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From "Response" to "Rehearsal": Construction of Public Opinion Risk Simulation and Strategic Intervention Model Based on Artificial Intelligence Emotion Computing

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ABSTRACT

With the rapid development of artificial intelligence technology, emotion computing has become a key technology in the field of public opinion analysis. This paper proposes a public opinion risk simulation and strategic intervention model based on Artificial Intelligence (AI) emotion computing, aiming to achieve the transformation from passive response to proactive prevention in public opinion governance. Through the integration of natural language processing, deep learning, and multi-modal data analysis technologies, the model realizes the whole-process management of public opinion monitoring, risk early warning, and strategic intervention. The research results show that the model can significantly improve the accuracy and timeliness of public opinion risk identification, providing scientific decision support for government departments and enterprises in public opinion governance.

KEYWORDS

Artificial intelligence; Emotion computing; Public opinion risk; Simulation model; Strategic intervention

1 Introduction

In the era of digital transformation, the explosive growth of network information and the diversification of communication channels have made public opinion governance increasingly complex [1]. Traditional public opinion monitoring methods mainly rely on manual analysis, which has problems such as incomplete data coverage, subjective judgment bias, and delayed response, making it difficult to meet the requirements of modern society for efficient, accurate, and real-time public opinion monitoring [2]. The emergence of artificial intelligence technology, especially emotion computing technology, provides new solutions for public opinion analysis [3].

Emotion computing, as an important branch of artificial intelligence, aims to capture, understand, process, and simulate human emotions through technologies such as machine learning and natural language processing. In the field of public opinion analysis, emotion computing mainly includes sentiment polarity judgment and emotion intensity assessment of comments, articles, news reports, etc. For example, when a user publishes a comment about a brand on social media, emotion computing can analyze the comment text to determine whether the user's emotional attitude towards the brand is positive, negative, or neutral, as well as the intensity and tendency of the emotion.

The application of AI emotion computing in public opinion analysis has important value in multiple fields. In enterprise and brand management, public opinion analysis helps companies understand the public's likes and dislikes about their products, services, and advertisements. By monitoring and analyzing public opinion in real time, enterprises can take timely measures to improve products and adjust strategies to better meet consumer needs. In government decision-making and public management, public opinion analysis provides government departments with strong evidence of public opinion tendencies and public concerns, helping the government better formulate policies and adjust measures. Additionally, in public opinion guidance and intervention, public opinion analysis based on emotion computing also has important application prospects.

However, the current application of AI emotion computing in public opinion analysis still faces some challenges. First, the accuracy and stability of emotion computing need to be improved. Due to the polysemy and complexity of text, the effectiveness of emotion computing may vary in different texts, contexts, and languages. Second, emotion computing often relies on large-scale text data training, so for certain specific fields and small-scale datasets, the effect of emotion computing may not be as good as manual judgment. Additionally, emotion computing also faces issues of subjectivity and individual differences, as people's understanding and evaluation of emotions vary, which poses challenges to the accuracy of emotion computing.

This paper aims to construct a public opinion risk simulation and strategic intervention model based on AI emotion computing, achieving the transformation from "response" to "rehearsal" in public opinion governance. By integrating multi-source data collection, intelligent text analysis, emotion computing, and simulation prediction technologies, the model provides scientific decision support for public opinion governance.

2 Literature Review

2.1 Research Status of AI Emotion Computing

Emotion computing technology attempts to capture, understand, process, and simulate emotions through machine learning and natural language processing technologies [4]. With the development of artificial intelligence, emotion computing technology has received increasing attention. Emotion computing technology can be applied in many fields, such as natural language processing, human-computer interaction, and social media analysis [5].

There are many different methods of emotion computing technology, such as facial expression recognition, speech tone analysis, and text sentiment analysis. With the continuous development of emotion computing technology, the methods of emotion computing technology are also constantly improving. Emotion computing technology is playing an important role in many fields, such as customer service, marketing, and healthcare [6].

In the field of public opinion analysis, emotion computing technology has made significant progress. Through natural language processing technology, AI can identify the emotional tendency of text, such as positive, negative, or neutral. Sentiment analysis can not only be applied to text data but also extended to multimedia content such as images and videos [7]. Through sentiment analysis, enterprises and governments can understand the public's emotional response to specific events or topics, thereby formulating corresponding strategies.

2.2 Application of AI in Public Opinion Analysis

The application of AI technology in public opinion analysis has become increasingly widespread. AI-driven public opinion monitoring systems mainly use natural language processing (NLP) technology to analyze massive text data [8]. Through semantic understanding, vocabulary analysis, etc., they achieve real-time tracking and emotional judgment of public opinion.

