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# Online Public Opinion Evaluation of Governmental Public Events Based on Deep Neural Networks with Multi-criteria Decision Making

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Abstract. *In the context of China's social transition, complex challenges arise from economic shifts and value diversification, heightened by Internet technology and public engagement, making online sentiment a key influence in governmental public events. Rapid sentiment spread can escalate issues, posing threats to social stability and government credibility. This study conducts an in-depth analysis of the challenges faced by local governments in managing online public sentiment associated with governmental public events, identifying shortcomings in information aggregation, crisis management, and steering public discourse through case studies. To counter these challenges, the paper introduces a novel deep neural network model grounded in multi-criteria decision-making. This model integrates multiple critical factors, including emotional inclination, dissemination velocity, and influence, to create an adaptive online public sentiment evaluation system. Employing sophisticated techniques in data preprocessing, feature extraction, and model training, the system enhances the precision, robustness, and timeliness of sentiment analysis. The empirical findings demonstrate the system's marked superiority over traditional approaches in accuracy, robustness, and real-time analysis. Furthermore, the paper advances innovative policy suggestions, such as refining the conceptual framework for online public sentiment response, fortifying emergency response mechanisms, and developing a holistic response system. These recommendations are designed to augment the government's capacity and efficacy in managing online public sentiment, enabling a more effective navigation through sentiment crises and contributing to the preservation of social equilibrium and governmental reputation.*
**Keywords:** multi-criteria decision making; deep neural networks; governmental public events; online public opinion; response strategy

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1. **Introduction.** In modern society, online public opinion management of governmental public events plays a crucial role in maintaining social stability and preventing and reducing social conflicts. With the deepening of social transformation, the adjustment of economic structure, the reshaping of interest patterns, and the diversification of social values, governmental public events occur frequently, and the rapid development of

Internet technology and the popularization of social media make these events quickly arouse widespread concern and discussion in cyberspace, forming complex online public opinions [1]. These online public opinions not only spread quickly and have a wide range of influence, but are also often accompanied by emotional and extremist characteristics, posing serious challenges to the government's decision-making and response strategies. However, traditional methods for analyzing online public opinion have obvious shortcomings in handling massive data, identifying key information, and predicting the direction of public opinion [2]. These methods often rely on manually set rules and thresholds, lack an in-depth understanding of the inner laws of online public opinion, and are difficult to adapt to the rapid changes in the online environment and the subtle changes in public sentiment [3]. Therefore, there is an urgent need for an innovative and intelligent solution to enhance the effectiveness and efficiency of online public opinion management [4]. In this paper, a deep neural networks model based on multi-criteria decision-making is proposed by considering multiple key dimensions such as emotional inclination, propagation speed and influence. The model constructs an online public opinion evaluation system capable of automatic learning and continuous optimization through advanced data preprocessing, feature extraction and model training techniques. Compared with traditional methods, the system has significant advantages in processing massive data, identifying key information, and predicting the direction of public opinion, and can provide the government with more comprehensive, accurate, and timely results of online public opinion analysis [5] [6]. Deep neural networks technology is particularly useful in online public opinion evaluation, as it is capable of automatically extracting high-dimensional features from online public opinion data and discovering complex patterns and potential associations in the data by constructing a multi-layered neural network structure [7]. This ability gives deep neural networks a unique advantage in handling nonlinear, high-dimensional data, and enables them to effectively capture the subtle changes and deep-level features of online public opinion [8]. Meanwhile, the multi-criteria decision-making technique provides a method for online public opinion evaluation that takes various factors into account in a comprehensive manner. It provides the government with a more comprehensive and balanced basis for decision-making by integrating several key dimensions, such as emotional inclination, speed of dissemination, and influence [9]. This multi-dimensional evaluation method helps the government more accurately grasp the overall situation of online public opinion and make more scientific decisions [10].

In summary, the paper presents a deep neural networks model that incorporates multi-criteria decision-making, offering a novel framework for assessing online public sentiment in response to governmental public events. This approach is expected to enhance governmental responsiveness to digital discourse, encourage societal cohesion, and significantly bolster the field of online sentiment analysis, thereby fostering advancements in public opinion management.

