

## *Retraction*

# **Retracted: Prediction of the Forwarding Volume of Campus Microblog Public Opinion Emergencies Using Neural Network**

### **Mobile Information Systems**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### **References**

- [1] Z. Lv, "Prediction of the Forwarding Volume of Campus Microblog Public Opinion Emergencies Using Neural Network," *Mobile Information Systems*, vol. 2022, Article ID 3064266, 8 pages, 2022.

## Research Article

# Prediction of the Forwarding Volume of Campus Microblog Public Opinion Emergencies Using Neural Network

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With the continuous expansion of colleges and universities, the proportion of college students among netizens has increased rapidly. They have become an important component of Chinese netizens and the main audience of Weibo. It is easier for online public opinion to form in some social media platforms than in others. We explain places for political conversation in Chinese cyberspace in terms of interaction, which results in various types of political discussion, based on research on authoritarian deliberation. The crisis of college network public opinion caused by the improper use of Weibo by college students occurs frequently. College network public opinion has become an important factor affecting the development and stability of colleges and universities. Social network rumor forwarding behavior refers to whether users forward specific rumors. Also, there is no surety about the truthfulness of the rumor. Taking Weibo as an example, this paper proposes a neural network-based model for predicting the forwarding volume of public opinion emergencies on campus Weibo. It solves the problem of low prediction accuracy of traditional SVM and other models. The data-driven experimental findings suggest that the technique described in this study can increase the accuracy of predicting forwarding volume in unexpected campus public opinion events.

## 1. Introduction

The features of new media of independence and autonomy have brought about significant changes in the spread of public opinion. The activity of network public opinion in colleges and universities is now confronted with a slew of new difficulties. College students are paying more and more attention to social hotspot events because of the growth of new media [1]. As a result, they are directly forming campus network public opinion. The distribution channels for campus network public opinion are becoming more diversified. When it comes to ideological and political education, new media provides a new vehicle for college students because of its high levels of involvement, rapid knowledge acquisition, and rapid distribution [2]. In addition to having a considerable influence on college students' thinking and conduct, the fast rise of new media has created new challenges in regulating campus network public opinion [3, 4].

Mostly three elements influence online public opinion in colleges and universities. They are as follows:

- (i) International and domestic political hotspot events;
- (ii) Events that are relevant to the vital interests of students;
- (iii) Events that are related to the vital interests of students.

During the 2018 Shanghai Cooperation Organization (SCO) Summit in Qingdao, many students from a Shandong institution posted comments on the Internet that disrupted the order of the Qingdao SCO Summit. Investigation revealed that these students did not have any evil intentions but merely wanted to attract attention by dressing in a way that would attract followers. They behaved in this way because the issue piqued their interest [5]. It appears that there is a connection issue in the linking mechanism between the network public opinion management and control of schools and the government's public opinion management and control systems as a result of this incident [6, 7]. When students engaged in relevant behaviors, counselors failed to advise them of the serious consequences of their actions

promptly. In the course of the government's special era of public opinion control, students crossed the red line of public opinion control. It had a negative impact on their academics as well as their personal lives [8, 9].

It is important to remember that Weibo, as a key social network carrier, is also in charge of the essential functions of public emotional expression and public opinion transmission. As the campus public opinion emergencies are concerned with the health and safety of college students; therefore, college students are more attentive to such information than the general public. Following an incident involving public opinion on campus, material that is difficult to identify between real and false might readily exacerbate the fear of the public and create a network of public opinion that is always fermenting. Recent years have seen an increase in the frequency with which campus public opinion emergencies have happened on the Internet. The forecast of the forwarding volume of college Weibo public opinion emergencies has also been one of the primary topics of network public opinion research [10, 11].

