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Retraction

Retracted: Audience Dissemination Response Law and Action Mechanism Based on Internet Rumor Computer Big Data

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] J. Jiang, Y. Li, W. Yu, N. Li, and X. Tao, "Audience Dissemination Response Law and Action Mechanism Based on Internet Rumor Computer Big Data," *Security and Communication Networks*, vol. 2022, Article ID 3737527, 9 pages, 2022.

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Research Article

Audience Dissemination Response Law and Action Mechanism Based on Internet Rumor Computer Big Data

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Various novel Internet rumors have also emerged. This article mainly researches the audience dissemination response law and the mechanism of action. This paper constructs a model of network rumor spreading. In the homogeneous network, we know that for the rumors that the initial infection rate is large, the increase caused by the herd phenomenon is not very large. For heterogeneous networks, we need to separately examine the increase of nodes and sparse nodes in the network under different initial infection rates. With the change of time, the number of nodes in each state will change due to interaction. When an ignorant person contacts a communicator, the ignorant person will be converted into a rumor communicator with a certain probability. Affected by the memory ability of individual user nodes, each online rumor support node and online rumor opposition node becomes an online ordinary user node with a constant probability *f*. Affected by the rumor support node, an online ordinary user node is transformed into a receiving unread node by a rumor support node with probability β at time t. Experimental data shows that when the herd effect is not considered, it is found that the transmission peak is 0.4328 at $t = 10$. When the herd effect is introduced, the spread of rumors reaches the transmission peak 0.5431 at $t = 8$. After the introduction of the herd effect, the peak value increased by 25.5%, and the time to reach the peak was shortened by 20%. The results show that computer big data technology has a significant inhibitory effect on the spread of Internet rumors.

1. Introduction

From a realistic point of view, with the penetration of the Internet into all aspects of our production and life, if we allow the accelerated spread of online rumors, it will inevitably cause social panic and even cause dissatisfaction and venting of anger, and to a certain extent, it is more likely to cause social instability. With the rapid development of big data technology, various technologies of big data family are updated frequently. There are more and more big data platform users and application cases, and the application industry is more and more extensive. Throughout the rumor in recent years, microblog, WeChat, and SMS are the main spreading platforms of rumors. These Internet rumors have seriously disturbed the normal social order, damaged the national image, and caused great losses to the economic interests of individuals and the collective. Moreover, these rumors spread through the new media, which have a rapid and wide range of influence. Even if they are refuted, their influence is difficult to control. Therefore, the study of Internet rumors of public emergencies from the perspective of sociology can help us clarify the current social reality and structure, political system, ideology, personal psychology and relationship, and also help the authority to face and deal with rumors rationally and orderly.

Under the premise of lack of truth, lack of facts, and vague information, rumors induce the curiosity of the audience and lead to the occurrence of rumors. The use of big data technology can play a certain role in inhibiting the spread of online rumors. Zhang et al. believes that nowadays, the advancement of information technology has witnessed the tremendous advancement of healthcare technology in various fields. His research lacks a certain degree of innovation [1]. Baccarelli et al. believes that research focus is rather vague [2]. Yang et al. believes that in the past few years, big data has become a new paradigm, it provides a wealth of data and opportunities for research and decision support applications, digital earth applications provides unprecedented value. He examined the two fields of big data and related scientific fields. His research lacks necessary experimental content [3]. Chen et al. believed that the lack of accuracy is caused by the discomfort caused by wearing the device for a long time. Therefore, it is difficult to maintain health monitoring through traditional wearable devices. His research lacks necessary data [4], such as how to excavate the law of spread of online rumors, how to grasp the influence of online rumors, how to eliminate the impact, save economic losses, block the unstable factors caused by online rumors, and improve the response strategies of the government and its related subjects.

Based on the definition of online rumors, the characteristics and propagation paths of online rumors are summarized and the theory of online rumor management is improved from a deeper level. When studying the mechanism of social trust on Internet rumors, this paper subdivides social trust into interpersonal trust and government trust. This article starts from the characteristics, types and causes of Internet rumors, systematically analyzes the composition and influencing factors of college students' values, and on the basis of investigation and research, reveals the influence of Internet rumors on contemporary college students' values, and attempts to resolve this negative impact from different levels. The strategy provides theoretical and practical innovation for guiding college students to form correct values.

