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Retraction

Retracted: Analysis of Dynamic Influence Mechanism of Network Public Opinion Based on Simulation Feature Extraction

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Manipulated or compromised peer review

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.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

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] Y. Zhang, "Analysis of Dynamic Influence Mechanism of Network Public Opinion Based on Simulation Feature Extraction," *Security and Communication Networks*, vol. 2022, Article ID 8423643, 12 pages, 2022.

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Research Article

Analysis of Dynamic Influence Mechanism of Network Public Opinion Based on Simulation Feature Extraction

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In order to improve the effect of network public opinion management, this paper constructs an intelligent computer network simulation model to analyze the dynamic influence mechanism of network public opinion. This paper converts semistructured text information into a form that is easy for computer analysis and recognition, which facilitates opinion extraction and sentiment analysis. Moreover, by analyzing the text content to be mined, this paper uses a specific algorithm to select different words that best represent the text to be tested as the characteristic words of network public opinion. These network public opinion feature words can classify texts, thereby reducing the complexity of text classification. The experimental study shows that the dynamic influence mechanism analysis model of network public opinion based on intelligent computer network simulation constructed in this paper has a good effect.

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1. Introduction

Different from single text and pictures, short videos integrate various forms of expression, such as text, pictures, and videos, and are mainly divided into the following categories. One is pure picture stitching, which combines multiple pictures into a form similar to an electronic album. The second is to add subtitles to pictures, which are based on the combination of multiple pictures and add text descriptions. The third is video one-shot or mixed-cut, which simply processes the captured video and uploads it directly, or stitches multiple video clips together. The fourth is the form of video plus text, which is supplemented by text description on the basis of video. The fifth is pure text, which transforms the text in various forms to form a video. Metaphorization mainly refers to the dissemination of public opinion in an indirect and concealed way. Moreover, various forms of communication have prompted netizens to express and disseminate public opinion in various ways such as text, video, pictures, and actions. The process of metaphorization of social public opinion is consistent with the process of development and evolution of social public opinion. It is also under the stimulation of emergencies, the public responds to it, chooses metaphorical methods to express public opinion, and finally, public opinion superimposes and spreads. In the process of metaphorical dissemination of social public opinion, there is a phenomenon of mutual transformation between explicit and implicit public opinion, which brings a test to the guidance of social public opinion. Due to the limited duration of short videos, they are fragmented. First, because the content narrative is incomplete, a complete video may be divided into multiple short video segments for dissemination. The second is the fragmentation of the push sequence. The algorithmic recommendation mechanism of short videos makes the content presented to the audience more of their favorite content rather than the latest content in chronological order. Fragmentation of content narrative may lead to public opinion in the first half of the video, and when the public opinion enters a quiet period, it will stir up again due to the release of the second half of the video. At the same time, the fragmentation of the push sequence may lead to the fact that when the public opinion returns to a quiet period, the video that caused the public opinion is pushed to the public who do not know the truth, causing a public opinion crisis again, which constitutes the characteristic of the repeated crisis of social public opinion communication.

The traditional text public opinion cycle shows a development process from latent to outbreak, and finally to a quiet period. If there is a subsequent release of text content that will trigger public opinion, it will enter the latent period again, forming a closed-loop process. The intervention of short videos has made public opinion show a step-by-step rise and the characteristics of a reciprocating crisis. There must be contradictions behind the crisis of public opinion. There are many subjects involved in the society, the social ecology is complex, and the social system concentrates various contradictions. These contradictions can become the signs of the outbreak of public opinion.

Based on the above analysis, this paper constructs an intelligent computer network simulation model to analyze the dynamic impact mechanism of network public opinion and provides a reference for the subsequent management and control of network public opinion.

2. Related Work

The literature [1] found that news reports can set agendas for audiences, and this agenda setting is achieved through the number of reports, titles, layouts, etc., from which the influence of mass media on public opinion is obtained. The literature [2] uses the methods of social network and statistical analysis to analyze the influence of public political attention on election results and public opinion surveys. The literature [3] mainly starts from the perspective of public sentiment, by correlating the emotional information released by netizens on the network platform and related news content, and using the method of public opinion link tracking to monitor netizens' sentiments towards political actors.

The literature [4] uses the Delphi method to design the weight of the early warning indicator system, conducts in-depth research on the development, changes, and process of network public opinion, analyzes its propagation law, and accurately predicts the development trend of network public opinion. The literature [5] expounds the research on the three subsystems of the network public opinion early warning mechanism, including the database research and judgment analysis system, the public opinion information processing and mining system, and the early warning joint control and disposal system, early warning mechanism. The literature [6] improves and optimizes the traditional topic tracking model on the basis of Rocchio algorithm. The literature [7] proposes a topic detection algorithm, which is based on K-means clustering, a detection method.

On the basis of the four-dimensional indicators studied in the literature [8], dimensional indicators including audio, video, and images are introduced, thereby establishing a network public opinion security evaluation system with five dimensions. Through this evaluation system, network public opinion can be studied. More comprehensively monitor the development trend of network public opinion; based on the research method of intuitionistic fuzzy reasoning, the literature [9] determines the weight of the evaluation index elements, so as to implement monitoring, early warning and evaluation of network public opinion. The literature [10] systematically detects leaders in the dissemination of network public opinion, mainly using frequent pattern mining algorithm for monitoring. The literature [11] builds a network public opinion monitoring and early warning model and further improves network public opinion by proposing a single-granularity opinion mining algorithm early warning model.

Based on the analysis of the characteristics of network public opinion, such as fast dissemination speed, wide dissemination range, and large dissemination base, the literature [12] proposes a strategy to deal with network public opinion and a path selection method to guide it. The literature [13] puts forward relevant methods to deal with the outbreak of network public opinion and measures to guide the development of public opinion in a benign direction through in-depth analysis of various aspects of network public opinion.

The literature [14] established a system dynamics model for the dissemination process of network public opinion based on the SIR model. Through experimental simulation to find its propagation law, to find out the factors that affect the trend of public opinion propagation and to maintain a balance that is conducive to the stability of the system. The literature [15] mainly conducts in-depth and comprehensive research on the popularity of network public opinion and establishes a model that can predict the development trend of network public opinion. It mainly conducts in-depth research on the comprehensive application of events, media, netizens, and government and proposes solutions and coping strategies when the network public opinion crisis occurs through the simulation results of the model. The literature [16] considered the characteristics of network public opinion dissemination, combined AHP with system dynamics, and established a model with network public opinion early warning mechanism that can be analyzed from both the government and the media. The model is simulated, and through the simulation results, a reasonable early warning mechanism for network public opinion is proposed.

