Available online at www.HighTechJournal.org

HighTech and Innovation Journal

ISSN: 2723-9535

Vol. 6, No. 4, December, 2025

# Public Opinion Guidance Model in Major Public Crisis Events Based on Accelerated Genetic Algorithm

Xiaoyu Chang [1*]

[1] School of Information Technology, Changchun Finance College, Changchun, 130124, China.

Received 04 June 2025; Revised 18 November 2025; Accepted 23 November 2025; Published 01 December 2025

**Abstract**

The research aims to enhance the effectiveness of the public opinion evolution guidance model, with a particular focus on the influence of opinion leaders, and address the shortcomings of traditional models, such as neglecting opinion leaders and insufficient network topology. Therefore, the relevant scale-free network is used to improve the traditional public opinion evolution model. An improved model integrating the two is proposed by introducing a real coded accelerated genetic algorithm. The experimental results show that the proposed model converges to four opinion clusters, with the average values of negative and positive opinions being 0.399 and 0.370, respectively, demonstrating the trend closest to the actual data. When the parameters are fixed, the ultimate development of public opinion shows obvious changing trends in different situations, and the validity of the model has been proved by practice. The research innovatively introduces the scale-free network based on Barabasi and Albert, and improves the Hegselmann Krause model. Meanwhile, by comprehensively considering the influence of opinion leaders and network topology factors, the model overcomes the shortcomings of traditional models in public opinion guidance and also demonstrates good practicability in practical applications.

*Keywords:* RAGA; Major Public Crisis Events; Public Opinion Guidance Model; Opinion Leader; Scale-Free Network.

## 1. Introduction

Public opinion refers to the sum of opinions and attitudes of the public towards specific events, individuals, etc. in social life, and its formation is influenced by various factors. In the digital age, the role of social media platforms has become more prominent. For example, Lee et al. believed that digital media provides supporters with a centralized communication platform, promoting discussions on sports goals and information sharing. This finding demonstrates the relationship between the unique effectiveness of social media platforms and sports dynamics [1]. In recent years, the research on public opinion and social media has been on the rise, revealing the key roles of various platforms in social mobilization, public opinion evolution, and brand loyalty. Exploring the dissemination and evolution process of public opinion information can better understand the occurrence, development, and evolution process of public opinion in specific social networks. It can also better understand the public opinion, so as to enrich and improve the social Network theory. Gopi et al. emphasized the significance of sentiment analysis in social networks, and demonstrated how people express their opinions in various forms on social media. A classification framework was constructed based on sentiment polarity, which delved deeply into the diversity of information transmission during the public opinion formation [2].

* Corresponding author: 0170@cjgz.edu.cn

doi http://dx.doi.org/10.28991/HIJ-2025-06-04-06

Park and Jiang discussed how corporate social advocacy activities can enhance brand loyalty through brand community participation, emphasizing the close connection between social public opinion and brand image [3]. However, current research often neglects the role of opinion leaders in the evolution of public opinion and the influence of different users on social media. Moreover, existing public opinion evolution models fail to fully consider the topological structure of the network and its impact on the dissemination of public opinion. Therefore, the research proposes an improved public opinion evolution model to address the aforementioned blank issues. This study utilizes the BA scale-free network proposed by Barabasi and Albert to improve the traditional classic model of guiding public opinion evolution. The Real-coded Accelerated Genetic Algorithm (RAGA) is introduced to optimize its parameter selection process. The improved Real-coded Accelerated genetic algorithm - Improved Hegselmann-Krause (RAGA-IHK) that integrates the two is obtained. The purpose is to solve the problem that the current public opinion evolution guidance model ignores the reasons why public opinion leaders are driven by public opinion, and does not fully consider the network topology structure of actual public opinion. Meanwhile, it is excepted to better align with the evolution of online public opinion, explain the evolution laws, and help stakeholders better guide public opinion.

The study consists four sections. The first section discusses and summarizes the current research achievements and applications. The second section mainly elaborates on the relevant guidance model for the evolution of public opinion in major public crisis events based on RAGA. In this section, an Improved HK (IHK) model considering opinion leaders is constructed and the parameters optimization of the IHK model based on RAGA is realized. The third section is to verify the availability of the RAGA-IHK, including the effectiveness and practicality. The final section is a summary and discussion of the entire article.

## 2. Related Work

Network topology is the basis for public opinion dissemination. The dissemination requires specific network structures. Therefore, compared with the simple network structure, complex network is more consistent with the real network characteristics [4, 5]. Meanwhile, the dissemination and evolution of online public opinion is the process of information spreading from one person to several people, including the online public opinion evolution in this process, which is extremely important for guiding public opinion [6]. A large number of domestic and foreign scholars have conducted research on it. Zhang et al. [6] analyzed the internal public opinion communication mechanism for the COVID-19 related communication problems in major public health emergencies, providing data support for managers to make scientific decisions. Liu et al. [7] analyzed the dissemination mechanism of public opinion on the forest fire in Liangshan Prefecture using crawler technology and data collection, providing theoretical assistance for implementing disaster relief plans and communication between the government and the public. Regarding the impact of social media on government structure attitudes, Zhang et al. [8] conducted a survey on the impact of relevant competitive information on social media on government satisfaction through data collection, providing a data basis for the public opinion guidance. The prediction error of online public opinion dissemination in actual crisis warning was relatively large. Therefore, Cai et al. proposed a new crisis warning method related to online public opinion dissemination based on feature mining, effectively improving the effectiveness of crisis warning [9]. Aiming at the role of key opinion leaders in e-commerce marketing, Liao et al. [10] proposed an evolutionary model for relevant marketing and promotion strategies based on opinion leaders and the game model of public opinion evolution, thus effectively improving the advantages of brand enterprises.

In addition, false information released by relevant social media websites during the COVID-19 epidemic caused widespread anxiety. Chintalapudi et al. [11] analyzed the problems published by Indian netizens in the COVID-19 epidemic using two-way encoders. Thus, a deep learning model was constructed. This effectively improved the accuracy of public opinion evolution and reduced the probability of unnecessary anxiety. Malecki et al. [12] constructed the corresponding framework through the COVID-19 analysis to solve the problems related to the impact of public opinion guidance on the public in major public crisis events, effectively reducing the misleading of social media misinformation on patients. Siddiqui et al. [13] increased the understanding of word-of-mouth marketing through corresponding empirical models to explore the relevant mechanisms of social media in guiding public opinion. It provided theoretical support for relevant enterprises to build brands.

For the public opinion analysis problem of PON 2024, Mansyur et al. [14] proposed an SVM algorithm based on cosine similarity, which improved the accuracy of sentiment analysis to 88.73%. Ahrens [15] reviewed the impact of public opinion on democratic politics and proposed corresponding theoretical perspectives, emphasizing the imprecision and endogeneity of public opinion, and providing new insights for future comparative political economy research. Guo et al. [16] explored how the framework of immigration news affects public attitudes and policy preferences towards immigrants. The research proved that the framework of mainstream media directly led to support for strict immigration policies, while partisan media indirectly influenced public sentiment. Bashiri & Naderi [17] proposed multiple methods based on converter models for sentiment analysis problems. The T5 model performed best on multiple datasets, demonstrating its flexibility and generalization ability. Do et al. [18] proposed a research model based on stimulus-organization-response and cognitive dissonance theories regarding the impact of negative online word-of-mouth on brand hate and brand activism. Collectivism plays an important moderating role between consumer psychological discomfort and brand hate.

From the research, the current classic public opinion evolution model fully considers the characteristics of node domains. However, integrating opinion leaders only carries out simple weighting, which overlooks the difference between opinion leaders and ordinary netizens in the reasons for driving public opinion. Meanwhile, the structure of the network itself is not fully considered. In addition, the current network public opinion evolution model only combines relatively primitive algorithms when combining relevant computer algorithms. More advanced or optimized algorithms have not been combined. Therefore, BA scale-free network is used to improve the traditional classic public opinion evolution guided HK model. The RAGA-IHK model constructed after introducing the RAGA is innovative. It expands the direction for the development of network public opinion evolution guidance models and also expands the development field of RAGA.

## 3. The Public Opinion Evolution Guidance Model Analysis for Major Public Crisis Events Combined with RAGA

The evolution of public opinion is an important research direction in public opinion studies. Opinion leaders are nodes with greater influence in the social public opinion network, which plays a critical role in the evolution of public opinion. Therefore, this section improves the traditional HK model based on opinion leaders to give full play to the action of opinion leaders.

### 3.1. Construction of IHK Public Opinion Evolution Model Based on Opinion Leaders

The current public opinion evolution guidance model ignores the reasons driven by opinion leaders and does not fully consider the network topology of actual public opinion. Therefore, the traditional classic public opinion evolution guidance HK model is improved by the BA scale-free network. The parameter selection process is optimized by introducing RAGA. The main reason for introducing the RAGA in the research lies in its certain advantages in multivariable optimization problems. Compared with traditional genetic algorithms, RAGA uses real number encoding, which greatly simplifies complexity and improves computational accuracy, effectively avoiding the common accuracy loss problem in binary encoding. In addition, RAGA can quickly converge to the optimal solution by introducing an adaptive search strategy, thereby enhancing the convergence speed and efficiency of the algorithm. These characteristics enable the RAGA to respond more sensitively to data changes during the parameter optimization process of the public opinion evolution model, ensuring the accuracy of the model parameters and thereby enhancing the overall performance and reliability of the public opinion evolution guidance model. The current applied network topology includes regular networks, random networks, small world networks, and scale-free networks. However, none of these four classic network topologies can provide a good fit for actual social networks. A network with both scale-free and small clustering characteristics is selected for the construction of an actual network structure evolution model for authentic social networks. The BA scale-free network has already met the scale-free characteristic. Therefore, an improved edge generation algorithm is taken to introduce high clustering characteristics. Generally speaking, the two connection methods of priority and domain are the main components of generating edge connections. Considering the theoretical domain connection methods in actual networks, the generation algorithm integrates priority and scale-free connections in the actual network construction process. Therefore, the improved scale-free network is shown in Figure 1 [19].