2. Internet Rumors and Computer Big Data

2.1. Computer Big Data. The Spark architecture is shown in Figure 1. According to the big data processing process, the storage medium [5], streaming processing technology is a big data processing technology following the emergence of batch processing technology. The emergence of stream processing is mainly to solve the problem of slow timeliness of batch processing. The so-called streaming data refers to an infinite data sequence, which often contains order, such as timing. Streaming data is not static, but constantly changing over time, with the characteristic of being disposable. Generally, the stream processing system is required to be able to quickly use local data for calculations and to deposit value from it [6].

$$d_{ij} = \left\| x_i - \mu_j \right\|_2^2. \tag{1}$$

The expression is as follows:

$$\mu_j = \frac{1}{\left|c_j\right|} \sum_{x \in c_j} x. \tag{2}$$

The definition of accuracy is as follows:

$$\mathrm{AC} = \frac{\sum_{i=1}^{n} \delta\left(r_i, \operatorname{map}\left(l_i\right)\right)}{n}. \tag{3}$$

In the formula, $\delta(x, y)$ is the Dirac delta function.

The mutual information measure is as follows:

$$\mathrm{MI}\left(C, C'\right) = \sum_{c_i \in C, c_j' \in C'} p\left(c_i, c_j'\right) * \log \frac{p\left(c_i, c_j'\right)}{p\left(c_i\right) p\left(c_j'\right)}. \tag{4}$$

The expression of the normalized mutual information is as follows:

$$\begin{aligned}
\mathrm{NMI}\left(C, C'\right) &= \frac{\mathrm{MI}\left(C, C'\right)}{\max\left(H(C), H\left(C'\right)\right)}, \\
R &= \frac{\operatorname{cov}(x, y)}{\sqrt{D(x)} * \sqrt{D(y)}}, \\
\widehat{e} &= \frac{1}{N} \sum_{i=1}^{N} I_{\left\{S\left(x_i\right) \geq \gamma\right\}} \frac{f(x, p)}{f(x, q)}, \\
v^* &= \arg\max_{v} E_u I_{\{S(X) \geq \gamma\}} \ln f(X; v).
\end{aligned} \tag{5}$$

First, extract the required data from the original format of the complex data, discard some unimportant fields, clean the data, filter, and eliminate incorrect data. From the perspective of information transmission, the more important the node with the larger the betweenness to the network data information transmission, the greater the impact of deleting these nodes on the data transmission effect of the entire network [7, 8].

2.2. Internet Rumors. Before the emergence of mass media, the main way of spreading rumors was word-of-mouth transmission between people. On the one hand, this mode of transmission lacked the speed of spreading, and on the other hand, it was also subject to many restrictions and was easily managed by related organizations. However, after the emergence of mass media, especially after the emergence of online media, the spread of rumors no longer requires word-of-mouth transmission. Instead, they can be transmitted instantaneously when the communicator and the recipient have never met. In addition to space constraints, on the other hand, it also gets rid of the supervision of regulatory agencies [9]. The calculation formula of TF is as follows:

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}. \tag{6}$$

Among them, the numerator is the frequency of the current word in the file d_j.

The formula of TFIDF is as follows:

$$\mathrm{tdid}f_{i,j} = tf_{i,j} \times \mathrm{id}f_j. \tag{7}$$

Compared with the Boolean model, the vector space model introduces the concept of reverse document frequency in addition to the word frequency when representing words, thereby correcting the errors caused by commonly used words and is suitable for text classification tasks. However, the vector space model is essentially a text representation method based on word frequency, and lacks effective processing of the deep features of the text, such as

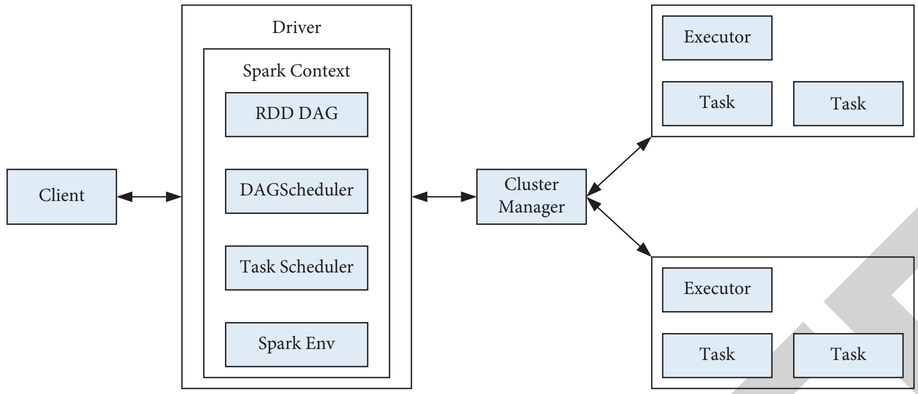

Figure 1: Spark architecture.