The term "social network" was first proposed by Brown and gradually formed the current social network analysis method that can be applied to many fields such as psychology, sociology, and statistics. The literature [17] proposed a classic rumor propagation SIR model when studying the law of rumor spreading. In the model, two parameters that affect rumor spreading, diffusion rate and removal rate, are set as constants. After simulating the model, it is concluded that the whole process of rumors from spreading to disappearing will not be known to everyone. The literature [18] uses the social network analysis method to analyze the density, diameter, clustering coefficient, etc. The relevant parameters are divided into trees.

The literature [19] proposed a traversal algorithm that can move the cell, also considered the firmness of the cell, and designed the calculation formula of the majority rule. Four parameters are defined in this formula, namely, tendency strength, tendency aggregation degree, cell peak value, and cell tendency value, and the influence of the changes of their set values on the process of public opinion dissemination is discussed separately. The literature [19] introduced the algorithm of fuzzy reasoning in the cellular automata model to fuzzify some information in the process of network public opinion. At the same time, in the established network public opinion propagation model based on fuzzy cellular automata, two parameters are set: environmental fitness and preference, and their impact on public opinion dissemination is analyzed through simulation results.

3. Intelligent Network Public Opinion Dynamic Text Analysis

The network public opinion feature words are generally divided into two categories, one is the general network public opinion feature term, and the other is the exclusive network public opinion feature term. The so-called general network public opinion feature terms refer to words that appear frequently in a specific document. The extraction of these terms is based on a weight function, and the network public opinion feature weight calculated by the function is used to measure the frequency of the term. The larger the value, the higher the occurrence frequency, and the stronger the representativeness of the network public opinion feature word in the text. Proprietary network public opinion feature terms are different from general network public opinion feature terms. Proprietary network public opinion feature terms are words with specific and special meanings, such as proper nouns, time nouns, person names, place names, and numbers. Proprietary network public opinion feature items must be extracted according to the specific network public opinion feature words themselves.

Information gain refers to calculating the frequency of a specific network public opinion feature word appearing or not appearing in the text, so as to measure the probability that a document is classified into a certain category. The main idea of the algorithm is that specific network public opinion feature words can provide a certain basis for the classification of texts. For example, for a specific network public opinion feature word, its existence can provide a certain amount of information for document classification. The dispersion value formed in the process of changing the amount of information represents the gain information provided by the network public opinion feature word for a certain type of text.

The information gain is expressed by the following equation.

In the process of information gain, the value of x is $x_1, x_2, \ldots, x_n, p_1, p_2, \ldots, p_n$ represents the classification probability, and the entropy of x is defined:

$$H(x) = -\sum_{i=1}^{n} p_i * \log_2 p_i. \tag{1}$$

For the appeal equation, the more feasible values of x, the more informative it is to prove it.

C is the text category set, c is the text category variable. Then, the information gain formula is

$$\begin{aligned} IG(t_k) &= H(C) - H(C \mid t_k) \\ &= -\sum_{c\in C} p(c)\log(p(c)) + p(t_k)\sum_{c\in C} p(c \mid t_k)\log(p(c \mid t_k)) \\ &\quad + p(\overline{t_k})\sum_{c\in C} p(c \mid \overline{t_k})\log(p(c \mid \bar{t}_k)) \\ &= \sum_{c\in C}\left(P(c,t_k)\log\left(\frac{P(c,t_k)}{P(c)P(t_k)}\right)\right. \\ &\quad \left. + P(c,\overline{t_k})\log\left(\frac{P(c,\bar{t}_k)}{P(c)P(\overline{t_k})}\right)\right), \end{aligned} \tag{2}$$

where $H(C)$ represents the entropy value change function in the whole process of information gain, and $H(C \mid t_k)$ represents the conditional entropy of the system under the condition that the network public opinion feature t_k occurs. The larger the entropy value is, the better the network public opinion feature words can represent the text.

Mutual information of two random events x and y is specified:

$$MI(x, y) = H(x) + H(y) - H(x, y), \tag{3}$$

where $H(x, y)$ is the joint entropy value, and the H function is defined as follows:

$$H(x, y) = -\sum p(x, y)\log p(x, y). \tag{4}$$

It is generally believed that if the frequency of a certain network public opinion feature word in a certain category of documents is much higher than that in other categories of texts, it is considered that the network public opinion feature word has a greater amount of mutual information for this type of document. Therefore, mutual information is a measure of the relationship between characteristic words of network public opinion and classified documents. The more the network public opinion feature word can express a text, the greater the calculation value of its mutual information.

The mutual information of network public opinion feature word t_k and document category c is defined as follows:

$$\begin{aligned} M(c, t_k) &= \log\left(\frac{p(c, t_k)}{p(c)p(t_k)}\right) \\ &= \log\frac{p(t_k \mid c)}{p(t_k)} \approx \log\frac{A \times N}{(A + C)(A + B)}, \end{aligned} \tag{5}$$

where N refers to the number of documents to be classified, A is the number of network public opinion features t_k included in class c documents, B is the number of documents that contain t_k but do not belong to class c, and C is the number of documents belonging to c but not including t_k.

The chi-square test is a widely used statistical test algorithm. In text classification, the chi-square test is used to measure the association between documents. The chi-square statistical test is a measure of the dispersion between the

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theoretical value and the sample to be tested. It is used to analyze the degree of association between two network public opinion feature words. Moreover, the characteristic of the chi-square test is that it counts the presence or absence of the characteristic words of network public opinion. Therefore, in some respects, the chi-square test is more accurate than the mutual information calculation.

The formula for calculating χ^2 of the network public opinion feature word t_k, t_k is as follows:

$$\chi^2(c, t_k) = \frac{p(c, t_k) p(\bar{c}, \overline{t_k}) - p(c, t_k) p(\bar{c}, t_k)}{p(c) p(t_k) p(\bar{c}) p(t_k)}. \tag{6}$$

Fitting the feature word t_k of network public opinion, the following function is obtained:

$$\chi^2_{\text{avg}}(t_k) = \sum_{c \in C} p(c) \chi^2(c, t_k). \tag{7}$$

The larger the chi-square statistic value, the higher the correlation degree between the network public opinion feature t_k and the document category c.

