Evolutionary Logic of Public Emergencies Based on Event Logic Graph

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Abstract—**In response to the suddenness, uncertainty, and complexity of public emergencies, this paper presents an analytical framework for the evolution of public emergencies based on the research idea of "event-relationship-logic". The aim is to comprehensively grasp, comprehend, and predict the development logic and internal mechanisms of public emergencies, assisting emergency departments in promptly understanding the progression of events. Building upon this foundation, this paper proposes a complete process for constructing an Event Logic Graph (ELG) in the field of public emergencies and introduces a multi-structured convolutional neural network model that incorporates word position features to extract causality between events. Experimental findings indicate that the multi-structured convolutional neural network model demonstrates higher accuracy and effectiveness compared to the traditional template matching method. Furthermore, through the empirical analysis, we find that the evolutionary path of the causal event chain is relatively short, and the evolutionary motivation of public emergencies is intricate throughout their entire lifecycle. Consequently, emergency departments should focus more on key nodes, central nodes, and intermediate nodes within the causal event chain and adeptly identify these specific nodes to swiftly uncover correlations between events. Additionally, public emergencies easily convert into public crisis, underscoring the necessity for emergency departments to comprehend the evolutionary motivation and inducement factors of public emergencies.**

Index Terms—**public emergencies, event logic graph, causality extraction, evolutionary path.**

I. Introduction

In recent years, a wide variety of public emergencies have emerged, exerting a significant impact on society due to their suddenness, complexity, and other distinctive qualities. Specifically, public emergencies erupt rapidly in a relatively short period, leading to distinct social crisis. Consequently, it is essential to lessen the effects of such crises by taking required and timely action [1]. At present, China is going through a social transitional period. Failure to promptly respond to emergencies may provoke extreme public emotions, which could lead to serious damage to the stability and harmony of society. With the rapid development of the Internet, the attention to public emergencies has significantly intensified. Online public opinion has the characteristics of "offline occurrence, online dissemination", which can lead to substantial social impacts. Additionally, the numerous comments and opinions from the public can contribute to the complexity and extremism of events, making it difficult for the emergency departments to accurately understand the development pattern of events [2]. The formation logic of public emergencies is intricate and sophisticated, resulting in a dynamic and complex evolutionary process for public emergencies. Currently, analyzing the evolutionary logic of public emergencies has become a critical aspect of public emergency management research. Therefore, given the current circumstances, enhancing the emergency management system to achieve more effective and timely warning and response to public emergencies has emerged as a research imperative.

This paper presents a comprehensive investigation into the evolutionary logic of public emergencies based on prior research. It examines the evolutionary pattern, evolutionary motivation, and evolutionary trend of public emergencies by establishing an analytical framework. The objective is to offer targeted governance guidelines and regulatory measures for the decision-making authorities. Specifically, this paper adopts a causality perspective to analyze the evolutionary characteristics and patterns of public emergencies by constructing an Event Logic Graph (ELG). It also seeks to uncover potential correlation links between events to provide a realistic foundation for event decisions.

This paper is structured as follows: Section 1 presents an introduction to the study. Section 2 discusses the relevant literature. Section 3 constructs the evolutionary model of public emergencies based on ELG. Section 4 gives the empirical analysis. Finally, the research findings are summarised in Section 5.

II. Related Works

A. Construction of Event Logic Graph

The related research work of ELG was first initiated in 2014 [3]. Goran and Jan introduced the concept of ELG as an innovative approach for organizing event-based information extracted from text [4]. The concept of abstract ELG and the entire process of constructing an ELG was formally proposed by Professor Liu Ting's team in 2017 [5]. According to Professor Liu Ting, ELG is an event-centered paradigm that serves as an event logic knowledge base capable of unveiling evolutionary pattern and developmental logic inherent in real-world events. Although both Knowledge Graph and ELG store knowledge is stored in a directed cyclic graph, there exists a fundamental distinction between them. The purpose of Knowledge Graph is to represent static relationships between entities, while it fails to capture the dynamic evolutionary

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rule [6]. Therefore, the establishment of ELG is crucial to comprehending human behavioral patterns.

Gradually, the theory of ELG has garnered increasing attention from researchers and has found application across diverse domains. ELG has gained significant progress in the realm of accident diagnosis. Du et al. employed the ELG approach to construct a chemical Event Evolutionary Graph, aiming to enhance the safety management level and emergency response capabilities of chemical enterprises [7]. Deng et al. focused on the historical maintenance logs of robot transmission systems and proposed a top-down approach for constructing a fault diagnosis Event Logic Knowledge Graph, aiming to provide decision-support for autonomous fault diagnosis of the system [8]. Meanwhile, ELG has also found application in the military domain. Li et al. developed a Tactical Mission Event Logic Graph (TMELG) and applied it in the Military Internet of Things, which can facilitate the analysis of the composition and evolutionary process of tactical missions [9]. In addition, ELG can also be utilized to address downstream tasks such as event prediction problems, owing to dynamic character. Li et al. proposed the construction of an ELG for solving the script event prediction based on network embedding [10]. Experiments have demonstrated that ELG can achieve superior learning outcomes in event representation and event prediction. Gao et al. introduced a conditional Event Evolutionary Graph, which effectively leverages contextual information for classifying event relationships and determining the direction of event evolution. Experimental results indicate that this approach substantially enhances the accuracy of downstream tasks [11].

Consequently, ELG primarily focuses on events and their developmental process [12]. The evolution of public emergencies is a complex process involving multiple elements that interact and influence one another, necessitating an in-depth analysis of the evolutionary pattern among events. Liu et al. introduced a multilingual event mining model for automatic event detection and the creation of an evolution graph. The final experiments demonstrate the model's exceptional efficiency and effectiveness in discovering evolutionary pattern [13].

In conclusion, extensive research has been conducted on the applications of ELG in various fields. However, research on public emergencies is still very limited. Therefore, this paper focuses on the suddenness, complexity, and dynamics of public emergencies, and proposes a framework for analyzing the evolutionary logic of public emergencies. By constructing the ELG, and generating the event evolution graph, the aim is to provide decision support for the emergency response and management of public emergencies.

B. Causality Extraction Method

Relationship extraction is a crucial task in the field of information extraction in natural language processing, serving as a pivotal step in constructing ELG [14]. Furthermore, causality, as a crucial form of relationship, represents the most significant comprehension of events. In conventional approaches, causality extraction is treated as a classification task, in which the presence of causal trigger words in sentences is determined using predefined domain-specific templates [15].