semantics and word meaning [10]. For food consumers, it will affect consumers' conventional choices of food and cause consumption panic. It will also adversely affect market order and deepen the distrust between producers and consumers. In terms of political influence, food safety network rumors need to be supervised by relevant government departments and promptly refute the rumors, and its proliferation will leave a negative impression in the eyes of the public that government supervision is weak, thereby weakening the public's respect and trust in government authority. The supervision of language tests the government's ability and level of governance [11].

X_{ij} represents as follows:

$$\log X_{ij} = v_i^T v_j + b_i + b_j. \tag{8}$$

The loss function of GloVe is as follows:

$$J = \sum_{i,j}^{N} f\left(X_{ij}\right)\left(v_i^T v_j + b_i + b_j - \log X_{ij}\right)^2. \tag{9}$$

There are three ways to represent fuzzy sets.

(1) Zadeh notation

$$A = \frac{A\left(x_1\right)}{x_1} + \frac{A\left(x_2\right)}{x_2} + \cdots + \frac{A\left(x_n\right)}{x_n}. \tag{10}$$

(2) Sequence pair notation

$$A = \left\{\left(x_1, A\left(x_1\right)\right), \left(x_2, A\left(x_2\right)\right), \ldots, \left(x_n, A\left(x_n\right)\right)\right\}. \tag{11}$$

(3) Vector representation

$$A = \left(A\left(x_1\right), A\left(x_2\right), \ldots, A\left(x_n\right)\right). \tag{12}$$

In the Internet age, the arbitrary development of online rumors has continuously invaded the people's ideology. As college students with immature values, outlook on life, and world outlook, if they indiscriminately accept the role of all online information, they will naturally inevitably get rid of the side effects of online rumors. At present, Internet rumors mainly have negative effects on college online, which weaken mainstream ideology, damage foundation of social trust and harmony, and cause college students to conduct anomie [12].

2.3. Audience Communication Law. Compared with general rumors, Internet rumors have some special features. Firstly, the conversion events from formation to climax of Internet rumors become shorter, which is attributed to the timeliness of Internet communication. Once the rumors are formed, they will be spread at high-speed to reach climax. Secondly, the time from the peak period to the weak period also becomes shorter, which is also due to the high-speed transmission characteristics of the network. After the rumor reaches the climax period, after the superposition of information on the network and the continuous process of "falsification," and the positive response of the rumor refutation, the rumor quickly turns into a weak period, and finally, the rumors disappear [13].

The stronger the individual's cognitive ability, the more rationally he can treat rumors, distinguish between true and false, and not blindly believe and spread rumors. Through network representation learning, an optimization algorithm can be automatically used to obtain a nonfeature engineering low-dimensional dense feature vector to be applied to subsequent application scenarios, such as link prediction, recommendation system, and other tasks. These low-dimensional and dense node vector representations make efficient statistical learning methods possible by getting rid of the original complex network structure [14].

In the era of Internet, the information audiences who originally existed as individuals have been connected together, and their status has also changed dramatically. They began to get rid of the label of "passive receiver." In the dissemination of public events, the audience is no longer in the marginal position of the communication mode, but has entered the core area and become the disseminator of information, promoting process event [15].

In the network information dissemination, the role division between the disseminator and the receiver becomes fuzzy. When the audience obtains the information, they can also actively release the information through the network. When they are given the power of communication, they also undertake the corresponding responsibilities. In the process of rumor spreading, there are two main factors affecting the herd effect: one is the credibility of the rumor itself, which is determined by the content of the rumor itself and reflected in the initial rumor spreading probability. The other is their own cognitive level and psychological quality. Individuals with lower cognitive level tend to follow the attitude of their neighbors towards rumors. Individuals with weak psychological quality are more willing to get the sense of inner security through the way of gregarious [16, 17]. Group effect means that when people face a group, they will be affected by group behavior, so as to integrate into the behavior of the group, which will aggravate the influence of the group.