Real-time sentiment analysis is one of the core functions of AI public opinion analysis[9]. AI can quickly identify the emotional tendency of text and determine whether it is positive, negative, or neutral. For example, on social media, when a user posts a comment like "This product is great, highly recommended!", AI can quickly determine that the emotional tendency of this comment is positive by analyzing keywords such as "great" and "highly recommended". Negative emotion early warning is another important function. When a large amount of negative emotion text is detected, the system triggers an early warning mechanism. For example, after a company launches a new product, if a large number of negative comments about product quality issues suddenly appear on social media, the public opinion monitoring system will immediately capture this information and send an early warning to relevant personnel.

2.3 Research Status of Public Opinion Risk Simulation

In the field of public opinion risk simulation, domestic and foreign scholars have conducted extensive research. In China, since 2016, the number of papers published annually on public opinion simulation and risk prediction [10] has not been less than 100. However, the pain points of a national comprehensive base include that the amount of data monitored by the platform far exceeds the processing limit of manual risk assessment and event dispatch; the domestic risk assessment ability cannot keep up with the development of public opinion monitoring ability; in the field of public opinion simulation, there are many studies but relatively few practical applications.

The reason is, first, the over-simplified individual modeling [11]. The behavior of real people in the network is difficult to describe with traditional statistical behavior probabilities. Only by understanding the internal mechanism of individual decision-making can we understand and predict the behavior logic of the crowd. Second, the empirical analysis of historical cases becomes ineffective. The occurrence of public opinion events is not as easy to predict as the sun rising in the east. Even if similar events occur again, the social environment and participants are also changing. Therefore, fine-grained modeling of individuals in the network is a prerequisite for obtaining accurate predictions.

As shown in Figure 1, the multi-level public opinion governance model based on AI sentiment computing has achieved a paradigm shift from passive response to active rehearsal by integrating data collection, processing, sentiment computing, dissemination simulation and simulation deduction. This model utilizes deep learning technology for fine-grained emotion recognition, combines network dynamics models to simulate the diffusion path of public opinion, and ultimately evaluates and optimizes the effect of intervention strategies through multi-agent simulation, providing decision-makers with visual and verifiable scientific support, significantly enhancing the accuracy and forward-looking nature of public opinion governance.

3 Model Framework Design

3.1 Overall Architecture

The public opinion risk simulation and strategic intervention model based on AI emotion computing (Figure 1) adopts a multi-layer architecture design, including data collection layer, data processing layer, model construction layer, simulation prediction layer, and decision support layer. (1) Data Collection Layer: Responsible for collecting multi-source heterogeneous data, including social media data, news website data, forum data, video data, etc. Through API interfaces, web crawlers, and third-party database interfaces, multi-source information is automatically aggregated to form a complementary and redundancy-controllable information acquisition network. (2) Data Processing Layer: Performs data cleaning, preprocessing, and feature extraction on the collected data. Including HTML tag removal, special character filtering, encoding unification, case normalization, user nickname replacement, URL replacement, emoji standardization, etc., to ensure data quality and consistency. (3) Model Construction Layer: Based on deep learning algorithms, emotion computing models, and public opinion propagation models are constructed. Including sentiment classification models, emotion intensity assessment models, topic recognition models, public opinion propagation prediction models, etc. Simulation Prediction Layer: Through multi-agent modeling and simulation technology, the public opinion propagation process is simulated, and the evolution trend of public opinion events is predicted. Including public opinion heat prediction, emotion trend prediction, risk level assessment, etc. Decision Support Layer: Based on the simulation prediction results, strategic intervention schemes are formulated, and visual analysis reports are generated to provide decision support for public opinion governance.

