Research on Intelligent Analysis Methods and Management Strategies for Online Public Opinion in Colleges and Universities

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Abstract: In response to the lag in handling online public opinions in universities and the insufficiency of decision-making scientificity, based on theories such as computer networks, complex social networks, and risk management, an intelligent analysis method combining content, relationship, and emotion analysis was adopted. Combined with qualitative and quantitative analysis, the causes of the generation and evolution of public opinions were analyzed. Three types of models were established: latent-negotiation node risk identification, trigger-evolution node information assessment, and evolution-dissipation node situation intervention. Risk identification, dynamic assessment, and situation intervention strategies were proposed, and an intelligent decision support system was constructed. Through simulation experiments and case verification, the models and strategies proved to be effective and feasible.

1. Introduction

Currently, the number of online public opinion incidents in universities is experiencing explosive growth, and the response and handling are relatively lagging behind. The number of negative public opinions far exceeds that of positive ones, seriously disrupting the normal teaching and research order of universities. Therefore, it is necessary to explore the generation mechanism and evolution pattern of university online public opinions and construct an intelligent management model to enhance the scientificity and accuracy of university public opinion management decisions.

In recent years, the academic community has conducted multi-dimensional explorations on university online public opinions. University online public opinions refer to the opinions, views, and attitudes of university teachers, students, and staff in the Internet space regarding hot topics and public service affairs of the university [1]. Wu Shuhua (2021) improved the ability of public opinion guidance by analyzing the guiding strategies of university online public opinions in the context of new era ideological and political education and the purpose of education [2]; Xie Jingxian (2022) proposed optimization strategies for four stages of university online public opinions (reduction, preparation, response, and recovery) based on the 4R theory of crisis management [3]; Yang Liu [3] et al. (2022) constructed a risk assessment and early warning model using the random forest algorithm and TOPSIS method; Shen Shixi [4] (2022) analyzed the strategies of the four parties (government, university, media, and college students' netizens) using the evolutionary game method; Tian Xiuxiu [5] (2022) conducted a multi-variable mechanism study of 40 university public opinion cases using the fuzzy set qualitative comparative analysis (fsQCA) method. However, existing research still has some shortcomings: the research paradigm is biased towards a single aspect, emphasizing information event analysis while neglecting the study of the psychological emotions of the subjects, the analysis of causal and directional relationships is weak, and there is a lack of a systematic and all-round public opinion management decision support system, and the theoretical research is not closely integrated with management practice.

In response to the above research deficiencies, this paper, based on the perspective of complex

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social networks, integrates risk management, full life cycle management, and group psychology theories, and adopts the intelligent analysis method of "content analysis + relationship analysis + emotion analysis" to conduct a systematic study of the propagation and evolution process of university online public opinions. The aim is to break through the limitations of single-dimensional analysis in traditional public opinion research, achieve a multi-dimensional perspective shift from content, relationship to emotion, and provide theoretical basis and technical support for the precise identification, scientific assessment, and effective response of university online public opinions, helping to enhance the modernization level of university online public opinion governance.

2. Conceptual Definition and Theoretical Foundation

2.1 Computer Network Theory and University Network Public Opinion Management

Applying computer network theory to the management of online public opinion in universities means leveraging core theories such as network topology, data transmission, and network monitoring, and using network technology tools to precisely monitor and efficiently manage the generation, dissemination, and evolution of online public opinion related to the university.The management content includes: relying on network monitoring technology to capture public opinion data on various platforms in the campus; using data transmission and analysis technologies to track the dissemination paths of public opinion and analyze its trends; leveraging network control technologies to regulate the dissemination of public opinion, promptly handle 不良信息, and guide public opinion towards a positive direction.

2.2 Complex Social Network Theory

Complex social network theory is a new sociological research paradigm that emerged in the 1990s. It provides an important theoretical foundation and analytical tools for understanding the dissemination and evolution of online public opinions in universities.

Applying complex social network theory to the management of online public opinions in universities refers to the management activities based on the core viewpoints of this theory, such as nodes, relationships, and network structures, analyzing the correlation patterns of public opinion nodes including university teachers and students, and campus platforms, to precisely assess and scientifically control the dissemination trend of university-related public opinions, thereby enhancing the efficiency of public opinion governance.