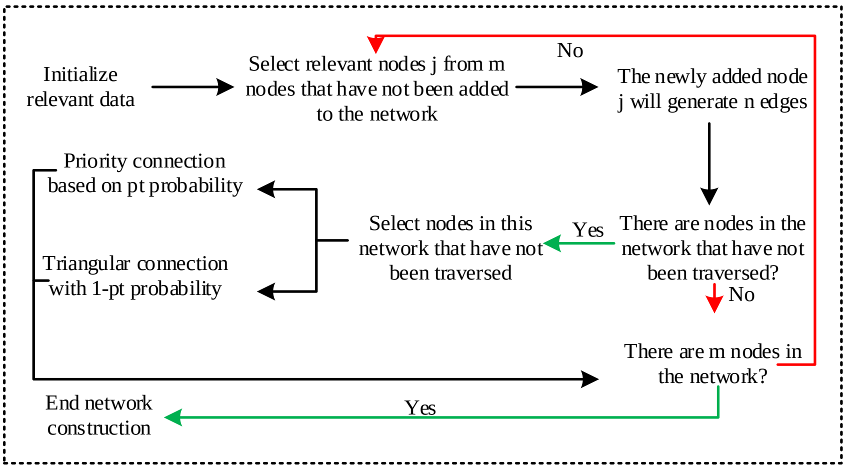



**Figure 1. Flow diagram of improved scale-free network**

In Figure 1, the improved scale-free network process starts with corresponding initialization. Assuming that there are m nodes in the network at this time, a fully connected graph containing $n_0$ nodes needs to be generated. Secondly, relevant nodes j from m nodes that have not been added to the network is selected. Then, they are added to the network. At this point, the newly added node j will generate n edges ($n<n_0$). When there are nodes in the network that have not been traversed, the non-traversed node i in the network is selected for priority connection with a probability of pt, and triangular connection with a probability of 1-pt. Finally, it is determined whether there are m nodes in the network. If not, the relevant repetitive process will be redone. If so, the network construction is ended. Nodes j and i establish a connection relationship with probability p during priority connection. In triangular connection, node j triangulates with the domain of node i with a probability of p (1-pt)/p+1.

When n is 5 and m is 200, the average clustering coefficient of the original BA scale-free network is 0.124. When pt is 0.7 for priority connection and p is 0.35 for domain connection, the average clustering coefficient of the improved scale-free algorithm is 0.447. The average clustering coefficient of the Twitter social circle published by Stanford University is 0.565. Obviously, the improved structure is more in line with the actual situation. Although it considers priority connections, it ignores the randomness of node degrees. Therefore, the clustering scale-free network that improves the influence of decreasing distance is further optimized. The current mainstream research direction is to use a continuous public opinion evolution model with bounded trust. The traditional HK evolution model ignores the internal motivation of opinion leaders and public opinion. That is, opinion leaders are often driven by their own interests to gain high attention. The public is often influenced by those around them. The current definition of opinion leaders is simplified, referring to the node with the largest number in the actual network. That is, the nodes in the top 5% of the network are opinion leaders.

When opinion leaders express positive and negative views, they will attract netizens' attention. The benefits of both are U and V. The additional effect that negative views bring to users is defined as V1. The loss caused by the difference between opinion leaders and the public is W1. The loss caused by the difference between the negative views of opinion leaders and authorities is V2. Therefore, the views of opinion leaders and the public can form a game matrix, that is, the game between positive affirmation, negative negation and adoption, and non-adoption. The HK model utilizes the concept of bounded trust. Therefore, under the opinion value of the opinion leader and other public, the probability of the public trusting the opinion of the opinion leader at a certain time is shown in Equation 1 [20].

$$\rho^{\tau} = \frac{Neig\square bor_{i,1}^{\tau}}{\lambda} \tag{1}$$

In Equation 1, $\rho^{\tau}$ represents the probability that the public will trust the views of opinion leaders at moment $\tau$. $i$ stands for the opinion leader. $\lambda$ represents the actual total size of the network. The equation obtained by converting Equation 1 based on two different income expressions is shown in Equation 2.

$$\begin{cases} F_p = \rho U + (1-\rho)(U - W1) \\ F_{1-p} = \rho(U + V1 - V2) + (1-\rho)(U - W1 - V2) \\ F(P) = pF_p + (1-p)F_{1-p} = p[\rho(W1 - V1) + V2] + \rho V1 + U - W1 - V2 \end{cases} \tag{2}$$

In Equation 2, $F_p$ refers to the expected actual total income of opinion leaders. $p$ refers to the actual probability of opinion leaders expressing positive opinions at the next moment. $U$ refers to the benefits brought by the positive opinions of opinion leaders. $W1$ refers to the loss caused by the difference between opinion leaders and public opinion. $F_{1-p}$ refers to the actual income expectation of opinion leaders when they express negative opinions. $V1$ represents the additional effect that negative views bring to users. $V2$ refers to the loss caused by the difference between the negative views perceived by opinion leaders and authorities. If $f$ is the function of the opinion leader when selecting the relevant strategy, and the independent variable is $p$, the expression is shown in Equation 3.

$$f(p) = p\left[F_p - F(p)\right] = p(1-p)(V2 - \rho V1) \tag{3}$$

From Equation 3, when the value of $p$ is at [0,1], $\rho = \frac{V2}{V1}$. Regardless of the value of $p$, $f(p)$ is 0. That is, no matter how opinion leaders evolve, they will not have an impact on the next moment's earnings. At this time, the actual opinion of the selected opinion leader remains unchanged. If $\rho \neq \frac{V2}{V1}$, $\frac{df(p)}{dp=(2p-1)(\rho V1-V2)} = 0$. At this point, two situations will occur. If $\rho < \frac{V2}{V1}$, $df(p)|p = 0 > 0$. At this moment, $df(p)|p = 1 < 0$, $p = 1$s the equilibrium point. The opinions of opinion leaders will actively evolve in the next moment. On the contrary, if $p = 0$ is the balance point, their opinions will evolve negatively at the next moment. In the evolution of opinion leaders' views on gaming, $\rho$ is a fixed value rather than a variable, which can also provide relevant control opinions for relevant governments or social network platforms. If managers want public opinion to develop in a positive direction, and the large network user base is not easy to directly control them, then a few opinion leaders may become the target of managers. The risk of opinion leaders expressing negative views is increased. An increase in $V2$ value can lead opinions to develop in a positive direction. The HK model is a continuous model related to the evolution of public opinion. Therefore, this conclusion can lead to the actual evolution direction of opinion leaders, namely $V = \frac{V2}{V1}$. The actual opinion expression of opinion leaders in the final evolution of the next moment is shown in Equation 4.

$$Z_i^{\tau+1} = Z_i^{\tau} + \frac{1 - \rho^{\tau} \times V^{-1}}{V} \tag{4}$$

In Equation 4, $Z_i^{\tau+1}$ stands for the actual opinion of the opinion leader's final evolution at the next moment. $Z_i^{\tau}$ stands for the opinion of the opinion leader at this moment. $V$ indicates the evolution direction of the opinion leader. In the actual online public opinion dissemination, ordinary netizens usually tend to view opinions similar to their own to gain a sense of identity. The HK model is proposed based on this idea. However, opinion leaders in actual social networks are usually big $V$ users. When the opinions of opinion leaders differ from those of ordinary users, they may not initially agree. However, since opinion leaders are big V users, they will be coerced to accept this view passively in the long run. After accumulating memory and viewpoints, it will have an impact on the opinions of ordinary users. This memory effect essentially has a relatively small impact on the evolution of public opinion among ordinary netizens, as most netizens do not actively seek opinions that contradict their own views. In response to this phenomenon, the HK model is further improved. This is to optimize the way their opinion leaders actually influence ordinary Internet users.

In the substantial evolution process of the opinions of ordinary netizens, if the opinions of opinion leaders are only within the trust threshold with the opinions of ordinary netizens, the influence of opinion leaders on ordinary netizens will remain unchanged. It still follows the rules of the HK model. If the difference between the opinion value of opinion leaders and that of netizens is large, the corresponding memory value will be introduced. After the cumulative number of iterations and memory value reach a certain level, the opinions of opinion leaders will participate in the evolution of ordinary netizens' opinions. In reality, some Internet users with extreme views are less affected by the views of opinion leaders. Even if they repeatedly consult the views, they will still distrust them. Therefore, when the views of opinion leaders do not belong to [0.1, 0.9], ordinary netizens will not remember relevant views. If the memory value generated by ordinary netizens and opinion leaders is $\omega1$, the calculation expression is shown in Equation 5.

$$\omega_1 = D_h - D_g \tag{5}$$

In Equation 5, $\omega_1$ represents the memory value generated by ordinary netizens and opinion leaders. $D_h$ represents the opinion value of the opinion leader $h$. $D_g$ represents the opinion value of ordinary netizen $g$. If the memory threshold is M at this time, two situations will occur. They are the newly introduced relevant memory values and the values that exceed the threshold of the memory after being stacked. At this point, the relevant views on memory values are included in the main model and the memory values of ordinary netizens are initialized. The updated memory value of ordinary netizens each time is shown in Equation 6.

$$\begin{cases} J_{h\_g}^{\tau+1} = J_{h\_g}^{\tau} + \omega_1 \\ S_{h\_g}^{\tau+1} = S_{h\_g}^{\tau} + 1 \end{cases} \tag{6}$$