News and comments in the sphere of public events, as well as product or service reviews in the sector of e-commerce, are frequently at the center of network public opinion research projects. A critical link in the realization of network public opinion monitoring, which is critical to network public opinion analysis and constitutes a significant component of the field of network public opinion, is the ability to predict public opinion. Network public opinion is defined by the persistence, interaction, and evolution of a large amount of network data, as well as the ability to anticipate to some extent. In a short amount of time, public opinion on the Internet will spread on a big scale and at a rapid pace. The social amplification theory of risk posits that, if the handling of public opinion on public health crises is not done appropriately, it is simple to incite negative feelings among the public. It can cause ripple effects and result in a public opinion crisis. In order to effectively supervise network public opinion and maintain social stability, it is necessary to establish an appropriate prediction model to simulate the popularity of online public opinion. By establishing such a model, relevant departments can grasp social conditions and public opinion as soon as possible. Identify work deficiencies and their impact on problems and contradictions promptly, and correctly guide negative voices. When it comes to public health emergencies, the occurrence of online public opinion is frequently triggered by the lack of public understanding of the trend in public opinion. It results in the spread of panic. Due to the lack of a sense of security, the worry and terror of the public are even more vital to understand. Users can fully express their emotions through emotive words on the web platform. It allows them to fully express themselves [12–14]. There are more negatives than positives in online public opinion. Passion often takes precedence over reason, and negative emotions encourage the fermentation of public opinion to continue. This makes it even more difficult to monitor online public opinion during public health emergencies.

As a consequence, this research provides a neural network-based methodology for estimating the amount of

campus microblog public opinion emergency forwarding. It can be used to provide early warning and analysis of campus public opinion emergencies, as well as data support for the dissemination of campus microblog public opinion.

The rest of the research paper is organized as follows: Section 2 will explain the related work done in this research. Section 3 will elaborate on the characteristics of public opinion dissemination. Similarly, Sections 4 and 5 will explain the method followed in this research and their results, respectively. Finally, the concluding remarks are illustrated in Section 6.

## 2. Related Work

Presently, researchers from both domestic and international universities are predominantly employing time series analysis or grey theory in their studies of network public opinion forecast. This paper describes a research approach that blends public opinion forecasting with time series analysis. In order to anticipate network public opinion, one method is to use past network public opinion heat. It is a common practice to quantify past network public opinion heat using the Baidu index, the number of published articles, and other metrics. Emotional tendencies are investigated in the context of changes across time. According to the findings of a study combining public opinion prediction and grey theory, one approach of conducting network public opinion prediction research is to employ only a single public opinion observation value. However, the other method of realizing the prediction research of network public opinion is to use a variety of different observation values of network public opinion [15–17]. Some researchers use the Baidu Index as a measure of public opinion heat. The prediction results of the Markov modified grey model are used to make their decisions. Others use the micro-index, Baidu index, and Toutiao index as measurement indicators of event heat [18–20]. They employ the grey model to realize prediction and the grey relational analysis method to propose a network public opinion event classification scheme. Still, others use multiple index data to establish a multi-factor grey model, employ the BPNN (Back-propagation neural network) to correct the prediction residuals of the multi-factor grey model, and the grey relational analysis method to achieve accurate prediction of network public opinion [20–22].

Network public opinion prediction approaches also include the Logistic model, the fuzzy comprehensive evaluation method, the Markov chain, the Bayesian probabilistic neural network, and other variants. Based on the grey correlation method, some researchers have developed a network public opinion heat model. Based on this, a multi-dimensional Logistic model has been developed to predict public opinion information from multiple media platforms [23–25]. To screen the public opinion index system, some researchers employ the rough set theory. However, others employ an analytic hierarchy process to determine the weight of the index and still employ the fuzzy comprehensive evaluation method to predict and evaluate the development trend of public opinion [26–28]. According to some researchers, based on developing an assessment index system

for Weibo public opinion heat, they have developed a BPNN-based public opinion heat trend prediction model for infectious diseases that occur suddenly. Some researchers combine the commonly used Logistic model with other models such as the exponential smoothing model and the grey model and then use the analytic hierarchy process to assign weights to the optimized network public opinion data to obtain the predicted value of the network public opinion data [29, 30].