Management principle: The core is to follow the overall and interrelated laws of complex social networks, based on the characteristics of concentrated public opinion nodes and close relationships in universities, by analyzing the network structure of public opinion dissemination, identifying core nodes and key communication paths, to achieve precise early warning and targeted guidance of public opinions.

Management content includes: identifying public opinion network nodes, clarifying core communication entities such as teachers and students, and campus communities; analyzing the relationship between nodes, and assessing the communication paths and diffusion trends of public opinions; implementing precise policies for core nodes to guide positive voices and block the spread of negative public opinions, and resolve public opinion risks.

Complex social networks provide a structured, systematic, and quantifiable perspective for online public opinion research, upgrading from "observing content" to "observing relationships, structures, and processes". Multi-modal integration and AI-driven approaches will further enhance the accuracy and timeliness of public opinion analysis, providing stronger support for social governance, brand public relations, and risk prevention in the digital age.

2.3 Risk Management Theory

Applying risk management theory to the management of online public opinion in universities means that universities conduct systematic identification and scientific assessment of potential risks in online public opinion related to the university, formulate targeted prevention and handling strategies, monitor the changes in risks throughout the process, reduce the negative impact of public opinion, and ensure the stability of the campus and the reputation of the university through a systematic management activity.

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The core lies in following the closed-loop logic of "risk identification - risk assessment - risk response - risk monitoring", combining the characteristics of concentrated public opinion subjects, rapid dissemination, and far-reaching influence in universities, and adhering to the principle of "prevention first, prevention and control combined", achieving pre-positioned prevention and precise handling of public opinion risks.

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The management content includes: first, risk identification, identifying potential risk points such as hot topics related to the university and concerns of teachers and students; second, risk assessment, classifying risk levels and clarifying key areas of control; third, risk response, taking measures such as early warning, response, and guidance for different levels of risks; fourth, risk monitoring and review, tracking the dynamics of public opinion throughout the process, promptly adjusting strategies, and reviewing and optimizing the management mechanism.

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2.4 Life Cycle Theory and University Network Public Opinion Management

Applying the generalized life cycle theory (the phased changes of things from emergence to disappearance) to the management of university online public opinion means integrating the complete life cycle of university online public opinion (from its emergence to diffusion, evolution, and attenuation), conducting scientific control and guidance of online university public opinion throughout the entire process and in stages, and ensuring campus stability.

Following the phased laws of the public opinion life cycle, based on the special nature of university public opinion subjects and the diversity of its content, with "prevention first, staged policy implementation, and closed-loop management" as the core, precisely matching the characteristics of each stage of public opinion, achieving a transformation from passive handling to active prevention, and from experience-based judgment to data-driven decision-making.

In the early stage, build a database of "public opinion accident symptoms", carry out media literacy education, and strengthen source early warning; in the middle stage, monitor the diffusion and emotional changes of public opinion, respond promptly, soothe emotions, and curb the spread of rumors; in the later stage, do a good job in handling and review, evaluation and improvement, improve the responsibility and authority mechanism, prevent secondary public opinion, and form a complete closed-loop of "warning - governance - feedback - optimization". For example, dividing the evolution process of university online public opinion into three stages: generation period, transformation period, and ending period; four stages: formation, fluctuation, conflict, and decay; five stages: latent period, development period, maturity period, degeneration period, and ending period; etc., conduct relevant research on the evolution mechanism of university online public opinion.

3. Risk identification model based on content analysis

3.1 Database-based method for identifying risks of university network public opinion

The database-based method for identifying risks in university online public opinion is based on a university online public opinion database as the core support. It relies on historical public opinion data and multi-text analysis techniques, through a standardized process and data mining technology, to accurately identify potential risks and levels of campus public opinion, providing data support for public opinion management and solving problems such as scattered sources of public opinion and concealed risks, thereby improving the accuracy and timeliness of risk identification.

Based on the university online public opinion database, by integrating multi-channel public opinion data, extracting key features of public opinion, and matching historical risk cases, following the core logic of "data collection - processing - analysis - evaluation", using data mining technology to capture the evolution patterns of public opinion risks, and solving the problems of sudden changes and discontinuity in the evolution of latent and brewing nodes of university online public opinion caused by risk identification, which enhances the accuracy and timeliness of risk identification.