In Equation 6, $J_{h\_g}^{\tau+1}$ represents the memory value of ordinary netizens for opinion leaders at the next moment. $J_{h\_g}^{\tau}$ represents the memory value of ordinary netizens to opinion leaders at this moment. $S_{h\_g}^{\tau+1}$ stands for the actual time for ordinary netizens to browse the comments of opinion leaders in the next moment. $S_{h\_g}^{\tau}$ stands for the actual time that ordinary netizens browse the comments of opinion leaders in the next moment. If the value of $|J_h^{\tau+1}|$ is greater than M and $S_h^{\tau+1}$ is greater than the set actual number of times, S must be browsed multiple times, and the actual field of ordinary netizens will be expanded. The updated equation expression is shown in Equation 7.

$$\begin{cases} J_{h\_g}^{\tau+1} = 0 \\ S_{h\_g}^{\tau+1} = 0 \\ Neighbor_{h,1}^{\tau+1} = Neighbor_{h,1}^{\tau+1} \cup g \end{cases} \tag{7}$$

If the value of $|J_h^{\tau+1}|$ is greater than M and less than S, it means that the memory value of ordinary netizens has exceeded the memory threshold but have not browsed the information multiple times. At this point, based on the principle of bounded trust, ordinary netizens will not be influenced by opinions that are significantly different from their own. Therefore, the iterative equation is shown in Equation 8.

$$\begin{cases} J_{h\_g}^{\tau+1} = 0 \\ S_{h\_g}^{\tau+1} = 0 \end{cases} \tag{8}$$

The resulting IHK evolutionary model utilizing opinion leader games and memory methods is shown in Figure 2 [21].

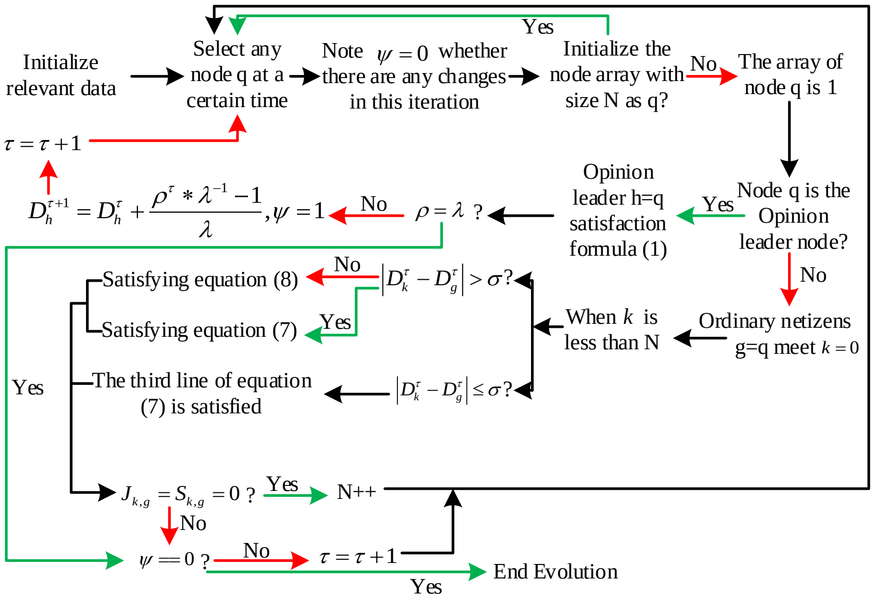



**Figure 2. An IHK evolution model based on opinion leader games and memory**

From Figure 2, the IHK model first initializes the relevant data. Secondly, at a certain moment, any node q is selected to observe and record. $\psi = 0$ represents whether there have been any changes in this iteration. If the initialization size of the node array with N is q, the node is re-selected. If not, it is 1. At this time, the node is determined whether it is a opinion leader node. If so, the opinion leader node will evolve. If not, it will be evolved as a node for ordinary netizens. Equation 1 is introduced into the evolution of opinion leaders to determine whether it is $\rho = \lambda$. If so, $D_h^{\tau+1} = D_h^{\tau}$. If not, $D_h^{\tau+1} = D_h^{\tau} + \frac{\rho^{\tau} * \lambda^{-1} - 1}{\lambda}, \psi = 1$. If $\tau = \tau + 1$, this operation is returned to the network node to repeat the process. The evolution of ordinary netizen nodes is $k = 0$. When $k$ is less than N, if $\left|D_k^{\tau} - D_g^{\tau}\right| > \sigma$ ($k$ represents the opinion leader node and $\sigma$ represents the bounded trust threshold), Equation 7 is satisfied. Otherwise, Equation 8 is satisfied. If $\left|D_k^{\tau} - D_g^{\tau}\right| \le \sigma$, only the third row of Equation 7 is satisfied. If $J_{k,g} = S_{k,g} = 0$, the number of nodes is expanded to repeat the process. Otherwise, the next step is taken. Next, if $\psi == 0$, it means that the actual views of all nodes will no longer change, that is, the evolution is over. If not, $\tau = \tau + 1$, and this operation is returned to the network node to repeat the process.

### 3.2. Parameter Optimization of IHK Public Opinion Evolution Guidance Model Based on RAGA

There are many parameters obtained from the IHK model based on the improved network structure. Their different combinations have different impacts on the actual evolution results. Public opinion guidance should be provided for major public crisis events after actual evolution. Therefore, the RAGA is introduced in the actual parameter selection process to optimize and achieve subsequent public opinion guidance. This RAGA-IHK public opinion evolution guidance model is obtained. The built-in RAGA in Matrix Laboratory (MATLAB) is used to calculate parameters. The public opinion guidance of major public crisis events is a form of crisis communication and also a part of risk management. Essentially, risk management selects all comprehensive measures to reduce the probability of emergencies, which is reflected in public opinion guidance to improve the efficiency of emergency situations.

Currently, genetic algorithms are often used to overcome continuous objective functions and local optima when dealing with multivariable problems in traditional methods. However, this algorithm uses binary encoding, which is cumbersome and requires high accuracy. Therefore, the RAGA is selected for parameter optimization of the IHK model to achieve subsequent public opinion guidance. The RAGA utilizes the space contained in the excellent individuals searched by the standard genetic algorithm during the evolution process to gradually adjust the search space for optimization variables. This can greatly improve the optimization speed. The shortcomings of binary encoding have been overcome, greatly improving the optimization ability. In the constructing the RAGA, the first step is to encode the parameter set and calculate the fitness values of the relevant individuals. Secondly, the related operations of genetic operators are executed. If the termination condition is not met, then the excellent change interval generated by the previous two generations of evolution can be used as the initial interval again. The fitness calculation and genetic operator operations are performed again, which can accelerate the iteration until the termination condition is met. Therefore, the flowchart of the RAGA is shown in Figure 3 [22].

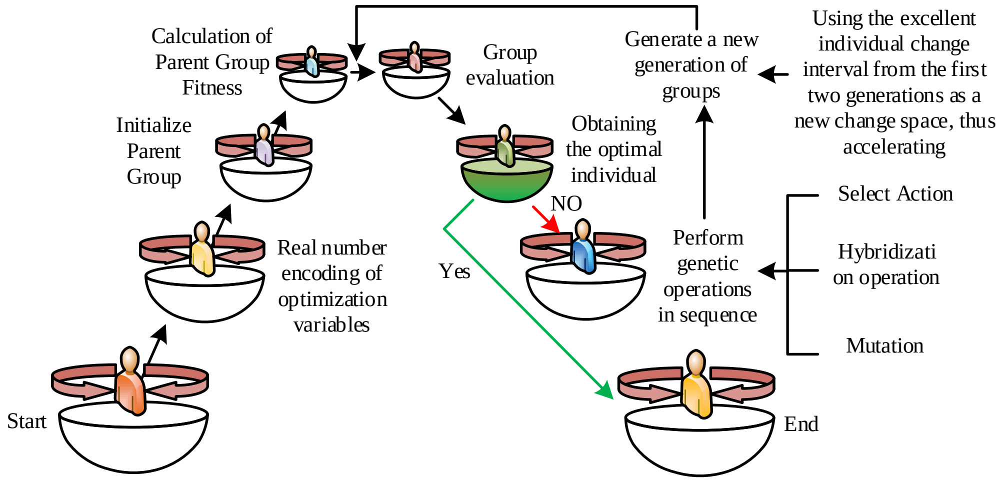



**Figure 3. Flow diagram of RAGA**

From Figure 3, the RAGA is used to obtain the projection function to be optimized to solve the minimization related problems. The corresponding expression is shown in Equation 9.

$$\begin{cases} \min f^{'}(x) \\ s.t. b(j) \leq x(j) \leq c(j) \end{cases} \tag{9}$$

In Equation 9, $\min f'(x)$ represents the minimization problem of the projection function. $b(j)$ and $c(j)$ represent the minimum and maximum values of the initial variation interval. $f'$ represents the objective function. $x$ represents the variable to be optimized. $j$ represents the number of optimization variables. Therefore, the RAGA first encodes the optimized variables with real numbers. The corresponding linear transformation expression is shown in Equation 10.

$$x(j) = b(j) + y(j)\big(c(j) - a(j)\big) \tag{10}$$

In Equation 10, $y$ represents a real number, which is the genetic gene in the RAGA. The actual encoding method of the solution formed by concatenating the genes corresponding to the variables to be optimized is called chromosome. The value of $x$ is maintained at [0,1]. Secondly, the corresponding population is initialized. The fitness of the subsequent parent population is calculated. Calculating the relevant fitness values requires an evaluation function to evaluate them. Specifically, it means assigning a probability to each individual in the parent group. The probability of an individual being selected follows a corresponding pattern with their fitness value. At this point, the evaluation function is not based on actual values. Instead, individual fitness values are allocated based on individual fitness values. If the adaptability of chromosomes is strong, the probability of their selection is higher. The evaluation function proposed on the order basis is shown in Equation 11.

