and humans on Twitter and found that users with disagreement were often assessed as more bot-like than users with the agreement [19]. It has also been found that the overall engagement of users' social networks predicts interactions and responses with social bots, the number of friends and followers predicts whether users

will interact with bots [20]. This also confirms the existence of different clusters of bots in the interactive network of Twitter, that a significant proportion of users are systematically exposed to bot-generated content and interact with bots, and that the symbiotic dynamics between human and bot users are presented on social media [21].

The behavioral characteristics of social bots are manifested in three main aspects. First, one of the most obvious behavioral characteristics is the imitation of human behavior by social bots. In social media, social bots imitate human users to retweet and collect information, and establish false interactions through the number of followers and fans, thus achieving misleading human users and influencing the behavior of other users [22]. Related studies have also found that social bots can post relevant content based on the recognition of popular discourse keywords and thus achieve mimicry of human behavior [17]. And this imitation behavior is also reflected in the public opinion of unexpected events. When an unexpected event occurs, a large number of social bots imitate real users and occupy an important position in public opinion after the event [23]. Second, social bots play an important role in the process of information dissemination. Social bots achieve the amplification of opinions or information and promote the diffusion of information by repeatedly copying and forwarding relevant information on a large scale [24]. In the case of emergencies, social bots may either release a large amount of false information and rumors to increase the public's negative emotions and form a negative effect in information diffusion [25], or they may awaken the public's risk awareness by releasing event-related information to play a positive effect in information diffusion [26]. Finally, important behavioral characteristics of social bots are also reflected in the interaction process with human users. In social media platforms, social bots interact and engage with human users not only in their daily lives, but also in the discussion of topics and emotional support [27, 28]. The interpersonal communication capabilities of social bots can even increase the social presence of human users more than human-to-human interactions and activities [29]. However, interaction with social bots may also mislead human behavior and even cause negative problems such as privacy leakage [30].

## 2.2 Social Bots and Public Opinion Research

Social bots also play an important role in public opinion analysis. Usually, related studies define the propaganda or communication method using technical means such as social bots as computational propaganda [31]. Compared with traditional information dissemination methods, information under computational propaganda achieves a larger scale and scope through a more covert, precise and automated form [32]. And with the support and help of algorithms such as social bots and botnets, computational propaganda facilitates the spread of fake news and misinformation in social media. At the same time, the interactive nature of social networks and the automaticity of account creation and management allow computational propaganda to customize different social bots to personalize

the propaganda approach to users and form new forms of public opinion [33]. In addition to public opinion applications for calculating propaganda, social bots can also play a role in analyzing users' opinions and network structures. For example, neutral bot users are deployed on social media platforms to investigate users' political biases [34]. Meanwhile, the endogenous structure of filter bubbles in social networks can be further explored by analyzing the text content received by bots on social media [35].

In the public opinion caused by emergencies, social bots play an important role in generating fake traffic, guiding opinions, and establishing fake social relationships. For example, in an analysis targeting social security events, it was found that social bots amplify the impact of emergencies and human users contribute to the dissemination of bot-generated content. Also, studies have found that social bots influence human behavior by promoting the spread of disinformation in social media through diverse information strategies such as sharing and retweeting [36]. In the analysis of natural disasters, it was found that social bot users were able to form larger, more discrete, and hierarchical communication networks than human users. At the same time, this allows for more rapid reposting and diffusion of false news and ambiguous information spread by social bots on social media [37]. Similarly, in the analysis of public health events, social bots influence opinion trends based on a certain viewpoint by automatically posting a large number of messages, which in turn influence human behavior. At the same time, the retweeting and sharing behavior of social bots makes human users who hold the same opinion more obstinate and difficult to accept information under a different point of view [38]. In summary, social bots may generate a large amount of false information and promote the spread of false information, distort normal human behavior and destabilize the social order in emergencies [39]. Therefore, comparing the behavioral differences and diffusion mechanisms between social bots and human users in the context of emergencies can make a proper contribution to the emergency management of emergencies.

## 2.3 Impact of Social Bots

Social bots mimic human behavior to occupy an important role in public opinion research and amplify their influence through social networks, which in turn change human opinions and behaviors. First, as previously described, social bots spread false news and rumors on social media through computational propaganda and other means, and further amplify the impact of false news and information [40]. For example, social bots were discovered to facilitate the rapid spread of disinformation through geographic disguise, interaction with influential users, etc. [41]. Second, social bots are often thought to manipulate and control social media opinion, an effect that has been extensively validated in the political sphere [42]. For example, during the 2016 US elections, some candidates used automated accounts or bots to increase their social media following and followers [43]. During the 2016 municipal elections in Rio de Janeiro, Twitter bots fabricated different supporter identities to match potential voters, making collective identities and views more homogenous

[44]. It has also been argued that the degree of influence of bots depends on whether the bots provide information that is consistent with human *a priori*, and that the participation of Twitter bots has the potential to increase the polarization of politics, among others [45]. Finally, social bots can have an impact on public perception. Based on computational propaganda, social bots are able to automate the tailoring of information content to different users and thus distort public perceptions. For example, social bots are more likely to post hashtags about smoking cessation and new products than non-bots, causing the public to form relevant impressions [46]. Another example is the higher percentage of social bots posting a large number of posts indicating that marijuana can alleviate health concerns, which in turn has an impact on the public's preconceptions [47].

However, some studies have also concluded that the impact of social bots is not significant, for example, one study found no signs of collective political strategies and minimal influence of identified social bots during the 2017 German state elections [48]. Another study has shown through an experiment of social bots intervening in political discussions on Twitter that bots had little impact on the discussion network and analyzed the role of capital [49]. Some researchers have pointed out that although the high level of intelligence of chatbots has been demonstrated and assumed to be the same for social bots, the observed level of intelligence achieved by social bots is limited [50]. In this paper, however, we will further verify the impact of social bots on information dissemination by studying public opinion during emergencies and compare in-depth the differences between the impact of social bots and human users on information dissemination.

### 3 RESEARCH METHODOLOGY

In this paper, we took the public opinion triggered by the epidemic event in X city, China, on Sina Weibo as our data source for the study of emergencies. First, the study classified users into two types of users, bot users and human users, based on user characteristics and content characteristics. Secondly, the text data was divided into different topic categories and sentiment categories, and the differences in behavioral characteristics between bot users and human users were compared. Also, the study further compared the differences in diffusion characteristics between posts made by bot users and human users using social network analysis methods. Finally, a multi-factor ANOVA was used to further investigate the differences in information dissemination between posts made by bot users and human users. Based on the comparison of the differences in behavioral characteristics and diffusion characteristics between bot users and human users, the study can make some contributions to the identification of bot users and emergency management of public opinion in emergencies.