In text representation, the selection of text network public opinion features is also crucial. As a text network public opinion feature that refers to a text, its granularity can be word, phrase, sentence, or paragraph. The selection of text network public opinion features with different granularities will also achieve different text representation effects. Generally speaking, the language granularity of words is selected as the basic unit of the characteristics of text network public opinion.

There are many methods of text representation, and the most commonly used method with ideal effect is the Vector Space Model. The model vectorizes the document and replaces the text with a vector d, which is represented by the formula

$$d_i = (w_{i1}, w_{i2}, \ldots, w_{\text{in}}), \tag{8}$$

where t_k represents the feature of the text network public opinion and w_{ik} represents the weight of the k-th network public opinion feature item entry t_k of the text d_i, that is, the proportion of the network public opinion feature word in the text d_i. The larger the value of w_{ik}, the greater the importance of the network public opinion feature in the text d_i, and the high proportion value also indicates that the network public opinion feature item is more representative of the text d_i.

This paper is also dynamically analyzing the online review information, among which, an essential step is text representation, which converts semistructured text information into a form that can be recognized and processed by computers. In order to analyze the comment text dynamically, this paper uses the content network public opinion feature information of the text and the external network public opinion feature information to represent the text.

Naive Bayes is a calculation method based on the theory of statistical probability. The Naive Bayes algorithm assumes that the distribution of network public opinion feature words in document D_i is irrelevant. The basic idea is to calculate the probability that an unknown document belongs to a certain category through the prior probability of the category and the conditional probability of the network public opinion feature distribution relative to the category.

$TF(W_k)$ is the frequency of network public opinion feature word W_k appearing in a certain document. $P(C_j)$ is the probability of belonging to a class:

$$\frac{P(C_i) P\left(D_j \mid C_i\right)}{P\left(D_j\right)} = \frac{P(C_i) \prod_{k=1}^{D_j} P(W_k \mid C_i) TF(W_k)}{P\left(D_j\right)}. \tag{9}$$

Among them, C_i represents a specific category i, D_i represents the text of the category to be tested, and W_k is the characteristic word of network public opinion that appears in D_j. $P(C_i)$ and $P(W_k \mid C_i)$ can be obtained in advance by training.

The algorithm process of Naive Bayes classification $W = (W_1, W_2, W_3, \ldots, W_k)$ represents the probability of occurrence of network public opinion feature words:

$$W_k = P\left(W_k \mid C_j\right) = \frac{1 + \sum_{i=1}^{|D|} N(W_k, d_i)}{|V| + \sum_{s=1} \sum_{i=1}^{|D|} N(W_s, d_i)}, \tag{10}$$

where N is the frequency of network public opinion feature words appearing in a document and n is the number of network public opinion feature words.

$P(C_r \mid \theta)$ represents the similarity value between documents. If the documents continue to increase, according to the segmentation results of the characteristic words of network public opinion, the probability that the document d_i to be tested belongs to class C_j can be expressed as

$$P\left(C_j \mid d_i; \quad \theta\right) = \frac{P\left(C_j \mid \theta\right) \prod_{k=1}^{n} P\left(W_k \mid C_j; \theta\right)^{N\left(W_k, d_j\right)}}{\sum_{r=1}^{|C|} P(C \mid \theta) \prod_{k=1}^{n} P(W_k \mid C_{\text{r}}; \theta)^{N\left(W_k, d_j\right)}}. \tag{11}$$

In the above formula, $|C|$ represents the number of categories, and $P(C_j \mid \theta)$ is the ratio of the number of training document C_j to the total number of documents. The probability value of the newly added document belonging to each category is calculated, and then, the text to be tested is classified into the category with the highest calculated probability.

The support vector machine first constructs the decision function and then substitutes the quantized test samples into the decision function to calculate the category. N is the number of sample sets, the training sample set is $\{(x_i, y_i), i = 1, 2, \ldots, N\}$, and x_i and y_i, respectively, represent two types of sample labels.

In the linear condition, $W^* X + b = 0$ is used to represent the decision function, that is, the optimal classification surface or hyperplane. W, b is the two parameters of the hyperplane, which determine the way of classification, and $W^* X$ represents the inner product of the sample vector and X. If $X \in RN$ belongs to the first category, the variable flag is defined as positive $(y_i = 1)$; otherwise, the variable flag is defined as negative $(y_i = -1)$.

The discriminant equation is adopted: $g(x) = w^T x + b$. On this basis, it is normalized so that the hyperplane function can correctly classify the test data and satisfy:

$$y_i\left(w^T x_i + b\right) - 1 \geq 0, \quad i = 1, 2, \ldots, n. \tag{12}$$

It can be used under the above conditions to solve the minimum problem of the following equations instead of solving the optimal classification surface problem:

$$\phi(w) = \frac{1}{2}\|w\|^2 = \frac{1}{2}\left(w^T w\right). \tag{13}$$

The Lagrange function is defined as follows:

$$L(w, b, \lambda) = \frac{1}{2} w^T w - \sum_{i=1}^{n} \lambda_i \left[y_i\left(w^T x_i + b\right) - 1 \right]. \tag{14}$$

Among them, ▭$_i$□0 is the Lagrange coefficient. Differentiating the equations with respect to $w, b,$ ▭$_i$ and making them equal to 0, we get

$$\begin{aligned} \frac{\partial L}{\partial w} &= 0 \Rightarrow w = \sum_{i=1}^{n} \lambda_i y_i x_i, \\ \frac{\partial L}{\partial b} &= 0 \Rightarrow \sum_{i=1}^{n} \lambda_i y_i = 0, \\ \frac{\partial L}{\partial \lambda_i} &= 0 \Rightarrow \lambda_i \left[y_i\left(w^T x_i + b\right) - 1 \right] = 0. \end{aligned} \tag{15}$$

Under the above three formulas and constraints, the problem is transformed into the following dual problem, and at the same time, a quadratic function mechanism problem under inequality constraints is formed:

$$L_D = \sum_{i=1}^{n} \lambda_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \lambda_i \lambda_j y_i y_j \left(x_i^T x_j\right). \tag{16}$$

If λ_i^* is the optimal solution of the equation, then

$$w^* = \sum_{i=1}^{n} \lambda_i^* y_i x_i. \tag{17}$$

Among them, the sample of $C_i \neq 0$ is the support vector. By linearly fitting the coefficient vector and support vector of the optimal classification hyperplane, b^* can be solved by the constraints $\lambda_i[y_i(w^T x_i + b) - 1] = 0$, and the optimal classification function can be expressed as

$$f(x) = \operatorname{sgn}\left(\left(w^*\right)^T x + b^*\right) = \operatorname{sgn}\left(\sum_{i=1}^{n} \lambda_i^* y_i x_i^* x + b^*\right). \tag{18}$$

In the solution of nonlinear problems, only one hyperplane cannot completely distinguish the categories, so the loose variables can be used to assist.