Sheikh et al. proposed a rule-based relational extraction framework that combines manual and automated methods to generate semi-automated causal networks from raw text [16]. Currently, with the continuous advancement of deep learning technology, an increasing number of researchers are employing the deep neural network model for extracting causal relationship. Li et al. proposed a knowledge-oriented convolutional neural network for causal relation extraction by integrating human prior knowledge to capture linguistic clues of causality [17]. Yu et al. introduced a multi-scale event causality extraction method, incorporating knowledge-attention and convolutional neural network, demonstrating its superior performance compared to alternative approaches through experimental evaluation [18]. Li et al. treated causality extraction as a sequence labeling problem, and proposed a neural causality extraction model incorporating transfer embedding to directly extract cause and effect without extracting candidate causal pairs, which greatly improves the performance of causality extraction [19]. Zhu et al. integrated sentiment polarity and knowledge base to acquire comprehensive entity features, and proposed a two-stage GCN approach for extracting potential causality among cascading entities, enabling multi-level reasoning for deep causality [20].

III. Methods

A. Research Ideas

Public emergencies are sudden, intricate, and detrimental. When confronted with such crises, most decision-makers and ordinary individuals often struggle to resolve them effectively due to their limited expertise and knowledge. Mishandling these emergencies can result in irreparable harm and societal losses. Therefore, comprehending and elucidating the evolutionary mechanism of public emergencies is of paramount significance for effectively responding to and managing such crises.

The causal logic underlying these emergencies can unveil their intrinsic nature. By constructing ELG of public emergencies, it becomes feasible to trace the spatio-temporal information evolution, perceive the evolutionary trend of events, and predict the risk of events. This enables more accurate management and control of public emergencies. Therefore, this paper constructs an analysis framework for the evolution of public emergencies based on the "event-relationship-logic" concept, aiming to comprehend, elucidate, and forecast the overall development trend of public emergencies. Through a comprehensive analysis of the causality between events, this paper unveils the evolutionary pattern and development logic of public emergencies, thereby enhancing early warning systems and response strategies for emergency management departments. The model framework is illustrated in Fig. 1.

Fig. 1 illustrates the framework for the evolution of public emergencies and the working mechanism of each link. Public emergencies often give rise to a substantial surge in information both in the physical world and the network world. The abundance of data complicates the development of events and enhances the challenge of elucidating the causal logic of public emergencies.

To begin, observing the evolutionary logic of public emergencies from a cognitive perspective in order to establish

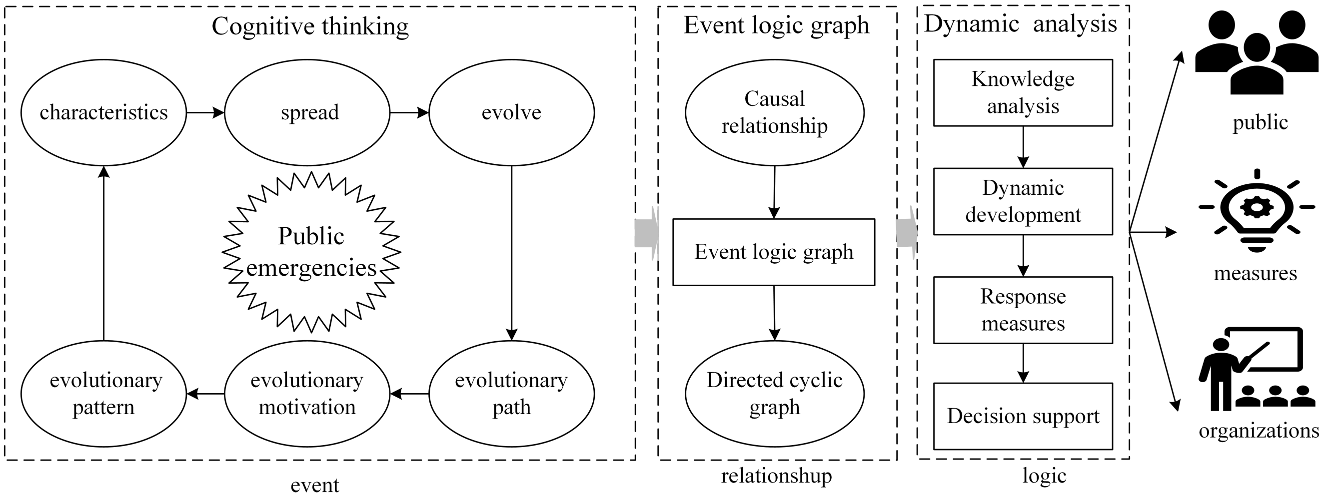

Fig. 1. A famework for the evolution of public emergencies

a systematic understanding of them. Focusing on public emergencies, the logic of the events is explored according to the idea of "what are public emergencies - what are their characteristics - how do they spread - how do they evolve". After elucidating the cognitive perspective of public emergencies, the ELG of public emergencies is constructed based on the causal relationship between events. Specifically, the ELG explicitly maps textual descriptions of events onto a directed cyclic graph structure, with each serving as a fundamental unit. The ELG provides a detailed depiction of information associations among events, thereby facilitating in-depth comprehension of the logical relationships.

B. Event Logic Graph Modeling

As illustrated in Fig. 2, we propose a framework to construct an ELG, including a data layer, event layer, and graph layer. After establishing the domain corpus, the causality of public emergencies is extracted, and the ELG is constructed to unveil the evolutionary pattern.

1) Data Layer: The data layer utilizes data collection technology to acquire relevant information regarding public emergencies from social media platforms. Following a series of data pre-processing procedures, the original dataset is generated, providing robust data support for the construction of the ELG.

2) Event Layer: The application of Natural Language Processing (NLP) technology is essential for addressing relationship extraction, event extraction, and clustering generalization in the context of public emergencies. Among these tasks, causality extraction plays a critical role in constructing the ELG. Hence, the traditional template matching method and the current mainstream sequence labeling method are employed for causal relationship extraction. The extracted results from these two approaches are evaluated and analyzed based on accuracy, recall, and F1-score, aiming to explore the most suitable model for causality extraction in the field of public emergencies. Following causality extraction, event extraction involves extracting and storing crucial event information from public emergencies, thereby establishing the foundation for graph visualization.

3) Graph Layer: The graph layer serves as the final layer in the ELG. The Neo4j Graph Database is utilized to describe the event relationships and mine the causal logic of public emergencies, aiming to provide decision support for the response and prediction of emergencies.

C. Causality Extraction

The causal relationship refers to the connection between the cause event and the effect event, signifying that the cause event prompts the occurrence of the effect event. If the occurrence of an event directly or indirectly leads to another event, it indicates the presence of a causal relationship between them. Furthermore, causality represents the fundamental understanding of events essential for investigating their evolutionary pattern and development logic [21].

