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Research on the Evolution and Response to Network Public Opinion in Accident Disasters

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Abstract: *This study focuses on the evolutionary mechanism and governance path of network public opinion in sudden accident-disaster events, taking the "3.13 Yanjiao Gas Explosion Incident" as an empirical case, and constructing a public opinion evolution model based on the theory of Event Logic Graph. The study finds that driven by modern information technology, network public opinion exhibits the characteristics of "interweaving virtual and real elements, and rapid detonation", and the traditional emergency management model faces significant challenges in coping with the complexity of public opinion. By collecting 8,370 pieces of Weibo data through big data mining technology, using syntactic pattern matching and TF-IDF+K-Means clustering algorithms, 25,614 events were extracted and generalized into 267 abstract event pairs, constructing an Event Logic Graph containing 107 nodes and 267 directed edges. The analysis shows that there are three core contradictions in the evolution of public opinion: the value conflict between "efficiency priority" and "public opinion effectiveness" in emergency response, the right mutual exclusion between "risk control" and "public informedness" in safety information disclosure, and the mechanism imbalance between "irrational resonance" and "factual guidance" in emotional communication. Based on this, a three-dimensional response approach is proposed: strengthening government credibility construction through Event Logic Graph early warning, improving conflict prediction and emotional guidance capabilities with dynamic game models, and achieving multi-stakeholder governance of public opinion through cross-subject collaborative networks. The study confirms that the Event Logic Graph can reveal the evolution logic of public opinion by visualizing event transition probabilities, providing a quantitative tool for improving the precision of emergency management.*

Keywords: *Accident-Disaster; Event Logic Graph; Public Opinion Evolution*

1. Introduction

With the rapid development and in-depth application of modern information technology, emerging technologies such as "big data, intelligence, cloud computing, IoT, and mobile internet" have profoundly reshaped the way the public acquires information. The popularization of network information and communication devices has made the virtual and real worlds interweave and influence each other, and public social activities are widely recorded, stored, and shared. The rise of various social media platforms has provided space for the public to share information, exchange opinions, express emotions, and collide ideas, promoting the gradual transformation of social behaviors and relationships into network behaviors and relationships [1].At the same time, humanity is facing a high-risk social environment, with frequent sudden accident-disasters, posing severe challenges to social stability and public safety. Especially in the context of frequent virtual-real information interaction, the network has deeply intervened in the formation, dissemination, and evolution of sudden accident-disasters, changing the social public opinion ecology in China and forming a new network public opinion field [2].From the "1·10" major explosion accident at the Hushan Gold Mine invested by Shandong Wucailong Investment Co., Ltd. in Qixia City in 2021 to the "4·29" extremely serious collapse accident of resident self-built houses in Changsha, Hunan in 2022, the "2·22" extremely serious collapse accident at the open-pit coal mine of Inner Mongolia Alashan Xinjing Coal Industry Co., Ltd. in 2023, and the "3·13" gas explosion accident in Yanjiao, Hebei in 2024, after the accidents, safety warning information, real help-seeking information, rescue information, and rumor-hyping information quickly diffused through social media platforms, forming a complex situation where positive and negative energy in the network society and public

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opinion shocks interweave and evolve, triggering significant social group effects [3].It can be seen that the network public opinion of sudden accident-disasters has evolved from the initial "intermittent occurrence" to a situation where it quickly detonates the entire network space once it occurs [4],bringing unprecedented pressure to emergency management of sudden events. If not controlled in a timely manner, it will trigger a series of secondary public opinion disasters, causing great threats to social stability and government image.