The specific steps of the agglomerative hierarchical clustering algorithm are as follows:

(1) $D = \{d_1, \ldots, d_i, \ldots, d_n\}$ is a set of documents, d_i is an independent cluster, denoted as $c_i = \{d_i\}$, and a large cluster C is used to contain all documents in D, namely, $C = \{c_1, \cdots, c_i, \cdots, c_n\}$.

(2) The algorithm calculates the similarity $\operatorname{sim}(c_i, c_j)$ between any two clusters in C.

(3) According to $\operatorname{sim}(c_i, c_j)$, the algorithm selects a pair of clusters c_i, c_j with the largest similarity, and combines c_i and c_j into a new cluster $c_k = c_i \bigcup c_j$, and the new combination formed by the tuples in Dd is $C = \{c_1, \ldots, c_{n-1}\}$.

(4) The algorithm repeats steps 2 and 3 until all the clusters in C are merged into one cluster or a preset condition is satisfied. The algorithm of split hierarchical clustering is just the opposite of this algorithm, that is, all documents are classified into the same class at the beginning, and then new classes are continuously split on the basis of this class until the termination condition of the clustering is satisfied.

4. Analysis of Dynamic Influence Mechanism of Network Public Opinion Based on Intelligent Computer Network Simulation

The Internet is a virtual world, the identities of speakers are not disclosed, and there is a lack of corresponding rules and effective supervision. The Internet has gradually become an external space for some netizens to vent their emotions. Due to the influence of various environmental factors, some online speech is irrational, easily sentimental, and emotional, and some people use the Internet as a place to vent their negative emotions and spread and infect each other through the Internet. These emotional remarks are likely to gradually develop into public opinion that is harmful to society under the response of the public. Moreover, with the development of cyberspace, more and more technical methods and ideas have been applied to network public opinion. The components of network public opinion can be divided into the subject, object, ontology, media, and network public opinion environment. The elements of network public opinion are shown in Figure 1.

The dissemination of online public opinion is a process of continuous fermentation and dissemination on the Internet through communication channels after the formation of public opinion. Moreover, the network public opinion dissemination channel is an important part of the occurrence and development of public opinion. Online public opinion dissemination channels are mostly online social platforms such as "two microchannels, one end, and one forum," while knowledge platforms, live webcasts, and microvideos have also become one of the channels for online public opinion dissemination. The dissemination channels of online public opinion are shown in Figure 2.

According to the actual application requirements of the new media industry network public opinion monitoring and analysis subsystem, this paper combines the crawler technology and sentiment analysis technology to design the overall architecture of the new media industry network public opinion monitoring and analysis subsystem. The framework of this system is mainly divided into six layers: public opinion collection, public opinion

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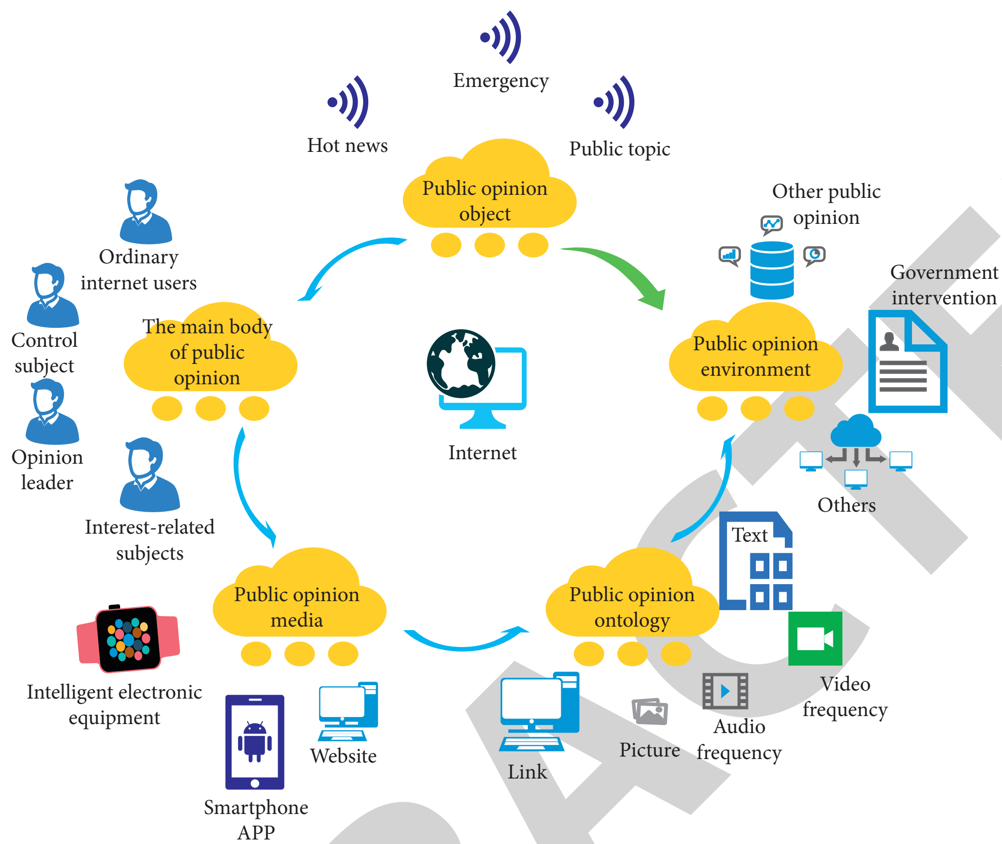

Figure 1: Diagram of the elements of network public opinion.