1) Method Based on Template Matching: Causal sentences typically contain specific causal cue words. This paper utilizes the template matching method to directly identify potential instances of causality. Firstly, in this paper, six distinct types of syntactic patterns are established based on the diverse positions of causal cue words, accompanied by corresponding causal cue words, as presented in TABLE I. Secondly, rule templates are generated according to the defined syntactic patterns. Specifically, the rule templates represent the extraction rules formulated based on the syntactic pattern presented in TABLE I for discerning causal sentences, as demonstrated in TABLE II.

This paper assumes that W represents a set of words, and the set $S = \{w_1 w_2 ... w_n\}$ can be expressed into a sentence S. After S is labeled with part-of-speech, the resulting set $S' = \{w_1/d_1, w_2/d_2 ... w_n/d_n\}$ can be obtained, where d_i denotes the part-of-speech for w_i. Subsequently, part-of-speech tagging and dependency parsing techniques are utilized to extract the subject, object, predicate, and other components of events for extracting causality pairs and constructing causal triplets.

The causality extraction based on the template matching method possesses the advantages of simplicity, efficiency, and high extraction accuracy, making it well-suited for constrained domains. However, the template matching method relies on predefined rules or patterns and requires substantial time and effort investment in rule formulation.

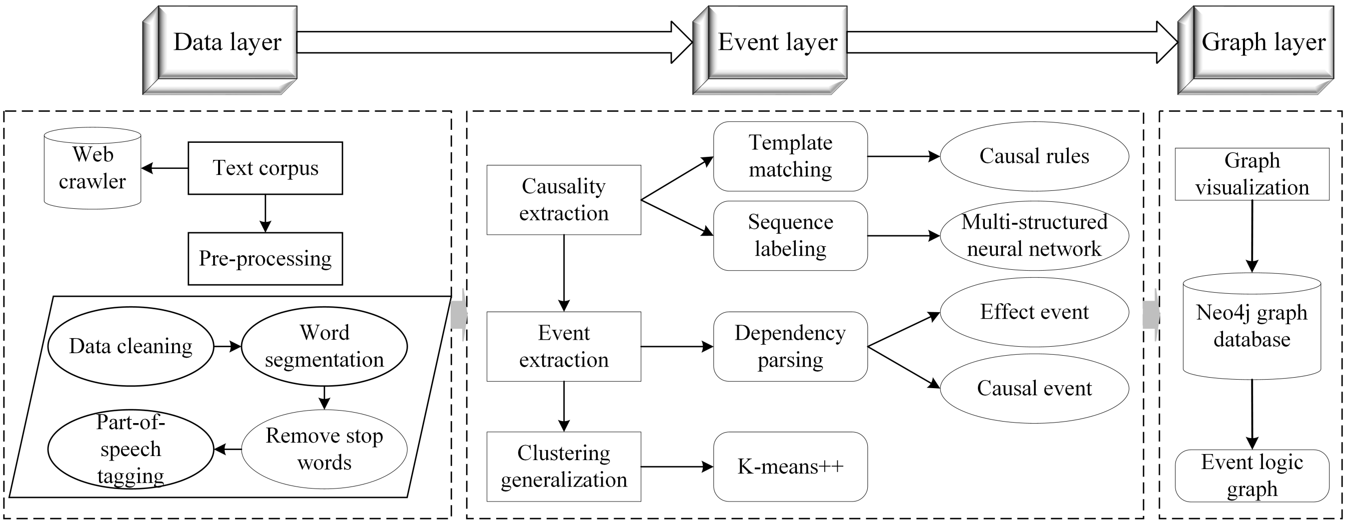

Fig. 2. The process of constructing ELG

TABLE I
SYNTACTIC PATTERNS OF CAUSALITY

Linguistic pattern	Causal cue word
Cue1[Cause][Effect]	because/due to/as long as/if/since
[Cause]Cue2[Effect]	so/therefore/thus/so that/result in /then/lead to/cause/bring out/make
[Effect]Cue3[Cause]	because/is due to/reason for /attribute to/result from/depend on
Cue4[Cause]Cue5[Effect]	(because,so)/(because,thus)/(due to,so that) /(since,therefore)/(only,can)/(as long as)
Cue6[Effect]Cue7[Cause]	(the reason,because)/(the reason,due to) /(the reason,because of)
[Effect]Cue8[Cause]Cue9	(is the reason for)/(is the reason of)

TABLE II
RULE TEMPLATES OF CAUSALITY

Rule	Extraction rules
Rule1	If $w_1 \in$ Cue1 and d_1= conj then S is a causal sentence for pattern 1 and Cause=$\{w_2 \cdots w_i\}$, Effect=$\{w_{i+1} \cdots w_n\}$
Rule2	If $w_i \in$ Cue2 and d_i= conj then S is a causal sentence for pattern 2 and Cause=$\{w_1 \cdots w_{i-1}\}$, Effect=$\{w_{i+1} \cdots w_n\}$
Rule3	If $w_i \in$ Cue3 and d_i= conj then S is a causal sentence for pattern 3 and Effect=$\{w_1 \cdots w_{i-1}\}$, Cause=$\{w_{i+1} \cdots w_n\}$
Rule4	If ($w_1 \in$ Cue4 and d_1= conj) and ($w_i \in$ Cue5 and d_i= conj) then S is a causal sentence for pattern 4 and Cause=$\{w_2 \cdots w_{i-1}\}$, Effect=$\{w_{i+1} \cdots w_n\}$
Rule5	If ($w_1 \in$ Cue6 and d_1= conj) and ($w_i \in$ Cue7 and d_i= conj) then S is a causal sentence for pattern 5 and Effect=$\{w_2 \cdots w_{i-1}\}$, Cause=$\{w_{i+1} \cdots w_n\}$
Rule6	If ($w_i \in$ Cue8) and ($w_n \in$ Cue9 and d_n= noun) then S is a causal sentence for pattern 6 and Effect=$\{w_1 \cdots w_i\}$, Cause=$\{w_{i+1} \cdots w_{n-1}\}$

2) Method Based on Sequence Labeling: To address the limitations of strong dependency, low recall rates, and poor cross-domain applicability associated with the template matching approach, this paper proposes converting causality extraction into sequence labeling problems. Specifically, it involves assigning labels to each character in the text string based on a selected labeling strategy. In this paper, we employ the "BIO" (begin, inside, other) labeling strategy to represent the position information of the words. Additionally, we categorize causality into five distinct types: cause, trigger, trigger-pre, trigger-post, and effect. These categories serve to represent the semantic roles associated with causal events. Consequently, the total count of tags is 11. Fig. 3 demonstrates an exemplification of such causality sequence labeling. Specifically, the tag "O" represents "other", indicating that the corresponding word is irrelevant in any causality components. Tag "B-t" represents "causal cue word begin", tag"I-t" represents "causal cue word inside", tag "B-c" represents "cause begin", tag "I-c" represents "cause inside", tag "B-e" represents "effect begin", and tag "I-e" represents "effect inside".