$$eval\big(y(j,i^{'})\big) = \beta(1-\beta)^{i^{'}-1} \tag{11}$$

In Equation 11, $i'$ represents the individual serial number. The maximum value is $O$. The smaller the value, the better the chromosome. $\beta$ represents a constant between (0,1). Subsequently, selection, hybridization, and mutation operations are performed. The selection operation is based on the Y-round selection mechanism. Each rotation generates a chromosome. The relevant chromosomes selected are based on fitness. After this operation, a group of offspring will be born. The specific selection process is expressed in Equation 12.

$$\begin{cases} L_0 = 0 \\ L_{i^{'}} = \sum_{j=1}^{i^{'}} eval\big(y(j,i^{'})\big) \end{cases} \tag{12}$$

In Equation 12, $L$ represents the cumulative probability of each chromosome, and the value is maintained at $[0, L_{i'}]$. By randomly selecting a value r in this interval, the corresponding chromosome can be selected based on the probability value of r. After Y repeated population initialization and parent population fitness calculation steps, a new generation of individuals composed of Y chromosomes can be obtained. In the hybridization operation, a parameter Pb is selected to indicate the presence of Pb$O$ chromosomes in the paternal individual. It is the most important evolutionary method in genetic algorithms. Before performing hybridization operations, a paternal individual needs to be determined first. $i'$ is any one of the $O$ chromosomes. Then a random number r is generated in [0,1]. When the value of r is less than the crossover probability, $y(j,i^{'})$ will be selected as the paternity. By analogy, the corresponding chromosome of the parent individual can be obtained. The expression after pairing it in pairs is shown in Equation 13.

$$\left(y_1'(j,i'), y_2'(j,i')\right), \left(y_3'(j,i'), y_4'(j,i')\right), \left(y_5'(j,i'), y_6'(j,i')\right) \tag{13}$$

To ensure that chromosomes can be paired, when the actual parent individual is odd, one chromosome can be added or removed to ensure that its actual number is even. Therefore, the operation process of arithmetic crossover is similar to the actual association phenomenon of homologous chromosomes in biological clocks. A parameter is generated from (0,1), which can be either a constant or a variable. The offspring obtained are shown in Equation 14.

$$\begin{cases} X = a * y_1'(j,i') + (1-a) * y_2'(j,i') \\ Q = (1-a) * y_1'(j,i') + a * y_2'(j,i') \end{cases} \tag{14}$$

In Equation 1, $X$ and $Q$ represent the two offspring generated. $a$ represents the parameter generated from (0,1). After extensive hybridization operations, a second-generation population can be obtained. In mutation operations, selecting two-point mutations is more helpful for population diversity. Pm represents the probability of relevant variation in genetic operations. The presence of Pb$O$ chromosomes in the relevant population may result in corresponding mutation operations. The selection of parents to be mutated is similar to the crossover process. The corresponding variant expression is shown in Equation 15.

$$y_3'(j,i') + M\gamma \tag{15}$$

In Equation 15, $y_3'(j,i')$ represents the parent. $M$ represents a random number that ensures population diversity. $\gamma$ represents the randomly selected direction of variation. Then, iterative evolution is carried out. According to three operations, 3n offspring individuals are obtained. Based on the numerical value of the related matters, the offspring individuals ranked higher will be re-selected as the parent population for the next round. The fitness of the parents is recalculated until the preset number of evolutionary iterations is reached. Finally, the algorithm process is accelerated to output the final optimization result. According to the corresponding calculations, the actual size of the group is 30. The iterations are 50. The mutation rate of the population is 9%. The genetic crossover rate of the population is 80%.

In the experiment, the Weibo data of the “5.30 Headlines Tencent Battle” is test dataset to simulate the RAGA-IHK model. The microblog data of “10.28 Chongqing bus falling into the river event” is original data to verify the feasibility of the model. In the research, the Weibo dataset used is captured by a web crawler tool, covering Weibo comments related to major public crisis events within a specific time period. During the data preprocessing process, deduplication and noise reduction are carried out first to ensure the accuracy and reliability of the data. Subsequently, the popular Chinese word segmentation tool jieba is used to perform word segmentation on the text, and snowNlp is employed for sentiment scoring. This tool can provide sentiment analysis based on text content, including sentiment polarity (positive, negative, or neutral) scoring. The hardware environment for the experiment is Intel Core processor, model i7-6700HQ, central processor 2.60GHz, and Random-access memory 8.00GB. The software environment includes Win10 flagship version (x64), Octopus crawler, MATLAB R2017b, and Pychar. The programming language is Python 3.0. All data sources are topics on Weibo. Verifying that the RAGA-IHK model can reflect the actual process of social network public opinion changes is mainly achieved by crawling relevant data from the initial and end stages of public opinion. The comments on Weibo are extracted for relevant emotional analysis. The results of sentiment analysis in the initial stage of public opinion are imported into the RAGA-IHK model as raw data. The sentiment analysis data related to the end of public opinion stage is used as the final measurement result. The selected sentiment analysis databases are wordCloud, jieba, and snowNlp. The data in MATLAB is used as the initial network public opinion distribution. The evolution results are compared with the emotional analysis data at the end of online public opinion. The actual case analysis process is shown in Figure 4.

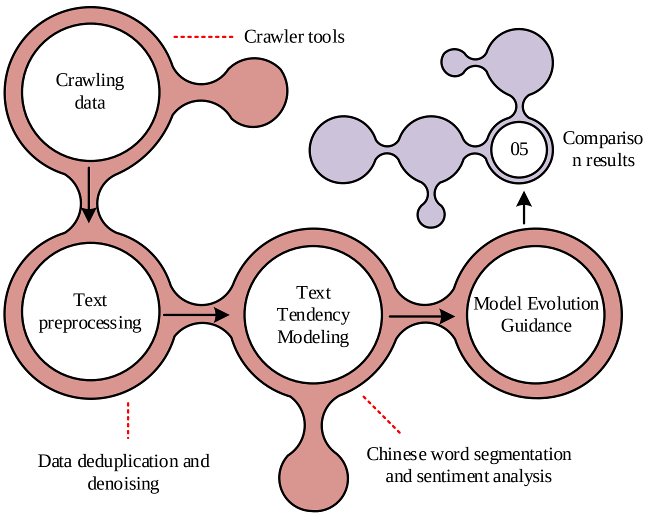



**Figure 4. Schematic diagram of case analysis process in the experiment**

From Figure 4, the case analysis process is simple. Firstly, crawler tools are used to crawl relevant data. Secondly, data is deduplicated and denoised to achieve text preprocessing. Subsequently, Chinese analysis and sentiment analysis are used to model text bias. Then, the evolutionary guidance of the RAGA-IHK model is executed. Finally, the results were compared. The process of sentiment value processing for single Weibo topic changing in the relevant sentiment analysis database is shown in Figure 5.

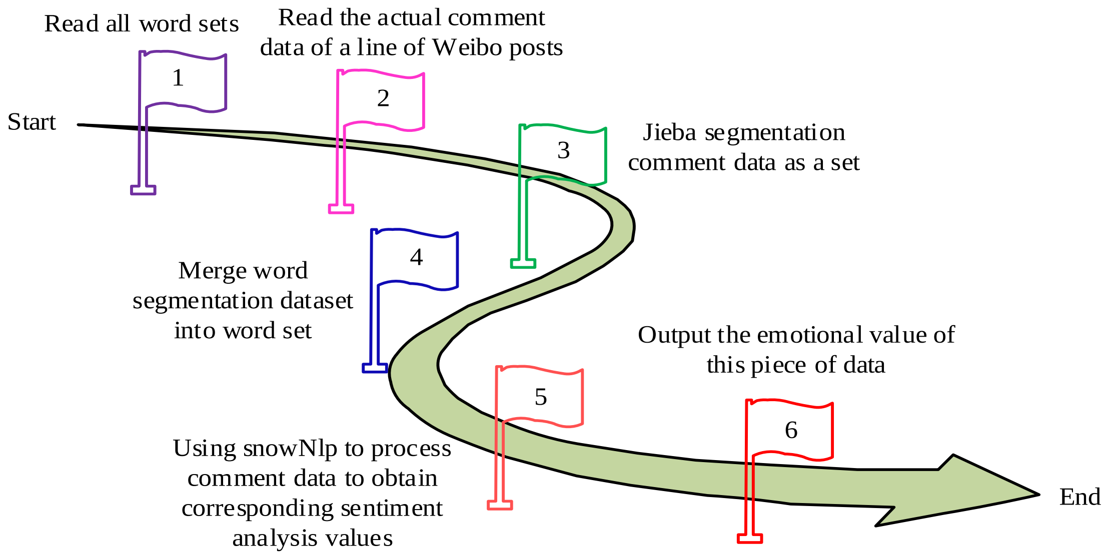



**Figure 5. The emotional value processing process of changing questions on a single Weibo account**

From Figure 5, the emotional value processing process of changing questions on a single Weibo first reads all word sets and actual comment data on Weibo. Secondly, jieba segmentation comment data is used as a set. Then, the set is merged into the word set and the comment data is processed using snowNlp to obtain the corresponding sentiment analysis values. Finally, the emotional value of the data is output. The processed relevant data is imported into MATLAB. In the relevant network generated by the scale-free network with decreasing distance influence, opinion leaders should be the relevant nodes that joined the network earlier. In addition, nodes of ordinary netizens interact with nodes of other ordinary netizens based on the original HK model. When the difference in opinions between the two is less than the memory threshold, it is merged into the domain. The relevant nodes of ordinary netizens and opinion leaders have been introduced into the memory mode. If the difference between the two opinions is greater than the memory threshold, ordinary netizen nodes will remember the relevant nodes of opinion leaders.

## 4. Performance Analysis of Improved Public Opinion Evolution Guidance Model

To verify the effectiveness of the RAGA-IHK, the parameters of the model are first obtained. The improved network topology parameter determination, degree distribution, and training set data changes are shown in Figure 6.