3. Experiments on the Audience Dissemination Response Law of Online Rumors

3.1. Experimental Environment. The experimental environment of this article is CPU frequency 2.40 GHz, memory 8.00 GB, operating system is Windows10, JAVA language environment. The specific parameters of the experimental data set are shown in Table 1.

3.2. Parameter Setting. In this article, it is assumed that in a scale-free network of N nodes, each WeChat user is a node, and the relationship between users is connected by edges, and the total number of nodes in the network is set to $N = 1000$. There is only one rumor spreading node in the initial network, and the others are ignorant [18]. As rumors are passed between friends, the scope of the rumors will gradually expand, and then relevant departments or official media will urgently dispel the rumors, and the rumors will gradually spread, so that more users will learn the truth, and the rumor spreaders will gradually become those who are immunized and those who spread the truth will eventually control the rumors [19, 20].

3.3. Construction of Network Rumor Spreading Model. In the homogeneous network, we know that for the rumors that the initial infection rate is large, the increase caused by the herd phenomenon is not very large. For heterogeneous networks, we need to separately examine the increase of star nodes and sparse nodes in the network under different initial infection rates. The spread of rumors on the Internet is abstracted into an undirected graph $G\,(V, E)$ composed of nodes and edges, where V is the entity that propagates the message in the network and E represents the associated edge between the nodes. With the change of time, the number of nodes in each state will change due to interaction. When an ignorant person contacts with a disseminator, the ignorant person will change into a rumor disseminator with a certain probability. When an ignorant person contacts with a rumor disseminator or of the truth of a rumor, affected by the knowledge experience of the ignorant person, he may find out the rumor. However, it can be transformed into a rumor disseminator with a certain probability.

3.4. Model Simulation

(1) Offline nodes are all ordinary users (because the rumors have a short spread time, so most of the online users are basically ordinary users), and they go online with a constant probability μ
(2) Each online node goes offline with a constant probability δ
(3) Due to the influence of users reading unread messages and the differences of users' subjective consciousness, each online receiving unread node becomes a rumor supporting node and a rumor opposing node with a constant probability αb and αd, respectively
(4) Affected by the antirumor work of relevant agencies, each online rumor support node becomes a rumor opposed node with a constant probability γ
(5) Affected by the memory ability of individual user nodes, each online rumor support node and online rumor opposition node becomes an online ordinary user node with a constant probability f
(6) Affected by the rumor support node, an online ordinary user node is transformed into a receiving unread node at time t with probability β by a rumor support node

3.5. Statistical Analysis. This article uses SPSS22.0 (a data processing software) to analyze the reliability of the data, including the analysis of the reliability and validity of the data, and then through the correlation analysis of each variable in the model, to determine the correlation of each variable, which is the subsequent structure equation model analysis, is used to pave the way.

4. Spread Law of Internet Rumors

4.1. Time Series Characteristics of Rumor Data. From the perspective of sociology and journalism, the occurrence of social hot events is the result of a combination of many factors, which are highly random according to the constant change of time. Most online rumors are generated based on hot events, so they will show different characteristics in different time periods. From the perspective of online rumors detection, the periodicity of online rumors embodies the two characteristics of rumors. On the one hand, with the continuous enrichment of rumor-defying methods, rumors can continue to harm the Internet only through continuous adjustment and modification of rumors. The clustering coefficient distribution of each node is shown in Figure 2. Through calculation, the average clustering coefficient of the associated network is 0.465. Because the value of the coefficient is small, it can be concluded that the clustering effect of the associated network is not high. Although the connections between nodes are relatively close, they cannot be clearly divided into many large and small clusters form a large group approximately as a whole. It can be seen that the data points in the point degree distribution are a diagonally lower right line. A few nodes have high degrees and most of them have low degrees, that is, they obey the power-rate distribution. It can be considered that the network conforms to the scale-free characteristics.

It is recommended that the team first add a monitoring and warning function to this part of the strong reliance on

Table 1: Experimental data set.