#### 3.1 Identification of Social Bots

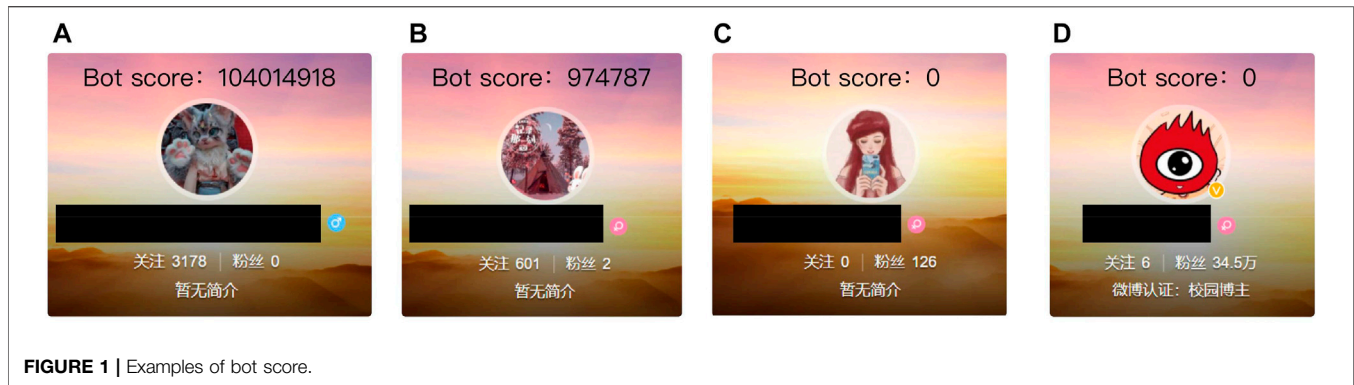
As bot users who can publish and promote information dissemination on their own and interact with other users,

social bots have been widely distributed on various social media platforms and play an important role in the dissemination of public opinion in emergencies [51]. Therefore, it is particularly important to identify bot users in social media and then compare the behavioral characteristics of bot users and human users in social networks and enable better public opinion management. For the identification of bot users on social media, research teams in different countries and regions have conducted studies by adopting different methods and detection tools, different criteria and thresholds, but the methods and criteria have not been unified [52]. Considering the data properties of social media, machine learning-based recognition methods and classification by purely metric features have been adopted by most social scientists in the identification of bot users [53, 54]. Machine learning algorithms first need to be trained based on obtaining classification labels with bot users and human users to improve the accuracy of user identification. After the training and testing of the implemented algorithms, feature-based algorithms are used to classify bot users and human users in the data. However, the highly dynamic nature of users on social media, the variability of their behavior, and the accuracy of the recognition features tend to make the method somewhat questionable [55]. Some rules-based metric approaches have been proposed, for example, one study treated users who post 50 tweets a day as highly automated, and users with bots in their account descriptions or hashtags as self-disclosure bots [53]. This single indicator approach is easy to interpret but tends to be oversimplified.

Existing studies have pointed out that social bot recognition is not an exact science, and different recognition methods will produce very different results [52], which will lead to difficult dialogue between the results obtained by different recognition algorithms. Moreover, the black box principle presented in the algorithmic tools represented by Botometer makes it difficult to know the specific details of the variables and the process of calculating the resultant scores. However, existing research on the characteristics of the bot has reached some consensus, for example, such as the total number of tweets and release frequency (bot show the continuous activity and too many tweets), forward than the proportion of the original tweet (bot forwarding content far more often than generating new tweets), pay attention to the fans and the proportion of (bots usually focus on the more and less number of fans) [39]. Therefore, the object of this study is "suspected" social bot users with bot characteristics, and a rule-based social bot recognition method is proposed.

In the process of identifying users with bot characteristics using user indicator features, the ratio of the number of followers and the number of fans of a user is one of the commonly used measures in the study [39]. Compared to normal users, social bots tend to follow a large number of normal users to gain benefits or to increase their influence [56]. Therefore, social bots are usually characterized by a high number of followers and a low number of fans. This result has also been confirmed in other studies that users with high follower counts are less likely to be bots [57]. Also, due to the ability of social bots to automate the posting of





information, bot users tend to retweet and post a large number of tweets in social media to create their active status and use this to increase their influence on social media [58]. Therefore, the study implements the classification of bot users and regular users based on the number of followers and fans combined with the number of posts made by the users. The classification criteria are shown in Eq. 1.

$$\text{Score} = \frac{\text{FollowNum} \times \text{WeiboNum}}{\text{FansNum} + 1} \quad (1)$$

Where, *FollowNum* and *FansNum* denote the number of followers and fans of the user, respectively. *WeiboNum* denotes the number of posts made by the user. Adding one to the denominator is to avoid the result being uncountable due to the number of followers being zero. The equation considers those users who follow a large number of users, post a large amount of content and lack followers as suspicious. Before applying this classification metric, this study treated users who had obtained authentication and personal description as human. Then, the study calculated the bot score for each user based on Eq. 1. Secondly, by repeatedly setting and observing the actual situation of sample data, the classification threshold of bot users and human users was finally determined to be 2,064. Users larger than the classification threshold were classified as bot users.

Direct observations of the data help to understand which users the metric classifies as bots. **Figure 1** shows some examples of the identification, where (a) and (b) were randomly selected from users with high bot scores, and (c) and (d) were randomly selected from users with low scores. User (a) followed 3,178 users and had no followers. He posted 203,530 posts and did not post any original posts. It's highlighted that when we looked at the account, the user (a) was banned for violating community rules. User (b) is similar to the user (a), with a high number of followers and almost no fans. She posted 31,466 posts. Most microblogs of hers were reposted from a few fixed accounts. They are thought to be suspected forwarding bots. User (c) has 126 followers but does not follow any users. It is more likely that she is a human account because she has some original content and exposes her selfies in her microblogs. User (d) is unlikely to be a bot, as it is an authenticated user in the campus content domain.

### 3.2 Topic Modeling

In the field of natural language processing, topic modeling is used to analyze the semantic structure and topics of different text contents to achieve the classification of large-scale texts. Therefore, topic modeling is often used with the social media domain to extract meaningful information from social media data [59]. When an unexpected event occurs, the public expresses a large number of views and opinions with the help of social media to form an event-related public opinion. With the help of topic analysis, research can further analyze the evolution trend of public opinion and achieve more effective public opinion governance [60]. Among them, in the field of topic modeling, the LDA model and PLSA model have been widely used and are among the most commonly used topic modeling methods [61, 62]. However, compared with traditional models such as LDA, the topics discovered by Top2Vec have more advantages in terms of information quantity and representativeness, and they do not need to set the appropriate number of topics in advance, which can realize the automated querying of topics. Moreover, compared with traditional methods represented by LDA, the deep learning model represented by Top2Vec has better performance in the interpretability and applicability of topic modeling. Therefore, to achieve a more accurate topic classification of text, the study uses the newly proposed Top2Vec method for modeling text topics [63]. This method has shown better results in topic classification based on social media data [64].

As a distributed representation of the topic vector model, the Top2Vec model is obtained by computing the dense regions of the document vectors. The dense region is the region formed by the aggregation of similar documents. The number of topics into which the text is divided is determined by the number of dense regions in the semantic space. By calculating the centroids, i.e., the arithmetic mean of all document vectors in each dense region, we can obtain the topic vector, which is represented as the most representative average document in the region. After obtaining the topic vector, the study searches for a word vector that is closer to the topic vector to represent the topic formed by that dense region with the help of semantic embedding. The semantic similarity is represented by the distance between the word vectors [63].

Based on the Top2Vec model, the study used the following steps to achieve the classification of text topics. First, the study used the BERT model to learn the jointly embedded document vectors and word vectors. Based on the Transformer language model, BERT achieved the extraction of text features and the fusion of contextual semantics through an encoder-decoder structure [65]. Secondly, to find dense clusters of documents in the dimensionality reduction space more efficiently and accurately, the study used UMAP, a dimensionality reduction method based on the manifold learning technique [66]. The method consists of two main parts: graph construction and layout optimization. Among them, the former is represented by Eqs 2–4. As in Eq. 2, the similarity of high-dimensional data points in the model is calculated based on the exponential probability distribution. Where  $\omega$  represents the distance from the  $m$  point to the first nearest neighbor point.  $D(x_m, x_n)$  denotes the distance between the  $m$  th point and the  $n$  th point in the high-dimensional graph. To determine the local metric space of each point, UMAP calculates two parameters  $\rho_m$  and  $\sigma_m$ . Where, the parameter  $\rho$  is also used to represent the distance between  $m$  and its nearest neighbor point. When the weights of the high-dimensional graph formed between points  $m$  to  $n$  differ from the weights between points  $n$  to  $m$ , UMAP makes it symmetrical by computing a single edge with combined weights. This is shown in Eq. 3. Where,  $\omega_{m|n}$  represents the weight of the edge formed from the point  $n$  to  $m$ .  $\omega_{mn}$  represents the similarity between the point  $m$  and the point  $n$  in the original space. Meanwhile, as shown in Eq. 4, based on the likelihood graph constructed by the above equation, the study further specifies the number of nearest neighbors  $k$ , which in turn generates the weighted  $k$ -nearest neighbor graph.