For the task of causality extraction in the field of public emergencies, we propose a multi-structured convolutional neural network model that incorporates word position features. By introducing position features (PF) into the multi-head attention mechanism, the model effectively integrates these features and enhances extraction efficiency. Specifically, the PF represents the vector obtained by mapping the relative positional distance between the current word and the causal cue word [22]. Taking Fig. 3 as an example, the word PF of "Tangshan" in relation to "because" and "of" can be represented as [9,8].

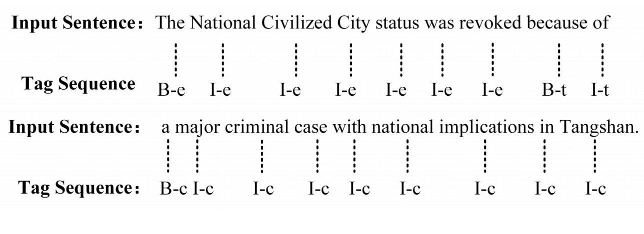

Fig. 3. Example of Causality Labeling

Fig. 4 illustrates the main structure of our model for causality sequence labeling. The causality extraction model comprises six components, which are the Input layer, CNN layer, BiLSTM layer, Multi-head Attention layer, LayeNorm layer, and Output layer. Firstly, word vector features are input into the convolutional layer to capture both syntactic and semantic information of words [23]. Subsequently, the fusion vector matrices are passed into the BiLSTM layer, enabling the bidirectional LSTM to capture causal semantic features from both forward and backward directions[24]. Furthermore, the multi-head attention mechanism is introduced, which assigns distinct weights to each word, demonstrating its effectiveness in capturing long-range dependency [25].

Simultaneously, the word position embedding is added to the layer, which then feeds into the LayerNorm layer for feature vector normalization. Finally, the Conditional Random Field (CRF) is employed to predict scores for each label and output the optimal label sequence with the maximum score. By considering correlations between tags, the CRF enables a globally optimal labeling chain for a given sequence [26]. By calculating the relative positional distance between each word and the causal word, it becomes possible to track the proximity between the word and the causal entity, thus facilitating the extraction of semantic feature information. Specifically, the incorporation of PF into a multi-head attention structure not only improves the learning of long-term dependency between words but also reduces the correlation between features, thereby resulting in improved performance and stability of the model.

D. Experiments and Evaluation

1) Dataset: Due to the lack of public and high-quality datasets, this paper adopts the template pre-labeling method to construct a causality dataset. Firstly, candidate sentences and their corresponding triplet causal event pairs are identified based on the rule templates. Secondly, we manually annotate the dataset to identify the cause, cue, and effect in causal sentences. Finally, we obtained a total of 928 valid data, which were divided in the ratio of 8:1:1, with 742 causal sentences in the training set, 93 in the validation set, and 93 in the test set.

2) Evaluation of Experimental Results: The evaluation metrics employed in this paper include standard precision (P), recall (R), and F1-score (F1), which can be computed using the formulas provided by [27]:

$$P = \frac{T_P}{T_p + F_P} \times 100\% \tag{1}$$

$$R = \frac{T_P}{T_P + F_N} \times 100\% \tag{2}$$

$$F1 = \frac{2PR}{P + R} \times 100\% \tag{3}$$

where T_P denotes the number of correctly predicted labels by the model; F_P represents the count of incorrectly predicted labels; F_N signifies the quantity of unrecognized labels by the model.

By excluding the label type “O” , we evaluated both the template matching model and the multi-structure convolutional neural network model for effectiveness in extracting causality. The detailed experimental results are presented in TABLE III. From the results, it can be observed that the template matching method exhibits a higher recall rate but lower precision and F1 values compared to the sequence labeling model. This result indicates that the efficacy of the traditional method heavily relies on the setting of rule templates. Therefore, our model can effectively capture the features of cause words and trigger words. Furthermore, transforming the problem of causality extraction into a sequence labeling task can effectively address the poor domain portability of the traditional method, demonstrating feasibility and correctness.

TABLE III
COMPARISON OF EXPERIMENTAL RESULTS OF CAUSALITY EXTRACTION

Method	Precision/%	Recall/%	F1/%
Template matching	58.97	100.00	74.21
Sequence labeling	84.42	83.85	83.00

E. Event Generalization

Given the large number of event pairs extracted in previous steps, we employ the K-means++ algorithm to generalize specific events into abstract events within the ELG. However, traditional K-means clustering suffers from issues such as initial center point instability and local optima. To address these challenges and enhance clustering performance, we introduce the Silhouette Coefficient (SC) to optimize the K-means clustering algorithm. The SC index evaluates clustering effectiveness by comparing intra-cluster similarity with inter-cluster dispersion [28]. It can be calculated using the following formulas:

$$S(X_i) = \frac{b(x_i) - a(x_i)}{max\{b(x_i), a(x_i)\}} \tag{4}$$

$$SC = \frac{\sum s(x_i)}{N} \tag{5}$$

where $a(x_i)$ represents the intra-cluster dissimilarity; $b(x_i)$ denotes the inter-cluster dissimilarity; $S(X_i)$ represents the silhouette coefficient of the sample point; SC refers to the silhouette coefficient of the entire cluster.

The basic steps of the improved K-means++ algorithm for event clustering generalization are as follows:

1) Utilizing the Word2vec word vector model to structurally represent events, where each vector serves as a sample point for clustering.

2) According to the K-means++ algorithm, K sample points are randomly selected as initial clustering centers, so that the initial centers are as far apart as possible.

3) Calculating the Euclidean distance between each sample point and the initial center of mass, and subsequently assigning them to their nearest center of mass.

4) Recalculating the vector mean value of each cluster as the updated center of mass and constantly updating iteration.

5) Repeating this process until the cluster center no longer changes.

F. Event Logic Graph Construction

The degree of correlation between two events, which represents the weight of the edges, is quantified by counting the number of event occurrences. The degree of correlation can be calculated using the following formula:

$$P(E_j|E_i) = \frac{count(E_i, E_j)}{\sum_k count(E_i, E_k)} \tag{6}$$

where $P(E_j|E_i)$ demotes the probability of E_j occurrence under the condition of E_i occurrence; $count(E_i, E_j)$ represents the number of occurrences of E_i and E_j together; $\sum_k count(E_i, E_k)$ signifies the total number of possible events under the condition of E_i occurrence.