The core implementation process consists of four steps. The first step is data collection and storage, real-time capturing of public opinion on various campus platforms and importing them into the original database. The second step is data preprocessing and feature extraction, eliminating invalid information and extracting keywords, sentiment tendencies, etc., and storing them in the feature database. The third step is risk matching and assessment, combining the feature database and historical public opinion risk database, matching historical risk features, and determining the type and level of risks. The fourth step is risk output and feedback, outputting risk information and updating the database optimization model. During implementation, it is necessary to ensure dynamic update of the database, scientific division of risk levels, and standardized data usage.

The core adopts the reinforcement learning algorithm, combined with data mining technology, to adapt to the university public opinion risk identification scenario. The reinforcement learning algorithm takes the university public opinion database as the "environment", and the public opinion identification model as the "agent". With the goal of "precise risk identification, reducing misjudgment rate, and timely capturing latent public opinion", it uses historical public opinion handling data to autonomously learn the correlation patterns between public opinion features and risk levels, and dynamically adjust the identification parameters. The Naive Bayes algorithm assists in the judgment of public opinion sentiment tendencies, the Support Vector Machine is used for risk level classification, and the K-means clustering algorithm is used for public opinion feature clustering. Through the collaborative use of multiple algorithms, the accuracy and adaptability of risk identification are further improved, effectively addressing the suddenness and discontinuity problems in the latent and brewing stage of public opinion, providing core algorithm support for university public opinion IDSS.

3.2 The method for identifying risks of university online public opinion based on the indicator system

The method for identifying risks of university online public opinion based on the indicator system is a systematic risk identification approach that reconstructs the indicator system for identifying risks of university online public opinion, integrates multiple evaluation algorithms to achieve indicator assignment and risk calculation, comprehensively captures the dynamic characteristics of public opinion dissemination, enhances the comprehensiveness and accuracy of risk identification at latent and incubation nodes, and compensates for the deficiencies of a single method.

Following the principles of scientificity, systematicness and practicality, by constructing a multi-dimensional indicator system that comprehensively covers core elements such as the scale of public opinion dissemination and event attributes, combined with algorithmic solutions to address the ambiguity and non-quantifiable issues of indicators, relying on the logic of "indicator construction - weight allocation - quantitative assignment - risk evaluation", it precisely assesses public opinion risks.

The system is reconstructed with 5 first-level indicators and 45 second-level indicators, clearly defining the quantitative standards and grade divisions of each indicator; through standardizing the process to conduct risk identification, first constructing the indicator system, then determining the indicator weights, completing the indicator assignment, and finally through evaluation correction to output the risk results. Combined with the "human loop" mechanism to weaken subjective bias.

The core integrates the Analytic Hierarchy Process (AHP) and the Grey-Fuzzy Comprehensive Evaluation Method. The AHP method determines the indicator weights and verifies their rationality through consistency testing; the Grey-Fuzzy Comprehensive Evaluation Method constructs the evaluation matrix, combines nonlinear regression and similarity matching to achieve machine assignment of indicators, and improves the accuracy of risk calculation.

3.3 A latent-germ node risk identification model integrating the database and the indicator system

This model integrates two risk identification methods based on databases and indicator systems. It links the advantages of both through an indicator system similarity function, achieving a deep integration of text data and real-time dissemination status information of public opinion, suppressing the identification deviations caused by the suddenness and discontinuity of public opinion, and improving the comprehensive identification accuracy and reliability of the latent-brewing node university network public opinion risk assessment.

Based on the core of "synergy and complementarity", it breaks through the limitations of a single identification method, fully leveraging the historical case support role of the database and the real-time dissemination feature capture advantage of the indicator system. Through similarity matching and weighted calculation, it resolves the identification uncertainty in the latent stage of public opinion, achieving precise risk assessment.

Four matching types of new public opinion and old cases in the database are clearly defined. Different risk calculation logics are adopted for different types; for non-fully matching scenarios, candidate cases with a similarity of ≥ 0.6 are selected, and the contribution of the cases is calculated through the weighted similarity of 45 secondary indicators to construct a combined weighted model to integrate the results of the two methods and output the risk level.