The arrival of the big data era has greatly improved the propagation speed and coverage of network public opinion. The traditional expert-led decision-making model for network public opinion on sudden accident-disasters faces severe challenges in dealing with massive data information. At the same time, emerging information and communication technologies are rapidly changing the current working paradigm of the government in the field of emergency management. Emergency management is an important part of the national governance system and governance capabilities, undertaking the important responsibility of preventing and defusing major safety risks and timely responding to various disaster accidents, and shouldering the mission of protecting the lives and property safety of the people and maintaining social stability [5].The Third Plenary Session of the 20th Central Committee of the Communist Party of China emphasized that "it is necessary to strengthen public opinion guidance and effectively prevent and defuse ideological risks." [6]In this context, how to identify true and false information in complex public opinion text data, grasp the evolution trend, alleviate negative emotions, and occupy the main position of public opinion has become a key issue in improving the government's emergency management capabilities and constructing a modern emergency management system.

To address the above challenges, this paper uses big data mining technology to collect text data such as network public opinion, rescue operations, and secondary disasters related to sudden accident-disasters, uses pattern matching methods to extract causal event pairs, and constructs an Event Logic Graph of network public opinion in accident-disaster categories. Through the key nodes and evolution paths in the graph, the evolutionary mechanism of network public opinion is deeply analyzed, the contradictions and conflicts of network public opinion are clarified, and scientific basis and response approaches are provided for guiding and governing network public opinion in accident-disaster categories.

2. Literature Review

Network public opinion in accident-disaster categories is characterized by instant interaction, aggregation and diffusion, and cross-border communication, showing characteristics such as unpredictability, high attention, strong diffusivity, and far-reaching influence [7].Focusing on the evolution process, mechanism, and modeling of network public opinion, many scholars have carried out in-depth research. The evolution of such public opinion shows periodicity, and studying its evolution process helps to grasp dynamic changes and provide support for timely and effective guidance of public opinion. Current studies generally divide the evolution process of network public opinion into three-stage [8], four-stage [9]and five-stage [10]models, and analyze their evolution mechanisms based on this. For example, Yao Leye proposed a framework for the evolutionary elements of network public opinion based on the 5W communication theory, and revealed the dynamic mechanism of interaction by analyzing the coupling relationship between each element, so as to more comprehensively understand the process of public opinion evolution [11].In addition, some scholars focus on the research of hot topics and emotional tendencies: hot topic research aims to identify the focus of netizens' attention and determine the optimal communication path [12]; emotional tendency research discusses the intensity of public emotions and the key impact of specific emotions on the development of public opinion events [13].Some researchers use big data resources to locate the key issues in each stage of public opinion evolution, providing a reference for the government or relevant departments to control public opinion and guide emotions [14-15].The core of the research on the evolution mechanism of network public opinion is to reveal its internal operation mechanism. Through a variety of quantitative analysis methods such as system dynamics [16], qualitative comparative analysis [17], clustering algorithms [18], dynamic game models [19], numerical simulation [20], and random forests [21], scholars have constructed a simulation and modeling analysis system to reveal the laws and communication characteristics of public opinion evolution. However, these methods have problems such as unclear and intuitive expression in dealing with the logical evolution relationship and visual analysis of complex public opinion data, and there is an urgent need for improvement or the introduction of new methods to extract more valuable public opinion knowledge from massive text information and apply it to emergency management decision-making.