1.1. **Related work.** Since China began to pay attention to public opinion research in 1999, and especially since online public opinion became the focus of research in 2005, although the research on local government's response to online public opinion started late, domestic scholars and research organizations have quickly followed up, explored in depth the laws of the development of online public opinion, and achieved a series of influential research results [11]. These results not only mark a new stage in the study and practical application of online public opinion, but also provide valuable insights and lessons for guiding online public opinion and government response to online public opinion events triggered by public crises. Sharma and Shekhar [12] suggest that when dealing with online public opinion issues, local governments should make full use of media resources, bring in professionals, speed up the implementation of the real-name system on the Internet, and update their network management techniques in order to continuously improve their ability to handle online public opinion. Sun et al. [13] highlighted the necessity for local governments to genuinely enhance their public opinion crisis management capabilities. They stressed the importance of stringent online information oversight, the institution of robust emergency protocols, and the cultivation of robust official- public dialogue to ensure the transparent dissemination of authentic information via official channels. Zhang and Wang [14] point out in their studies that governments need to take comprehensive measures in terms of conceptual updating, innovation in governance mode, improvement of mechanisms and emotional communication when properly handling online public opinion crises of public events. From a philosophical perspective, Wang and Peng [15] propose that local governments should strengthen the legal system and mechanism construction in order to continuously improve their ability to respond to online public opinion crises. Liu [16] focuses on the attributes of sudden crisis of public events, and suggest that after the crisis is dealt with, the effect analysis should be carried out from multiple perspectives, such as information coding, transmission, noise processing to information feedback, in order to optimize the crisis management process. Zhang et al. [17] point out that after a public event, if the government does not take the initiative to release information, the public's access to information will be limited, and it is easy to misbelieve rumors and doubt the credibility of the government. Therefore, when the government responds to a public opinion crisis, it should take the initiative to disclose information about the event to ensure that the public can obtain authoritative and accurate information. Yang and other scholars emphasized in their study that the government has an unshirkable responsibility in releasing information about public events, and it is an important duty of the government to ensure that the public can obtain true information in a timely manner. To summarize, the effective management of online public opinion not only requires the innovation of technical means and the improvement of legal mechanisms, but also requires the government to take comprehensive measures at multiple levels, such as conceptual updating,

information supervision, emergency response, and communication between the government and the people. Through these measures, a more open, transparent and efficient online public opinion management system can be constructed to effectively guide public opinion, enhance the government's ability to respond to online public opinion crises, and maintain social stability and national security. At the same time, because many new forms and applications have emerged in the development of the Internet, there are also many new changes in online public opinion, and local governments have not yet launched an in-depth exploration of coping strategies for responding to online public opinion in public events, and many existing strategies do not match with the actual situation. The urgent task in China's internet landscape is to establish a mechanism for local governments to effectively manage online public opinion crises during public events and to enhance their capacity to address such crises swiftly and efficiently.

1.2. **Motivation and contribution.** Driven by the wave of digitization, online public opinion has become a force to be reckoned with in the government's handling of public events, with profound impacts on policy orientation, social order, and even national tranquility. In this context, the dynamic and unpredictable nature of online public opinion has put forward higher requirements for the government's rapid response and accurate evaluation capability. Nevertheless, the current online public opinion evaluation techniques are still insufficient in terms of processing capability, depth of sentiment analysis, and accuracy of trend prediction, making it difficult to keep up with the pace of the times and satisfy the needs of real-time monitoring and in-depth analysis. Therefore, this paper proposes an innovative deep neural networks model based on multi-criteria decision-making, which seeks to break through the limitations of existing techniques. By integrating advanced data processing techniques, deep sentiment analysis algorithms, and precise trend prediction mechanisms, the model aims to significantly improve the government's response speed and assessment accuracy of online public opinion on public events. The proposed model can not only optimize public opinion guidance strategies, effectively prevent and mitigate social conflicts, but also provide strong data support and scientific basis for government decision-making. The contributions of the thesis are mainly in the following areas: (1) This paper develops a comprehensive decision-making framework that integrates critical factors like emotional tone, propagation velocity, and overall impact, offering novel insights for evaluating online public sentiment. This approach to multi-dimensional analysis more effectively encapsulates the intricate nature of online discourse, equipping authorities with profound and nuanced understanding. (2) In this paper, deep neural networks technology is applied to online public opinion evaluation, which significantly improves the depth and breadth of data processing through automatic feature extraction and pattern recognition. Compared with the traditional rule-based method, the deep learning model can more accurately identify and predict the trend of public opinion, which enhances the adaptability and foresight of the evaluation system. (3) This paper not only proposes a model theoretically, but also verifies the validity of the model through actual cases, and puts forward specific policy recommendations based on the model results. These recommendations aim to help the government optimize its online public opinion response strategies, improve its crisis management capabilities, and promote social harmony and stability.

## 2. Theoretical analysis.

2.1. **Multi-criteria decision-making.** Multi-criteria Decision Making (MCDM) is an emerging discipline that developed rapidly in the 20th century. In 1972, the first international conference on multi-criteria decision making was held, which is considered to be the sign of the beginning of the development of MCDM [18]. Roughly speaking, the so-called decision problem is to compare and evaluate a number of candidate programs from a number of (finite or infinite) candidates, and finally make a choice. The so-called decision problem, roughly speaking, is the problem of comparing and evaluating several (finite or infinite) candidate programs, and finally making a choice. Multi-Criteria Decision Making is categorized into two distinct types based on the nature of the decision-making process: Multi-Attribute Decision Making (MADM), which deals with decisions among alternatives based on multiple attributes, and Multi- Objective Decision Making (MODM), which addresses decisions with multiple, often conflicting objectives. Multi-Attribute Decision Making refers to selecting the best among many options for the purpose of decision making, usually the comprehensive index of each option is given, and the optimal option is selected through the comprehensive index; Multi- Objective Decision Making refers to determining the optimal option in a certain sense among the alternatives for the purpose of conflicting objectives, and the set of alternatives is given by some objective constraints. Multi-attribute decision-making is usually used to solve ranking problems, site selection problems, risk assessment problems, etc. The government public event network public opinion evaluation problem studied in this paper is a typical multi-attribute decision-making problem; multi-objective optimization is usually used to solve the portfolio problem with large returns and small risks, optimal scheduling of hydroelectric power plants and other problems. The construction process of multi-criteria decision-making model is to obtain decision-making information firstly, then process the decision-making information of the alternatives in a certain way, and then rank and optimize the alternatives [19]. The whole decision-making process is shown in Figure 1.