After sorting through the relevant literature published both domestically and internationally in recent years, it is discovered that domestic and international scholars are still in the exploratory stage of their research on online public opinion forecasting. To attain the study aim, most extant public opinion forecasting research relies on time series analysis or grey theory. A subset of the wider category of online public opinion prediction is online public opinion prediction. Forecast of an online public opinion involves not only the prediction of the popularity of online public opinion but also the prediction of topic evolution and the prediction of public opinion. In the related research on the forecast of network public opinion heat, few researchers have examined the forwarding volume of campus Weibo public opinion emergencies to better understand the phenomenon. This work presents an NN (Neural Network)-based campus microblog public opinion emergency forwarding volume prediction model, and it introduces the LSTM (Long Short-Term Memory) model to accomplish accurate forwarding volume prediction [31–33].

### 3. The Characteristics of Public Opinion Dissemination

In this section, the extensive sources of online public opinion, the hidden main body in the dissemination of network public opinion, the diverse performance of online public opinion, and the group nature of the influence of online public opinion will be discussed thoroughly. This will help characterize the dissemination process of public opinion. The explanation is as follows:

*3.1. The Extensive Sources of Online Public Opinion.* The degree to which the network environment is open has a significant impact on all aspects of the politics, economy, and culture of the country. According to the 45th “Statistical Report on the Development of China’s Internet,” which was released by the China Internet Network Information Center, China completed the construction of the world’s largest Internet network in 2019. There are more than 450 million households with access to the fixed Internet broadband network. The proportion of optical fiber and mobile communication networks in administrative villages surpasses 98 percent. As of March 2020, China had 904 million netizens, with an Internet penetration rate of 64.5 percent. The number of young people between the ages of 10 and 65, as well as the silver-haired population, had reached 320 million, with the number of young and silver-haired people continuing to grow. Netizens can obtain news by browsing a

variety of websites and social platforms, such as government official websites, corporate websites, personal websites, INS applications, and Weibo, and participate in a wider range of activities and topics, thanks to the maturing network technology and rapid development of informatization.

Network public opinion sources, such as Weibo, popular forums, QQ groups, and WeChat groups, are the most important sources of news dissemination. When it comes to breaking news in the age of new media, social software, by its inherent benefits, can transmit information to people from all walks of life in a short period of time. If during an emergency, the official government website does not release mainstream information promptly, the public will immediately seek information from various existing social platforms, websites, official accounts, and other sources of information out of concern for their safety and the safety of their property. Several false rumors that were difficult to discern between real and fake spread quickly and widely among acquaintances in the early days of the new crown pneumonia outbreak. Due to their inability to distinguish between real and incorrect information, the elderly are readily misled by Internet rumors. As a result, people become more vulnerable to the transmission of misleading information. This type of blind forwarding frequently involves the dissemination of pseudoscience or pseudo-health publications or videos. The proliferation of sources has led to an increase in the number of middle-aged and senior mobile phone users becoming major victims. It is impossible to determine the veracity of the information.

*3.2. The Hidden Main Body in the Dissemination of Network Public Opinion.* Legal name, identification document, address, registered nickname, location information, social traits (gender and age, religious beliefs and occupation, among other things), and identification are all examples of personal identifying information in the real world. Although, these factors of identification can be manipulated to varying degrees in cyberspace. Network users can expect varying degrees of concealment depending on the level of modification. Netizens take use of this identity masking feature to establish their emotional venting zone on the Internet. It is a place where everyone has the right to express themselves. Users who are used to obtaining information from unusual sources in real life and who want to seek support for their beliefs on the Internet can think of it as a route through which they can both get knowledge and express their will. Another viewpoint is that the anonymous online environment has a greater likelihood of exposing individuals’ illogical sides, especially the most primal parts of human nature. Some of the most popular domestic games now available have very low participation criteria or even do not require registration to enjoy the trial mode. This results in a large number of players dangerously attacking others, posting illegal adverts, and so on.