In order to improve the quality of knowledge representation and information acquisition, Google proposed the concept of "Knowledge Graph" in 2012 [22]. The Knowledge Graph stores real-world entities and their relationships in the form of structured triples and displays them in a graphical way, where nodes represent entities and directed edges represent relationships between entities. However, the Knowledge Graph is mainly used to describe static knowledge, and its description of event dynamic characteristics and event logic is relatively insufficient. In 2017, Professor Liu Ting proposed the concept of "Event Logic Graph" [23], taking "event" as the core of description, structuring unstructured text data through information extraction and fusion technologies, and constructing an event logic knowledge base presented in the form of a directed cyclic graph to reveal event evolution laws. Compared with the Knowledge Graph, the Event Logic Graph has significant advantages in the field of network public opinion in accident-disaster categories: first, the Event Logic Graph records and analyzes the event development process by combining the event logic system, and can refine the event evolution path [24-25]. For example, Zeng Ziming et al. revealed the evolution law of public opinion from the perspectives of emotional factors, event influence, and event duration by constructing an Event Logic Graph; second, the Event Logic Graph can quickly integrate event information, clarify the development context, and predict subsequent events, providing strong support for emergency decision-making [26-27].For example, Shan Xiaohong predicted the development trajectory of network public opinion events by analyzing the evolution direction and probability of graph nodes, making up for the shortcomings of traditional public opinion analysis in dimensions such as heat, emotion, and topic [28]; third, the visual display of the Event Logic Graph intuitively presents the basic characteristics, evolution path, and logical relationship of public opinion events. For example, the Event Logic Graph constructed by Xia Lixin et al. generated multi-dimensional visual event summaries, which is convenient for analyzing events from different perspectives [29].In addition, introducing information retrieval technology can achieve cross-departmental information sharing, avoid information silos, and improve the efficiency and accuracy of emergency decision-making. For the dynamic changes of complex public opinion events, a real-time updated graph system can also be built to support multi-dimensional public opinion analysis and prediction, providing a more comprehensive scientific basis for the governance of network public opinion in accident-disaster categories.

3. Research Methods

In sudden events, events and their complex correlation relationships will generate multi-level network public opinion, which has the characteristics of multi-event coupling and complex situation. The Event Logic Graph can dynamically present the correlation between events in a graphical form, helping to comprehensively grasp the event development dynamics and the public opinion evolution path. Therefore,this paper uses the theory of Event Logic Graph to mine the logical evolution relationship and path between each event in the network public opinion text information, deeply analyze the evolution mechanism of network public opinion, clarify the contradictions and conflicts of network public opinion, and provide scientific basis and response approaches for guiding and governing network public opinion in accident-disaster categories. The research framework of this paper is shown in Figure 1.

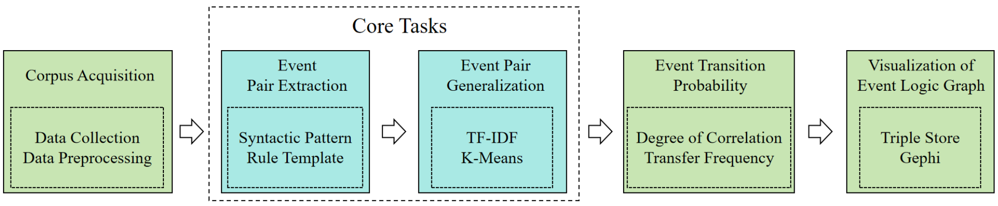

Figure 1: Event Logic Graph construction process

3.1 Corpus Acquisition

Social media has become an important way for information dissemination and public opinion exchange due to its low interaction cost and strong convenience. After a public opinion event occurs, the text data published by the public on social media platforms usually has high logic, containing rich event information and emotional factors, which is of great significance for situation awareness and public opinion guidance. Therefore, this paper selects social media as the source of the corpus, collects text data of relevant public opinion events through a Python self-compiled program, and carries out integration, noise reduction, and deduplication processing on the data. Then, natural language processing tools are used to carry out sentence segmentation, word segmentation, stop word filtering, part-of-speech tagging, and dependency syntax analysis on the data [30], laying a foundation for the subsequent construction of the Event Logic Graph.

3.2 Event Pair Extraction

Step 1: Syntactic Patterns. This study designs 9 syntactic patterns in the form of " “<cause1>[result],<cause2>[reason]” according to causal relationship markers such as "because, due to, lead to, cause" [31],where cause represents causal relationship markers, reason represents the cause event, and resultrepresents the result event. Table 1 lists the causal relationship markers that may appear in different patterns. For example, in Pattern 1, the words " Because, Due to, Originating from " included in cause2are all conjunctions; in Pattern 4, the words " influence, cause, lead to, guide " included in cause6are all verbs or adverbs; in Pattern 6, the words " In order to avoid, in order to, for this reason, therefore " included in cause8 are all prepositions.