Data set	Number of items	Number of transactions	Minimum support	Minimum confidence
Retail	16470	88162	0.01	0.25

the upstream, and the discovery cycle of online faults has been shortened from the original hourly or even daily level to the minute level. After the failure is quickly discovered, the recommended team will contact the corresponding team to deal with the failure based on the actual situation, greatly reducing the average recovery time of the failure. In the case of a larger learning rate, the training continues, because the learning rate is too large, the weight will be too large and exceed the minimum error in the correction process and will not converge. Moreover, a larger learning rate is also easy to cause oscillations in the expected goal. Therefore, in this process, the method of learning factor optimization is used to adjust the step size of the entire learning factor when the minimum error is continuously approached to make it converge quickly and no limit violation occurs. The execution time of the algorithm on multiple nodes is shown in Table 2. For a certain size of data, the more nodes in the cluster, the shorter the algorithm execution time and the higher the data processing efficiency. It can be inferred from this that when the scale of processing data is large, reaching the level of GB or TB or even PB, can effectively shorten the running time of the algorithm.

The comparison of $k = 10$ and $k = 40$ propagation processes is shown in Figures 3 and 4. As the degree increases, the speed at which rumors are received and disseminated increases sharply, the time for the receiver to transform into a disseminator shortens, and the rumors latency decreases rapidly. The maximum proportion of recipients was increased from 52% to 69%, which was a large increase. When $k = 10$, the time for the communicator to reach the maximum was 22.3. When $k = 40$, the time for the communicator to reach the maximum is only 12.9, which shortens the time by nearly 10 units, that is to say, the more people netizens can reach and spread, the easier it is for rumors to be received and spread. The time from the incubation period to the outbreak period is drastically shortened, making the rumor control reaction time shorter and the rumor quelling time significantly long. This will bring greater difficulties and challenges for the control of rumors.

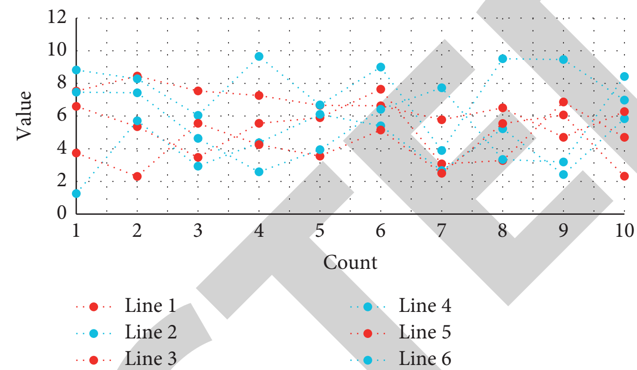

Figure 2: Distribution of clustering coefficient of each node.

Table 2: Algorithm execution time on multiple nodes.

Number of nodes	Algorithm running time (minutes)
3	48
4	40
5	36
6	27
7	24
8	21

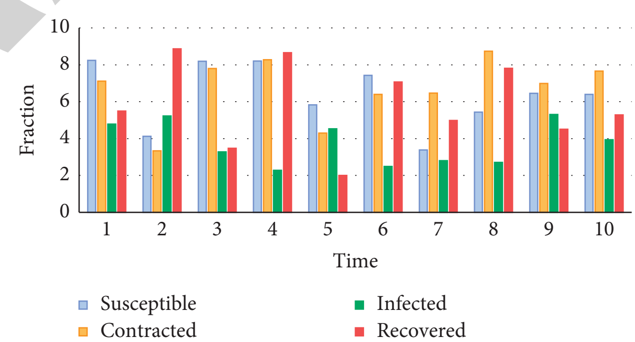

Figure 3: The propagation process of $k = 10$.

4.2. Evolution Process of Rumors. The evolution process of UBEN single rumor explosion is shown in Figure 5. The density of rumor exploder $E(t)$ and rumor deflator $B(t)$ increases rapidly and decreases gradually after reaching the peak value and tends to the stable state. The density of rumor unburned $U(t)$ gradually decreases and of rumor extinguisher $N(t)$ increases gradually and finally tends to the stable state. Finally, the rumor blaster $E(t)$ and the rumor deflator $B(t)$ approach to zero, and only the rumor unburned $U(t)$ and the rumor extinguisher $N(t)$ remain in the system. The rumor spreading stops and reaches a stable state. It is not difficult to see that the changes of population density in the system are consistent with the results of the average field equation in the model. This shows that individuals who do not know rumors will not only become communicators after contacting rumors, but also some individuals will be in a state of silence or hesitation. When these individuals choose to spread rumors, the density $E(t)$ of explosives will increase. Obviously, this is more in line with the situation of rumor spreading in reality.