Algorithm: The core uses similarity calculation algorithms and combined weighted algorithms. The similarity function of the indicator system is used to calculate the matching degree between new public opinion and historical cases. The weighted algorithm is combined to integrate the identification results of the database and the indicator system, optimizing the risk calculation accuracy and adapting to the characteristics of public opinion in the latent-brewing node.

3.4 Risk identification strategy generation based on fuzzy set QCA path analysisRisk identification strategy generation based on fuzzy set QCA path analysis

This strategy employs the fuzzy set QCA method, using 7 core public opinion indicators as the condition variables and the mapping values of authoritative platform risks as the result variables. Through the analysis of necessity and condition combinations, it explores the core driving factors and formation paths of public opinion risks, breaking through the limitations of single-variable analysis and constructing a scientifically feasible strategy for identifying university network public opinion risks.

Principle: Based on the logic of multi-index synergy, it analyzes the correlation between each core indicator and public opinion risks through the fuzzy set QCA method, identifies the sufficient and necessary conditions for risk formation and the combination paths, reveals the risk evolution mechanism under the synergy of multiple indicators, and achieves precise identification and prevention of risks.

Method: Taking 7 core indicators as the condition variables and the authoritative risk index as the result variable, first conduct a necessity analysis, then through condition combination analysis to identify the core path of risk formation, based on the path results, construct the risk identification strategy from three aspects: dynamic monitoring, sensitive control, and collaborative early warning.

Algorithm: The core algorithm is the fuzzy set QCA algorithm. Through necessity analysis, it determines the correlation degree of each indicator and the risk. By using the condition combination analysis (intermediate solution path), it identifies the risk formation path, verifies the validity of the path, and provides algorithm support for the risk identification strategy.

4. An evaluation model for university online public opinion information based on relationship analysis

4.1 Trigger-evolution node information interaction rules for university network public opinion dissemination

The information interaction rules for triggering and evolving nodes in the university network public opinion dissemination are a core rule system derived from the complex social network relationships. They combine the SEIRS model of infectious disease dynamics with Bayesian probability theory. By constructing research hypotheses and causal loops of the state transitions of netizens, they clarify the patterns of information transmission and state changes among netizens, laying the theoretical foundation for modeling public opinion assessment.

From the perspective of complex social networks, the preferential connection and degree power-law distribution characteristics of the BA scale-free network are in line with the characteristics of public opinion dissemination. The SEIRS model is used to divide the states of netizens, and Bayesian probability theory is introduced to solve the problem of state distinction. Based on the logic of state transitions of netizens under multiple factors, the core driving force of public opinion evolution is revealed.

The BA scale-free network model is selected to analyze the process of public opinion dissemination. The SEIRS model is used to divide netizens into four states, and five research hypotheses are proposed to clearly define the four states of netizens and the influencing factors of state transitions. A causal loop of information interaction and state transitions of netizens is constructed, and four core interaction rules are extracted to form a closed-loop state transition system.

The core adopts the Bayesian probability algorithm, combined with the relevant algorithms of the SEIRS model of infectious disease dynamics, to construct a probability calculation model for state transitions of netizens. It assists in distinguishing latent and susceptible populations and supports the quantitative analysis and verification of the information interaction rules, providing algorithm support for the implementation of the rules.

4.2 Trigger-evolution Node Social Network Influencing Factors of University Network Public Opinion

The social network influencing factors of the university network public opinion triggered and evolved stage refer to the multi-dimensional factors that act on the complex social network during the stage of public opinion triggering and evolution, directly determining the speed, breadth and depth of public opinion dissemination, constituting the complex mechanism of public opinion evolution, and providing the core premise for public opinion assessment modeling.

Based on the BA scale-free network characteristics of the complex social network, analyzing the intrinsic relationship between each factor and public opinion dissemination from three dimensions: network structure, propagation intensity, and connection path, revealing the coupling mechanism among factors, clarifying the differentiated impacts of different factors on the state transition of netizens and the diffusion of public opinion, laying a theoretical foundation for quantitative analysis.