Table 1: Syntactic Patterns of Causal Sentences.

Serial Number	Pattern Type	Syntactic Pattern	Causal Markers
Pattern 1	Result-Tracing Cause Supporting Type	$< cause1 > [result],$ $< cause2 > [reason]$	$cause1 \in$ {The reason why}; $cause2 \in$ { Because, Due to, Originating from }
Pattern 2	Cause-to-Result Supporting Type	$< cause3 > [reason],$ $< cause4 > [result]$	$cause3 \in$ { Because, since, due to, only, unless, if, as long as}; $cause4 \in$ { therefore, for this reason, so, in order to, to the extent that, however, then, thus, consequently, hence, resulting in, so that }
Pattern 3	Cause-to-Result Middle Clear Type	$[reason], < cause5 >$ $[result]$	$cause5 \in$ {therefore, so, hence, resulting in, leading to, thus, consequently, thereby, and therefore }
Pattern 4	Cause-to-Result Middle Precise Type	$[reason], < cause6 >$ $[result]$	$cause6 \in$ { influence, to guide, to cause, to evoke, to introduce, to direct, to provide, to produce, to facilitate, to result in, to lead, to create, to bring about, to cause, to guide, to foster, to bring about, to trigger, to permeate, to promote, to arouse, to induce, to attract, to precipitate, to induce, to infect, to bring, to carry, to relate }
Pattern 5	Cause-to-Result Front Fuzzy Type	$< cause7 > [result],$ $[reason]$	$cause7 \in$ {For the sake of, based on, for, according to, because of, in accordance with, relying on, in comparison with, by virtue of, due to}
Pattern 6	Cause-to-Result Middle Fuzzy Type	$[reason], < cause8 >$ $[result]$	$cause8 \in$ {In order to avoid, in order to, for this reason, therefore}
Pattern 7	Cause-to-Result Front Precise Type	$< cause9 > [reason],$ $[result]$	$cause9 \in$ {Since, because, if, due to, as long as}
Pattern 8	Result-Tracing Cause Middle Fuzzy Type	$[result] < cause10 >$ $[reason]$	$cause10 \in$ {Originating from, depending on, derived from, stemming from, arising from, based on }
Pattern 9	Result-Tracing Cause End Precise Type	$[result] < cause11 >$ $[reason]$	$cause11 \in$ {Because, due to}

Step 2: Rule Templates. The rule template is a regular expression based on syntactic patterns, used to judge causal sentences, generally composed of a matching rule(Pattern)and a sentence

priority(Priority),expressed as <Pattern,Priority>. Among them, the priority is determined by the occurrence frequency of causal relationship markers in the "Peking University Modern Chinese Corpus". By marking the part-of-speech characteristics of causal relationship markers to construct rule templates, the cause events and result events in sentences can be accurately identified. Suppose there is a public opinion data set E, which contains m events, that is, $E=\{e_1,e_2,\cdots,e_m\}$, and each event e is composed of $n$words, recorded as $\{w_1,w_2,\cdots,w_n\}$.After part-of-speech tagging, the event$e$can be expressed as $e=(w_1/d_1,w_2/d_2,\cdots,w_n/d_n)$, where $d_i$is the part of speech of w_i. Based on the rule templates in Table 2, different types of causal event sentences can be matched.

Table 2: Rule Templates for Causal Sentences.