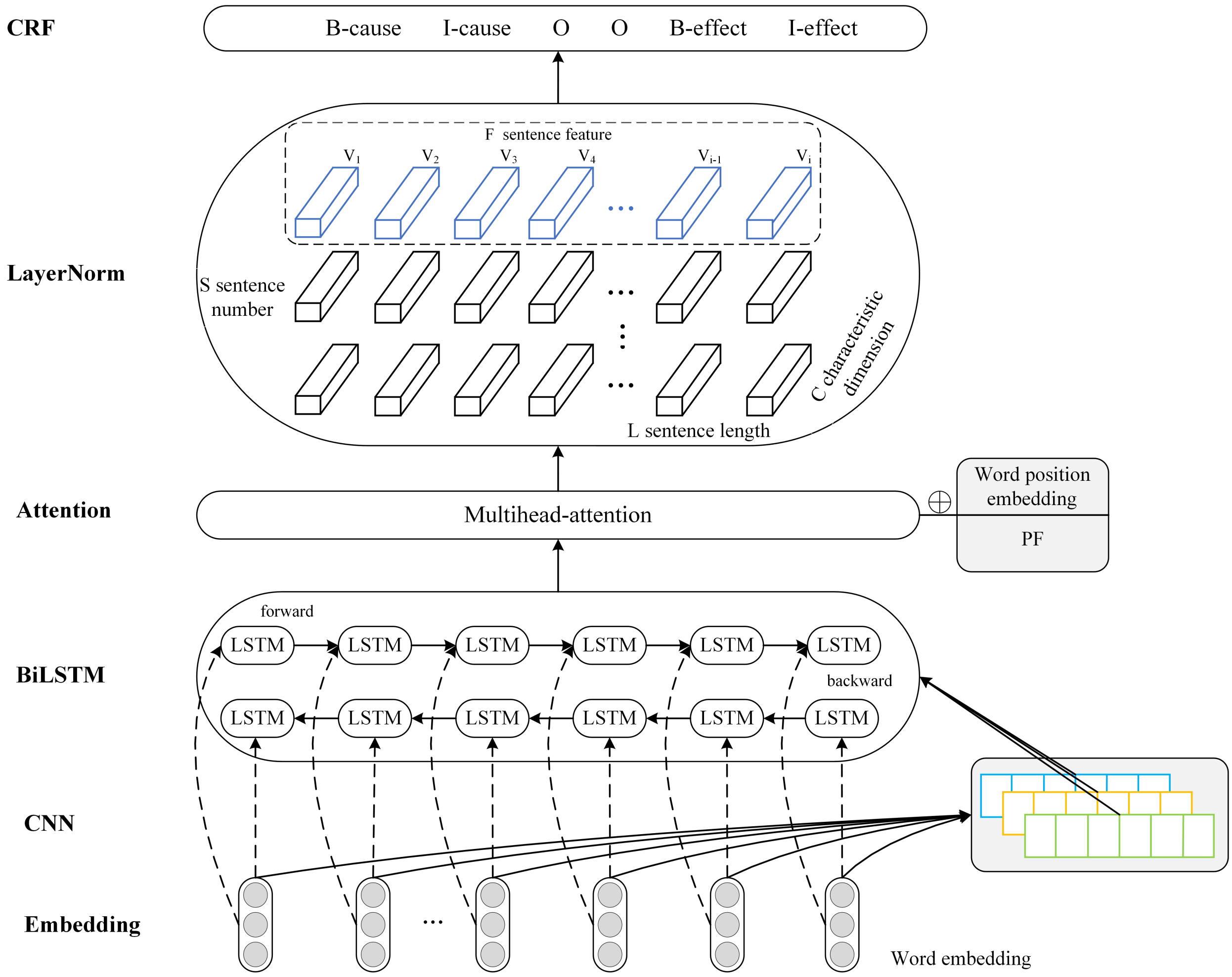

Fig. 4. Multi-structure convolutional neural network model

Building on previous research, this paper utilizes the Neo4j Graph Database for graph visualization. A graph database, as a type of non-relational database, stores events from the ELG as nodes, and causal relationship between events are stored as edges in the graph database. By utilizing the graph database to construct the ELG and form a logical knowledge base, significant events in the development process can be identified. Specifically, this paper uses the Cypher language to build nodes and relationship entities in the Neo4j Graph Database, and the specific code is illustrated in TABLE IV. The final implementation interface is shown in Fig. 5.

TABLE IV
NEO4J GRAPH DATABASE REPRESENTATION

Neo4j database
Server version: Neo4j/5.1.0 Server address: localhost:7687 Input: LOAD CSV WITH HEADERS FROM “file:///events.csv” AS line merge (p:events{allid:line.allid,event:line.event}) LOAD CSV WITH HEADERS FROM “file:///guanxi.csv” AS line match (from:allid{bid:line.bid}),(to:allid{eid:line.eid}) merge (from)-{r:weight{guanxi:line.guanxi}}→(to)

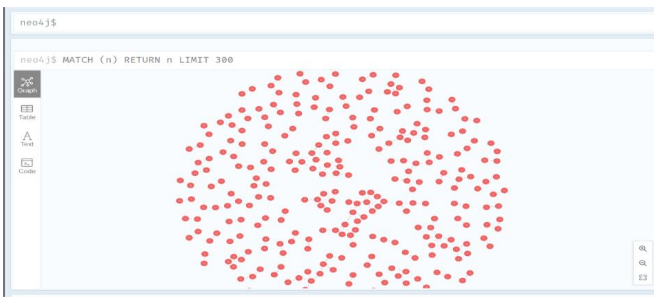

Fig. 5. ELG storage of Neo4j

IV. CASE STUDY

A. Dataset Description

In this section, we exemplify specific events and construct the ELG to demonstrate the viability of our approach, to uncover the evolutionary logic underlying public emergencies. For the selection of public emergencies, we choose the “Tangshan Incident” as the topic source due to its significant impact on both the public and society. To ensure a comprehensive analysis, we conducted web scraping from the microblogging platform to collect the top 40 topics related to this event, including user names, posting times, posting content, retweet counts, comment counts, and the number of likes. Subsequently, data pre-processing tasks were performed, which included removing duplications, deleting irrelevant and invalid words, removing stop words, word segmentation, and part-of-speech tagging. Eventually, a total of 17,176 valid texts were obtained to successfully construct the event corpus. TABLE V displays some trending topics related to the event.