After the construction of the high-dimensional graph was completed, UMAP further optimized the layout of the low-dimensional simulation graph to make the low-dimensional simulation graph and the high-dimensional graph as similar as possible. Among them, Eq. 5 represents the modeling distance of the low-dimensional based on the probability distribution similar to the Student  $t$ -distribution. Where, constants  $a$  and  $b$  are approximately 1.93 and 0.79 respectively.  $y_m$  and  $y_n$  represent the projections of  $x_m$  and  $x_n$  in lower dimensional projection space respectively.  $\phi_{mn}$  indicates the similarity between the projection points  $y_m$  and  $y_n$ . Eq. 6 represents the calculation of the binary cross-entropy. In the study, binary cross-entropy was used as a cost function to capture the global data structure. Where,  $C_{UMAP}$  represents the cross-entropy between  $\omega_{mn}$  and  $\phi_{mn}$ . With the derivative of cross-entropy, UMAP updates the coordinates of low-dimensional data points for layout optimization. Meanwhile, UMAP was applied by stochastic gradient descent to speed up the convergence speed and thus reduce the memory consumption [67, 68].

$$\omega_{m|n} = \exp\left(-\frac{D(x_m, x_n) - \rho_m}{\sigma_m}\right) \quad (2)$$

$$\omega_{mn} = \omega_{m|n} + \omega_{n|m} - \omega_{m|n}\omega_{n|m} \quad (3)$$

$$k = 2 \sum_m^{\omega_{mn}} \quad (4)$$

$$\phi_{mn} = (1 + a(y_m - y_n)^{2b})^{-1} \quad (5)$$

$$C_{UMAP} = \sum_m \sum_n \left[ \omega_{mn} \log\left(\frac{\omega_{mn}}{\phi_{mn}}\right) + (1 - \omega_{mn}) \log\left(\frac{1 - \omega_{mn}}{1 - \phi_{mn}}\right) \right] \quad (6)$$

Afterward, the model used HDBSCAN, a hierarchical density-based spatial clustering method to find dense regions of document vectors, by which the calculation of topic vectors is achieved [69]. The calculation formula is shown in Eq. 7. Where the mutual reachability distance is expressed by  $D_{mrd}(x_m, x_n)$ , which is the maximum value of the core distance between  $m$  and  $n$  points and the distance between two sampling points.  $Core_k(x_m)$  and  $Core_k(x_n)$  denote the core distances of  $m$  and  $n$  points, respectively, i.e., the distances from  $m$  and  $n$  points to the nearest  $k$  sampling points.  $D(x_m, x_n)$  is then used to denote the Euclidean distance between  $m$  and  $n$  points [70, 71]. Finally, we can then compute the center of mass of the document vector based on the dense regions found to obtain the topic vector for each dense region and achieve the classification of text topics.

$$D_{mrd}(x_m, x_n) = \max(Core_k(x_m), Core_k(x_n), D(x_m, x_n)) \quad (7)$$

### 3.3 Emotion Modeling

As one of the most dominant areas in natural language processing, sentiment analysis is widely used in the analysis of social media and online opinion. When an emergency event occurs, emergency managers can learn the emotional dynamics of most users and the emotional impact of user interactions through web analytics [72]. Traditional approaches to sentiment classification, such as support vector machines, require extensive feature engineering efforts and are often time-consuming and resource-intensive [73]. With the development of deep learning techniques, neural network models have proliferated and have shown better results in terms of accuracy and recognition efficiency. Among them, BERT (Bidirectional Encoder Representations from Transformers) has demonstrated better results in several tasks including sentence-level sentiment classification and is widely used in the field of sentiment analysis [74]. In this paper, we construct a sentiment classifier based on the BERT model to achieve the recognition of the sentiment embedded in social media data.

The main framework of the BERT model as an embedding layer consists of a multilayer transformer structure. Compared to traditional CNN and RNN networks, the BERT model can solve the long-term dependency problem common in existing models based on the ability to convert the distance between two words at any position to 1 [75]. Meanwhile, the BERT model is a multi-task model, which consists of two self-supervised tasks, MLM (Masked Language Model) and NSP (Next Sentence Prediction), in the pre-training phase. In the MLM task, 15% of the input data will be randomly Masked, while in the training process, after identifying the Mask-related words, 80% of the data will be replaced with Mask, 10% with other words, and 10% will remain in the original state. In the NSP task, two randomly selected consecutive sentences will be fed into the model, and the model will determine the relationship between the two sentences,

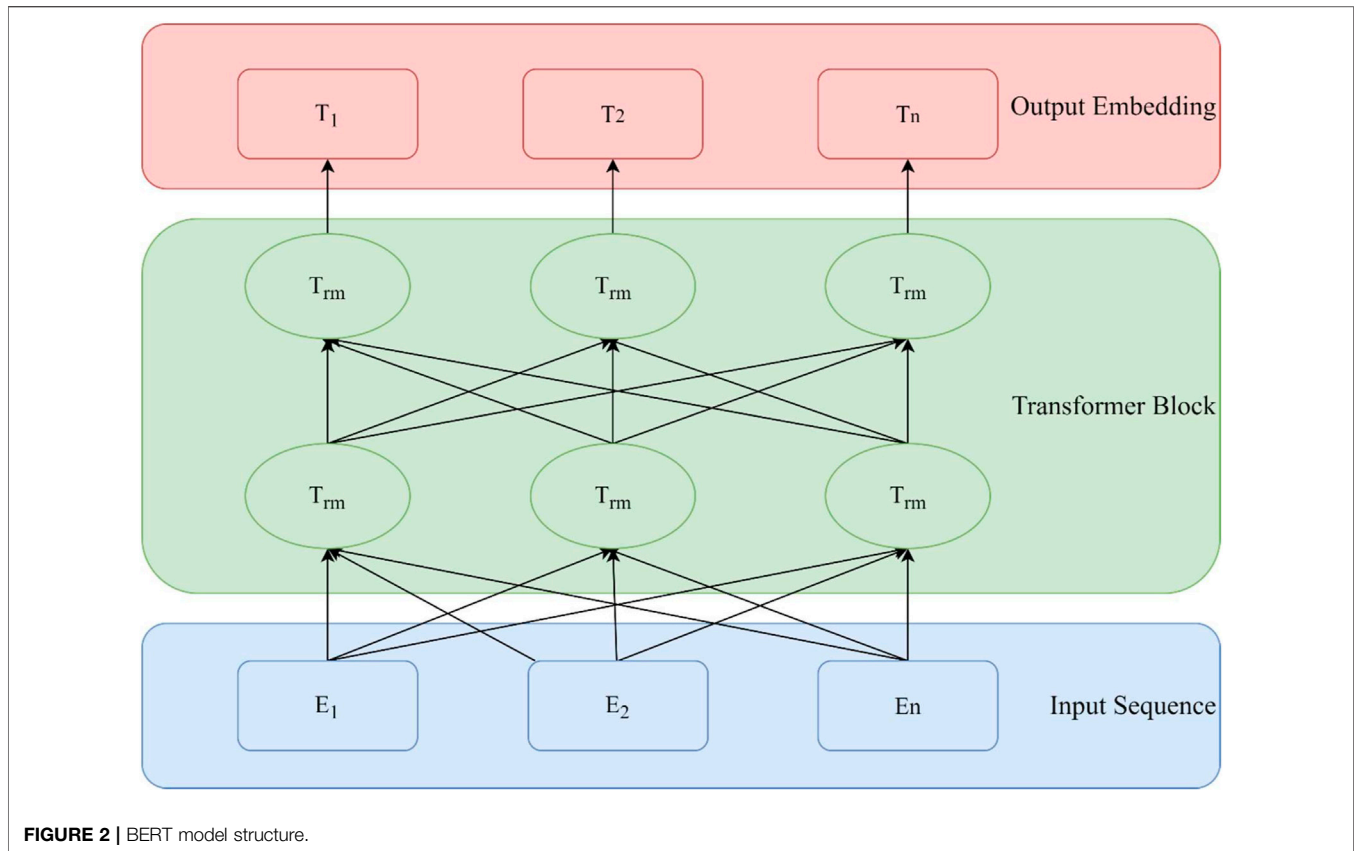


FIGURE 2 | BERT model structure.