Serial Number	Pattern Type	Rule Expression
Pattern 1	Result-Tracing Cause Supporting Type	$if(w_i \in cause1andpog_i = conj)$ $if(w_j \in cause2andpog_j = conj)$
Pattern 2	Cause-to-Result Supporting Type	$if(w_i \in cause3andpog_i = conj)$ $if(w_j \in cause4andpog_j = conj)$
Pattern 3	Cause-to-Result Middle Clear Type	$if(w_i \in cause5andpog_i = conj)$
Pattern 4	Cause-to-Result Middle Precise Type	$if(w_i \in cause6andpog_i = verb/adverb)$
Pattern 5	Cause-to-Result Front Fuzzy Type	$if(w_i \in cause7andpog_i = prep)$
Pattern 6	Cause-to-Result Middle Fuzzy Type	$if(w_i \in cause8andpog_i = prep)$
Pattern 7	Cause-to-Result Front Precise Type	$if(w_i \in cause9andpog_i = conj)$
Pattern 8	Result-Tracing Cause Middle Fuzzy Typ	$if(w_i \in cause10andpog_i = prep)$
Pattern 9	Result-Tracing Cause End Precise Type	$if(w_i \in cause11andpog_i = conj)$

Step 3: Event Pair Extraction. By applying rule templates, the cause events and result events in causal sentences are extracted to form causal event pairs. Taking the vocabulary w_i and w_j as examples, if both satisfy the rule expressions of Pattern 1: “if(w_i∈cause1 and pog_i=conj)” and “if(w_j∈cause2 and pog_j=conj)”, and w_i and w_j are respectively the causal relationship markers reason1 and reason2 , and the parts of speech are both conjunctions, then the sentence containing w_i and $w_j$can be determined as a clear causal sentence conforming to Syntactic Pattern 1. In this sentence, the part after w_i is the cause event reason, and the part after w_j is the result event result.

3.3 Event Pair Generalization

TF-IDF can transform the text features of event pairs into a vector form that can be recognized and processed by computers. The K-Means clustering algorithm has good interpretability and accuracy, which helps to generalize event pairs of the same topic [32]. Therefore, in order to achieve more reasonable event representation and evolution logic, this paper uses the TF-IDF+K-Means clustering algorithm to generalize event pairs.

Step 1: Use the TF-IDF method to vectorize the event pairs of network public opinion on accident-disasters, and take each vector as a clustering sample point;

Step 2: Select k event pairs from the sample set as initial centroids, which are used as the starting point of the clustering process;

Step 3: Calculate the distance between each sample and each centroid through the Euclidean distance, update the centroid position according to the distance, and iterate N times;

Step 4: When the centroid position no longer changes, the clustering process ends, and the final clustering clusters are output.

This study uses the SSE method to determine the selection of the k value, and its calculation formula is shown in Equation (1):

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$$SSE=\sum_{i=1}^{k}\sum_{c\in C_i}|p-m_i|^2 \tag{1}$$

In the formula, C_i represents the $i-$th clustering cluster;p represents the sample points in C_i; and m_i represents the centroid of C_i (that is, the average value of all samples in the C_i cluster). As an indicator to measure the quality of clustering, SSE represents the clustering error of all samples. Usually, when the K−SSE curve presents an "elbow" shape, the $k$value at the inflection point is regarded as the optimal number of clusters.

3.4 Event Transition Probability

The Event Logic Graph can be expressed as $\mathrm{Graph}=\{\mathrm{Nodes},\mathrm{Edges}\}$, where $\mathrm{Nodes}=\{e_1,e_2,\cdots,e_p\}$ is the set of nodes, $\mathrm{Edges}=\{l_1,l_2,\cdots,l_q\}$is the set of edges, and $p$and q are the numbers of nodes and edges, respectively [33]. In this directed cyclic graph, each directed edge $l_i$connects node e_i and node e_j, and contains the corresponding event transition probability wei. The calculation formula of the event transition probability is shown in Equation (2):

$$wei(e_i,e_j)=\frac{count(e_i,e_j)}{\sum_k count(e_i,e_k)} \tag{2}$$

In the formula, $\mathrm{count}(e_i,e_j)$ represents the frequency of the joint occurrence of event e_i and event e_j, and $\sum_k \mathrm{count}(e_i,e_k)$ represents the sum of the frequencies of all possible events occurring under the premise of event $e_i$occurring.