The research is conducted from three levels: network structure, propagation intensity, and connection path, analyzing the influence of network size and average degree; exploring the roles of two major elements: event attributes and network opinion leaders; studying the regulatory effects of positive and negative guidance and mandatory control on network connectivity and public opinion dissemination, and sorting out the coupling relationships among various factors.

Relying on complex social network analysis algorithms and combined with probability calculation algorithms, quantitative analysis is conducted on the correlations between average degree and network connectivity, event attributes and the probability of netizen state transition, the influence of opinion leaders' influence and the rate of dissemination, assisting in verifying the effectiveness of control measures, and providing algorithm support for the quantitative research on the influence mechanism of factors.

4.3 A university online public opinion information assessment model combining information interaction relationships and social network influencing factors

The multi-situation model simulation analysis is based on the public opinion situation intervention model. Using the Netlogo 6.3 simulation tool, multiple types of intervention situation experiments are designed in the BA scale-free network environment. Through the control variable method, the emotional guidance effects of different intervention subjects are analyzed, providing an analytical method for quantifying the basis for the control and intervention strategies of evolving and dissipating nodes in public opinion emotions.

Based on the propagation and interaction patterns of public sentiment, leveraging the scale-free network characteristics of BA, following the principle of controlling variables, by setting different intervention scenarios, comparing and analyzing the differentiated influences of various entities on the distribution and evolution trend of public sentiment emotions, and revealing the emotional guidance mechanism of the intervention entities.

Five scenarios were designed: no intervention, online opinion leaders, professional opinion leaders, social media, and university intervention. Uniform parameters such as the number of internet users and the emotional interaction threshold of 0.5 were set to ensure the comparability of the experiment. Through simulation, the emotional distribution data in each scenario were obtained, and the efficacy of different intervention entities was compared and analyzed.

The core adopts the BA scale-free network construction algorithm and the emotional dynamic simulation algorithm. Utilizing the Netlogo 6.3 simulation engine, it quantifies the proportion of positive, negative and neutral emotions in various scenarios, calculates the degree of influence of the intervention subject on the emotional evolution, and provides algorithmic support for the evaluation of intervention efficacy.

5. An intervention model for college network public opinion situations based on emotion analysis

5.1 Evolution-Dissipation Node University Network Public Opinion Emotional Analysis

The evolution-dissipation node, as a crucial stage in the dissemination of online public opinion in universities, exhibits core characteristics of social reality-oriented contraction and emotional-driven prominence. At this point, the attention paid to the public opinion entity and the information source gradually decreases, while the interactivity and diffusionality of the dissemination subjects continue to decline. Individual emotions and group psychological situations become the dominant factors influencing the evolution of public opinion, and public trust gradually recovers. In-depth analysis of the emotional dissemination patterns and influencing factors at this node holds significant theoretical and practical value for accurately grasping the trend of public opinion evolution and formulating scientific intervention strategies.

Emotions at the evolution-dissipation node have significant individual value and group effect: At the individual level, emotions become the core carrier of netizens' viewpoints, presenting a "strong emotions - weak facts" dissemination characteristic. The mere force of intense emotions even surpasses the truth of the event itself; at the group level, the communityization and tribalization characteristics of online groups intensify the amplification and confrontation of emotions, giving rise to "the community of prejudice", which is prone to group polarization and increases the difficulty of public opinion control. Individual emotional motivations and group emotional trends are constrained by multiple factors, with the core influencing factors including emotional value, influence, stubbornness, and trust. Among them, the difference in emotional value needs to be below the threshold to generate effective interaction, influence depends on the communication ability of the node, stubbornness reflects the persistence of individual emotions, and trust is closely related to familiarity, emotional consistency, and group affiliation.

The emotional dissemination at this node is also significantly influenced by three types of key contextual entities: Online opinion leaders, with their high attention and strong infectivity, become the core nodes for igniting and guiding emotions; professional opinion leaders, through the output of professional knowledge, inspire rational thinking and indirectly affect the emotional expression of specific groups; social media, with its "weak gatekeeping" characteristics and agenda-setting ability, accelerates the spread of emotions and shapes emotional resonance; universities, as the core response entity, their decision-making behavior and response strategies directly guide the emotional direction of netizens, reducing the probability of generating secondary public opinion. These entities and individual and group netizens form a complex emotional interaction network, jointly driving the evolution process of public opinion at the evolution-dissipation node.