The horizontal axis 1-8 in Figure 6(c) represents the period from May 30th to June 6th. From Figure 6, after improving the network topology parameters, the actual generated network size is 1,000. The nature of Weibo is similar to Twitter. Therefore, the clustering coefficient of 0.565 is used as a reference value. When the ratio of priority connections to neighborhood connections is 0.8, and the generated edges in the near and sub domains are 0.28, the actual clustering coefficient of the network is 0.564, which is close to the clustering data of the Twitter network. The high ratio of priority connections to neighborhood connections indicates that the network has good scale-free characteristics. In addition, the actual Degree distribution of BA scale-free network approximates power law distribution. Meanwhile, the training dataset is from May 30th to June 6th. The data on Weibo is obtained using crawling tools. After analysis, the data traffic on Weibo reaches a peak on June 2nd. The online public opinion data from May 30th to 31st is introduced into the model. The online public opinion data from June 5th to 6th is used as the result value. During the gradual decline of public opinion popularity and the evolution of real public opinion, there is a certain random change in the number of participants. Therefore, the accuracy of the model can be determined based on this proportional result.

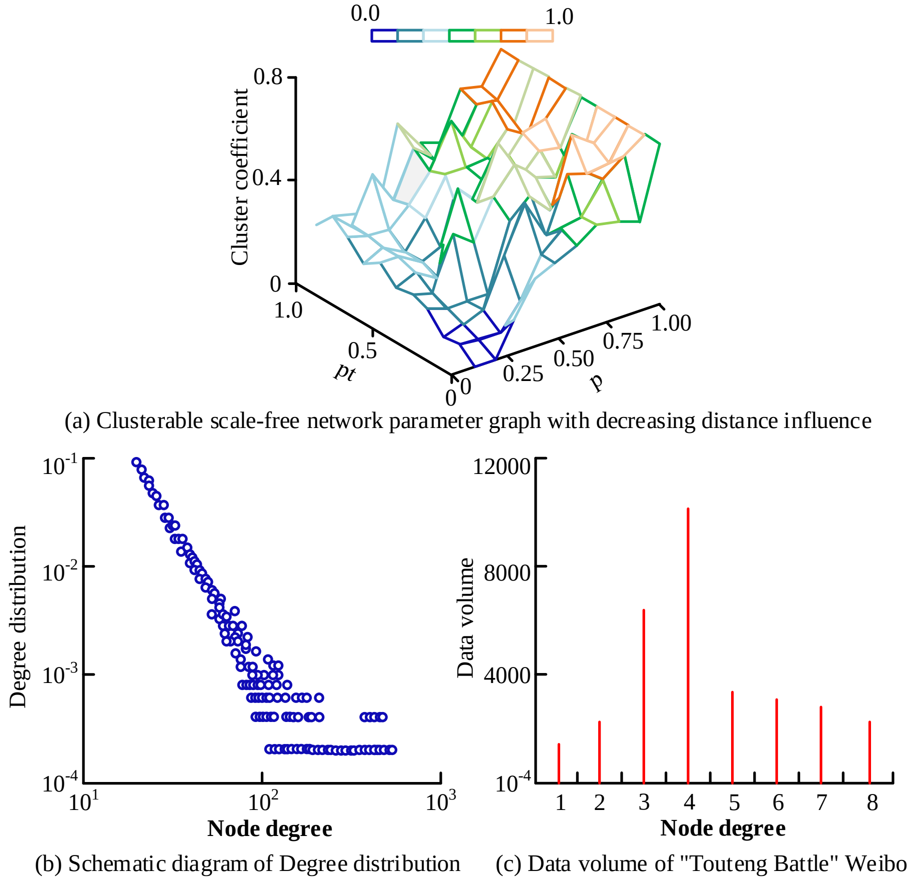



**Figure 6. Improved network topology parameter determination, degree distribution, and training set data change**

From the data from June 5th to 6th, the average public opinion is 0.599, with a positive to negative ratio of 1.518. The improved network topology parameters indicate that the adjusted BA scale-free network exhibits similar clustering coefficients to the Twitter social network. This result not only verifies the effectiveness of the BA scale-free network, but also shows that the model can generate more realistic user interaction patterns in complex networks. This clustering characteristic enhances the interaction opportunities between ordinary users and opinion leaders, thereby influencing the formation and evolution of public opinion. In the model setting, the "punishment" mechanism for negative opinion leaders is an important regulatory parameter. This "punishment" measure does not refer to a single sanction, but aims to suppress the impact of negative views by reducing their dissemination value. For instance, when negative opinion leaders' comments trigger negative public opinion, the model will reduce the weight of these negative comments in the dissemination of public opinion based on their influence. The fitness changes in the RAGA and the relationship between real values and fitness changes are analyzed. The results are shown in Figure 7.

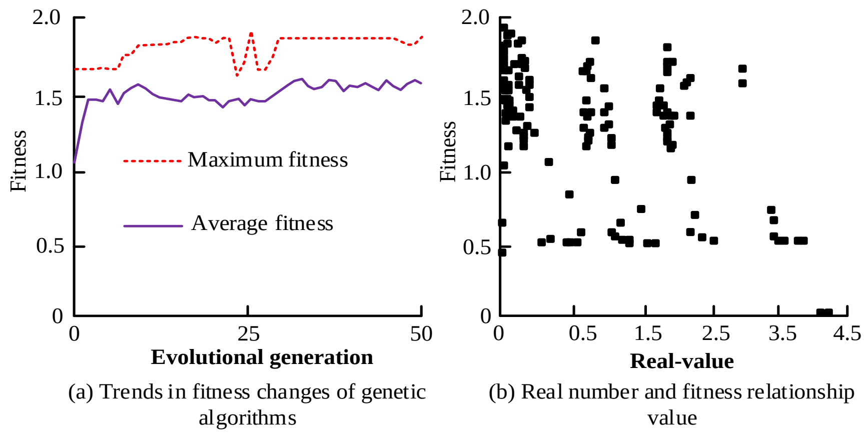
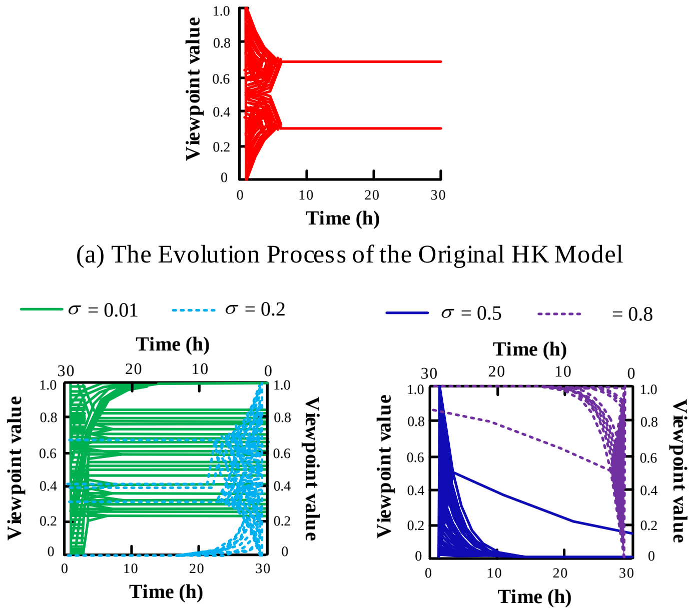



**Figure 7. The fitness trend of RAGA and its relationship with real values**

From Figure 7, the average fitness of the RAGA increases the fastest between 0 and 2.5, followed by an overall increase in upper bound volatility. The maximum fitness value remains basically unchanged between evolution algebras

0-8, and then shows fluctuating growth. After 30 evolutionary cycles, it remains basically unchanged, with a maximum fitness value of around 1.9. In addition, the relationship between real values and fitness also exhibits volatility, with a minimum of around 0.5 and a maximum of around 1.9. Overall, the maximum fitness value is 1.941. After dividing the real value by $10^6$, the best fit is around $1.6\times10^5$, indicating that a bounded trust threshold of 0.16 fits the dataset better. Based on Figures 6 and 7, the improved RAGA-IHK model has an optimal ratio of priority connections to domain connections of 0.7. The generation edge between the near domain and the sub domain is 0.35. The bounded trust threshold ($\sigma$) is 0.2. The ratio ($V$) between the line of negative comments and the benefits of paying attention to comments is 0.51. The memory threshold (M) is 0.94, and the memory frequency threshold (S) is 2. The results show that the fitness tends to stabilize after an initial rapid improvement, indicating that the model has found an effective configuration in the parameter adjustment. This fluctuation in fitness reflects the model's sensitivity and adaptability to data changes, which can effectively respond to the demands of dynamic changes in public opinion. Based on this parameter, the original HK model with a trust threshold of 0.2 and the RAGA-IHK model with trust thresholds of 0.01, 0.3, 0.5, and 0.8 are simulated. During this process, the control parameters $V$ and S remain unchanged. Figure 8 illustrates the results.