It is in a subconscious state, which is positioned at the bottom of Freud’s personality structure (id, ego, and superego), and is mostly composed of innate instincts and wants, as well as some basic physiological requirements. To

put it another way, it only cares whether your wishes are fulfilled, such as eating when you are hungry and acquiring anything you desire if you desire it. Consider it to be the small monster inside of us that is just concerned with our own wants. As a result, the id acts according to the pleasure principle and does whatever it pleases. Because of the disparities in objective experience and knowledge between individuals in public opinion, especially during times of crisis outbreak, those with independent consciousness frequently use interactive platforms that appear to communicate. However, in reality, it triggers an emotional mobilization effect that resonates with the public with their empirical theory and forms a biased opinion.

### 3.3. *The Diverse Performance of Online Public Opinion.*

When compared to traditional media distribution, online media distribution has the advantages of immediacy, efficiency, and engagement. Through the devices in their hands, ordinary people all around the world may submit what they have seen and heard in the form of text, photographs, and videos to share with the world. Create an online platform account and act as a real-time news reporter. It results in a more diverse performance of online public opinion. People can learn new things on major platforms at any time and from any location. In certain circumstances, the information provided by netizens is timelier and more reliable than that issued by official media organizations following a catastrophe. In addition to providing a venue for online rumor spreaders with ulterior objectives, the openness and freedom of online news releases also serve to create an artificial online public opinion dissemination chain, which is deceptive and misleading. Many individuals would prefer to believe and spread the news that is out of sync with current events than put their faith in the government and its integrity. High-profile media outlets have made information available. At this point, network public opinion needs to verify that it is oriented in the correct direction from the start, rectify or eliminate errors, maximize the positive value of network public opinion information, and guide it to perform its positive societal purpose as effectively as possible.

### 3.4. *The Group Nature Influence of Online Public Opinion.*

Statistical data studies have discovered that the reason for the emergence of online public opinion is not only due to the concentrated attention and expression of opinions of the public on a specific event but also due to the collective response resulting from the action of certain communication factors. Public opinion on the Internet is open and broad, with themes generated more informally than in traditional public opinion polls. With the use of new media platforms and mobile terminal operations, the general public can engage in real-time interaction. As a result of the comprehensive and in-depth conversation, the spread of Internet public opinion follows a specific development law, demonstrating a so-called butterfly effect, as well as collective reactions. When people are grouped together and separated by a particular distance, their emotions and thoughts are more likely to interact, resulting in debates or arguments.

For example, on a public online platform where there are a large number of college students, there are numerous traits that are shared by all of the participants. People participating in related topic discussions can easily increase their speed and click-through rate in a short period, and the impact of online public opinion on them can easily show a high degree of similarity, with the impact being several times greater than that of the general population. According to the theory, under the influence of emotional speech in a network environment, some people will unconsciously lose their individuality as a result of infecting one another and eventually merge with the popular speech of the majority of people to form group psychology.

## 4. Method

LSTM is introduced based on traditional NN in the NN-based campus microblog public opinion emergency forwarding volume prediction model suggested in this work, in addition to traditional NN. It is composed of three layers: the data processing layer, the sentiment analysis layer, and the forwarding volume prediction layer, among others. In a gradual fashion, layer upon layer, Figures 1 and 2 depict the NN structure and the LSTM structure, respectively.

Based on the data preprocessing, a structured corpus of text data is generated. The sentiment trend is obtained using the sentiment analysis method of multi-feature fusion, and the forwarding volume of public opinion and microblog is projected using neural networks. A structured corpus is obtained after four phases of data cleaning, sorting by time, word segmentation, and deleting stop words. These are all performed in the preprocessing stage. This layer receives its input data from the structured data of the data processing layer. This structured data is used by the sentiment analysis layer. The sentiment analysis layer captures dictionary features, expression features, and vector features using the multi-feature fusion sentiment analysis technique. These are fused into sentiment classification features, which are then used by machine classification algorithms to extract sentiment. As a result of sentiment analysis, there is a tendency. The sentiment value and the original blog post volume, as well as the forwarding volume in the initial cycle, the comment volume, and the public opinion popularity value, are used as relevant factors in the forwarding volume prediction layer. The forwarding volume in the next cycle is used as the output sequence. The LSTM is used to realize the forwarding volume of public opinion emergencies in the garden microblog. Figure 3 depicts the theoretical model that was developed.