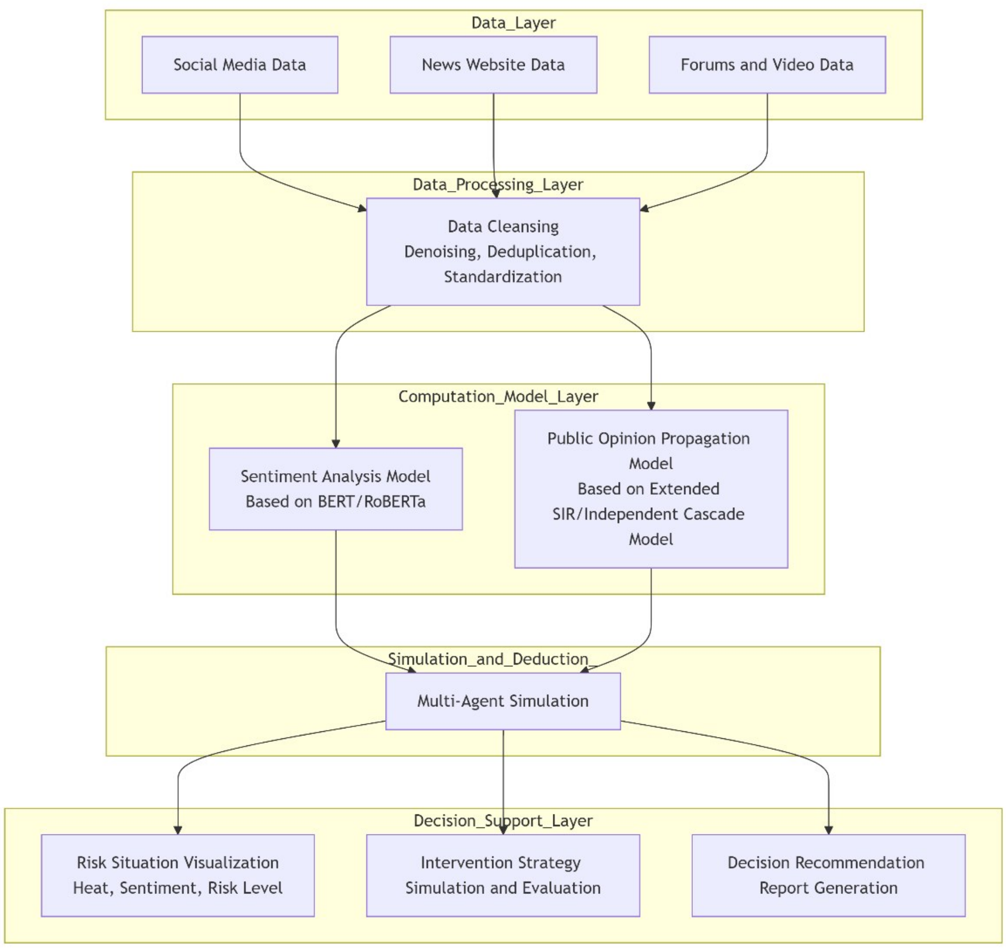

Figure 1 Framework of public opinion risk simulation and strategic intervention model based on AI emotional computing

3.2 Core Technology Module

3.2.1 Emotion Computing Module

The emotion computing module uses natural language processing technology to analyze the emotional tendency of text. Through technologies such as semantic understanding, vocabulary analysis, etc., the emotional tendency of text is identified, including positive, negative, and neutral emotions.

The emotion computing module adopts a multi-level classification system, including coarse-grained polarity classification and fine-grained emotion recognition. Polarity judgment determines whether the overall emotional tendency of the text is positive, negative, or neutral. This level is suitable for macro public opinion monitoring, such as brand reputation tracking or policy feedback aggregation. Fine-grained emotion recognition further distinguishes specific emotion types, such as anger, anxiety, expectation, joy, disappointment, etc. This subdivision helps reveal the psychological motivation of the public and supports deeper behavior prediction.

In terms of technical implementation, the emotion computing module adopts deep learning models [12] such as BERT and RoBERTa, combined with domain knowledge fine-tuning, to improve the understanding ability of professional terms, network language, and complex emotions. Through data enhancement technology and transfer learning technology, the model's industry adaptability and generalization ability are improved.

3.2.2 Public Opinion Propagation Simulation Module

The public opinion propagation simulation module uses network science methods to simulate the information propagation process in social networks. Based on the network structure composed of nodes (users) and edges (relationships, information propagation paths), it studies the macro laws and micro mechanisms of information diffusion, and simulates and predicts the propagation range, speed, and evolution trend of public opinion.

The module adopts the extended SIR model, extending the SIR (Susceptible-Infected-Recovered) model [13] of infectious disease transmission to the social network environment. The transfer probability of node state (such as unknown number, active spreader, immune person) is not only related to the node's own attributes but also related to the state of its connected neighbor nodes. For example, considering the threshold model, node activation (from unknown number to active spreader) requires a certain number of active neighbors around.

Based on the content method, the public opinion propagation process is abstracted as a content evolution process. By analyzing the structural characteristics of the network (such as centrality, clustering coefficient, community structure), the connectivity of the network, the obstruction of information propagation, and the formation of opinion leaders are evaluated. Content theory algorithms (such as shortest path algorithm, community detection algorithm) can be used to simulate information propagation paths and influence ranges.

4 Model Implementation Path

4.1 Data Collection and Preprocessing

Data collection is the starting point of the entire public opinion analysis process, and its coverage breadth and acquisition efficiency directly affect the comprehensiveness and real-time performance of subsequent modeling. However, public opinion data in reality usually comes from heterogeneous platforms, including social media, news portals, forum posts, and even short video comment areas. These data have significant differences in structural form, update frequency, and access permissions. Therefore, a unified data access layer must be built to integrate API calls, web crawlers, and third-party database interfaces to achieve automated aggregation of multi-source information.