(a) The Evolution Process of the Original HK Model

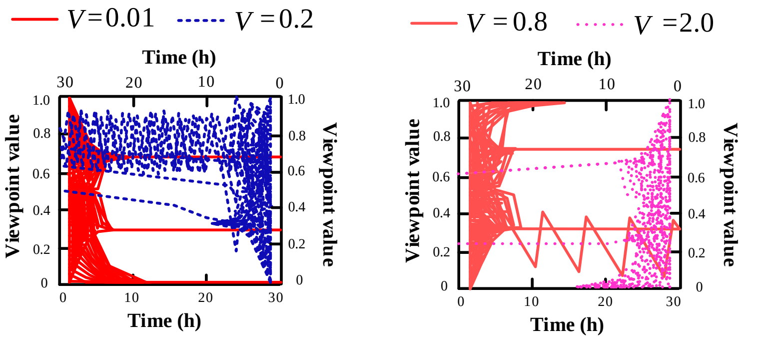
(b) Results with bounded trust thresholds of 0.01 and 0.2

(c) Results with bounded trust thresholds of 0.5 and 0.8

**Figure 8. Simulation results of RAGA-IHK model with original HK model and trust thresholds of 0.01, 0.3, 0.5, and 0.8**

From Figure 8, in the simulation results of the original HK, the viewpoint values of the population are tightly concentrated in the two clusters of 0.7 and 0.3 over time. In the RAGA-IHK model, the viewpoint values of the population no longer converge directly into two clusters. Some of the population whose final opinions converge to 0.4 in the original HK model will gradually evolve towards positive opinions. The reason is that the opinion leader did not take the mean value of nodes in the opinion neighborhood as the next evolution value. Therefore, opinion leaders are influenced by ordinary users in a different way and continue to guide public opinion changes. In addition, in the internal comparison of the RAGA-IHK model, the ratio between the risk of negative opinion loss and the return on opinion publication is 0.51. The memory threshold is 0.94 and the memory frequency threshold is 2. When the actual trust threshold is small, the RAGA-IHK model will bias opinions towards positive evolution guidance when the initial opinions are randomly distributed. On the contrary, it will bias opinions towards negative evolutionary guidance. When the actual trust threshold is greater than 0.5, the increase in the relevant trust threshold in the RAGA-IHK model will not have an impact on the actual evolution guidance results. Individual nodes exhibit smoother public opinion changes.

The results reveal the dialectical influence of trust thresholds on the direction of public opinion. A reassuring environment makes public opinion more likely to be guided by opinion leaders. A higher trust threshold makes public opinion more stable and avoids extreme phenomena. Therefore, setting an appropriate trust threshold can not only effectively promote the positive evolution of public opinion, but also reduce the differentiation of public opinion and effectively guide it. To observe the impact of $V$ values on the evolution guidance model of public opinion, the evolution guidance process of the RAGA-IHK model is analyzed under $V$ values of 0.01, 0.2, 0.8, and 2.0. This process controls the parameters $\sigma$, M, and S unchanged. Figure 9 illustrates the results.



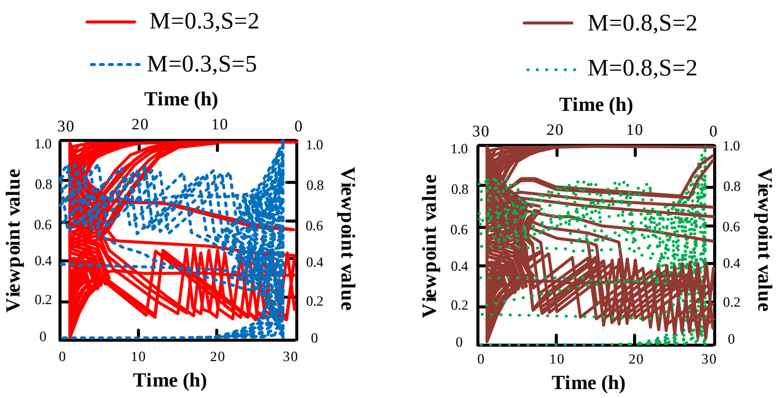

(a) Results of $V$ values of 0.01 and 0.2

(b) Results of $V$ values of 0.8 and 2.0

**Figure 9. Convergence of the RAGA-IHK model under different $V$-values**

From Figure 9, when the $V$ value is 0.01, the change in time causes the viewpoint values to converge towards the three clusters of 0.7, 0.3, and 0, indicating a decreasing trend. When the $V$ value is 0.2, the change in viewpoint values shows fluctuating changes, with some maintaining fluctuations between 0.1 and 0.4. When the $V$ value is 0.8, the fluctuation between viewpoint values decreases, with two clusters approaching 1.0 and 0.75. When $V$ is 2.0, the last cluster of viewpoint values gradually approaches 0.35, indicating an increasing trend. The trend analysis in Figure 9 shows the influence of various $V$ values on the public opinion, especially when the $V$ value is 2.0, public opinion converges to a more positive tendency. This further emphasizes the leading role of opinion leaders in the evolution of public opinion in the digital age, especially under a well-managed trust mechanism, positive opinions are more likely to spread. This result reinforces the significance of social media platforms in public opinion guidance, pointing out that implementing effective management strategies can leverage opinion leaders to steer public opinion in a positive and constructive direction.

However, at this point, this viewpoint often has a higher trust threshold compared to ordinary netizens. As a result, ordinary netizens are not affected. When the $V$ value is low, the same reason makes opinion leader evolve in the direction of negative opinions. At this point, the difference in trust threshold between the two is not significant, which affects the development of ordinary netizens in a negative direction. When the $V$ value is large enough, it generally guides public opinion towards a positive development. To sum up, in the RAGA-IHK model, increasing the punishment measures for opinion leaders to express negative opinions can influence opinion leader's ideas to guide the development of public opinion. According to this idea, directly closing topics on actual social platforms can easily cause public dissatisfaction. Therefore, in a major public crisis, the government changes the views of opinion leaders in different ways, thus affecting the views of the masses. In addition, parameters M and S also play a role in the interaction between opinion leaders and ordinary netizens. When the M value is large, it requires a sufficiently large memory value to affect ordinary netizens. When the S value is high, it also requires accumulating multiple ideas to have an impact on ordinary netizens. Therefore, when the $\sigma$ value is 0.2 and the $V$ value is 0.51, four different sets of M and S values are selected for comparison. Figure 10 illustrates the evolution of public opinion at this time.




(a) The result of an M value of 0.3, an S value of 2, and an M value of 0.3, an S value of 5

(b) The result of an M value of 0.8, an S value of 2, and an M value of 0.8, an S value of 5

**Figure 10. Evolution of M and S values in the RAGA-IHK model**

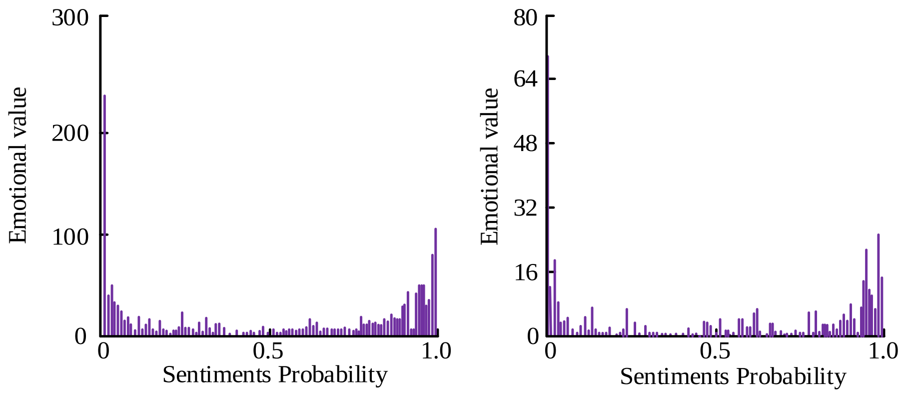
From Figure 10, changing the M and S values has a relatively small impact on the overall trend change. Overall, the changes in opinion values have evolved to a value of 1, becoming extreme opinions. Some viewpoint values evolve between 0.5 and 1.0. Some fluctuate between 0.1 and 0.5. In addition, smaller M values lead to more stable opinion changes, indicating that enhancing public memory of opinion leaders' opinions is not the only key factor. Faced with public opinion, ordinary netizens rely more on the trust and influence of opinion leaders rather than the quantity of a single viewpoint. This discovery suggests that in public opinion guidance, attention should be paid to the importance of establishing good trust relationships, rather than just increasing frequent contact with information. To sum up, the memory model is a way to introduce opinion leaders views into the overall model. However, the differences in their values only have a slight impact on the changes in specific opinion values, and do not have any impact on the overall trend of public opinion. Therefore, changing the parameter values in public opinion guidance can play a more effective role in leading the overall opinion towards a positive direction. On this basis, to further validate the practicality of the RAGA-IHK model, the “Chongqing Public Transport Falling into the River Incident” is used as the validation set for subsequent analysis. The data volume and relevant excerpts from Weibo from October 28th to November 4th of this event are shown in Table 1.

**Table 1. From October 28th to November 4th, the amount of Weibo data and excerpts from Weibo data for this event**

| The amount of Weibo data for this event | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Data volume | 9,545 | 6,321 | 5,125 | 5,001 | 3,945 | 20,000 | 8,215 | 2,516 |

| Selected Weibo data | | | | |
|---|---|---|---|---|
| **Time** | | **Content** | **Like count** | **Number of comments** |
| 10.28 | 12:00 | [# People’s Daily News #] [Chongqing Wanzhou Bus Falling into the River and colliding with a small car, then rushing out of the guardrail and falling into the river] | 367 | 454 |
| | 15:00 | #Will the female driver wearing high heels on Chongqing Zhuojiang No. 22 bus really hurt you? | 12 | 10 |
| 11.30 | 12:00 | Chongqing Wanzhou Bus Falling into the River: The second batch of divers got out of the water and retrieved the bodies of two victims. | 18 | 1 |
| 11.02 | 10:28 | #Chongqing Wanzhou Bus Falling into the River # Announcement of the Reasons for Chongqing Bus Falling into the River | 910 | 562 |
| 11.04 | 10:28 | Summary of Wanzhou Bus Falling into the River: If you don’t stand guard for justice, you will have to be buried with evil! | 29 | 16 |

From Table 1, climax occurs first during this time period. As the rescue progress progresses, the heat is gradually declining. However, public opinion reaches the highest point after the cause of the accident is announced. The data volume in Table 1 indicates that the activity level of Weibo is closely related to the progress of events over time. The high consistency between data peak and event information updates (such as accident cause announcements) emphasizes the immediacy of social media in information dissemination. By analyzing these data, decision-makers can better understand the changes in public sentiment and the ups and downs of public opinion, providing strong data support for responding to crises. Therefore, after using Jieba for word segmentation processing, WordCloud for word segmentation display, and SnowNlp for data sentiment analysis, the initial and final sentiment value distributions before the Black Clip is published, as shown in Figure 11.