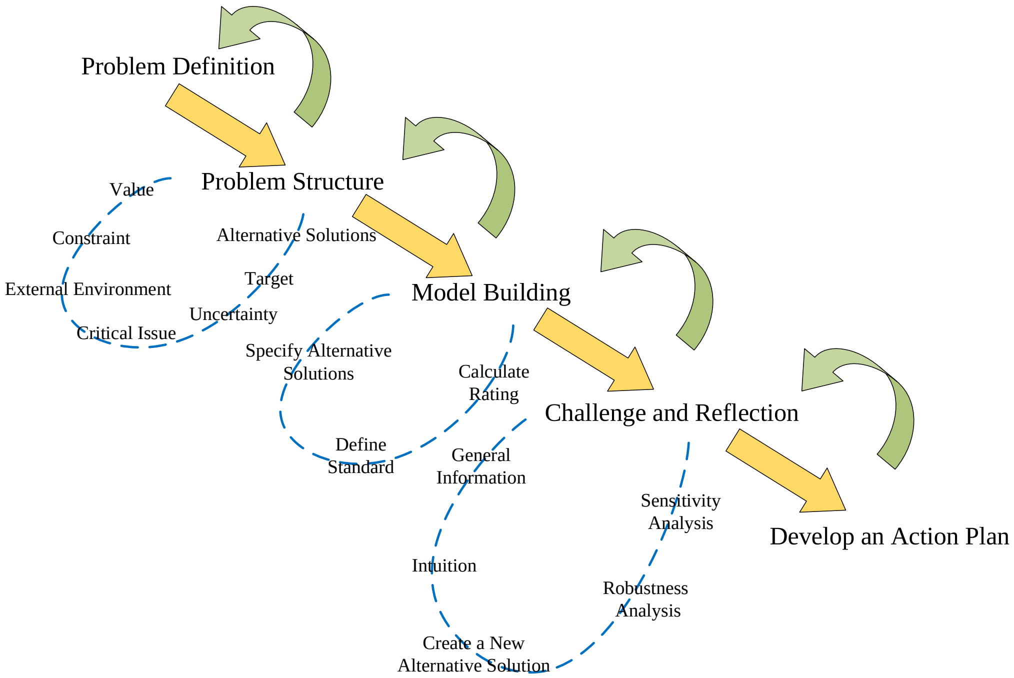


Figure 1. Multi-criteria decision-making process

Evaluate each criterion indicator for each possible scenario, and for each alternative Ai (i = 1,2,3,... ,m), denote its attribute value under attribute µj (j = 1,2,3,... ,n) under the attribute as aij . After obtaining all the attribute values, the attribute values are usually normalized to eliminate the differences caused by the different scales between different attributes. The standardized multi-criteria decision problem is shown in Equation (1):

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}$$

(1)

In multi-criteria decision-making, since the criteria indicators come from different data sources, they usually have different scales and orders of magnitude. In order to quantify the impact of different criteria on the decision target and eliminate the differences in the order of magnitude, the criterion indicators are usually processed by the standardization method, which ignores the order of magnitude of the criterion indicators, and converts the different values of each criterion into the [0,1] interval. Commonly used standardization methods include the maximum value transformation method and the Max-Min standardization method, and in practical applications, the Max-Min standardization method is the most widely used method [20]. (1) Maximum value transformation method For the benefit-based indicators, the linear transformation method is shown in Equation (2):

$$a_{ij} = \frac{a_{ij}}{\max_i\{a_{ij}\}} \tag{1}$$

For cost-based indicators, the linear transformation method is shown in Equation (3):

$$a_{ij} = 1 - \frac{a_{ij}}{\max_i\{a_{ij}\}} \tag{2}$$

where $a_{ij}$ denotes the original value of the j-th criterion in the i-th scenario, $\max_i\{a_{ij}\}$ denotes the maximum value of the original value of the j-th criterion in the i-th scenario, and $a_{ij}$ denotes the standardized value of the criterion indicator. (2) Max-Min standardization Also known as deviation normalization, the deviation transformation method is shown in Equation (4) for effectiveness indicators:

$$a_{ij} = \frac{a_{ij} - \min_i\{a_{ij}\}}{\max_i\{a_{ij}\} - \min_i\{a_{ij}\}} \tag{3}$$

For cost-based indicators, the deviation transformation method is shown in Equation (5):

$$a_{ij} = \frac{\max_i\{a_{ij}\} - a_{ij}}{\max_i\{a_{ij}\} - \min_i\{a_{ij}\}} \tag{4}$$

where $a_{ij}$, $\max_i\{a_{ij}\}$, $a_{ij}$ has the same meaning as the linear transformation method, and $\min_i\{a_{ij}\}$ denotes the minimum of the original value of the j-th criterion in the i-th scheme.