i.e., whether they match the corresponding contextual relationship. After completing the pre-training model, the study only needs to fine-tune the model parameters to adopt the model for various tasks in the field of natural language processing [65]. Among them, the structure of the BERT model is shown in **Figure 2**.

In our study, we used the BERT model to implement the computation of sequence embedding and to prevent overfitting and regularization by adjusting the dropout parameters during the training phase of the model. Finally, the softmax classification layer is used to classify the sentiment labels. The activation function of the softmax layer is calculated as follows. Where the number of output nodes, i.e., the number of categories to be classified, is denoted by  $M$ . The output value of the  $i$ th node is denoted by  $\varepsilon_i$ . The sum of the probability values of the output nodes is taken as 1 [76].

$$\text{Softmax}(\varepsilon_i) = \frac{e^{\varepsilon_i}}{\sum_{m=1}^M e^{\varepsilon_m}} \text{ for } i = 1, \dots, M \quad (8)$$

To train a sentiment classification model suitable for this research context, we fine-tune the BERT model using the dataset of Internet users' sentiment during the epidemic released by Beijing Municipal Government Data Resources (data.beijing.gov.cn). The dataset contains 100,000 sentiment-tagged tweets about COVID-19 from 1 January 2020, to 20 February 2020. The emotion tagging is divided into three

categories, respectively is 1 (positive), 0 (neutral), and  $-1$  (negative). By fine-tuning the BERT model, the accuracy of the model on the test set was 0.74, the recall rate was 0.73, and the F1 value was 0.69. The performance of the emotion classification model meets the needs of this study. Causing the regional epidemic data used in this study may be simpler than the training data, we randomly selected and manually coded 100 microblogs from the research data for verification. The prediction accuracy was 0.83, the recall rate was 0.80, and the F1 value was 0.82. In previous studies, the accuracy of the three-category emotion classification model was about 0.80 [77]. In this paper, the purpose of establishing the emotion classification model was not to optimize the model but to apply it. This emotion classification model can accurately predict the sentiment of most microblogs, which meets the needs of this study.

### 3.4 Social Network Analysis Methods

As an effective method to study group relations, social structure and interaction behavior, social network analysis (SNA) has been applied in many research fields [78]. In addition, social network analysis methods often construct network maps by presenting the relationships between actors to achieve visualization. In the visual network atlas, actors are often described as nodes, and the relationships between actors are defined as edges with goals. With the help of the network atlas, we can observe the status difference of nodes in social networks, namely important actors

and isolated actors. At the same time, research can also understand the structural differences of groups with different attributes in the network [79]. In this paper, based on the social media data under emergencies, the spread graph of information published by different user attributes in social networks was studied and drawn, and the difference in the spread of information published by bot users and human users was compared.

In addition, several network attributes were selected to further compare the differences in the diffusion characteristics of information published by bot users and human users. First, average-degree centrality was selected to measure the number of direct connections between users and other users in social networks. The calculation formula of degree centrality is shown in Eq. 9; [80]. Where  $i$  and  $j$  are not equal, and  $q_{ij}$  represents whether node  $i$  is related to node  $j$ . Secondly, we choose average centrality to measure the control ability of bot users and human users in social networks. The higher the centrality, the stronger the ability of users to control resources, the more important the status in social networks. The calculation formula of intermediate centrality is shown in Eq. 10; [80]. Where,  $p_{jk}(i)$  represents the number of geodesics passing through node  $i$  between node  $j$  and node  $k$ ,  $p_{jk}$  represents the number of geodesics between node  $j$  and node  $k$ . Finally, the indirect transmission trend of information is considered in addition to the direct transmission of information. Referring to existing studies, we adopt the PageRank index to further measure the probability of the node represented by bot users and human users moving randomly to the next node. At this point, the probability value of convergence to a stationary distribution is the PageRank index [81]. The higher the PageRank index, the higher the importance of nodes in the social network. The calculation formula is shown in Eq. 11; [82]. Where,  $M(\alpha_j)$  and  $N(\alpha_i)$  represent the number of directed edges emitted by nodes  $\alpha_i$  and the set of nodes pointing to node  $\alpha_i$  in the social network respectively. Through the comparison of different network attributes, the research further reveals the differences in information transmission characteristics between bot users and human users, and provides corresponding opinions for public opinion management under emergencies.

$$C_D(i) = \sum_{j=1}^n q_{ij} \quad (9)$$

$$C_B(i) = \sum_{j < k} \frac{p_{jk}(i)}{p_{jk}} \quad (10)$$

$$PR(\alpha_i) = \sum_{\alpha_j \in N(\alpha_i)} \frac{PR(\alpha_j)}{M(\alpha_j)} \quad (11)$$

## 4 RESULTS

### 4.1 Data Collection and Preprocessing

To compare the behavior differences between bot users and human users in public opinion caused by emergencies, the COVID-19 outbreak in X city of China was selected as the research object. On the one hand, the public health emergency broke out in December 2021 and ended in January 2022, reflecting the latest trends in public opinion. On the other

hand, to prevent the further spread of the epidemic, X city with a population of ten million took lockdown measures due to this event, which had a huge influence on all levels of society and has rich public opinion data. Therefore, the study selected the public data of the epidemic events in X city as the data source, and obtained relevant data from Sina Weibo (one of the largest social media platforms in China) by limiting time and searching keywords. Based on the advanced keyword search function of Weibo, the study takes “epidemic situation in X city” as the search keyword, and captures relevant microblog data from 13 December 2021, to 1 January 2022. In addition, after obtaining the relevant data, a series of methods such as filtering invalid information, word segmentation, and removing stop words were used to preprocess the data. Finally, 237,342 valid posts were obtained.

### 4.2 Behavioral Differences in Topic Types

In this study, the Top2Vec model was used to cluster topics under the public opinion of emergencies. To achieve better classification results, topics were divided into 10 categories. The clustering results of topics are shown in Table 1. As can be seen from Table 1, the public opinions caused by public health emergencies selected by the research mainly fall into four categories. For example, topics 2 and 7 reflected the public’s prayers and wishes for an end to the epidemic. Topics 3 and 9 reflected the response to COVID-19 at all levels of society during the outbreak. Topics 4, 8, and 10 reflected the problems and negative impacts of COVID-19 management. Topics 5 and 6 reflected the content of events during the epidemic and the public response to the epidemic information. Topic 1 was about the posts forwarded by the public during the COVID-19 outbreak, which only contained emoticons and words without substance. The results also proved that in the transmission process of emergencies, the number of forwarded microblogs without substance was the largest, which constituted a forwarding network in the process of emergencies and promoted the spread of all kinds of event-related information in social networks.