3.5 Visualization of Event Logic Graph

Taking the generalized events as nodes, the logical relationships between events as directed edges, and marking the event transition probabilities on the edges, the network public opinion Event Logic Graph is constructed. The Gephi graph database breaks through the limitations of traditional relational databases in dynamic relationship processing and can efficiently store and manage entities and their relationship information. Based on this advantage, this study selects Gephi as the storage and visualization tool for the network public opinion Event Logic Graph.

4. Case study

At 7:54 on March 13, 2024, a suspected gas leakage in a shop in Yanjiao Town, Sanhe City, Hebei Province triggered an explosion accident. Emergency, fire protection, health construction and other departments quickly rushed to the scene to carry out rescue. As of 23:00 on the same day, the rescue was basically completed. The director of the Emergency Management Bureau of Sanhe City said that the accident caused 7 deaths and 27 injuries. After the accident, all sectors of society paid great attention, and many media reporters went to the scene to report and release rescue dynamics in a timely manner. However, with the deepening of the rescue, the expert group of the command department detected the risk of natural gas leakage at the scene, and then forcibly persuaded the on-site reporters to leave. Due to the rude communication method, it caused misunderstandings among reporters and public opinion, causing certain social negative impacts. Followed by the release of the preliminary investigation results, Sanhe City, Hebei issued a notice on the secondary public opinion and publicly apologized, and the heat of public opinion then declined, showing an inverted "U" development trend. During this period, the Yanjiao explosion accident triggered multiple related public opinion events on social media, and its influence and attention far exceeded other events in the same period. As a typical sudden disaster event, the Yanjiao explosion accident has important reference significance for studying the network public opinion phenomenon and response strategies caused by accident-disasters.

Step 1: Data Acquisition. Using "Yanjiao Explosion" as the search keyword, original Weibo posts from March 13 to 31, 2024 were captured, and a total of 8,370 Weibo data were obtained;

Step 2: Data Preprocessing. Use natural and language processing tools to carry out noise reduction, sentence segmentation, word segmentation, stop word filtering, part-of-speech tagging, and dependency syntax analysis on the data;

Step 3: Event Pair Extraction. Based on the event relationship extraction template, carry out event extraction and representation on the network public opinion text, and finally obtain 25,614 events;

Step 4: Event Generalization: Determine the optimal clustering k value through the SSE method, and

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generalize the extracted event pairs into 267 abstract event pairs;

Step 5: Transition Probability Calculation: Taking the generalized event pairs as nodes, calculate the event transition probability according to Formula (2), and construct the relationship structure between nodes;

Step 6: Visualization of Event Logic Graph: Import the generalized event pairs into Gephi software in the form of a CSV file to generate a visualization graph, as shown in the following figure 2, which finally contains 107 nodes and 267 directed edges.