In the realm of multi-criteria decision making, the determination of weights is an essential phase, as these weights indicate the preferences of the decision-maker. Weight acquisition methods are typically bifurcated into subjective and objective approaches. The entropy technique serves as a mathematical tool for assessing the variability among indicators. Characteristically, a lower entropy value denotes greater variability, implying a more significant influence of the indicator on the outcome and consequently, a higher objective weight assignment, the entropy weight value of each indicator $\omega_i$ can be expressed as Equation (6):

$$\omega_i = \frac{d_i}{\sum_{i=1}^{n} d_i} \tag{5}$$

where $d_i$ denotes the entropy redundancy of the i-th indicator.

After obtaining the standardized guideline indicators and guideline weights, certain integration methods are usually used to organically combine the two as the basis for judging whether the program is good or bad. At present, the commonly used integration methods include hierarchical analysis method, ideal point method, linear weighted combination method, approximate ideal ranking method and so on. Among them, linear weighted combination has been widely used in multi-criteria decision making due to its simple principle and ease of use. The integration method used in this study is the linear weighted combination method, as shown in Equation (7):

$$H_i = \sum_{j=1}^{n} a_{ij} \times \omega_j \tag{6}$$

where $H_i$ is the public event online public opinion evaluation index at the i-th location in space, $a_{ij}$ is the standardized value of the j-th indicator in the i-th scenario, and $\omega_j$ is the criterion weight of the j-th criterion indicator.

2.2. **Deep neural networks.** Deep neural networks (DNNs) represent a significant advancement in deep learning, enabling the tackling of intricate problems that elude conventional, shallow neural networks [21]. Comprising an array of layered neurons, each neuron in a DNNs operates on a principle akin to that of a single-layer perceptron, as illustrated in Figure 2. The process commences with data introduction through the input layer, where each datum is assigned a corresponding weight w. Subsequently, the data is aggregated with its weights, transformed via a non-linear activation function, yielding the eventual output y. Throughout this training phase within the network, 'f' symbolizes the non-linear activation function, as detailed in Equation (8):

$$f = \sigma\left(\sum_i w_i x_i + b\right) \tag{7}$$

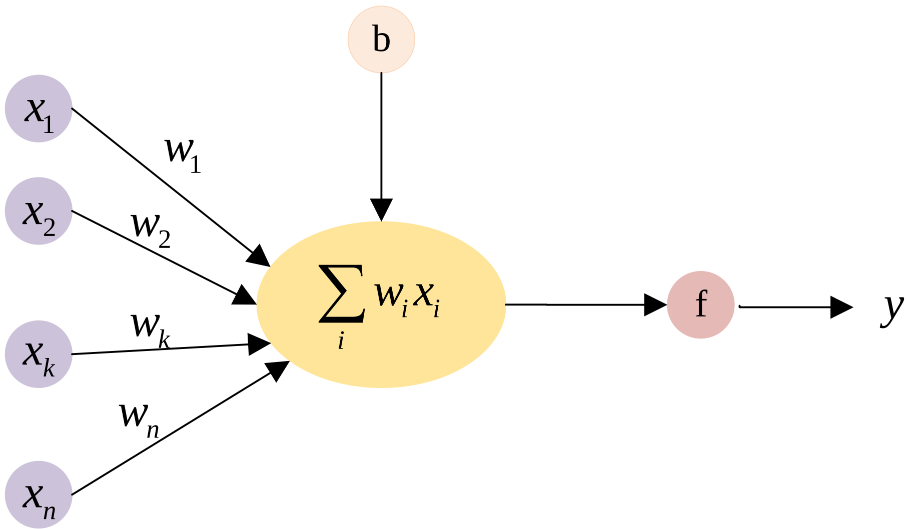


Figure 2. Single layer perceptron structure diagram

In neurons, the nonlinear activation function processes the data after weighted summation and converts the sum of input vectors to output vectors, and since most of the activation functions have nonlinear properties, the output vectors are converted to nonlinear vectors in multilayer perceptrons, which can be applied to nonlinear recommendation models. Typical non-linear activation functions include the Sigmoid, Rectified Linear Unit (ReLU), and Hyperbolic Tangent (Tanh), each defined in Equation (9) to Equation (11). These functions are pivotal for introducing non-linear properties to the neurons within a DNNs, enabling the network to solve complex problems that linear models cannot [22].

$$\mathrm{Sigmoid}(n) = \frac{1}{1+e^{-n}} \tag{8}$$

$$\mathrm{Tanh}(n) = \frac{e^n - e^{-n}}{e^n + e^{-n}} \tag{9}$$

$$\mathrm{ReLU}(n) = \max(0, n) \tag{10}$$

The architectural diagram of a DNNs is depicted in Figure 3, highlighting two principal components: the input layer I and several successive hidden layers. A distinguishing feature of DNNs, when compared to traditional neural networks like the Backpropagation (BP) neural network, lies in the extended depth of hidden layers—DNNs may encompass a dozen or more layers to accommodate complex processing needs [23].