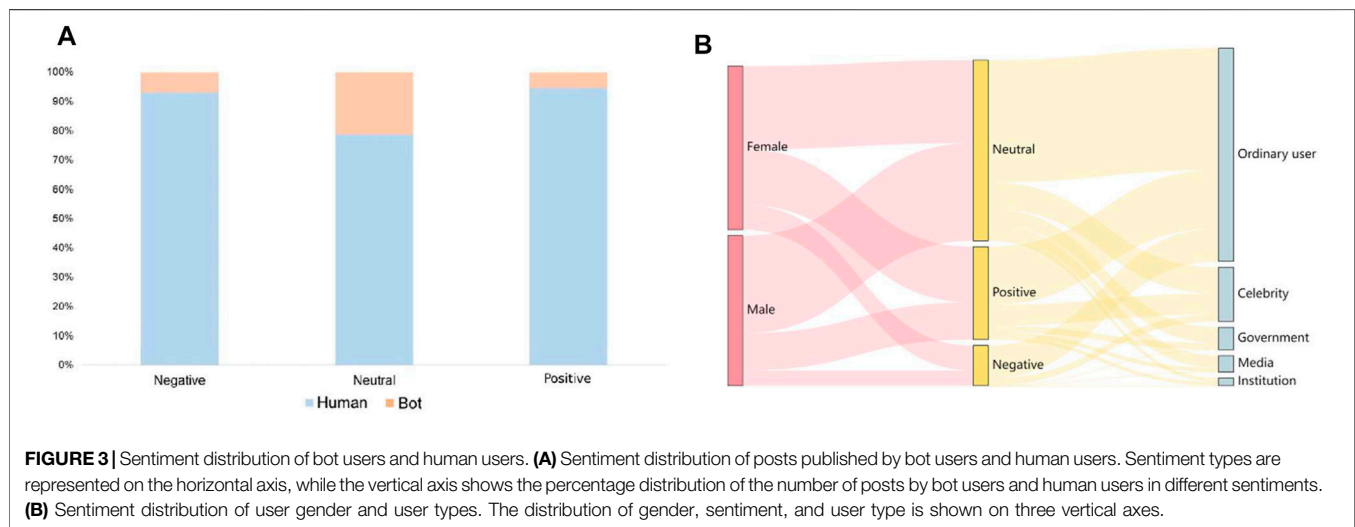
In addition, Table 1 also reflects the distribution of bot and human users on various topics. Table 1 shows that posts made by bot users account for about 10% of all posts, ranging from 9 to 15%, which is consistent with existing studies (8). At the same time, the differences between posts posted by bot users and human users were explored by the Chi-square test, and the results showed that there were significant differences in topic distribution between bot users and human users ( $p < 0.001$ ). Among them, the posts published by bot users were mainly distributed on topics 1, 4, 6, and 7. Firstly, the study found that the majority of posts were forwarded by bot users on Weibo. Considering that topic 1 was mostly forwarded without substance, this may be consistent with the ability of bot users to automatically publish information. Secondly, posts published by bot users also had more distribution in topic 4 and topic 7. Combined with the text, this may be due to the high impact of topics four and seven, which have received wide public attention during the COVID-19 pandemic. Bot users posted relevant information on such topics to increase their influence. Finally, Bot users also posted a lot of content related to topic six. Topic 6



**TABLE 1 |** Topic classification of information published by bot users and human users.

NO	Topic Labels	Size	Bot	Human
1	Information forwarding without substance	81,906	16,755	65,151
2	Pray for the end of the epidemic in X City	18,770	738	18,032
3	All sectors of society fought against the epidemic	20,302	213	20,089
4	Management problems exposed by COVID-19	22,089	1,807	20,282
5	Notification of epidemic Situation	15,936	176	15,760
6	Remarks on social news during the epidemic	11,799	1,170	10,629
7	Cheer for X City's fight against COVID-19	21,642	1,844	19,798
8	The impact of COVID-19 on food, clothing, housing and transportation	21,405	818	20,587
9	Nucleic acid testing for all people	10,815	386	10,429
10	Exposure of difficulties in buying vegetables during the epidemic	12,678	416	12,262
Total		237,342	24,323	213,019

Size denotes the number of posts, Bot denotes bot users, Human denotes human users.



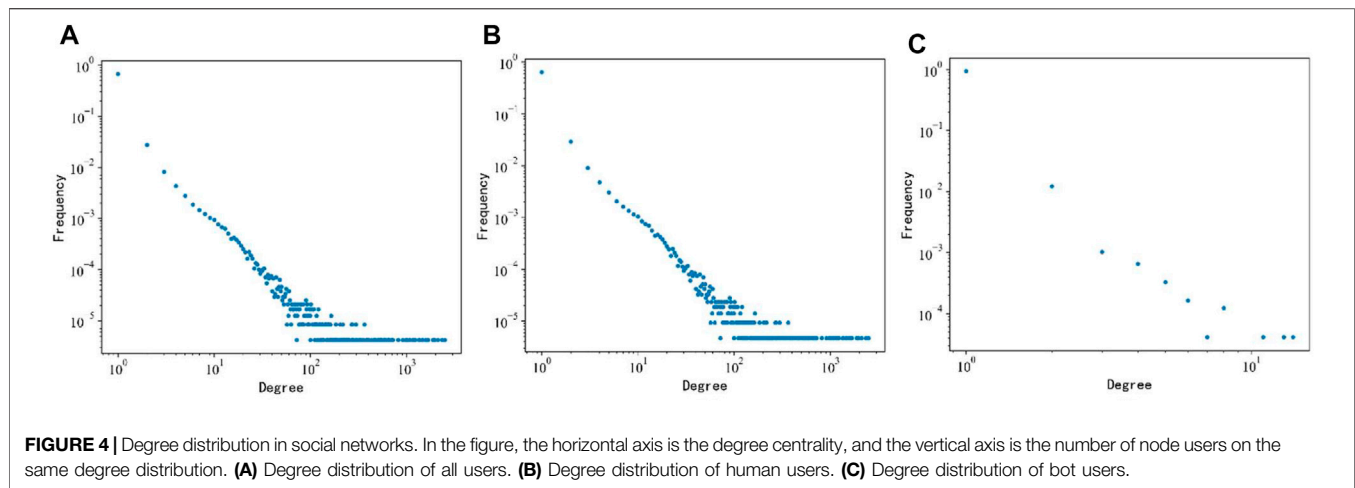
was a controversial topic during the COVID-19 pandemic, which could arouse all kinds of emotions of the public. It was easier for bot users to get attention and interaction from other users if they posted posts related to this topic. The posts that human users were concerned about mainly focus on topics 1, 3, 4, and 8, mainly involving social response to the epidemic, problems in the process of governance, and the impact of the epidemic. Compared with human users, bot users tended to post more controversial and influential topics. Posts published by human users covered a wider range of content, and paid more attention to the governance and response of emergencies and their impact on life.

### 4.3 Behavioral Differences in Sentiment Types

In this study, the BERT model was used to analyze the sentiment of text data, and then the differences in the sentiments of posts made by bot users and human users were compared. Based on the obtained data, the study tested the sentiments of posts published by different users by the Chi-square test, and the results showed that there were

significant differences in the sentiments of posts published by bot users and human users ( $p < 0.001$ ). At the same time, as shown in **Figure 3**, the sentiment distribution map of posts published by different users was also drawn. Among them, the user's gender is the public information of personal data. User types such as government, celebrities, and media are authenticated by Weibo with identifiable marks to distinguish them. All the relevant information is public, and the crawler is used to obtain the data.

As can be seen from **Figure 2A**, among the distribution of sentiments, neutral sentiment is distributed in large numbers among bot users and human users. Combined with text materials, the public sentiment caused by public health emergencies, including media users, celebrities, and institutional users, tended to release factual information with neutral sentiment. Relevant information would also be forwarded by different users to achieve information diffusion, and relevant content is also reflected in **Figure 2B**. Meanwhile, **Figure 2B** also reflects that in the distribution of neutral sentiment, the proportion of male users (65.09%) is higher than that of female users (50.74%). A higher percentage of female users posted emotional posts during the public health emergency.