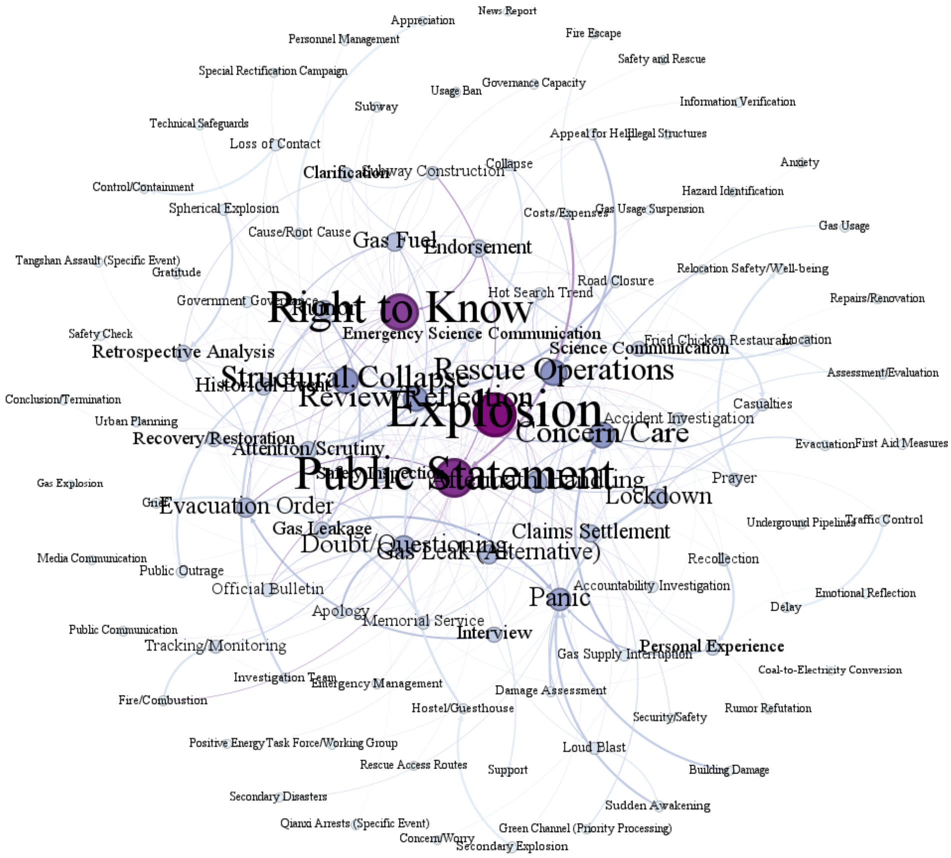

Figure 2: Event Logic Graph of Yanjiao Explosion Public Opinion.

5. Discussion

5.1 Conflicts and contradictions in accident and disaster online public opinion

Based on the topological structure and weight analysis of the Event Logic Graph (edge file weight value, node file label), three core contradictions are exposed in the evolution of network public opinion in the Yanjiao explosion incident:

(1) Efficiency and Effectiveness: Contradictions in the Public Opinion Feedback Mechanism.

In the "3.13 Yanjiao Gas Explosion Incident", although the emergency department responded quickly to the rescue (the transition probability between node N23 "rescue" and N1 "safety inspection" is 0.049), the public opinion evolution shows that there is a separation between the public's perception of rescue efficiency and the actual effectiveness. In the Event Logic Graph, the edge weight between "persuading reporters to leave" (N33) and " challenge " (N52) reaches 0.88, indicating that although the forced persuasion behavior was out of safety considerations (N65 "safety"), it caused public opinion backlash due to the lack of a communication mechanism. This contradiction is essentially the value conflict between "speed priority" and "effect optimization" in emergency management - the traditional emergency response model focuses on physical rescue efficiency but ignores the public's effectiveness needs for information transparency in the network public opinion field, resulting in a negative cycle between "rescue operations" (N23) and "public opinion challenge " (N52).

(2) Safety and Informedness: Mutual Exclusion in Sensitive Information Disclosure.

During the accident investigation stage, the professional judgment of "gas leakage risk" (N35) and the public's demand for "right to know" (N51) formed a significant tension. The connection weight between "risk warning" (N35) and " panic-stricken " (N26) in the graph is 0.75, while the weight between "information disclosure" (N44 "notification") and " public opinion challenge " (N52) also reaches 0.33, reflecting the dilemma of safety information disclosure: excessive secrecy is prone to breed "rumors" (N45), while the direct output of professional terms may amplify public anxiety. In the Yanjiao incident, the technical description of the "natural gas leakage risk" by the command department lacked a popular interpretation, resulting in the transition probability from " panic-stricken " (N26) to "secondary disaster" (N88) increasing by 0.18, highlighting the structural contradiction between safety control and the right to know at the information coding level.

(3) Communication and Response: Challenges in Public Emotion Guidance.