Data preparation and analysis are the foundations of the methodology for calculating the forwarding volume of campus Weibo public opinion emergencies. Preprocessing the original data can change blog articles written in natural language into a form that is convenient for machine learning methods to detect, as well as facilitate various follow-up time frames for different types of postings. The creation of sequencing data is required. The preprocessing section of the campus microblog public opinion emergency forwarding volume prediction model created in this study includes the following procedures:

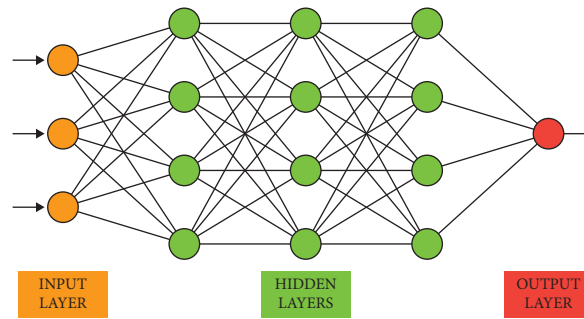


FIGURE 1: Structure of NN.

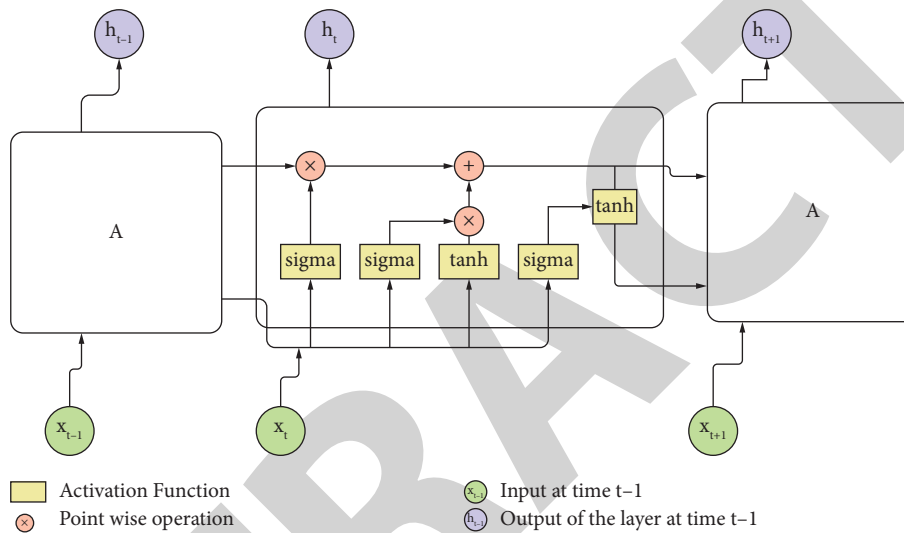


FIGURE 2: Structure of LSTM.

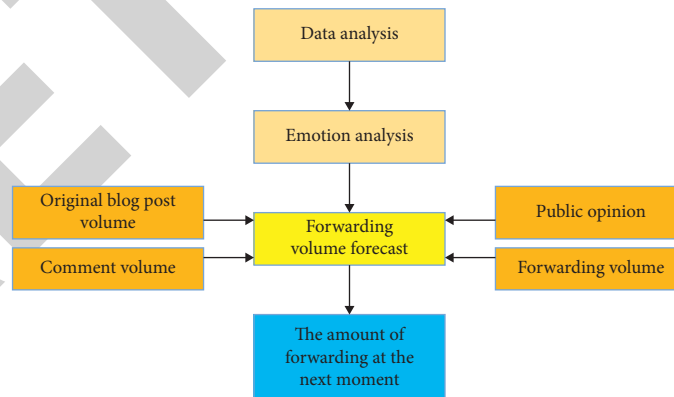


FIGURE 3: Framework of our approach.