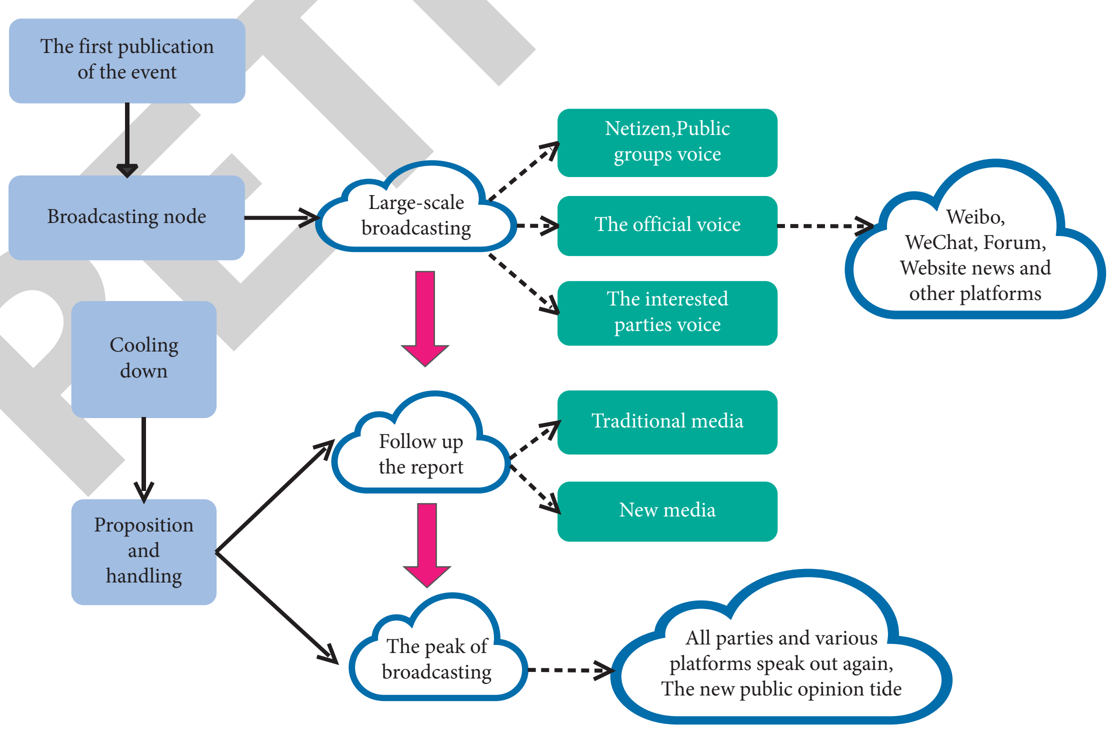

Figure 2: Network public opinion dissemination channel diagram.

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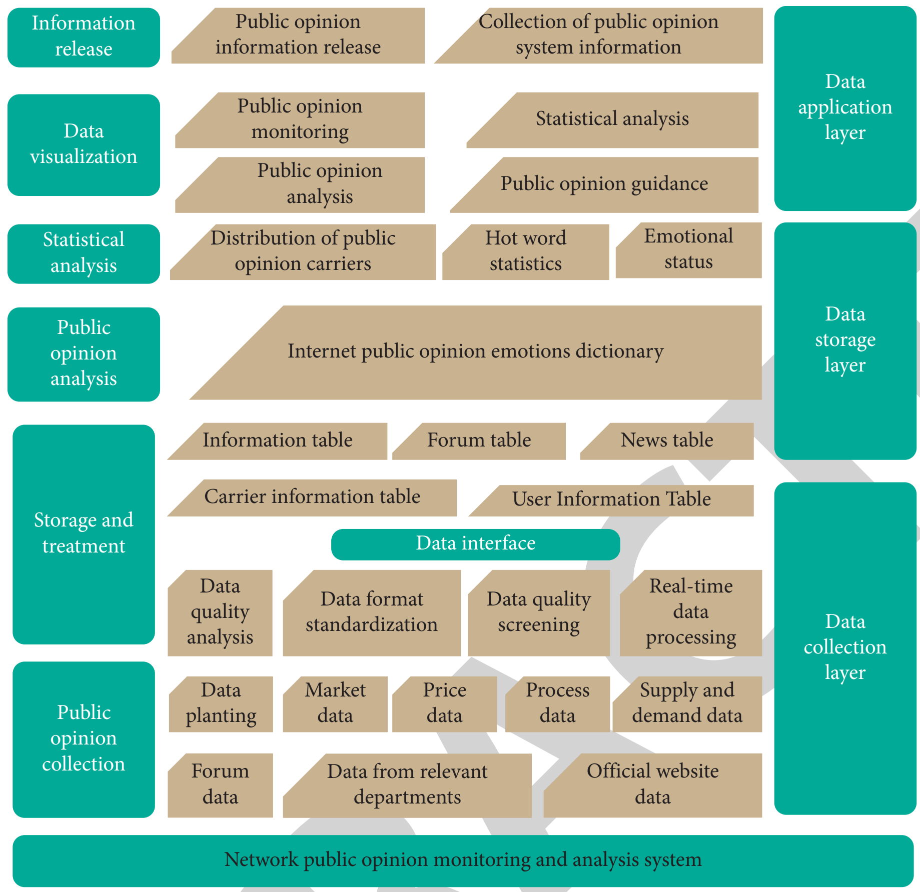

Figure 3: Architecture diagram of network public opinion monitoring and analysis system.