TABLE V
TOP 10 TRENDING TOPICS IN MICROBLOGGING PLATFORM

Number	Trending topic	Heat/million
1	#Tangshan beating#	47.3
2	#All nine people in the Tangshan beating have been arrested#	21.8
3	#The violent mobbing of the Tangshan girl is everyone's nightmare#	19.5
4	#AMen real-name reporting Tangshan underworld gang#	15
5	#Tangshan demands justice for the injured#	13.7
6	#The Tangshan beating incident was investigated by Langfang police#	12.8
7	#Tangshan city carried out the special struggle against blackness and evil#	12.2
8	#The suspect in the Tangshan cake store incident was arrested#	11.8
9	#Two arrests have been made in the Tangshan barbecue restaurant beating incident#	11.7
10	#Starting Tangshan hitters has many criminal records#	11.4

B. Event Logic Graph Visualization

Based on the evaluation results of the model, we utilize the final set of 928 accurately labeled causal sentences as the foundational data for constructing and visualizing the ELG. Following the event generalization method proposed in the previous section, we evaluate the SC for various k values using the K-means++ algorithm to generalize the extracted events. Fig. 6 illustrates the result of event clustering, revealing that an optimal k value of 2 was selected. The identified keywords for these two types of events are "Tangshan" "event" "beating" "umbrella of protection" and "law" for one type, and "female" "Tangshan" "barbecue" "male" and "girl" for another.

In this paper, "dynamic event" is regarded as the logical core for constructing the ELG. Fig. 7 demonstrates the specific ELG, which consists of 1024 nodes and 928 directed weighted edges. Specifically, each event node is represented as a subject-verb-object triplet, and the number between each edge is represented as the weight size. The intricate nature of these nodes reflects the complex and changeable evolutionary process of public emergencies, influenced by multiple factors.

To provide a clearer demonstration of the ELG, we further extracted the local graph from the overall structure, as depicted in Fig. 8. The local graph contains 20 nodes and 19 directed edges. For example, in the causal relationship of "Public attention to Tangshan case→Set off anti-triad storm", the former serves as the cause while the latter represents its effect. A causality value of 0.25 indicates a potential likelihood that the cause event leads to the corresponding effect event. Fig. 8 illustrates that a cause event can give rise to multiple effect events, while an effect event can also be attributed to various reasons, enabling the formation of dynamic chains of causal logic between events. For example, the occurrence of "Beating incident happened" has various consequences, including "Tangshan has negative news" and "Public lose sense of security". It indicates that the impact of public emergencies is diverse, encompassing not only the specific incident itself but also numerous aspects related to social life. Analyzing Fig. 8 reveals the existence of a causal event chain, namely "Beating incident happened→Tangshan has negative news→Beating incident is trending→Internet as a channel of exposure→Normal procedures are not trustworthy→Government credibility declined".

In summary, ELG can visually depict the correlation between different events and establish a causal relationship among them. Consequently, it enables us to acquire dynamic logical knowledge related to specific events. ELG unveils the underlying micro-level mechanisms, thereby facilitating emergency departments in analyzing and predicting public emergencies.

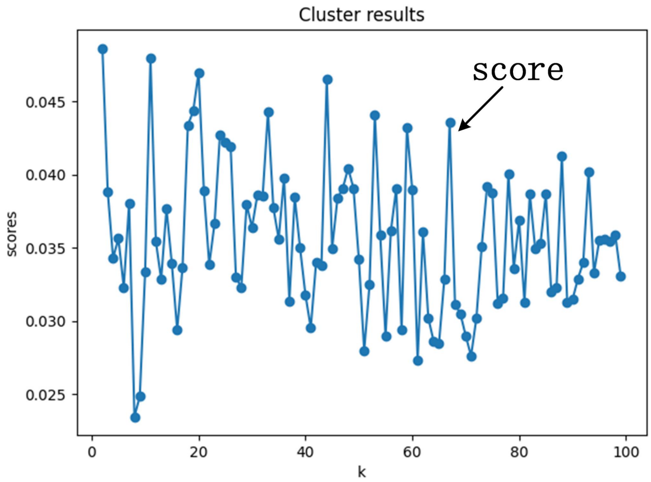

Fig. 6. Evaluation results of SC for different K values

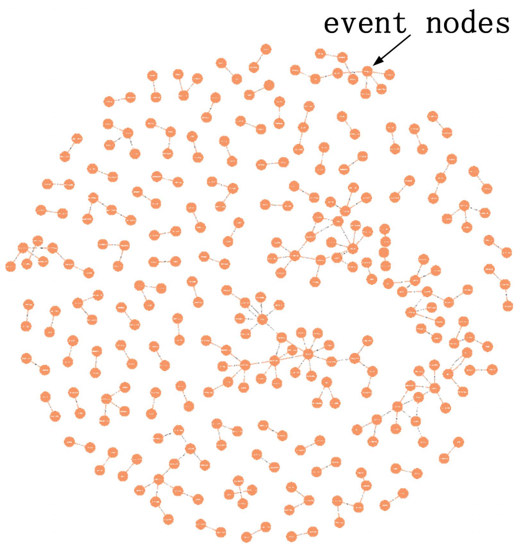

Fig. 7. ELG of "Tangshan Incident"

C. Causal Logic Analysis

The semantic relationship formed by nodes and edges reveals the evolution of event knowledge, while causal logic describes a cause-effect connection within a cognitive system. The concept of causal logic signifies that one event leads to the occurrence of another event, indicating that event A causes event B to happen, which can be represented in the form of knowledge as (event A, leads to, event B). Analyzing the causal logic relationship enables the deduction of the complete process of event evolution, which is crucial for investigating the event evolutionary mechanism.