The DBLP (data set) classification results are shown in Table 3 and Figure 6. Table that is using the attribute information, the AMLNE effect is 1.53%~2.23% higher than AMINE-without, which is at least 18.26% higher than Metapath2vec, 59.6% higher than LANE, 4.46% higher than LINE, and 20.73% higher than DeepWalk. In general, the representation vector effect learned by AMLNE in the classification task is better than other methods. According to

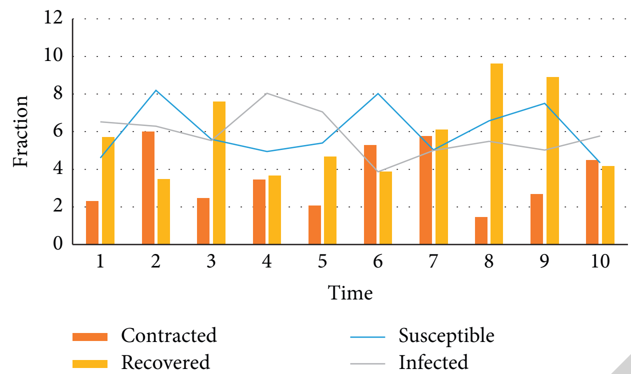

Figure 4: The propagation process of $k = 40$.

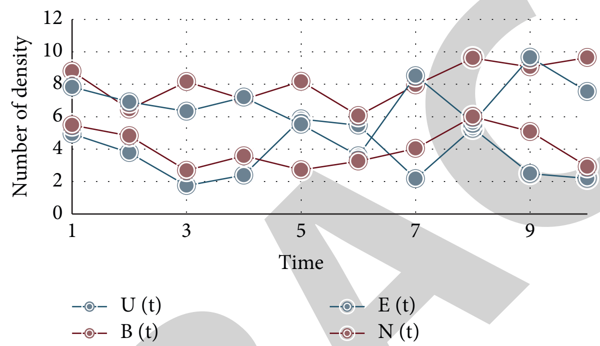

Figure 5: Evolution process of UBEN single rumor explosion.

Table 3: DBLP classification results.

DeepWalk	0.6668	0.6703	0.6765	0.6274	0.6503	0.6440	0.6643	0.6676	0.6680
LINE	0.6463	0.6654	0.6246	0.6330	0.6443	0.6643	0.6203	0.7044	0.7824
LINE-within	0.6433	0.6420	0.6748	0.6867	0.6562	0.6435	0.6654	0.6665	0.6734
Metapath2vec	0.6083	0.6534	0.6664	0.6746	0.6250	0.6272	0.7883	0.7586	0.7554
LANE	0.6430	0.6680	0.6643	0.6744	0.6204	0.6244	0.6070	0.6886	0.6308
AMLNE-without	0.6663	0.6752	0.6766	0.6247	0.6275	0.7802	0.7824	0.7303	0.7367
AMLNE-within	0.6667	0.6764	0.6727	0.6260	0.6264	0.7837	0.7824	0.7300	0.7344
AMLNE	0.6677	0.6776	0.6206	0.6288	0.6246	0.7344	0.7524	0.7443	0.7644

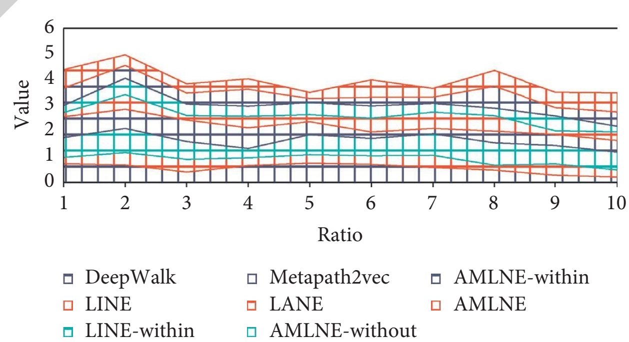

Figure 6: DBLP classification results.

the picture, the attitude of the people with a higher degree of outreach to the authenticity of rumors will directly affect the final spread of rumors. In a node set with a larger degree, the more individuals that can accurately identify the authenticity of rumors, the greater the number of groups that can be correctly judged after the evolution is over.

The comparison between the potential energy model and the SIR model is shown in Figure 7. The explosion time of the potential energy model is in step 8, and the model is basically stable in step 16, and the number of people who have spread rumors on the network is about 280. The energy curve in the potential energy model indicates that people are affected by rumors, and it reflects the change process of people from believing rumors to disbelief. However, the probability of infection and immunity of each individual in the SIR model is the same, ignoring individual differences and changes in external conditions are achieved by adjusting the two parameters a and b. It does not start from the essence of the spread of rumors out of the key factors affecting the spread of rumors. The SIR model is a propagation model and an abstract description of the information propagation process.