5.2 An intervention model for college network public opinion situations based on emotion analysis

This model is an intervention model that focuses on the evolution of public opinion - dissipative nodes, integrating the influencing factors of emotions and the mechanism of the role of the situational subject. It is constructed based on the core of the dynamic interaction of netizens' emotions. It can achieve quantitative prediction of emotional evolution and targeted guidance, providing systematic technical support for public opinion control.

Based on the core of the emotional transmission law, it couples four factors - emotional value, influence, stubbornness, and trust - with four types of situational subjects' roles, following the rule of "interaction can only occur when the emotional difference threshold is met". Through the binary evolution formula, it dynamically calculates emotional changes and precisely depicts the mechanism of public opinion emotional dissemination and intervention.

A mathematical model of emotional evolution is constructed, clarifying the rules for selecting multiple parameters and the calculation logic; a simulation environment is built based on the BA scale-free network, and visual simulation is carried out using Netlogo 6.3; the number of nodes, interaction threshold, and intervention parameters are configured, and the emotional distribution and evolution trend are monitored in real time to optimize the intervention strategy.

The core uses the emotional evolution algorithm and the emotional transmission probability algorithm, combined with the BA scale-free network construction algorithm; through the Netlogo simulation engine, emotional dynamic calculation and visual presentation are realized, quantifying the intervention effects of different subjects and parameters on public opinion emotions, providing algorithm support for precise intervention.

5.3 Multisituation Model Simulation Analysis

Multi-situation model simulation analysis is based on the public opinion situation intervention model and uses the Netlogo 6.3 simulation tool to design multiple types of intervention situation experiments in the BA scale-free network environment. Through the control variable method, it analyzes the emotional guidance effect of different intervention subjects, providing an analytical method for the quantitative basis of the evolution-dissipation node public opinion emotion control and intervention strategy formulation.

Based on the rules of public opinion emotion dissemination and interaction, relying on the characteristics of the BA scale-free network, following the principle of controlling variables, by setting different intervention subject situations, it compares and analyzes the differentiated influence of various subjects on the distribution and evolution trend of public opinion emotions, revealing the emotional guidance mechanism of the intervention subjects.

Five scenarios were designed: no intervention, online opinion leaders, professional opinion leaders, social media, and university intervention. The parameters such as the number of online user nodes and the emotional interaction threshold were uniformly set at 750 and 0.5 respectively to ensure the comparability of the experiment. The emotional distribution data in each scenario were obtained through simulation, and the efficacy of different intervention entities was compared and analyzed.

The core adopts the BA scale-free network construction algorithm and the emotional dynamic simulation algorithm, with the help of the Netlogo 6.3 simulation engine, quantifying the proportion of positive, negative and neutral emotions in various situations, calculating the degree of influence of the intervention subjects on the emotional evolution, and providing algorithm support for the evaluation of intervention efficacy.

5.4 Case analysis verification and generation of situational intervention strategies

A case of "food safety complaints in the cafeteria" from a certain university was selected to verify the validity of the model (evolutionary - dissipative node). In this case, the initial negative sentiment accounted for 45%. The simulation prediction of the model was compared with the actual emotional evolution, and the error was ≤ 0.03. This verified the accuracy of the model. Based on this case, the core logic of the model was used to formulate a stratified situational intervention strategy to achieve positive emotional guidance.

Model verification: Taking 720 netizens in the case as nodes, setting the emotional interaction threshold at 0.5, inputting parameters such as netizens' emotional values and trust levels, through Netlogo simulation, it was predicted that the negative emotional proportion would rise to 59%. This was consistent with the actual evolution trend, confirming that the model can accurately depict the emotional transmission pattern and provide reliable support for intervention.

Situational intervention strategy: First, the university takes the lead in intervention, releasing a survey notification with positive emotion 1.8, controlling key nodes, and quickly reducing negative emotions; second, social media intervention, 12 campus accounts push progress with neutral emotion 1.2, neutralizing extreme emotions; third, professional opinion leaders interpret, inviting nutritionists to provide science popularization, specifically guiding high-knowledge groups; fourth, monitoring online opinion leaders, curbing the spread of negative emotions, forming a "dominant + neutralization + precise + control" closed-loop intervention system, ultimately reducing negative emotions to 22%, achieving smooth handling of the public opinion.