(a) Initial emotional value distribution (b) Final emotional value distribution

**Figure 11. Initial emotional value distribution and final emotional value distribution results**

From Figure 11, the initial and final emotional values initially reach the highest values, followed by fluctuations. Therefore, during the initial emotion analysis, the top 5% of users who score and forward are regarded as the actual opinion leader. Figure 11 shows that over time, the sentiment value fluctuates and then stabilizes, reflecting the sensitivity of public sentiment to information dissemination. When the data shows a significant change in emotional values, it indicates the strong impact of a specific event on public sentiment. This result can help decision-makers respond promptly after an event occurs, reduce negative emotions by controlling information release and public opinion guidance, and enhance public recognition. According to Figure 7, $\sigma$ is 0.15, $V$ is 0.61, M is 0.19, and S is 2. The initial emotional distribution values are imported into the RAGA-IHK model in MATLAB. The evolution process of public opinion before releasing Black Clip is shown in Figure 12.

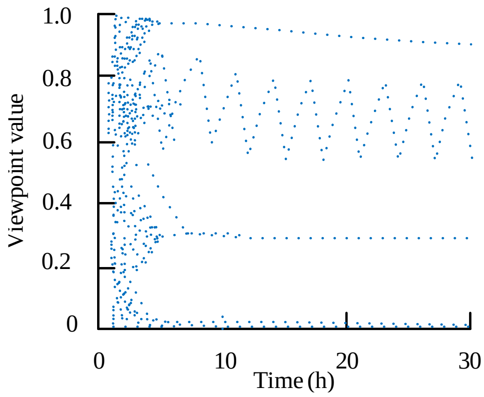
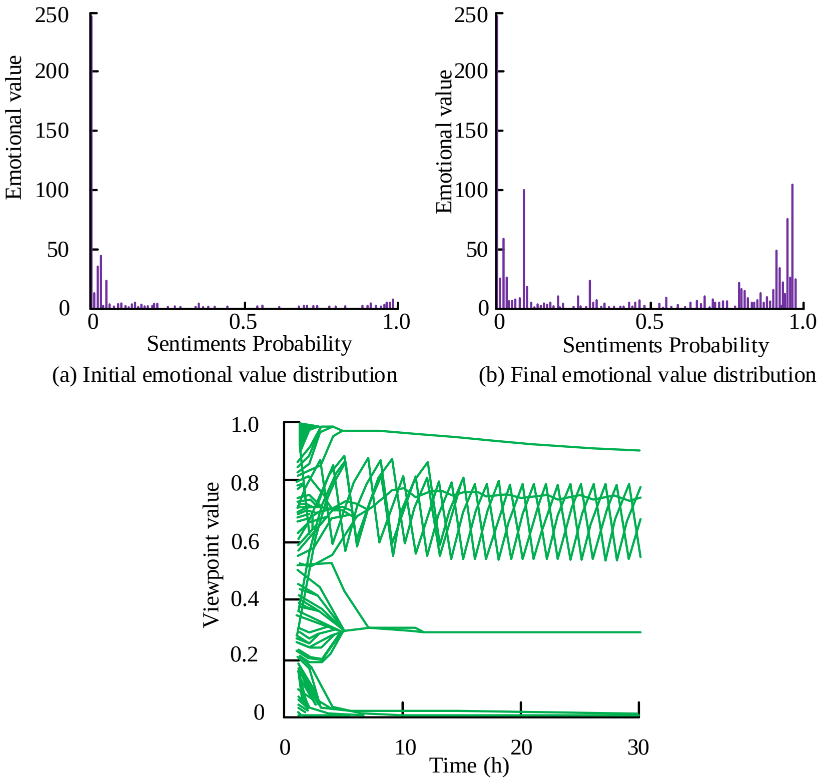



**Figure 12. The evolution process of public opinion before releasing Black Clip**

From Figure 12, the viewpoint values of the time lapse model tend to converge to multiple numerical values, at 0.9, 0.3, and 0.05, respectively. There is a fluctuation phenomenon when the values are between 0.6 and 0.85. Overall, the final evolution result is 1.81, which is close to 2.0. The evolution of public opinion in Figure 12 shows the fluctuations in public sentiment at different stages of the event. After releasing the black clip, there was a huge change in public opinion trends. This phenomenon highlights the significance of information control in public crises, indicating that timely and effective information dissemination strategies can significantly influence the direction of public opinion and help alleviate public anxiety and unease. Therefore, another analysis is conducted on it. The initial data is sentiment analysis data from November 2nd. The final comparison result is emotional data from November 8th to 10th. The results of the Black Clip exposure and the evolution process of public opinion are illustrated in Figure 13.




(a) Initial emotional value distribution (b) Final emotional value distribution

(c) Model Evolution Process after Black Clip Exposure

**Figure 13. The results of Black Clip exposure and the evolution of public opinion**

From Figure 13, both the initial and final emotional values reach their highest levels at the beginning. The difference is that the final emotional value also has a large emotional value when the emotional probability is between 0.8 and 1.0. Based on this result, when $\sigma$ is 0.2, $V$ is 0.51, M is 0.94, and S is 2, the ratio of positive and negative opinion leaders is 0.399. The final evolution result is 1.85, which is also close to 2.0. Figure 13 shows the public opinion feedback after exploring the Black Clip. The emotional value has significantly increased, reflecting the public's high attention and intense discussion on the incident. This indicates the duality of social media in public crises. On the one hand, it can quickly disseminate information and improve transparency. On the other hand, it may also exacerbate pain and trigger rumors. Therefore, the research results emphasize the sense of responsibility of social platforms in information release. Persistent emotional fluctuations should prompt platforms to enhance content review and the reliability of information sources to ensure the stability of public opinion. To demonstrate the evolutionary effect of the RAGA-IHK model, HK noise model and Deffaunt model are introduced. The two models are compared with the original HK model and RAGA-IHK model. Table 2 illustrates the results

**Table 2. Comparison results of different models**

| - | Real data | HK | RAGA-IHK | HK noise | Memory Deffaunt |
|---|---|---|---|---|---|
| Convergence duration | Long | Short | Longer | Long | Long |
| Convergent cluster | Incomplete convergence | 2 | 4 | Incomplete convergence | 3 |
| Mean Opinion | 0.320 | 0.430 | 0.370 | 0.402 | 0.670 |
| Front/Back | 0.333 | 0.720 | 0.399 | 0.656 | 0.630 |

From Table 2, the RAGA-IHK model has converged to 4 clusters. Meanwhile, the mean positive/negative and opinion values are 0.399 and 0.370, respectively, which are closest to the real data. Table 2 compares the performance of the RAGA-IHK model with the traditional HK model. The results indicate that RAGA-IHK outperforms other models in multiple dimensions. This not only proves the effectiveness of introducing opinion leaders and improving network topology, but also provides empirical evidence for optimizing future public opinion guidance mechanisms. In highly complex public crises, the improved model can provide practical tools and strategies for crisis management, with significant theoretical and practical value.

The study aims to verify the dynamic and real-time performance of the RAGA-IHK model in handling real-time crisis scenarios, especially by comparing it with existing studies to evaluate its effectiveness. The comparison methods include those proposed in references [5-7]. The study selects multiple crisis events that break out on social media as cases, such as the "COVID-19 pandemic" and the "COVID-19 vaccination controversy". The research utilizes web crawlers to capture social media data in real-time during these crisis events, ensuring the timely, accurate and rich relevant information, including comments, likes, shares, etc. The method in Vrontis et al. [5] study, is the traditional HK model. Zhang et al. [6] employed sentiment analysis and an opinion evolution model based on a fixed threshold. The method in Liu et al. [7] is an improved emotion propagation model. The experimental evaluation indicators are the convergence speed of viewpoints, the fluctuation range of emotional values, and the influence of negative public opinions. To demonstrate the real-time performance of the model in crisis events, the study sets different time nodes, namely 1 hour, 3 hours, 6 hours, and 12 hours. The specific results are shown in Table 3.

**Table 3. The dynamics and real-time performance of the model in real-time crisis scenarios**

| Time | Model | The speed of convergence of viewpoints | The fluctuation range of emotional values | Degree of influence of negative public opinion (%) |
|---|---|---|---|---|
| 1h | RAGA-IHK | 25 | 0.12 | 22 |
| | Vrontis et al. [5] | 10 | 0.25 | 38 |
| | Zhang et al. [6] | 15 | 0.20 | 30 |
| | Liu et al. [7] | 12 | 0.18 | 33 |
| 3h | RAGA-IHK | 45 | 0.08 | 15 |
| | Vrontis et al. [5] | 20 | 0.30 | 40 |
| | Zhang et al. [6] | 25 | 0.15 | 28 |
| | Liu et al. [7] | 22 | 0.22 | 35 |
| 6h | RAGA-IHK | 60 | 0.05 | 10 |
| | Vrontis et al. [5] | 30 | 0.35 | 50 |
| | Zhang et al. [6] | 35 | 0.12 | 25 |
| | Liu et al. [7] | 30 | 0.20 | 30 |
| 12h | RAGA-IHK | 80 | 0.03 | 5 |
| | Vrontis et al. [5] | 40 | 0.40 | 60 |
| | Zhang et al. [6] | 40 | 0.10 | 20 |
| | Liu et al. [7] | 32 | 0.18 | 28 |

Table 3 shows the dynamic and real-time performance of different models in handling the evolution of public opinion in real-time crisis scenarios. The RAGA-IHK model shows that at each time point, viewpoints converge faster and emotional fluctuations are smaller. At the 1-hour time point, the viewpoint convergence speed of the RAGA-IHK model reaches 25, significantly exceeding that of the other three methods. Over time, the convergence rates of the model at 3 hours, 6 hours and 12 hours rise to 45, 60, and finally 80, respectively. The emotional fluctuations gradually decrease, and the influence of negative public opinions also drops to 5. This result indicates that the RAGA-IHK model can more effectively guide public sentiment and quickly generate consensus in crisis events.