4.3. Mechanism of Online Rumors. The rumor burning process of the Single-DBFS model is shown in Figures 8 and 9. Changing trends of the four types of user status in the two networks are similar. With the burning and spread of online rumors in the system, the density of the number of smolders gradually decreases, some become rumor burners and some become rumor suppressors. Burners also have a certain probability to become a burn suppressor and no longer burn rumors. In the fourth step, burn suppressors are randomly added to the system to spread real information, and the number of burn suppressors starts to increase. Some smolders and burners have begun to transform into suppressors and spread the true information under the influence of the truth. The success of this model lies in changing a single model to handle multiple classification problems to multiple models to handle several binary classification problems. Complexity of the internal structure of the neural network model itself is effectively reduced and a network model with structural interpretability is constructed, which is conducive to the further research of interpretability theory. From the perspective of combustion theory, the spread of online rumors is highly similar to the phenomenon of combustion.

The density change trend of each network entity is shown in Figure 10. In the uniform network and the nonuniform network, the density of ignorant people shows a downward trend over time until it reaches zero. The density of immune people shows an upward trend over time. Rumor spreaders, and lurkers initially show an upward trend over time. After reaching the peak, it shows a downward trend with time. When the information aging rate is 0.02, the peak density of rumor spreaders in a uniform network is about 25%, and the peak density of rumor spreaders in a nonuniform network is about 0.05. From this point, it is easy to draw the same information aging. In the case of speed, the impact on the nonuniform network is greater. The density of

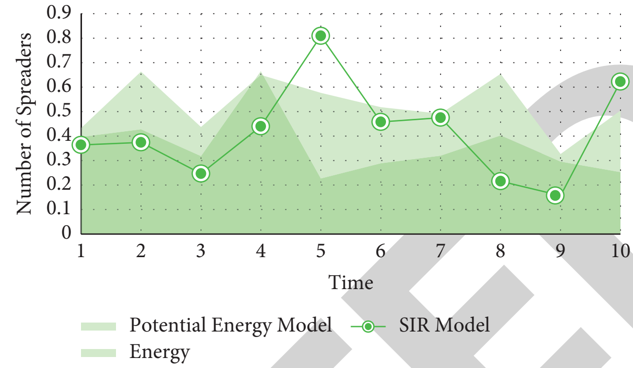

Figure 7: Comparison of potential energy model and SIR model.

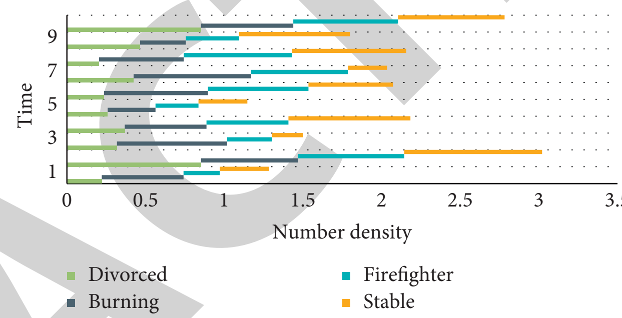

Figure 8: The dissemination process of Internet rumors.

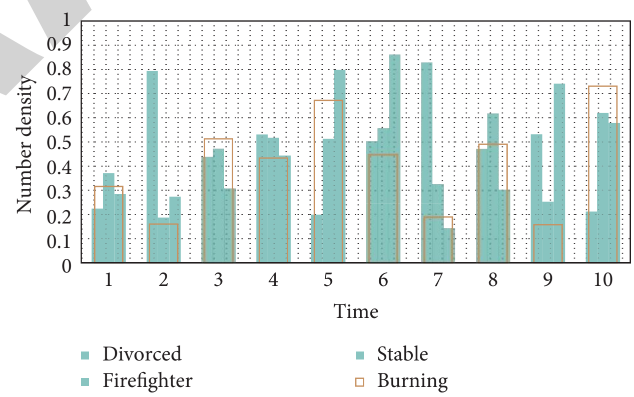

Figure 9: The burning process of internet rumors.