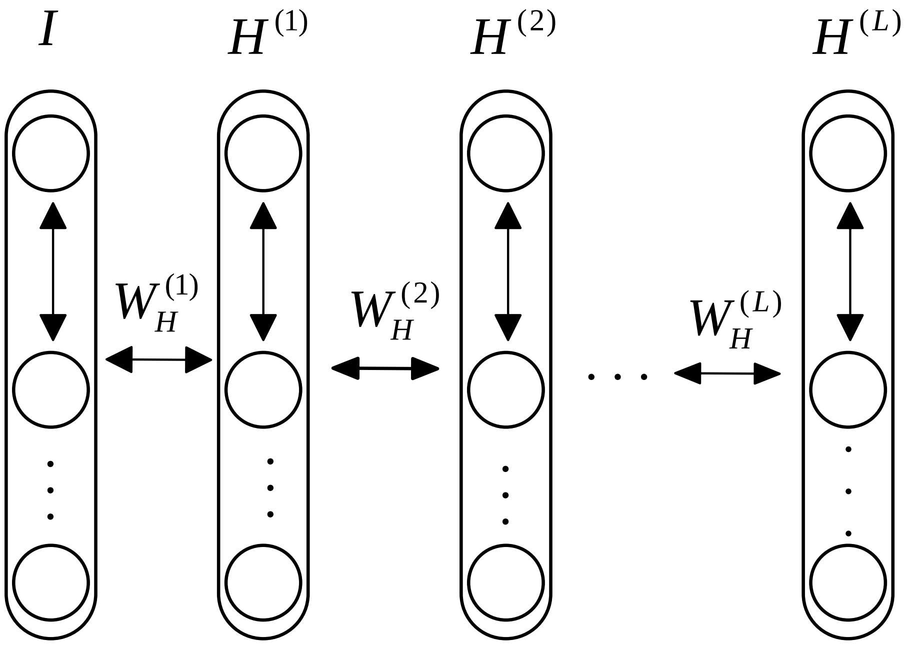


Figure 3. Schematic diagram of deep neural networks

Data initiation occurs at the input layer, proceeding sequentially through L hidden layers denoted as H(1), H(2), ..., H(L), where it undergoes progressive data abstraction and feature extraction. The final layer, H(L), encapsulates the desired data representation [24], signifying the output of the deep network's representation learning process. In line with the inherent attributes of DNNs, assuming an adequate count of nodes per layer, each hidden layer's output is imbued with the input data's comprehensive information, suggesting that each layer embodies a distinct representation of the input, albeit in varied forms [25].

## 3. **Evaluation system for online public opinion on governmental public events based on deep neural networks for multi-criteria decision-making.**

3.1. **The government's evaluation of online public opinion on public emergencies.** Confronted with public emergencies, the government's assessment of online public sentiment is of paramount importance. As the wielder of public authority, formulator of policies, overseer of administrative tasks, and provider of services, the government's precise interpretation of online discourse is essential for steering public perception towards rational understanding and upholding societal equilibrium. The establishment of a robust communication framework is vital for enabling accurate public comprehension of government-released information, thereby reinforcing the government's informational reliability and guaranteeing the seamless functioning of societal systems. Additionally, such mechanisms are pivotal in curbing the potential for negative escalation within online public sentiment. The government's analysis of online public sentiment is an element of its civic duty and a crucial avenue for enhancing governance capabilities and fostering a cohesive society. In the wake of evolving information technology and the dynamic online milieu, continuous innovation in the government's evaluative techniques is essential to augment the efficacy and precision of sentiment analysis. This progression is indispensable for optimizing public service, preserving societal stability, and safeguarding national security. Hence, it is imperative for the government to develop a credible framework for gauging online public sentiment and to institute rigorous criteria and techniques for information assessment. This encompasses validating the veracity of information, forecasting the trajectory of public opinion, and discerning the prevailing attitudes among the populace. By employing this systematic approach to evaluation, the government can promptly and precisely apprehend the shifts in public sentiment, devise appropriate strategic responses, navigate the discourse constructively, and foster a positive evolution of the online sphere.

3.2. **Evaluation system based on deep neural networks and multi-criteria decision making.** In assessing online public sentiment during public emergencies, the government may employ a sophisticated technical approach that integrates the multi-criteria decision-making method with deep neural networks, as depicted in Figure 4. This combination not only enhances the comprehensiveness and depth of the evaluation, but also strengthens the adaptability and analytical ability to the complex public opinion environment. The multi-criteria decision- making approach allows the government to evaluate public opinion from multiple perspectives, including key dimensions such as emotional inclination, speed of dissemination, and influence, ensuring that the evaluation results are multi-dimensional and balanced [26]. The introduction of deep neural networks models, on the other hand, allows the government to automatically extract features, recognize patterns, and predict trends from massive data, greatly improving the accuracy and foresight of evaluation [27]. At the level of technology application, the evaluation of the physical layer involves the consideration of external factors such as regional economic level and online public opinion

database, which pose objective limitations on the government's ability to manage online public opinion. The physical layer focuses on the government's internal organizational structure, such as connectivity and response capability [28], which are internal factors that directly affect the efficiency and effectiveness of online opinion management. The humanistic layer pays more attention to human factors, including the participation, cognitive level, and behavioral patterns of managers and the public, which are indispensable factors in the government's online public opinion governance.