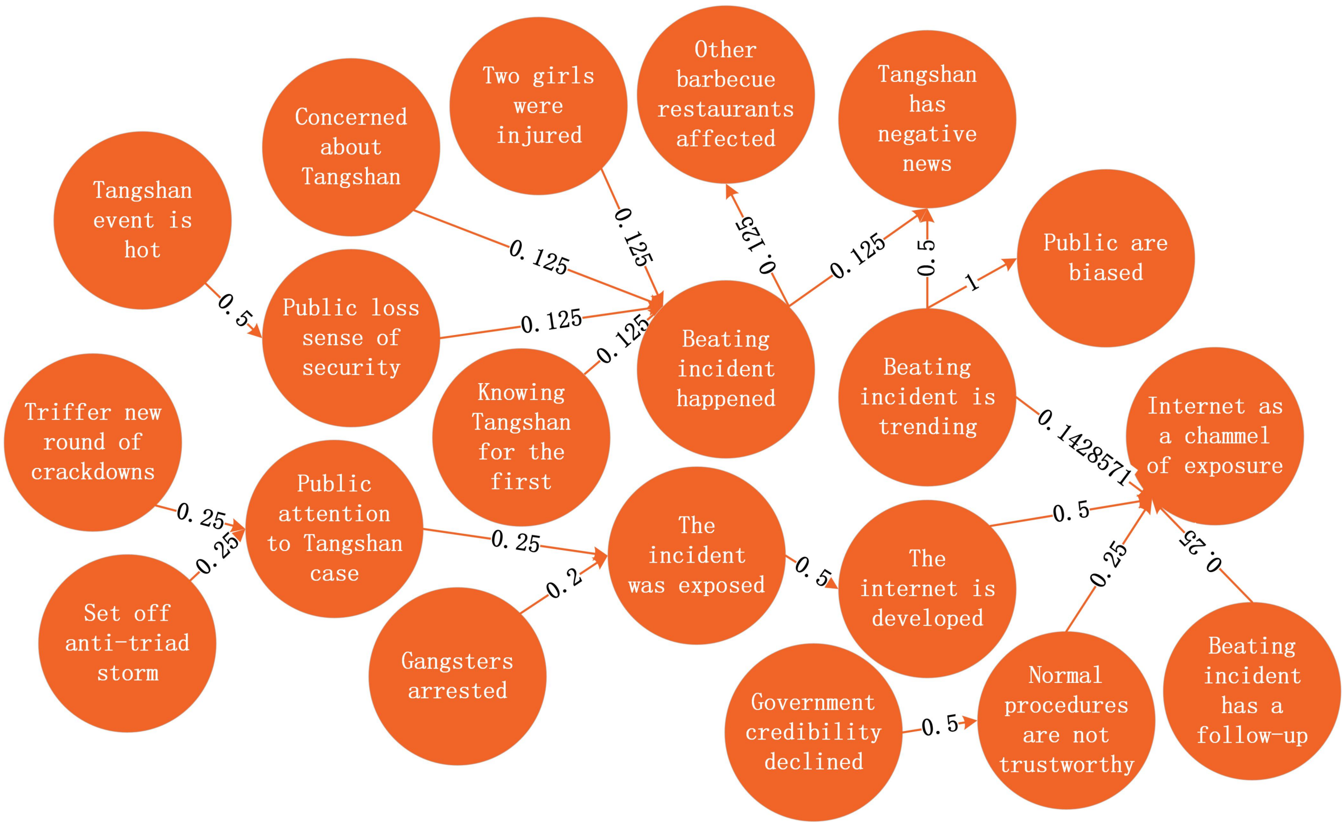

Fig. 8. The detailed ELG of “Tangshan incident”

Using the Tangshan emergency as an empirical case, this paper employs a dependency parsing analysis method to extract cause and result events from causal sentences, thereby acquiring logical knowledge about events. TABLE VI shows examples of partial causal logic relationships between events. By analyzing the causal logic relationships of events, it is possible to uncover implicit knowledge derived from these events. Implicit knowledge refers to objective knowledge that surpasses human reasoning and cognition. As presented in TABLE VI, multiple factors that can provoke “public feel very angry”, including the shocking nature of the event, shifts in public psychology, and the impact of gender. Summarizing these factors helps in effectively mitigating the harm and impact caused by such events, enabling appropriate actions to be taken for crisis management.

Therefore, the knowledge of causal logic in the ELG can facilitate the regulatory authorities in comprehending and elucidating the essence of public emergencies. This enables a comprehensive exploration of inter-event correlations, providing management departments with comprehensive guidance on effective problem-solving and response strategies, thereby effectively achieving decision-making support.

D. Evolutionary Path Analysis

From a structural perspective, the causal relationship between events is represented as a directed network graph, which connects independent logical relationships. Within the ELG, causal event chains are formed by connecting cause and effect events, as demonstrated in TABLE VII. It can be observed from TABLE VII that there is significant variation in the length of the evolutionary path within the ELG, reflecting the characteristics of a few causal events and a short evolutionary path. Specifically, the shortest evolutionary path of a causal event chain is 1, and it constitutes the majority of the graph. Additionally, implicit logical relationships of public emergencies are embedded within the causal event chains. By exploring the information within the causal event chains, three regularities of the evolutionary path of public emergencies can be identified, which are summarized as follows:

1) Key Node: It has been observed that certain nodes exhibit higher in-degree than others, indicating the presence of event nodes with multiple causes and a single effect, which can be referred to as a “key node”.

Different types of cause events can contribute to the occurrence of these events, suggesting their frequent incidence in the field. These key nodes warrant increased attention from regulatory authorities. For instance, as depicted in Fig. 9, three events namely “Crime not stopped” “Bad guys are spared”, and “Crime is not responsible” all lead to the effect event of “Bad guys are more arrogant”. The varying weights assigned to these events demonstrate that following the incident, public concern extended beyond just the incident itself to encompass discussions about a group of individuals labeled as “Bad guys”. The analysis of Fig. 9 indicates a negative trend in public opinion, as the focus gradually shifts from the incident to encompass crime and legal aspects. Therefore, it serves as a reminder that emergency departments should pay attention to public opinion and prevent the crisis from further expanding.

2) Central Node: It has been determined that certain nodes exhibit a high out-degree, indicating the presence of multiple effect events stemming from a single cause, which is referred to as a “central node”.

TABLE VI
EXAMPLES OF CAUSAL EVENT PAIRS

Cause event	Causal cue word	Effect event
Anomalies in media handing of cases	because of	Loss of judicial authority
The Tangshan incident has touched the bottom line of the heart	lead to	Public feel very angry
They will be beaten if they refuse sexual harassment	because	Women are afraid
The beating incident triggered a negative impression	because-so	Tangshan was disqualified as a civilized city
Everyone feels dangerous	the reason-because	The whole internet is outraged
Men possessing corrupt ideas	is the reason for	Women feel angry

TABLE VII
EXAMPLES OF CAUSAL EVENT CHAINS

Number	The causal event chains
1	Cost of crime is too low→Raising the cost of crime →Forming a rule of law society→Reduce the incidence of beating
2	Inaction of public security organizations→Tangshan police turn corrupt →Public officials fail to serve the people→Refunding taxpayer's money
3	Beating incident occurs→Tangshan has negative news →Beating incident is trending→Internet as a channel of exposure →Normal procedures are not trustworthy→Government credibility declined
4	The outbreak of events→Public lose trust in the government →Public are deeply distressed→Lost the hearts of the people
5	Woman are the weak side→Woman are easy to empathize with others →Woman feel fear→Girls are willing to speak out

These events are likely to trigger numerous other occurrences, thereby generating new public opinion and exerting a significant influence on the development trend of public emergencies. Therefore, identifying these nodes promptly is crucial for regulatory authorities to trace the source of events, effectively control crises, and mitigate negative impacts arising from such emergencies. For instance, as depicted in Fig. 10, the central node is identified as "Not strictly probe the incident", which can trigger a cascade of sub-events such as "Damage public's sense of security", "Everyone becomes a victim", and "Public lose trust in the government". This observation underscores that central nodes often serve as both the cause and catalyst for the emergence of online public opinion outbreaks, necessitating significant attention from relevant authorities.