- (i) Link for data cleansing.
- (ii) Arrange the number of Weibo reposts of all previous periods.
- (iii) Use the Jieba word segmentation script to segment the original blog post.
- (iv) Remove stop words from the original blog post.

Multivariate time series analysis refers to the study of multivariate time series. It is a method that combines multiple regression analysis and time series analysis. LSTM is an implementation of multivariate time series analysis. It is a variant of RNN, which is more complex internally and can handle long-term dependency problems. For sequence data, the advantage of LSTM is that it can improve the convergence

speed of the model and forecast. Therefore, LSTM is selected to predict the forwarding volume of public opinion emergencies on campus on Weibo. The expression is as follows:

$$\begin{aligned} f_t &= \sigma(W_{hf} * [h_{t-1}, x_t] + b_f), \\ i_t &= \sigma(W_{hi} * [h_{t-1}, x_t] + b_i), \\ o_t &= \sigma(W_{ho} * [h_{t-1}, x_t] + b_o), \\ \tilde{c}_t &= t(W_{hc} * [h_{t-1}, x_t] + b_c), \\ c_t &= f_t * c_{t-1} + i_t * \tilde{c}_t. \end{aligned} \quad (1)$$

The final output is

$$h_t = o_t * t(c_t). \quad (2)$$

The indicators of the popularity of public opinion  $I_{ij}$  are the strength of social connections, the influence of likes, the influence of reposts, and the influence of comments. The calculation formula is as follows:

$$\begin{aligned} X_{ij} &= \left( \frac{L_{ij} - L_{\min}}{L_{\max} - L_{\min}}, \frac{R_{ij} - R_{\min}}{R_{\max} - R_{\min}}, \frac{C_{ij} - C_{\min}}{C_{\max} - C_{\min}} \right), \\ R_{ij} &= \frac{\text{Like}_{ij}}{\sum_{h \neq i} \text{Like}_{hj}}, \\ L_{ij} &= \frac{\text{Repost}_{ij}}{\sum_{h \neq i} \text{Repost}_{hj}}, \\ L_{ij} &= \frac{\text{Comment}_{ij}}{\sum_{h \neq i} \text{Comment}_{hj}}, \\ I_{ij} &= \frac{X_{ij} - X_{\min}}{X_{\max} - X_{\min}}. \end{aligned} \quad (3)$$

Input the above indicators into the LSTM network, and then obtain the predicted value of the forwarding volume of public opinion emergencies on campus Weibo in the next stage.

## 5. Results

Due to the vast quantity of data acquired in this study, the training and test sets were separated by an eight-to-two ratio. The mean square error (MSE), the root mean square error (RMSE), and the mean absolute percentage error (MAPE) are three evaluation indicators that are introduced in this paper to evaluate the fitting effect of the model and facilitate the quantitative comparison between the prediction results and the actual data (MAPE). The smaller the error value of a certain error indicates the smaller the difference between the

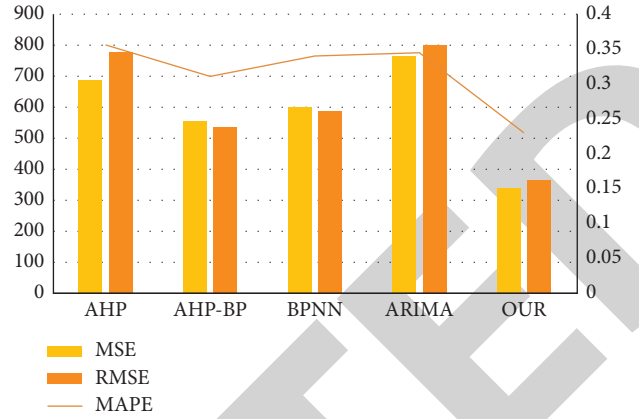


FIGURE 4: Model comparison with one day lag on the training set.