In terms of data cleaning, the collected original text often contains a large number of interference elements, which seriously affects the semantic parsing ability of the AI model. A systematic cleaning process needs to be implemented to improve input consistency. Including HTML tag removal, special symbol filtering, and advertising content removal. Social media exported data often embeds HTML fragments or Markdown tags. Regular expressions and Beautiful Soup can be used for purification to automatically strip all HTML tags and extract pure text.

For encoding issues, cross-platform data is prone to encoding confusion problems, especially in the Chinese environment, where GBK and UTF-8 mixed use can cause garbled characters. It is recommended to force conversion to UTF-8. For English text, it should be uniformly converted to lowercase to avoid vocabulary splitting caused by case differences.

4.2 Model Training and Optimization

Model training is the core link of the entire system. Based on industry corpora, incremental training is performed, domain knowledge is injected, and the industry adaptability of the model is improved. Transfer learning technology is adopted to use the general ability of pre-trained models to quickly adapt to different scenario needs.

In terms of model selection, deep learning models such as BERT and RoBERTa are selected [14]. These models have been trained on a large amount of text and have strong semantic understanding ability. According to their own business needs and data characteristics, the pre-trained models are fine-tuned. For example, an e-commerce enterprise can use its own product review data to fine-tune the model to more accurately judge the emotional tendency in the e-commerce field.

In terms of model evaluation, the accuracy, recall, F1 value, and other indicators of the model are evaluated through cross-validation and test set verification. At the same time, the interpretability of the model is considered, and attention mechanism visualization is introduced to show the decision basis of the model and improve the transparency of the model.

4.3 Simulation and Prediction Implementation

The simulation and prediction module uses multi-agent modeling technology to simulate the public opinion propagation process. By setting different parameters, such as network structure, node attributes, information characteristics, etc., the evolution trend of public opinion events under different conditions is simulated.

In terms of prediction algorithm, time series analysis models (such as LSTM) [15] are used to predict the propagation path, influence peak, and decline cycle of events. Through historical data training, the model can predict the future development trend of public opinion and provide decision support for public opinion governance. In terms of result visualization, heat maps, time axes, and other visualization tools are used to display public opinion trends, improving the intuitiveness of data interpretation. A multi-terminal platform (PC/mobile terminal) [16] is developed to achieve real-time interaction and meet the needs of different users.

5 Case Analysis

5.1 Case Background

Taking the "Red, Yellow and Blue Kindergarten Child Abuse Incident" in 2017 as an example, this paper analyzes the application effect of the public opinion risk simulation and strategic intervention model. The incident triggered widespread discussion on social media, forming a large-scale public opinion event.

5.2 Data Collection and Processing

Through the Weibo API interface, relevant Weibo data during the incident were collected, including Weibo content, release time, number of forwards, number of likes, number of comments, etc. A total of 1.2 million pieces of data were collected, and data cleaning and preprocessing were performed.

5.3 Emotion Analysis Results

Through the emotion computing module, the emotional tendency of Weibo comments was analyzed. The results show that negative emotions accounted for 68.5%, mainly anger and anxiety; positive emotions accounted for 15.2%, mainly support and encouragement; neutral emotions accounted for 16.3%.

5.4 Public Opinion Propagation Simulation

Using the public opinion propagation simulation module, the propagation process of the incident was simulated. The results show that the incident reached its peak within 24 hours, with the number of related Weibos exceeding 500,000, and then gradually declined, with a half-life of about 3 days.

5.5 Intervention Effect Evaluation

Through the strategic intervention mechanism, information release, authority interpretation, and emotional guidance measures were adopted. The evaluation results show that after the intervention, the proportion of negative emotions decreased from 68.5% to 42.3%, the proportion of positive emotions increased from 15.2% to 28.7%, and the public opinion heat decreased by 35.6%.

6 Conclusion and Outlook

This paper constructs a public opinion risk simulation and strategic intervention model based on AI emotion computing, achieving the transformation from "response" to "rehearsal" in public opinion governance. The research results show that the model can significantly improve the accuracy and timeliness of public opinion risk identification, providing scientific decision support for public opinion governance. Although this study has achieved certain results, there are still some limitations. First, the accuracy of emotion computing needs to be further improved. For complex emotional expressions or context-dependent texts, emotion computing may have errors. Second, the generalization ability of the model needs to be enhanced. For different fields and different cultural backgrounds, the model needs to be adjusted and optimized. Third, the interpretability of the model needs to be improved. The decision-making process of the AI model is often a "black box", which affects the credibility of the model.

In the future, research can be carried out from the following aspects: First, improve the accuracy of emotion computing, introduce multi-modal data analysis, and improve the accuracy of emotion recognition. Second, enhance the generalization ability of the model, build a cross-domain knowledge base, and adapt to different application scenarios. Third, improve the interpretability of the model, introduce attention mechanism visualization, and improve the transparency of the model. Fourth, strengthen the application of the model, promote it in more fields, and provide technical support for public opinion governance.

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