Through this three-dimensional evaluation system, the government is able to understand more comprehensively the internal mechanism and external manifestations of online public opinion, and formulate more precise and effective response strategies. This not only helps the government to play a leading role in public events and guide the direction of public opinion, but also helps to build a healthier and more positive online environment and promote social harmony and stability. As technology progresses and its applications expand, the utilization of multi-criteria decision-making techniques coupled with deep neural network models is set to become increasingly pivotal in the realm of online public sentiment analysis [29]. These tools are expected to offer the government formidable technological backing and enhanced decision- making support.

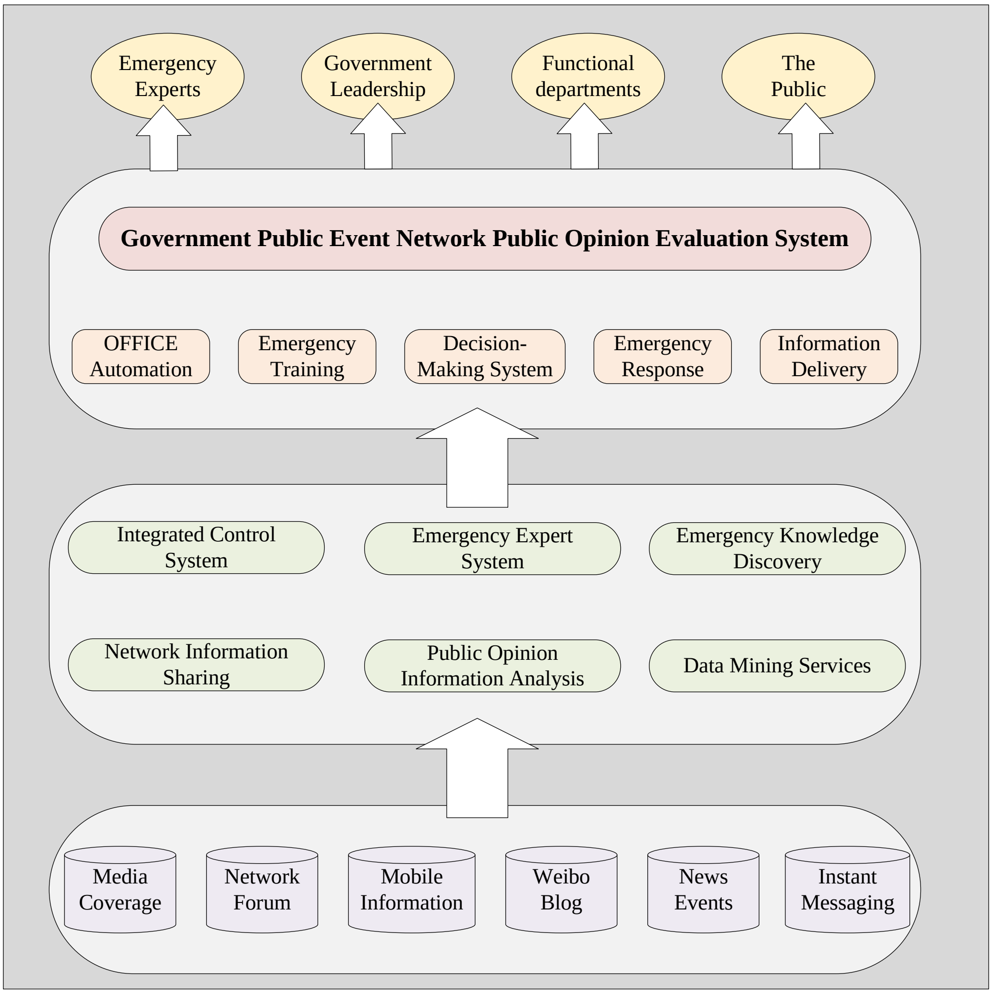


Figure 4. Government public event network public opinion evaluation system

3.2.1. *Physical hierarchy analysis of the government's online public opinion governance evaluation system.* The tangible aspects influencing the government's online public opinion governance evaluation system are encapsulated within the physical layer, predominantly characterized by societal informatization, infrastructural development, and the economic gradient of regions. The advancement of the information society stands as a principal external influence on this evaluative framework. Given the pronounced disparities in regional conditions across China, the state of infrastructure, which varies significantly from one area to another, is also a determinant factor in the system's assessment mechanisms. Moreover, the economic disparities between regions exert a notable influence on the governance evaluation system. Further, the pressure indices at the physical level of the evaluation system for government online public opinion governance signify the strain imposed by the evolution of the information society. The indices in this category include the information economy index,

network society index, and digital life index. The status indices reflect the current condition of the government's evaluative system amidst the pressures of societal informatization, with key indices being the internet index and infrastructure index. The Response Index indicates the government's countermeasures to the pressures of information societal development, with associated metrics such as the Hardware Resource Investment Index and the Regional Economic Development Index.