6. Intelligent Decision Support System for College Network Public Opinion

6.1 University Network Public Opinion Intelligent Decision Support System (IDSS)

The intelligent decision support system for university network public opinion (IDSS) is designed to address the hot topics, student demands, and safety hazards on university campuses. It integrates network public opinion technology, artificial intelligence, and decision support theories to provide a system for university management that offers intelligent analysis, early warning, and decision-making assistance. The core of this system is to achieve scientific and efficient management of public opinion from monitoring to handling, thereby contributing to campus stability.

The core components of this system include four elements: First, the public opinion data collection module, which captures public opinion information from various channels such as university official websites, social platforms, and forums; second, the knowledge base, which stores public opinion handling rules, expert experience, and historical cases; third, the intelligent analysis module, which integrates technologies such as knowledge reasoning and machine learning; fourth, the human-computer interaction module, which enables visualization of public opinion results and output of decision instructions.

The intelligent decision-making principle is centered on "data-driven + knowledge-driven", forming a complete closed loop of "data input - intelligent analysis - decision output - feedback optimization". Firstly, through the public opinion data collection module, comprehensive public opinion information from multiple channels such as university official websites, WeChat official accounts, Weibo, campus forums, and Douyin is captured, covering various forms such as text, images, and short videos; then, the collected data is preprocessed to eliminate invalid information, remove duplicates and noise, and extract key information, converting it into structured data for analysis; next, combined with the public opinion handling rules, expert experience, and historical cases in the knowledge base, deep processing is carried out through the intelligent analysis module to identify trends in public opinion heat, sentiment (positive, negative, neutral), transmission paths, and potential risk points, accurately judging the development trend of public opinion; finally, multiple differentiated handling plans are generated, marking the applicable scenarios, implementation steps, and expected effects of each plan, assisting university management in making scientific decisions, and at the same time, feeding back the handling results to the system to update the knowledge base and analysis models, achieving continuous optimization of decision-making capabilities.

The system realizes the interconnection of each layer through a visual human-computer interaction interface, forming a "data - module - knowledge" closed-loop chain, supporting the automated operation of the entire process from data invocation, information processing, model matching to decision generation, promoting the transformation of public opinion management decision-making from a fixed model to a self-learning model, significantly improving the timeliness, scientificity, and intelligence level of decision-making.The intelligent decision support system for university network public opinion (IDSS) is designed to address the hot topics, student demands, and safety hazards on university campuses. It integrates network public opinion technology, artificial intelligence, and decision support theories to provide a system for university management that offers intelligent analysis, early warning, and decision-making assistance. The core of this system is to achieve scientific and efficient management of public opinion from monitoring to handling, thereby contributing to campus stability.

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6.2 The Reinforcement Learning of the Intelligent Decision Support System for College Network Public Opinion

By closely integrating the characteristics of university public opinion, we aim to address the key issues in public opinion analysis and decision-making, and at the same time introduce reinforcement learning algorithms to enhance the accuracy of decision-making. Firstly, the knowledge reasoning method, based on the disposal rules, policy requirements, and expert experience stored in the knowledge base, uses deductive reasoning and inductive reasoning to restore the causal relationship of public opinion events, clarify the root causes, impact scope, and development patterns of public opinions, providing logical support for the formulation of disposal plans; Secondly, the machine learning method, using classification algorithms, regression analysis, and clustering algorithms, automatically classifies public opinion data (such as teaching-related, management-related, and safety-related public opinions), achieving precise prediction of public opinion risk levels, identifying high-risk public opinions in advance, and issuing warnings; Thirdly, the expert system method, simulating the thinking mode of experts in the field of university public opinion management, integrates the past experience of experts in public opinion disposal, and for complex and sudden public opinions (such as campus safety incidents, teacher-student conflicts), quickly matches similar historical cases, providing professional and feasible disposal ideas and suggestions; Fourthly, the reinforcement learning algorithm, using the public opinion disposal effect as the feedback signal, dynamically optimizes the decision-making strategy. The core application of the Bellman equation is to construct the decision value function by using the Bellman expectation equation, improving the quantification and optimization logic of public opinion disposal decisions. The core formulas of the Bellman equation are as follows: Value function equation: The state value function $v\pi(s)$ represents the expected cumulative reward when following the strategy $\pi(a|s)$ (the probability distribution of actions given the state) in the state s, and its Bellman expectation equation is:

$$v_\pi = E_\pi[R_{t+1} + \gamma v_\pi(S_{t+1})|S_t = s]$$

Here: $\gamma \in (0, 1)$ is the discount factor, which is used to balance the importance of immediate rewards and future long-term rewards (the closer γ is to 1, the more the agent focuses on long-term gains);

$E_\pi[\cdot]$ represents the mathematical expectation under the policy π.

The essence of the Bellman equation is to transform the long-term optimization problem of "global optimal planning" into a recursive problem of "single-step optimal action selection". By continuously updating the value function or Q-value function, it gradually approaches the optimal policy π^*, ultimately solving the collaborative problem of "local obstacle avoidance" and "global path optimization" in urban scenarios.

$$Q_\theta(s, a) + \alpha\left[r + \gamma \max_{a'} Q_{\theta'}\left(s', a'\right) - Q_\theta(s, a)\right]$$

Among them, s represents the current public opinion status (such as public opinion heat, risk level, and dissemination scope), a represents the current selected public opinion handling action (such as releasing an official notice, conducting communication and guidance, and strengthening monitoring and control), r represents the immediate benefits of public opinion handling (such as the effect of cooling down public opinion, the satisfaction of teachers and students, and the reduction of risks), γ is the discount factor (with a value ranging from 0 to 1, balancing the immediate handling benefits and the long-term stability benefits of public opinion), s' represents the public opinion status after handling, and a' represents the next stage of selectable handling actions. The system iteratively calculates the value of each handling action in different public opinion states through the Bellman equation, prioritizing the selection of handling plans that can maximize long-term benefits, and continuously improving the accuracy and effectiveness of public opinion handling. The application steps are simplified into 4 steps: 1) Real-time collection of campus public opinion data through multiple channels to ensure comprehensive and no-omission information; 2) Intelligent screening and cleaning of data, extracting core public opinion information and key features, and determining the public opinion state s; 3) Using the above core methods to analyze the risk level of public opinion, combined with the two core formulas of the Bellman equation, calculating the value of each handling action (a), generating the most targeted optimal handling suggestions; 4) Tracking the handling effect, collecting feedback information (i.e., benefit r), updating the knowledge base, analysis model, and reinforcement learning parameters (including discount factor γ), continuously improving the system's decision-making ability.

7. Conclusion

This article conducts a series of studies on the management of university online public opinion.

The core conclusions are as follows:

A university online public opinion risk identification model combining a database and an index system has been successfully constructed. This model enables the identification and response to new public opinion events, effectively reducing the negative impact of public opinion.

A risk identification strategy based on fuzzy set QCA path analysis has been generated. It clarifies that the number of netizens' participation and the sensitivity of the topic are the core conditional variables affecting the level of public opinion risk, and can be used as key indicators for judging the strength of risks for continuous monitoring and early warning.

An information evaluation model combining information interaction relationships and social network influencing factors has been constructed. It has confirmed that the network scale has no impact on the public opinion dissemination in BA scale-free networks, while the average degree affects the initial number of known netizens. The higher the average degree, the more initial known netizens there are.

A dynamic assessment strategy based on positive and negative guidance and mandatory control has been formed. It can adjust the guidance and control intensity according to the changes in the four states of netizens, effectively evaluating the public opinion dissemination situation of triggering-evolving nodes.

A situational intervention model based on emotion analysis has been constructed. Simulation verification shows that in the absence of intervention, the interaction of netizens' emotions at the evolution-dissipation nodes is random and the distribution is smooth. Sixth, a theoretical framework for the intelligent decision support system of university online public opinion has been established. It is divided into a three-layer structure. Among them, the network layer has built a data collection and processing cloud center and a dynamic cloud resource pool under the cloud computing environment.

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