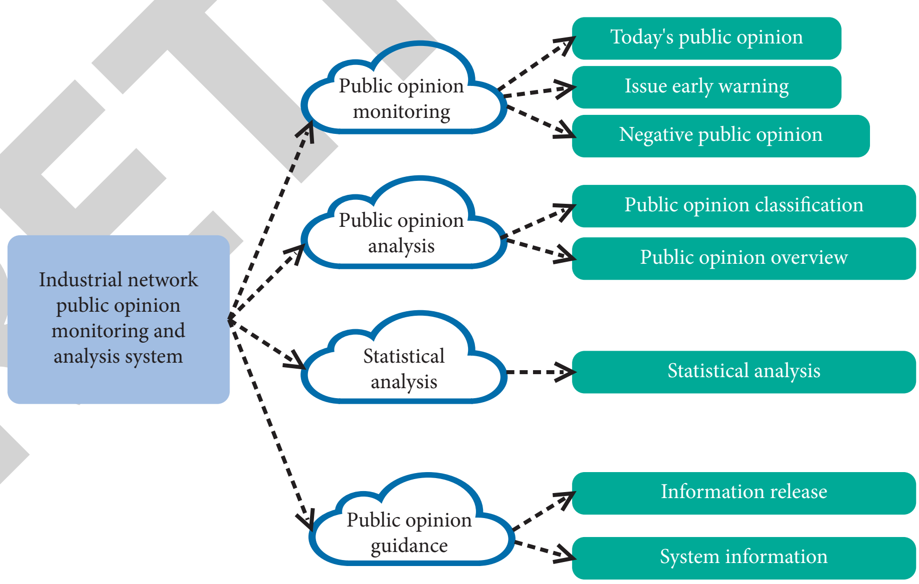

Figure 4: Functional structure diagram of the public opinion monitoring and analysis system.

storage and processing, public opinion analysis, statistical analysis, data visualization, and information release. The system can not only perform statistical analysis on the latest and historical network public opinion of the new media industry but also improve the system's ability of public opinion information storage, public opinion analysis, statistical analysis, and practical application. The architecture of the network public opinion monitoring and analysis subsystem of the new media industry is shown in Figure 3.

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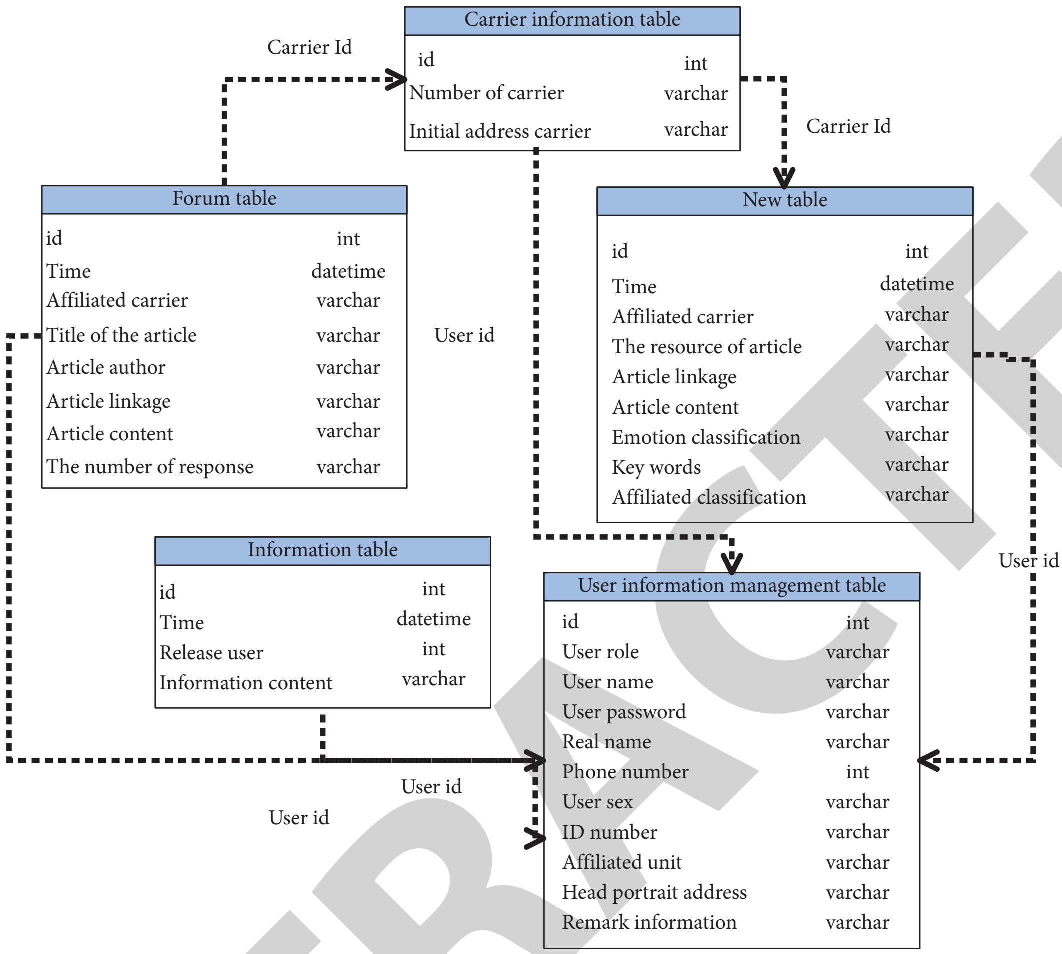
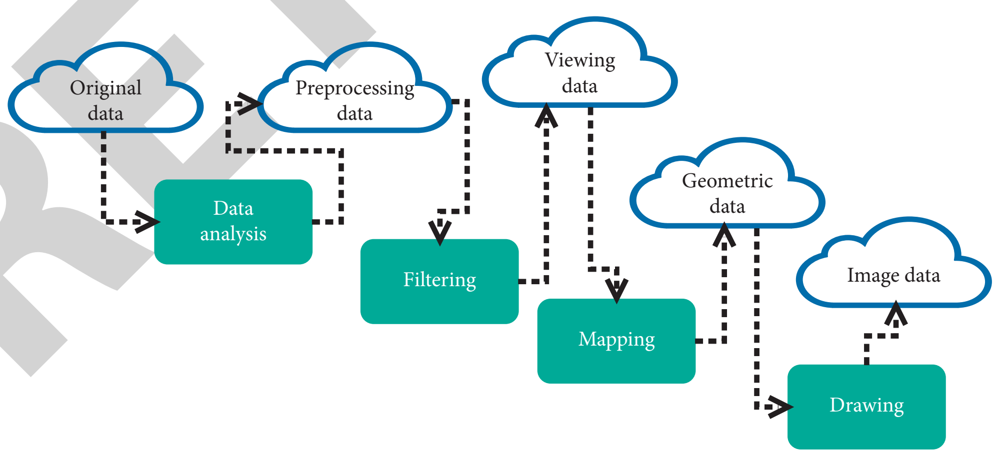
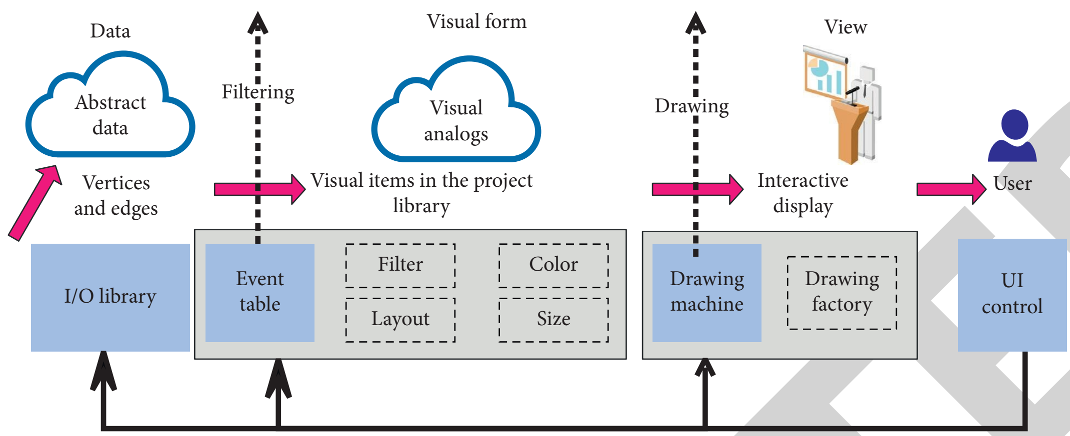