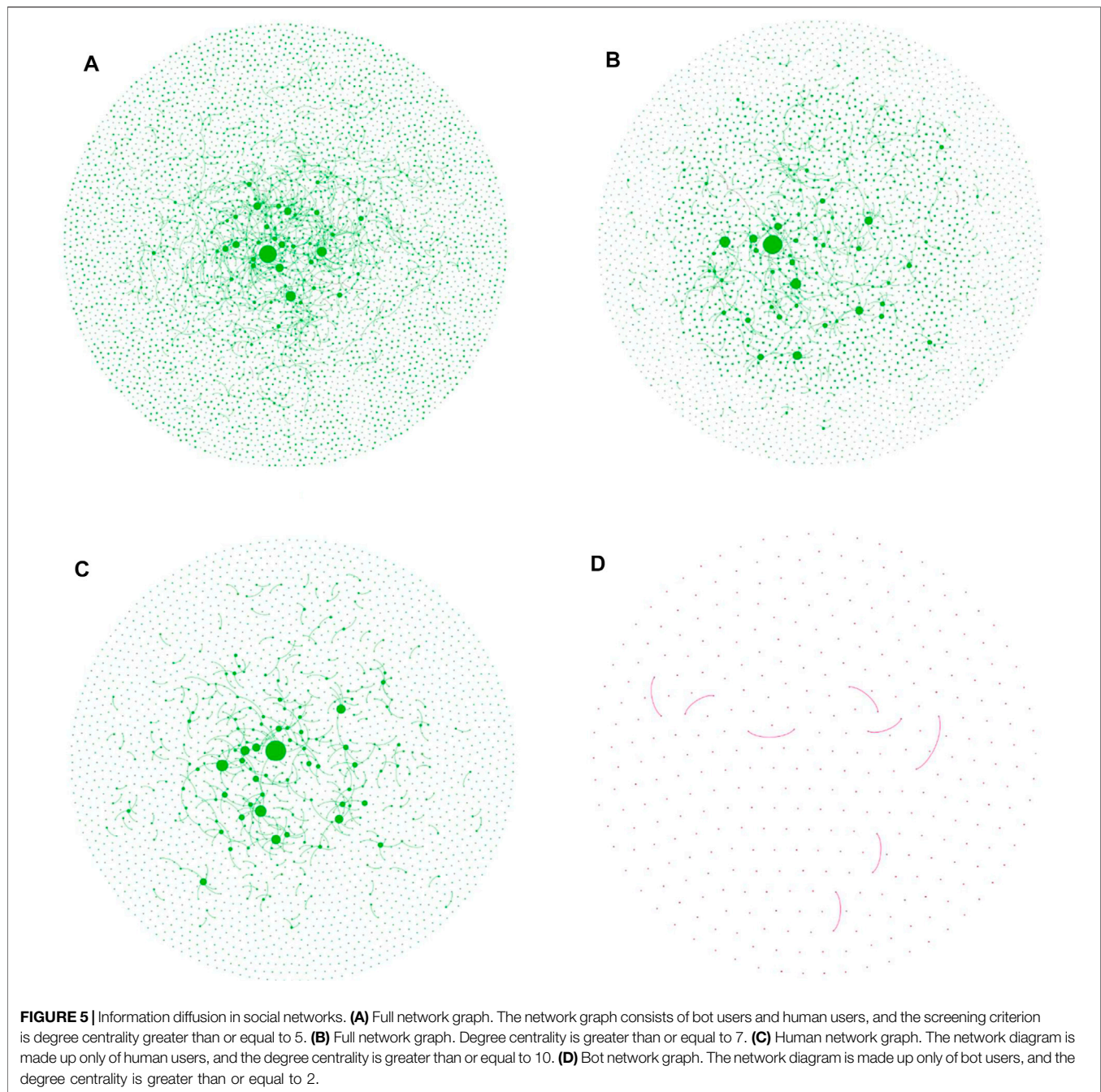
Secondly, it can be seen from **Figure 2A** that the number of posts containing positive sentiment of both bot users and human users is more than that of posts containing negative sentiment. This finding was also validated for user gender and user types. As shown in **Figure 2B**, for both male users (24.82% > 10.09%) and female (33.99% > 15.27%), the number of posts containing positive sentiment was much larger than that of posts containing negative sentiment. At the same time, **Figure 2B** also reflects that ordinary users (27.33% > 15.40%), celebrity (38.14% > 13.06%), government (28.47% > 0.39%), media (46.83% > 1.01%), and institution (24.46% > 0.41%), the number of posts containing positive sentiment is more than the number of posts containing negative sentiment. Especially, the difference was more pronounced among authoritative users such as government, media, and institution.

In addition, there were differences with human users. Among the posts made by bot users, the number of posts containing positive sentiment was close to that containing negative sentiment. It was because bot users aimed to increase their influence, and sentiments were not the primary prerequisite for posting information. But that doesn't mean we don't need to be wary of social bots. Of course, the positive information released by social bots can help regulate group emotions and maintain the stability of network order. However, taking the public health emergency as an example, the number of posts containing negative sentiment published by bot users on social media was close to that of posts containing positive sentiment. By publishing posts containing negative sentiment, bot users can guide the negative sentiment of the public, bringing challenges to public opinion management under emergencies. For human users, the number of posts containing positive sentiment was far greater than that of posts containing negative sentiment. Relevant findings are also consistent with existing studies, that is, when an emergency occurs, the public is more inclined to publish and forward posts containing positive sentiment, to encourage themselves and comfort others [83].

#### 4.4 Social Networking and Diffusion Trend

Based on the multi-stage forwarding data obtained under the public health emergency, the social network analysis method was used to draw the communication map of public opinion information in social networks, to further compare the diffusion trend of information published by bot users and human users in social networks. First of all, the study drew the degree distribution of bot users and human users in social networks, to more intuitively compare the role of bot users and human users in information diffusion. The degree distribution is shown in **Figure 4**. **Figure 4A** shows the degree distribution of all users. It was found that in the information diffusion network caused by emergencies, the degree centrality of most users was very low, and more users existed as information recipients. Only by a small number of users with a high degree, and as an important medium for information sharing. **Figure 4B,C** respectively show the degree distribution of human users and bot users. The study found that both human users and bot users have the characteristic of opposite direction in degree distribution and frequency. The difference was that the number of bot users was smaller and the degree distribution was sparser.

Considering the excessive number of nodes, this study conducted filtering according to degree centrality to build a communication map in social networks. The communication map is shown in **Figure 5**. When the degree centrality of screening is low, the number of core nodes is large, and it is difficult to draw a visual network map. However, when the degree centrality is high, the number of core nodes is small, which makes it difficult to present the integrity of the social network. Therefore, combined with the distribution of degree centrality in social networks, the study has made several attempts to develop appropriate screening criteria to maximize the completeness of network graphs. At the same time, considering the robustness of the research results, we draw the whole network graphs when the degree centrality is greater than or equal to 5 and greater than or equal to 7 respectively, to show the diffusion trend of information in social networks more comprehensively. The node size was measured by the PageRank index.



As shown in **Figures 5A,B**, it is found that in the communication network of information in social networks, most nodes with high centrality are human users, while bot users are few. This finding indicated that although bot users played an important role on social media and promoted the spread and diffusion of information, information published by human users still dominated the spread of public opinion caused by emergencies. **Figure 5C,D** respectively show the network graphs composed only by human users or bot users in the process of public opinion dissemination. The results showed that in the process of information diffusion, the forwarding

network formed between human users had a higher focus, while the forwarding network formed by bot users was more discrete.