In the current social media environment, robots and fake accounts have significant impacts on the formation and dissemination of public opinion. The RAGA-IHK model needs to effectively handle crisis events. This study suggests introducing a robot monitoring mechanism in the model to filter out potential fake accounts by identifying their activity patterns and behavioral characteristics. In addition, the model can design weight strategies for different types of accounts, treating the public opinion dissemination influence of real users and fake accounts differently. This strategy not only helps to improve the accuracy of the model in the evolution of public opinion, but also enhances the rationality and effectiveness of the final decision. In addition, integrating the data analysis tools of social networking platforms themselves can monitor and eradicate these fake accounts in real time, ensuring that public opinion develops on the basis of real users.

## 5. Conclusion

The current model for guiding the evolution of public opinion ignores the driving factors of opinion leaders and does not fully consider the network topology of actual public opinion. Therefore, the HK model is improved by BA scale-free network. RAGA is introduced and its parameter selection process is optimized to obtain the RAGA-IHK model. The effectiveness is experimentally analyzed. The experimental results show that when the parameters $V$ and S remain unchanged and $\sigma$ values are adjusted, some of the population in the RAGA-IHK model whose final views converge to 0.4 in the original HK model will gradually evolve towards positive opinions. When the control parameters $\sigma$, M, and S remain unchanged, and the $V$ value is 0.01, the passage of time causes the viewpoint values to converge towards the three clusters of 0.7, 0.3, and 0, indicating a decreasing trend. When applied to the actual case validation set, the evolution results of the Black Clip before and after publication are 1.81 and 1.85, both close to 2. The RAGA-IHK model has converged to 4 clusters. The mean positive/negative and opinion values are 0.399 and 0.370, respectively, which are closest to real data. To sum up, in the RAGA-IHK model, the concept of opinion leaders can be influenced by increasing the punishment measures for opinion leaders to express negative opinions. Furthermore, it guides the development of public opinion with effectiveness, which has high performance and practicality in practical applications. Although the research effectively analyzes the evolution of public opinion in Chinese social media through the RAGA-IHK model, there are still certain limitations. The research mainly relies on Chinese social media datasets for model testing and fails to explore social media platforms in other language or cultural contexts. This limits the wide applicability of the model, making the research results possibly unable to fully reflect the complexity of the evolution of public opinion on a global scale. Future research may consider introducing multi-channel social media datasets for cross-platform comparative analysis to verify the applicability of the model in different social media environments.

## 6. Declarations

### 6.1. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

### 6.2. Funding

The research is supported by the 2024 Jilin Province Youth Development Research Plan Project, “Innovative Research on the Construction Path of Vocational College Counselor Workshops from the Perspective of Party Building and Education” Project Number: 2024jpy-1s090.

### 6.3. Institutional Review Board Statement

Not applicable.

### 6.4. Informed Consent Statement

Not applicable.

### 6.5. Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## 7. References

[1] Lee, F. L. F., Liang, H., Cheng, E. W., Tang, G. K. Y., & Yuen, S. (2022). Affordances, movement dynamics, and a centralized digital communication platform in a networked movement. Information Communication and Society, 25(12), 1699–1716. doi:10.1080/1369118X.2021.1877772.

[2] Gopi, A. P., Jyothi, R. N. S., Narayana, V. L., & Sandeep, K. S. (2023). Classification of tweets data based on polarity using improved RBF kernel of SVM. International Journal of Information Technology (Singapore), 15(2), 965–980. doi:10.1007/s41870-019-00409-4.

[3] Park, K., & Jiang, H. (2023). Signaling, Verification, and Identification: The Way Corporate Social Advocacy Generates Brand Loyalty on Social Media. International Journal of Business Communication, 60(2), 439–463. doi:10.1177/2329488420907121.

[4] Zhong, Y., Liu, W., Lee, T. Y., Zhao, H., & Ji, J. (2021). Risk perception, knowledge, information sources and emotional states among COVID-19 patients in Wuhan, China. Nursing Outlook, 69(1), 13–21. doi:10.1016/j.outlook.2020.08.005.

[5] Vrontis, D., Makrides, A., Christofi, M., & Thrassou, A. (2021). Social media influencer marketing: A systematic review, integrative framework and future research agenda. International Journal of Consumer Studies, 45(4), 617–644. doi:10.1111/ijcs.12647.

[6] Zhang, X., Zhou, Y., Zhou, F., & Pratap, S. (2022). Internet public opinion dissemination mechanism of COVID-19: evidence from the Shuanghuanglian event. Data Technologies and Applications, 56(2), 283–302. doi:10.1108/DTA-11-2020-0275.

[7] Liu, Y., Zhu, J., Shao, X., Adusumilli, N. C., & Wang, F. (2021). Diffusion patterns in disaster-induced internet public opinion: based on a Sina Weibo online discussion about the 'Liangshan fire' in China. Environmental Hazards, 20(2), 163–187. doi:10.1080/17477891.2020.1758608.

[8] Zhang, Y., & Guo, L. (2021). 'A battlefield for public opinion struggle'': how does news consumption from different sources on social media influence government satisfaction in China?' Information Communication and Society, 24(4), 594–610. doi:10.1080/1369118X.2019.1662073.

[9] Cai, Q. (2022). Early warning method of network public opinion communication crisis based on feature mining. International Journal of Web Based Communities, 18(3–4), 288–300. doi:10.1504/IJWBC.2022.125501.

[10] Liao, M. Jie, Zhang, J., Wang, R. Mei, & Qi, L. (2021). Simulation research on online marketing strategies of branded agricultural products based on the difference in opinion leader attitudes. Information Processing in Agriculture, 8(4), 528–536. doi:10.1016/j.inpa.2020.12.001.

[11] Chintalapudi, N., Battineni, G., & Amenta, F. (2021). Sentimental analysis of COVID-19 tweets using deep learning models. Infectious Disease Reports, 13(2), 329–339. doi:10.3390/IDR13020032.

[12] Malecki, K. M. C., Keating, J. A., & Safdar, N. (2021). Crisis Communication and Public Perception of COVID-19 Risk in the Era of Social Media. Clinical Infectious Diseases, 72(4), 697–702. doi:10.1093/cid/ciaa758.

[13] Siddiqui, M. S., Siddiqui, U. A., Khan, M. A., Alkandi, I. G., Saxena, A. K., & Siddiqui, J. H. (2021). Creating electronic word of mouth credibility through social networking sites and determining its impact on brand image and online purchase intentions in India. Journal of Theoretical and Applied Electronic Commerce Research, 16(4), 1008–1024. doi:10.3390/jtaer16040057.

[14] Mansyur, A., Karo, I. M. K., Firdaus, M., Simamora, E., Badzlan, M., Darari, R. H., & Panggabean, S. (2025). Impact of Cosine Similarity Function on SVM Algorithm for Public Opinion Mining About National Sports Week 2024 on X. Jurnal Ilmiah Teknik Elektro Komputer Dan Informatika (JITEKI), 11(2), 263–275. doi:10.26555/jiteki.v11i2.30605.

[15] Ahrens, L. (2024). The impact of public opinion on voting and policymaking. Zeitschrift Für Politikwissenschaft, 34(1), 77–100. doi:10.1007/s41358-024-00366-w.

[16] Guo, L., Su, C. C., & Chen, H. T. (2025). Do News Frames Really Have Some Influence in the Real World? A Computational Analysis of Cumulative Framing Effects on Emotions and Opinions about Immigration. International Journal of Press/Politics, 30(1), 211–231. doi:10.1177/19401612231204535.

[17] Bashiri, H., & Naderi, H. (2024). Comprehensive review and comparative analysis of transformer models in sentiment analysis. Knowledge and Information Systems, 66(12), 7305–7361. doi:10.1007/s10115-024-02214-3.

[18] Do, H. N., Do, N. B., Nguyen, T. M., & Nguyen, H. M. (2024). Anti-Brand Activism in the Collectivist Orientation: The Case of Online-Consumers-Run Communities. Journal of Promotion Management, 30(5), 811–841. doi:10.1080/10496491.2024.2318665.

[19] Chen, Z. (2022). Research on Internet Security Situation Awareness Prediction Technology Based on Improved RBF Neural Network Algorithm. Journal of Computational and Cognitive Engineering, 1(3), 103–108. doi:10.47852/bonviewJCCE149145205514.

[20] Cao, B., Zhao, J., Liu, X., Arabas, J., Tanveer, M., Singh, A. K., & Lv, Z. (2022). Multiobjective Evolution of the Explainable Fuzzy Rough Neural Network with Gene Expression Programming. IEEE Transactions on Fuzzy Systems, 30(10), 4190–4200. doi:10.1109/TFUZZ.2022.3141761.

[21] Slothuus, R., & Bisgaard, M. (2021). How Political Parties Shape Public Opinion in the Real World. American Journal of Political Science, 65(4), 896–911. doi:10.1111/ajps.12550.

[22] Satir, E., & Baser, E. (2022). Optimization of Interval Type-2 Fuzzy Logic Controller Using Real-Coded Quantum Clonal Selection Algorithm. Elektronika Ir Elektrotechnika, 28(3), 4–14. doi:10.5755/j02.eie.31148.