3.2.2. *Hierarchical analysis of the government's online public opinion governance evaluation system.* The organizational elements influencing the government's online public opinion governance evaluation system constitute the matter layer, primarily encompassing participants in online public discourse, the government's responsiveness to such discourse, and the interconnectivity of governmental bodies. The extent of media and netizen engagement with online public opinion incidents serves as a primary impetus for governmental regulation of online discourse. The government's role in the propagation of online public opinion events is a direct indication of its responsiveness, while the interconnectivity of government departments is evident in the efficacy of their reactions to these events. At the factual level, the pressure index within the government's online public opinion management evaluation system indicates the influence of media and netizen attention on the evaluative process. Key metrics in this regard include the media activeness index and the netizen participation index. The state index portrays the current status of the government's online public opinion management system amidst this influence, with indices such as the Dissemination Index and the Service Index being central. Furthermore, the response index delineates the government's capacity to address media events given the current circumstances, highlighting its reactive capabilities to media occurrences. The state index reflects the state of the government's online public opinion management evaluation system under pressure, and the related indexes mainly include: communication power index, service power index; response index reflects the government's measures and means in the face of the pressure from the media and netizens under the existing state.

3.2.3. *Humanistic hierarchy analysis of the government's online public opinion governance evaluation system.* The humanistic layer encompasses the human elements that influence the assessment mechanisms within government online public opinion governance, focusing on demographic composition, the efficacy of online opinion management, and investments in talent development. Factors such as the populace's educational attainment, income levels, population distribution, and gender distribution all bear on the evaluative framework of government online sentiment management. The effectiveness of government strategies in this realm is also subject to public appraisal. Moreover, governmental allocations to educational sectors and information technology infrastructure significantly shape the online public opinion governance landscape. The pressure indices at the humanistic level of the government's online sentiment governance evaluation system signify the demographic pressures exerted on the system, with key metrics including the population density index, education level index, per capita income index, and gender structure index. Concurrently, the state indices illustrate the system's condition under demographic pressures, highlighting indices such as the public satisfaction index and government credibility index. The state index reflects the state of the government's online public opinion management evaluation system under the demographic pressure, and the related indicators mainly include: public satisfaction index, government credibility index; the response index reflects the existing state of the government's measures and means in the face of the demographic pressure, and the related indicators mainly include: education expenditure index, employment index.

## 4. **Experiments and Results.**

### 4.1. **Determination of indicator weighting factors.**

In this paper, a multi-criteria decision- making deep neural networks-based online public opinion evaluation system for governmental public events is constructed by using a combination of the gray correlation method and entropy value method to determine the weight coefficients of the indicators. The gray relational analysis is an integrative approach that blends subjective and objective assessment techniques. It ascertains the weighting of indicators based on the degree of resemblance in the developmental trajectories of the factors involved, without imposing stringent demands on the scale or distribution of the sample dataset. There are no strict requirements for the size and distribution of the sample size, however, the method is more subjective in determining the optimal value of each indicator. Therefore, this paper introduces the entropy value method to determine the weight coefficients of the indicators by measuring the degree of dispersion of the indicators, which is a kind of objective empowerment method, and the weight coefficients of the evaluation indicators of the government network public opinion governance are determined by combining the gray correlation method with the entropy value method, and the specific calculations are shown in the Equation (12-17).

$$\varepsilon_i(k) = \frac{\min\min|X_i(t) - X_0(t)| + \rho \max\max|X_i(t) - X_0(t)|}{|X_i(t) - X_0(t)| + \rho \max\max|X_i(t) - X_0(t)|} \tag{11}$$

$$r_i = \frac{1}{N}\sum_{k=1}^{t} \varepsilon_i(k), \quad (k = 1, 2, 3 \ldots t) \tag{12}$$

$$W_{1i} = \frac{r_i}{\sum_{i=1}^{m} r_i}, \quad (m = 1, 2, 3 \ldots n) \tag{13}$$

where $\varepsilon_i(k)$ is the gray correlation coefficient, $\rho$ is the discrimination coefficient, $|X_i(t) - X_0(t)|$ compares the absolute difference between the series and the reference series, $\min\min|X_i(t) - X_0(t)|$ represents the minimum value of the difference series, $\max\max|X_i(t) - X_0(t)|$ represents the maximum value of the difference series, $r_i$ represents the correlation of the series $X_i(t)$ to the reference series $X_0(t)$ , and $W_1$ is the weighting coefficient.

$$P_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \tag{14}$$

$$d = 1 + K\sum_{i=1}^{n} P_{ij}\ln(P_{ij}) \tag{15}$$

$$W_2 = \frac{d_i}{\sum_{i=1}^{n} d_i} \tag{16}$$

where $P_{ij}$ denotes the contribution of the y-th province under the i-th indicator, $d_i$ denotes the degree of consistency of the contribution of each province under the i-th indicator, and the constants $K = 1/\ln(n)$, $W_2$ are the weighting coefficients.