In addition, we further compared whether there were differences in network attributes between human users and bot users in communication networks. The results are shown in **Table 2**. Degree centrality reflected the number of direct connections between user nodes in the network. The independent sample *t*-test was used to test the degree centrality of human users and bot users. The results showed that there were significant differences in degree centrality

**TABLE 2 |** Network dissemination differences of information published by bot users and human users.

	The Whole Network		Bot		Human	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
DC	1.354	17.105	0.975	0.318	1.397	18.054
BC	0.290	6.890	0.051	0.917	0.317	7.266
PR	0.00000376	0.000042	0.00000208	0.00000104	0.00000396	0.0000444

DC, denotes Degree Centrality; BC, denotes Betweenness Centrality; PR, denotes PageRank Index.

**TABLE 3 |** Social interaction differences between the posts published by bot users and human users.

	Like		Comment		Forwarding	
	Bot	Human	Bot	Human	Bot	Human
Case	24,323	213,019	24,323	213,019	24,323	213,019
Mean	0.188	20.134	0.079	3.221	0.036	1.668
S.D.	2.520	1004.153	0.956	80.843	0.591	63.872
Min	0	0	0	0	0	0
Max	172	221669	47	11555	65	12311
T value	9.167 <sup>a</sup>		17.925 <sup>a</sup>		11.787 <sup>a</sup>	

Level of significance.

<sup>a</sup>Denotes  $p < 0.001$ .

between bot users and human users ( $p < 0.001$ ). It can be seen from **Table 2** that the average degree centrality of human users is greater than that of bot users. As a result, human users were more connected to other users in social networks. Betweenness centrality reflected the ability of users to control resources in social networks. The independent sample *t*-test was used to test the betweenness centrality of bot users and human users, and the results showed that there were significant differences in the betweenness centrality of bot users and human users ( $p < 0.001$ ). It can be seen from **Table 2** that the average betweenness centrality of human users is higher than that of bot users, and human users have a stronger ability to control resources in social networks. PageRank Index was different from the Index of centrality, indicating the user's position in the entire network (82). The independent sample *t*-test was used to test the PageRank Index of bot users and human users, and the results showed that there were significant differences in PageRank Index between bot users and human users ( $p < 0.001$ ). As can be seen from **Table 2**, the PageRank Index of human users in social networks is larger than that of bot users, with higher deviation and more discrete distribution.

### 4.5 Difference Analysis of Social Interaction

To analyze whether there were differences in information transmission between posts published by bot users and human users, the research not only analyzed the content published by social media users, but also further compared the differences in the number of forwarding, comments and likes between posts published by bot users and human users. The analysis results are shown in **Table 3**. First, the study found that posts by human users in social networks had a higher average number of likes,

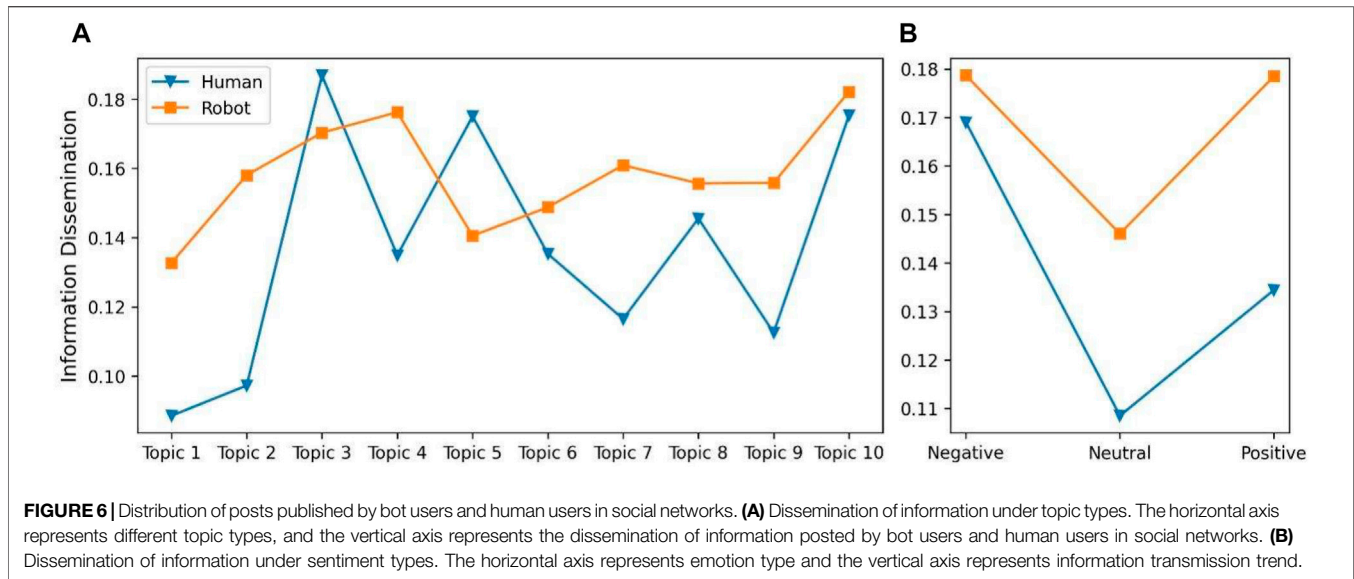
**TABLE 4 |** Influence of bot users and human users on information diffusion in social networks.

Source	Partial SS	Df	MS	F	Prob > F
Model 1	9927.106	25	397.084	1797.20	0.000
Topic	29,283	9	3.254	14.73	0.000
Bot	2.152	1	2.152	9.74	0.002
Topic * Bot	4.076	9	0.453	2.05	0.030
Male	19,439	1	19,439	87.98	0.000
Fans	3835.983	1	3835.983	17361.67	0.000
User types	67.813	4	16.953	76.73	0.000
Residual	52433.909	237316	0.221	—	—
Total	62361.015	237341	0.263	—	—
Model 2	9813.447	11	892.132	4029.29	0.000
Sentiment	21.997	2	10.999	49.68	0.000
Bot	9.466	1	9.466	42.75	0.000
Sentiment * Bot	1.624	2	0.812	3.67	0.026
Male	18,455	1	18,455	83.35	0.000
Fans	4662.635	1	4662.635	21058.69	0.000
User types	65.551	4	16.388	74.02	0.000
Residual	52547.567	237,330	0.221	—	—
Total	62361.015	237,341	0.263	—	—

comments, and forwarding than posts by bot users. A single post published by a human user received 20.134 likes, 3.221 comments, and 1.668 forwarding on average, while a single post by a social bot received 0.188 likes, 0.079 comments, and 0.036 forwarding on average. This also reflected that compared with the likes and comments, the diffusion of forwarding was a more in-depth participation behavior, so the number was smaller. Compared with the information released by human beings, the information released by bots was more difficult to spread in the network. Therefore, although bot users occupy an important position in the dissemination of public opinion under emergencies and have a significant impact on the diffusion of information, human users are always a major role in opinion analysis.

Secondly, the independent sample *t*-test was used to compare the differences in social interactions between bot users and human users. The results showed that there were significant differences in social interactions between bot users and human users. The research results also proved that in the process of public opinion dissemination, the bot users on social media play the role of followers and disseminators rather than manufacturers, to promote the further diffusion of information. In addition, although the *t*-test results showed that the bot users in the role of network public opinion, the influence of the bot was not the only obstacle to its behavior





patterns, also was limited by a variety of factors, such as user types, number of fans. As a result, the difference in information transmission ability between bot users and human users needs to be tested through further analysis.