Figure 5: Database structure diagram.



(a)

Figure 6: Continued.



(b)

FIGURE 6: Network public opinion visualization process. (a) Scientific visualization pipeline. (b) Information visualization process.

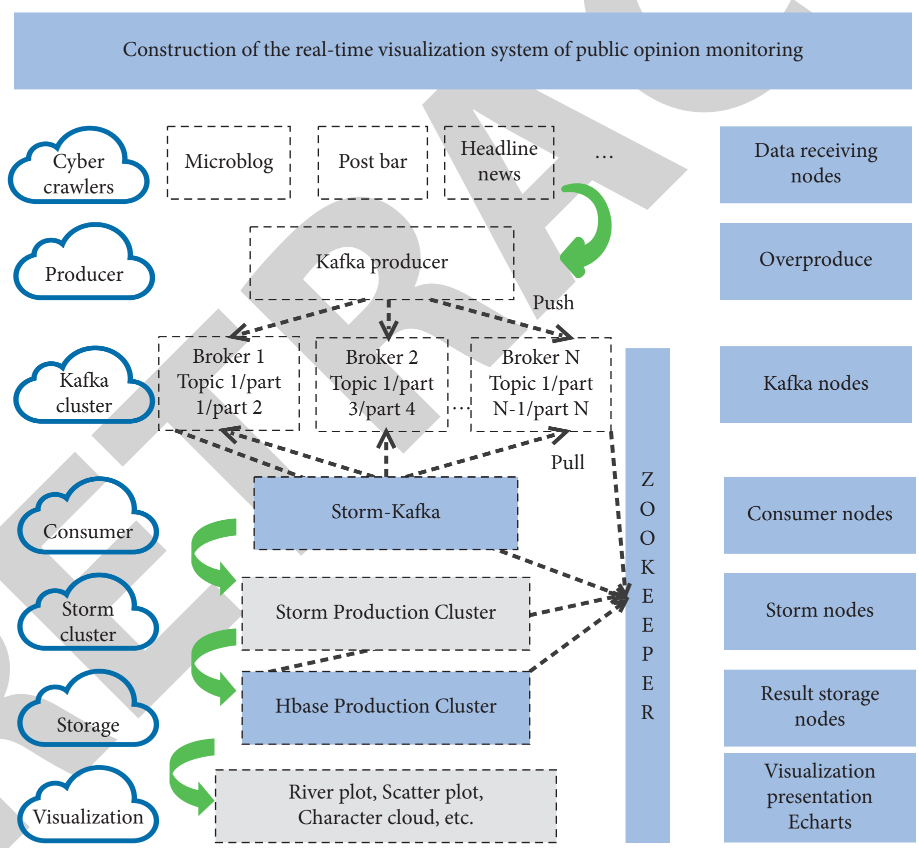


FIGURE 7: The architecture of the real-time visual monitoring system for network public opinion.

Based on the analysis of the actual needs of the new media industry, this paper designs the network public opinion monitoring and analysis subsystem of the new media industry, which is mainly composed of four modules: public opinion monitoring, public opinion analysis, statistical analysis, and public opinion guidance. Among them, public opinion monitoring includes three submodules: today's public opinion, issuing early warning, and negative public opinion. The public opinion analysis includes two submodules: public opinion classification and public opinion overview. The public opinion guide includes two submodules: news release and system news. The functional structure of the new media industry public opinion monitoring and analysis subsystem is shown in Figure 4.

According to the characteristics that most of the network public opinion data in the new media industry are in the

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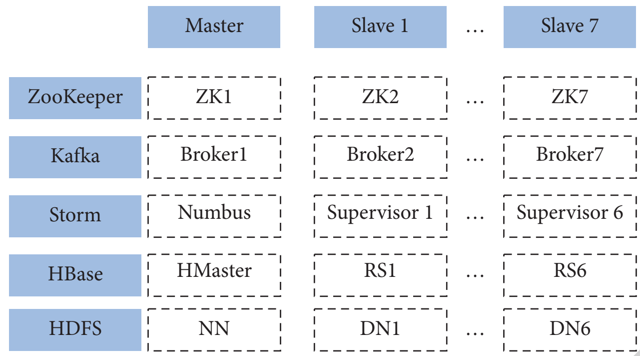

Figure 8: Schematic diagram of cluster deployment of network public opinion monitoring system.