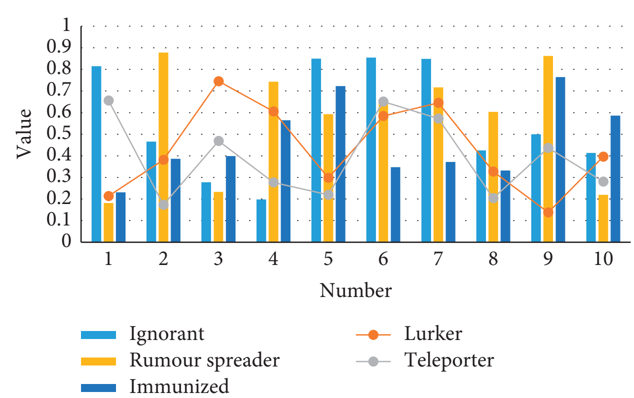

Figure 10: Density trend of each network entity.

Table 4: Rumor spread data of SHIR model.

$S(t)$	0.3321	0.3624	0.4123	0.5124	0.1578	0.4328
$H(t)$	0.5011	0.2311	0.5431	0.2674	0.3416	0.4455
$I(t)$	0.2615	0.3265	0.2574	0.4412	0.1647	0.3301
$T(t)$	0.6611	0.2305	0.3041	0.4125	0.3001	0.2652

rumor spreaders is 10%. When the information aging rate is 0.02, the density of rumor spreaders is 4%, and when the information aging rate is 0.03, the density of rumor spreaders the density is 2%. Through longitudinal comparison, it is easy to draw that the density of rumor spreaders is inversely proportional to the rate of information aging. The faster the rate of information aging, the lower the density of rumor spreaders and the less harmful.

The data of rumors spread in the shire model without social effect and with herd effect are shown in Table 4. Without considering the herd effect, it is found that when $t = 10$, the rumor reaches the peak value of 0.4328, and when the herd effect is introduced, the rumor propagation reaches the peak value of 0.5431 at $t = 8$. After the introduction of the herd effect, the peak value was increased by 25.5%, and the time to reach the peak was shortened by 20%. For the immune curve, when the rumors dissipated, the immune density in the network increased from 0.9313 to 0.942, which proved that the following effect accelerated the spread of rumors and expanded the spread range. The time to reach the peak of rumor propagation is only 35.0 times of that in Ba theory. BA is a scale-free network. The above results show that the trend of rumor spreading in BA network is consistent with the theoretical results, but the spreading speed is faster and the spreading range is wider.

5. Conclusions

This paper pays more attention to the social situation in China. This paper combines political science, communication, sociology, psychology, and other disciplines as theoretical research support to conduct case comparison analysis and case summary of events that have occurred in recent years. This article uses communication dynamics, based on social networks, establishes a social network rumors dissemination model, studies the laws and dissemination trends behind the dissemination of rumors, and provides constructive suggestions and theoretical foundations for government agencies to govern rumors. This article uses propagation dynamics, establishes the URBD theoretical model, and establishes the differential dynamics equation of rumor propagation. Theoretical methods are used to verify the model, and the stability and propagation threshold of the model are analyzed comprehensively. Numerical simulation experiments are used to verify the correctness of the theoretical analysis. Experimental simulation found that the act of publishing authoritative news has a better suppression effect on the spread of rumors.

Rumor spreading on social network by using communication dynamics, studies the law and trend of rumor spreading, and provides constructive suggestions and theoretical basis for government agencies to control rumors. In this paper, we use propagation dynamics to establish UBEN model and differential dynamic equation of rumor spreading. The model is verified by theoretical method, and the stability and propagation threshold of the model are analyzed comprehensively. The simulation results show that the behavior of publishing authoritative information has a good inhibitory effect on the spread of rumors.

The social attribute of social media promotes the spread of enterprise network rumors. The driving of economic interests makes the motivation of enterprise network rumors more complex. The release of social emotions incites the evolution of enterprise network rumors. Through the model, we can find that knowing the corresponding punishment system can effectively restrict the rumor from spreading false information. From the perspective of government trust, we can reduce the cost of releasing antirumor information and improve the government departments' attention to the credibility of the government. Once the government credit is lacking, the work is more difficult and the confidence is hard to establish again. To improve the government's additional benefits from timely release of clarification information is mainly reflected in maintaining social stability and improving the credibility of the government. The research on these parameters is relatively preliminary, and there are more influencing factors and research perspectives to be further explored and studied. Meanwhile, the rumor propagation model of various factors in neural network will be a further research direction.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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