To further explore the influence of bot users and human users on the spread of information in social networks, this study used multivariate analysis of variance to compare the difference in the number of posts published by bot users and human users based on controlling a series of variables. The analysis results are shown in **Table 4**. Among them, variables such as user gender, user types and the number of fans had a significant impact on information transmission, which need to be included in the model analysis to reduce the impact of confounding factors and improve the accuracy of the analysis. The results of model 1 showed that the topic type ( $F = 14.73, p < 0.001$ ), bot users or human users ( $F = 9.74, p < 0.01$ ), and the interaction terms ( $F = 2.05, p < 0.05$ ) all had significant influence on information transmission. The results of model 2 showed that the sentiment type ( $F = 49.68, p < 0.001$ ), bot users or human users ( $F = 42.75, p < 0.001$ ), and the interaction terms ( $F = 3.67, p < 0.05$ ) also had significant influence on information transmission. The results confirmed the difference in the spread of posts by bots and human users in social networks.

Dependent variable is the logarithm of the forwarding number plus one; Bot variable is a binary variable, with 0 representing human users and 1 representing bot users; Among the control variables, the male variable is a dichotomous variable, with 0 representing female and 1 representing male. Fans variable is the logarithm of the original variable plus one. User types variable is a multi-classification variable, representing ordinary users, celebrities, governments, institutions and enterprises, and media respectively.

In addition, the moderating effect map was drawn to analyze the spread and distribution of information in social networks when the users are bot users and human users respectively, to further compare the specific differences in the spread of posts

published by bot users and human users. The results of the moderating effect are shown in **Figure 4**. Relevant findings were different from *t*-test results, which further confirmed the importance of variables such as user gender, user types, and the number of fans in the process of information dissemination.

Among them, **Figure 6A** shows the difference in the spread of posts under different topics by bot users and human users on social media. The results showed that posts by bot users had more obvious advantages in implication topics 1, 2, 4, 7, and 9. Combined with text materials, the messages of blessing and controversy posted by bot users were more likely to be forwarded by other users. It was because relevant information can more easily arouse public emotions, attract public attention and interaction. In addition, controversial topics were more likely to cause confrontation between users and can improve the influence of the topic itself. Information published by human users with topics 3 and 5 had a more obvious advantage in communication. Combined with text materials, governance information and factual information under the epidemic situation posted by human users were more likely to be forwarded by other users in social networks. It was mainly because when it came to factual and governance-related information, the public was more likely to trust and forward the information published by authoritative users such as government agencies and news media. In topics 6, 8, and 10, posts published by bot users and human users were similar in the spread of social networks, with little difference. The results confirmed that bot users were better at attracting public attention and increasing their influence by publishing posts on specific topics. When facing the network public opinion caused by emergencies, the bot users are associated with specific topic information, to control the negative impact of bot users and stimulate the positive impact, which can further guide and dredge the network public opinion.

**Figure 6B** shows the spread differences of posts containing different sentiments published by bot users and human users in

social networks. The results showed that posts with different sentiments from bot users were more easily spread on social media than those from human users. Especially, the difference was more pronounced for posts with positive sentiments. The finding confirmed that bot users in social networks had high emotional mobilization. Even though the number of bot users was less than that of human users in the process of public opinion dissemination caused by emergencies, bot users were more likely to mobilize public emotions and create a collective emotional atmosphere, making public opinion management of emergencies more difficult to manage.

## 5 DISCUSSION AND CONCLUSION

In this paper, the public health emergency was taken as the research object to explore the differential impact of bot users and human users on public opinion dissemination. First, based on the existing research, we used the user feature to achieve the classification of users with bot characteristics and normal users. Secondly, the study compared the differences in behavioral characteristics between bot users and human users in social networks and further explained the results of differentiation. Finally, the study further explored whether there were differences in the diffusion mechanism of posts published by bot users and human users in social networks in the spread of public opinion under the COVID-19 pandemic, as well as the specific embodiment of the differences.

Before comparing the differences in behavioral characteristics, the research firstly used the deep learning method represented by Top2Vec and BERT to extract information attributes such as topic and sentiment of posts. Second, the study compared the differences in the topic content of posts published by bot users and human users. The study found that bot users tended to use high-impact topics and controversial words to increase their influence in social networks. Human users tended to be broader and more focused on governance efforts and the impact of emergencies during the COVID-19 pandemic. Finally, the study also compared the emotional distribution of posts published by bot users and human users. The study found that both bot users and human users were more likely to post positive sentiment during the outbreak of public health emergencies. And this finding was even more pronounced with human users. Relevant findings can help emergency management personnel guide public discussion topics, alleviate negative public sentiment, and better realize emergency management of emergencies.

In the comparison of diffusion mechanism, the study firstly drew the diffusion graph of information published by bot users and human users in social networks by combining the social network analysis method. It was found that although social bot users played an important role in information diffusion, human users in social networks still played a dominant role in information dissemination. Moreover, social networks based on human users were more aggregative than networks formed by more discrete bot users. Secondly, the research used degree centrality, betweenness centrality, and PageRank index to further

compare the differences in network attributes between bot users and human users in the same information transmission network. It was found that there were significant differences between bot users and human users in network attributes. Human users had a stronger ability to directly contact and control resources, but they were more discrete in the distribution of the PageRank index and had a higher bias. Finally, the study compared the differences in social interaction between posts published by bot users and human users and further explored the influence of bot users and human users on information diffusion in social networks. The results confirmed that there were significant differences in the impact of bot users and human users on information transmission. On the one hand, the study found that bot users had a high influence on specific topics, and by posting specific topics, they had a greater influence on information dissemination than human users. On the other hand, the research also found that bot users had higher emotional mobilization, and the posts containing sentiments published by bot users were more likely to be forwarded by other users than human users, promoting the further dissemination of information. In particular, the difference between bot users and human users was more obvious in the transmission process of posts containing positive emotional information. Relevant findings have proved the diffusion mechanism of posts published by bot users and human users in social networks during emergencies, which was more conducive to the processing of false information and rumors. In addition, it can guide the diffusion of positive sentiment in social networks, reduce the network mass incidents caused by negative public sentiment, and better realize the maintenance of network order and the management of emergencies.

Compared with existing studies on social media behaviors, the contributions of our study are mainly as follows. First, the study not only obtained the event information but also obtained the user's personal information according to the user tags in the event. Based on the characteristics of users' attributes, we distinguished bot users from human users and explored the relationship between user attributes and information transmission. Secondly, we compared the behavioral characteristics and diffusion mechanism of bot users and human users from the cognitive dimension and emotional dimension. Specifically, we used the latest deep learning model to identify different topics and sentiments from text content and used the network analysis method to compare the differences in network characteristics between bot users and human users. Compared with the research on social media behavior from a certain aspect, our methods are more diverse and can analyze the behavior differences between bot users and human users in a more comprehensive way. Finally, existing studies are more descriptive than causal in analyzing social media behaviors. Based on the text features extracted from the deep learning model, this study further compared the differences in information transmission between posts published by bot users and human users through a multivariate analysis of variance. These findings can more comprehensively explain the differences between bot users and human users on social media behaviors, which is also a better supplement to social media behavior research.

This paper compared the differences in behavior characteristics and diffusion mechanism between bot users and human users in the context of emergencies, but there are

still some deficiencies in the research. First, the black box problem in machine learning makes it difficult for us to understand the specific processing process, which requires us to continuously adopt more effective methods to improve the accuracy of variable classification. Second, the limitations of social media data make it difficult to obtain more specific data on web users, such as educational background and occupational category. In future research, we expect to achieve more control variables to reduce the influence of confounding factors. Finally, it is still difficult to determine whether the differences in behavioral characteristics and diffusion mechanisms between bot users and human users also exist in other types of emergencies. It is also the direction of our further research.

## DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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## AUTHOR CONTRIBUTIONS

MC and HL conceived the study and designed the research framework. HL and XM designed the research method and conducted relevant analysis, MC, HL, XM, and YC wrote the article. All authors have read and agreed to the published version of the manuscript.

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