In the context of social media, public opinion communication presents the characteristic of "emotion preceding fact". The Event Logic Graph shows that the transfer probabilities of emotional nodes such as " sorrowful " (N3) and " panic-stricken " (N26) triggered by "explosion" (N2) are generally higher than those of factual nodes (such as N4 "interview", N41 "accident investigation"). For example, the weight from " sorrowful " (N3) to " commemorate " (N63) is 1, while the weight from "accident investigation" (N41) to "accountability" (N69) is only 0.105, indicating that emotional resonance is more likely to dominate the communication chain than rational analysis. In addition, in the confrontational communication between "rumor" (N45) and " refute rumours " (N89), the transition probability from "rumor" to " panic-stricken " (N26) (0.67) is significantly higher than the probability from " refute rumours " to " elucidation " (N64) (0.35), reflecting the natural advantage of negative emotions in communication efficiency, which aggravates the complexity of public opinion guidance.

5.2 Responding to Internet Public Opinion on Accidents and Disasters

(1) Enhancing Government Social Credibility.

The public opinion early warning based on the Event Logic Graph needs to be embedded in the government affairs communication chain: by monitoring the transition probabilities of front-end nodes such as "safety inspection" (N1) and "hidden danger investigation" (N61), risk communication is planned in advance. For example, in the Yanjiao incident, if "emergency science popularization" (N62, weight 0.75) is strengthened in the "gas leakage" (N35) stage, the evolution probability of " panic-stricken " (N26) can be reduced. Specific measures include: establishing a "technical term - popular expression" conversion mechanism, setting the association path between N35 "gas leakage" and N62 "emergency science popularization" as the priority communication link; realizing the visual early warning of public opinion evolution by visualizing the "high-risk emotion chain" (such as N2→N26→N88) in the Gephi graph, and improving the pertinence of information release.

(2) Improving Self-Coping Capacity Building.

Construct an emergency decision-making model of "Event Logic Graph + dynamic game", focusing on optimizing two types of capabilities:

Conflict Prediction Capability: By analyzing the high-weight association (0.88) between "persuading to leave" (N33) and " challenge " (N52), establish a simulation deduction module of "communication method - public opinion response", deploy "media communication specialists" at the rescue scene, transform the mandatory behavior of N33 into N67 "public communication" (weight 0.0079), and reduce the generation probability of negative public opinion.

Emotional Guidance Capability: Aiming at the strong connection (weight 1) of N3 " sorrowful " → N63 " commemorate ", design a two-track communication strategy of "emotional resonance - factual guidance". For example, when releasing "casualty" (N39) information, simultaneously push "rescue progress" (N23) and "social support" (N56) nodes, and guide emotions to transform in a positive direction through the 0.117 weight link of N23→N56.

6. Conclusion

This study takes the "3.13 Yanjiao Gas Explosion Incident" as the breakthrough point and constructs an evolution model of network public opinion in accident-disaster categories based on the theory of Event Logic Graph. By mining the logical association of 25,614 event nodes, it reveals the three major contradictions and conflicts of efficiency and effectiveness, safety and informedness, and communication and response in public opinion evolution, and proposes response strategies from three dimensions: government credibility, response capacity building, and multi-stakeholder collaborative governance. The study shows that the Event Logic Graph provides a quantitative tool for analyzing the complex mechanism of public opinion by visualizing event transition probabilities (such as the weight of N23 "rescue" → N38 "aftermath" is 0.197), and its dynamic prediction function (such as public opinion risk early warning based on N33 "persuading to leave") can effectively improve the precision of emergency management.

Future research can be deepened in three aspects: first, expanding the data dimension, integrating multi-modal information such as videos and images to improve graph construction; second, optimizing the algorithm model, introducing deep learning to improve the accuracy of event pair extraction; third, strengthening cross-domain applications, docking the Event Logic Graph with the urban safety risk monitoring system to achieve integrated early warning of "risk - public opinion". With technological iteration and theoretical improvement, the Event Logic Graph is expected to become an important supporting tool for improving the modernization of the national emergency governance capacity.

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