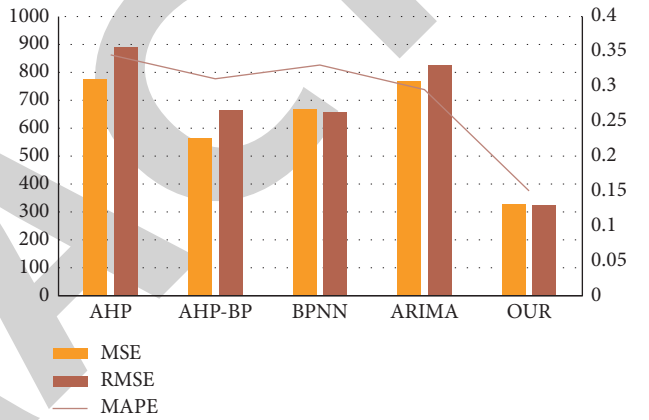


FIGURE 5: Model comparison with one day lag on the testing set.

anticipated value and the actual value, and the greater the prediction effect of the model. The AHP, AHP-BP, BPNN, and ARIMA models are used as comparative models in this article. Figures 4 and 5 depict the results of a comparison between different models in the training set and the test set with a one day lag.

Further, this paper selects the RMSE indicator to compare the performance of different models under different lag days as shown in Figure 6.

It can be seen that the performance of the proposed algorithm is better than the comparison algorithm. Figure 6 shows that, regardless of the number of lag days chosen for the time window, the effect of the neural network-based model for predicting the forwarding volume of public opinion emergencies on campus Weibo is better than the comparative prediction models. When the number of lag days chosen for the time frame is one day, the prediction impact is also the best.

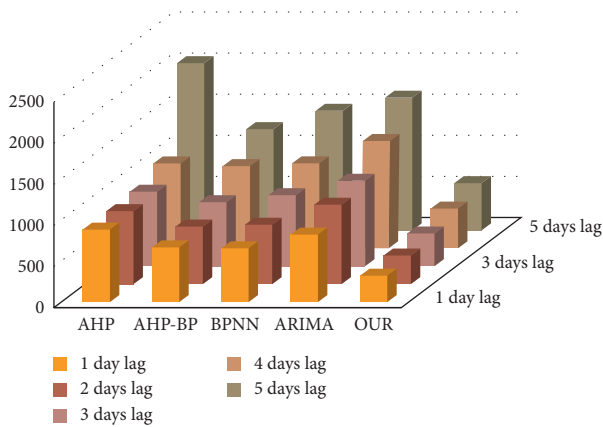


FIGURE 6: Performance comparison of different models on RMSE under different lag days.

## 6. Conclusion

Cyber-optimists and cyber-skeptics have debated the significance of social media in authoritarian nations thus far, focusing on how states filter and manipulate material, as well as how individuals might subvert official authority. Instead of focusing on state laws and the substance of online debates, we have chosen to focus on interactivity in order to investigate the many frameworks for political debate provided by social media firms' technical design. The significant increase in the proportion of college students among Internet users has resulted in them being an important segment of the Chinese Internet population and the primary audience for microblogs. The rumor forwarding behavior of individuals on social media refers to whether or not they transmit particular rumors. Using microblogging as an example, this study offers a neural network-based prediction model of campus microblogging public opinion outbreak retweets. It overcomes the problem of low prediction accuracy of classic SVM and other models by including neural network features. Data-driven experimental results demonstrate that the method suggested in the research can significantly enhance the accuracy of estimating the number of retweets of rapid occurrences affecting campus public opinion.

## Data Availability

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

## Conflicts of Interest

The author declares that he has no conflicts of interest.

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