4.2. **Experimental design.** This experiment is designed to empirically test a deep neural network model based on multi-criteria decision making, which is specifically designed for evaluating online public opinion related to government public events. The starting point of the experiment is to comprehensively collect online public opinion text data and its sentiment annotation from 31 provinces in China in response to various types of governmental public events at a given time, so as to build the basis of the dataset. In the data preprocessing stage, text cleaning, word segmentation, deletion of deactivated words, etc. will be performed, and sentiment analysis techniques will be used to extract sentiment tendencies and quantify multidimensional indicators such as spreading speed and influence, so as to lay a solid foundation for the construction of input features. Further, the experiment will carefully design the architecture of the deep neural network, which will contain an input layer, multiple hidden layers, and an output layer, in which the hidden layer will adopt the ReLU activation function to introduce nonlinearity, and at the same time, the generalization ability of the model will be improved by batch normalization and Dropout regularization techniques to avoid the occurrence of overfitting phenomenon. In terms of feature engineering, methods such as TF- IDF, Word2Vec or BERT will be applied to convert the text data into numerical feature vectors to adapt the deep learning model. In the experiments, the dataset will be divided into training set, validation set and test set. The training set is used for the initial learning of the model, the validation set is used for the hyper-parameter tuning of the model, including the learning rate, the number of hidden layers, the number of neurons, etc., while the test set is used for the final evaluation of the model performance. The performance evaluation will be comprehensively measured based on metrics such as accuracy, F1-score, recall to ensure the multidimensionality and comprehensiveness of the model evaluation. In order to show the advantages of deep learning models over traditional methods, the experiments will include a comparative analysis with traditional machine learning algorithms such as support vector machines and random forests. This comparison will not only highlight the ability of deep learning methods in dealing with complex pattern recognition tasks, but also provide new perspectives in the field of online opinion evaluation.

4.3. **Analysis of results.** In this study, we introduce and evaluate a deep neural network model grounded in multi-criteria decision-making, comparing its performance against conventional machine learning techniques across various quantitative benchmarks. Table 1 illustrates the comparative analysis of the online public opinion evaluation system for government public events. The results indicate that our proposed model outperforms traditional approaches across several critical performance indicators, showcasing its superiority in handling complex evaluative tasks related to online public sentiment.

Table 1. TABLE 1. Performance comparison of online public opinion evaluation system for government public events

| **Method** | **Accuracy** | **F1** | **Recall** |
|---|---|---|---|
| SVM | 71.07 | 82.51 | 79.78 |
| KNN | 69.52 | 83.74 | 80.43 |
| LSTM | 73.96 | 79.81 | 83.14 |
| Logistic Regression | 78.34 | 87.12 | 87.54 |
| OURS | 83.59 | 91.36 | 93.35 |

At the same time, analyzed from the perspective of composite score, the average value of government online public opinion governance level in 31 provinces in China is 0.4646, with an overall fluctuation range between [0.2,0.8]. At present, the government online public opinion governance level of each province in China is uneven, and the overall online public opinion governance level is not high. First, examining the weight coefficients across the dimensions of the physical, factual, and human layers, it becomes evident that Internet development and infrastructure are pivotal metrics in assessing government online public opinion management. Building upon this foundation, the Employment Index and the Information Economy Index significantly shape online public opinion governance. Furthermore, enhancing the public's knowledge literacy and economic status positively contributes to the effectiveness of government strategies in this domain. Second, from the governmental online public opinion governance evaluation results, it can be seen that the average governance level of government online public opinion in China's 31 provinces is not high, with 17 provinces' online public opinion governance level located below the average, 22.58% of provinces' online public opinion governance has reached a high-level, 29.03% of provinces' online public opinion governance is at an intermediate level, and 48.39% of provinces' online public opinion governance is still at a low-level, and the current China government. Third, the assessment outcomes for government online public opinion governance reveal disparities across geographical regions. The eastern region, comprising 11 provinces, records an average governance level of 0.5754. The central region, with 8 provinces, has an average of 0.4394, while the western region, encompassing 12 provinces, shows an average of 0.3797. These figures indicate a variance in the governance proficiency, highlighting regional discrepancies. The data underscores the uneven distribution of online public opinion management capabilities among China's provinces, with significant differences observable between the eastern, central, and western regions.

5. **Conclusions.** In this paper, the complexity and volatility of online public opinion are deeply analyzed, and a deep neural networks evaluation method based on multi-criteria decision- making is proposed. The article first identifies the key challenges in online public opinion management, such as the explosive growth of data volume, the instability of public opinion dynamics, and the inadequacy of and existing evaluation tools. To address these challenges, this paper fuses multi-criteria decision theory and deep learning techniques to develop a comprehensive evaluation model to enhance the government's rapid response and accurate assessment of online public opinion. The model utilizes data preprocessing, feature extraction, and deep learning algorithms to automate the screening of key information from huge network data and evaluate public opinion from multiple perspectives, such as emotional inclination, propagation speed, and influence. The experimental results prove that the model surpasses the traditional methods in terms of accuracy, robustness and real-time evaluation, providing

powerful technical support for the government's public opinion monitoring and crisis management. The article also discusses the optimization potential and future development direction of the model, highlighting the necessity of continuous technological innovation and the importance of maintaining adaptability and foresight in the evolving network environment. Overall, the research in this paper provides an innovative technical solution for online public opinion evaluation of governmental public events, and actively contributes to the theoretical and practical development of online public opinion management. As technology evolves and its applications become more ingrained, this research is poised to exert a greater influence in the sphere of online public sentiment analysis. It aims to assist governments in adeptly navigating the dynamics of public opinion, steering societal progress towards greater harmony and stability.

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