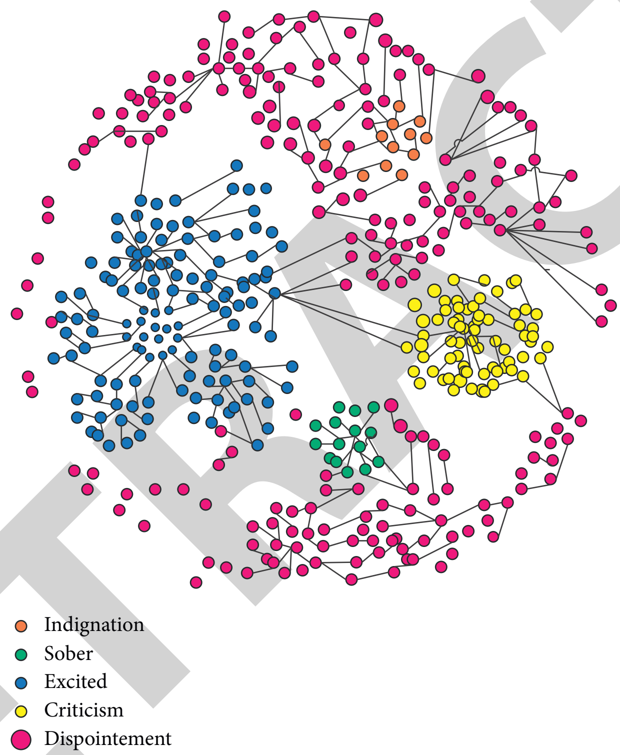

Figure 9: Diagram of audience sentiment clustering results.

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form of text, the system uses a MySQL database that has good storage and processing capabilities for structured data. In order to better manage these network public opinion data, the structure of each table needs to be designed. The main table structure of this system is shown in Figure 5.

Visualization technology specifically describes the conversion process from data to visualization and obtains image data step by step in a serial manner to realize data visualization, as shown in Figure 6.

According to the main functions and design goals, the entire network public opinion real-time visual monitoring system is divided into seven layers: data receiving layer, producer layer, message queue layer, consumer layer, business logic layer, storage layer, and visual presentation layer. Among them, the data receiving layer is to obtain network public opinion data through web crawler. The message queue layer is composed of Kafka, a high-throughput distributed publish-subscribe messaging system, which can process all action flow data in consumer-scale websites and support buffering. The business logic layer adopts the real-time stream computing framework Storm. The storage layer uses the distributed, column-oriented open source database Hbase. The final visualization display uses Baidu open source visualization processing controller Echarts as the visualization data display. The detailed architecture is shown in Figure 7.

The network public opinion monitoring system uses multiple distributed architectures, and the deployment and configuration of clusters in the early stage are complex. Figure 8 shows the cluster environment built and deployed by the network public opinion monitoring system.

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Table 1: Statistical table of the analysis effect of the analysis model of the dynamic influence mechanism of network public opinion based on intelligent computer network simulation.

Num	The effect of network public opinion analysis	Num	The effect of network public opinion analysis	Num	The effect of network public opinion analysis
1	89.23	25	82.65	49	87.69
2	84.74	26	82.15	50	85.83
3	91.25	27	86.26	51	80.75
4	85.94	28	86.55	52	93.84
5	80.86	29	80.83	53	92.93
6	79.19	30	80.48	54	92.69
7	87.29	31	91.26	55	80.16
8	80.35	32	81.92	56	92.27
9	89.33	33	82.15	57	84.46
10	87.30	34	93.21	58	89.93
11	89.68	35	89.47	59	93.94
12	84.96	36	85.67	60	90.32
13	85.46	37	88.75	61	79.96
14	85.37	38	79.71	62	79.34
15	91.82	39	83.13	63	85.45
16	82.66	40	81.49	64	84.63
17	84.62	41	86.55	65	86.64
18	89.17	42	85.79	66	90.03
19	82.86	43	92.15	67	89.97
20	79.93	44	83.02	68	87.67
21	84.57	45	83.94	69	92.02
22	82.00	46	79.75	70	81.99
23	90.95	47	88.64	71	90.22
24	93.00	48	92.04	72	91.33

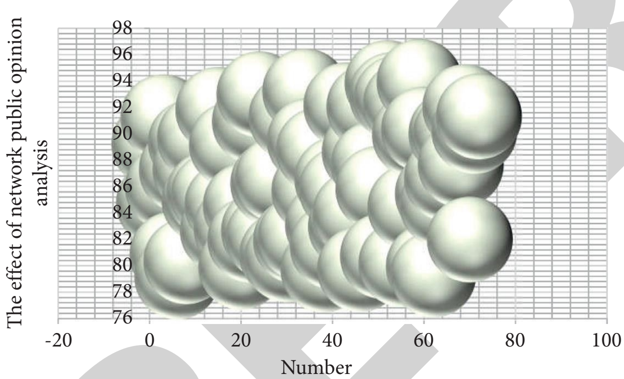

Figure 10: Statistical diagram of the analysis effect of the analysis model of the dynamic influence mechanism of network public opinion based on intelligent computer network simulation.

Cluster analysis and visualization visualize related information to help users quickly perceive the association between different data, so as to highlight the time-series evolution of cluster features. Figure 9 shows the clustering results of audience sentiment for D&G insulting China incidents analyzed by the model in this paper.

This paper takes the past network public opinion data as the output, processes it through the model of this paper, and verifies the effect of the intelligent network public opinion impact analysis model of this paper through network public opinion analysis, and obtains the results shown in Table 1 and Figure 10.

From the above analysis, it can be seen that the analysis model of network public opinion dynamic influence mechanism based on intelligent computer network simulation constructed in this paper has a good effect.

5. Conclusion

The interaction of circles, media reports, and the attention of opinion leaders have led to the outbreak of public opinion. The outpouring of public opinion in this period, short video rumors, follow-up videos, etc. may add another fire to public opinion, and the phenomenon of public opinion reversal occurs from time to time, which urges relevant departments to intervene. After the relevant parties involved took effective measures to deal with the public opinion, the public opinion also entered a recovery period and a calm period. However, the release of follow-up videos may push public opinion to an outbreak period again, and especially, some users of short video apps may not pay attention to other media such as Weibo and online media. In this paper, an intelligent computer network simulation model is constructed to analyze the dynamic influence mechanism of network public opinion. By analyzing the text content to be mined, this paper uses a specific algorithm to select different words that best represent the text to be tested as the characteristic words of network public opinion. These network public opinion feature words can classify texts, thereby reducing the complexity of text classification. The experimental study shows that the dynamic influence mechanism analysis model of network public opinion based on intelligent computer network simulation constructed in this paper has a good effect.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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