3) Intermediate Node: ELG contains seemingly unrelated event nodes, which are interconnected through cause or effect events to form a causal event chain, highlighting the intricate nature of causality in public emergencies and its susceptibility to multi-event cascades. In this paper, these connecting nodes are referred to as an "intermediate node".

Effectively identifying the intermediate nodes can provide practical support for emergency departments to respond promptly. As depicted in Fig. 10, the central node is labeled as "Not strictly probe the incident", while the key nodes include "Bad guys are more arrogant", and "Public are deeply distressed". Additionally, three intermediate nodes are identified: "Bad guys are spared", "Damage public's sense of security", and "Public lose trust in the government". The analysis reveals that these intermediate nodes serve as connectors between the central nodes and key nodes, thus forming multiple causal event chains.

Through analyzing the evolutionary path of public emergencies, it is evident that the formation logic of such events is rather complex, and various factors will influence the evolutionary trend and direction of events, potentially causing significant impacts on various aspects including the economy, social security, and public psychology.

This study reveals that within the ELG of public emergencies, the shortest evolutionary path is 1, while the longest evolutionary path is 6, with the former constituting the vast majority. Within the ELG, three types of special nodes exist - critical nodes, central nodes, and intermediary nodes - which often serve as important turning points in the development process of events. Therefore, emergency management departments need to promptly identify these nodes to prevent the occurrence of potential risk events.

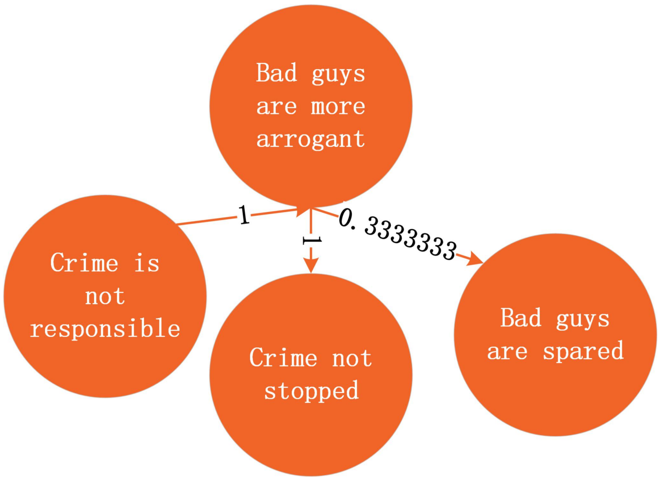

Fig. 9. A diagram of the key nodes

E. Evolutionary Motivation Analysis

Combined with the construction process of ELG with real-life instances of public emergencies, a scientific analysis is conducted on the evolutionary motivation of public emergencies. Through the visualization of ELG, we found that the evolutionary motivation of public emergencies is intricate throughout their entire lifecycle, exhibiting a complex and non-linear logical structure. The evolutionary motivation graph regarding this event is depicted in Fig. 11. The analysis reveals that the primary catalysts for this incident include gender dynamics, objective circumstances, and the actions of those responsible. The primary catalysts for the fermentation of the Tangshan incident are the heightened public attention and the proliferation of online public opinion. In ELG, social media platforms serve as fertile ground for the dissemination of public opinion, thereby expediting the progression of emergencies.

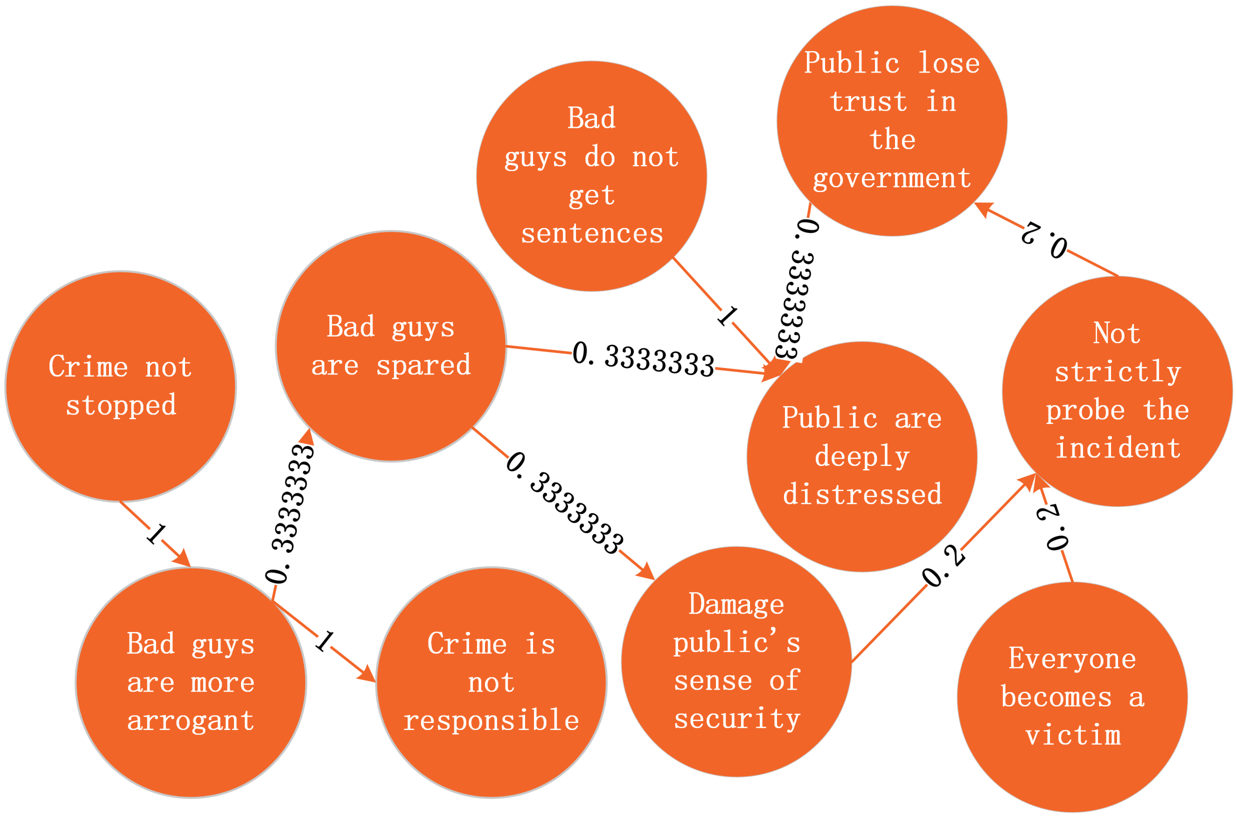

Fig. 10. A diagram of the central nodes and intermediate nodes

By elucidating the underlying factors driving event evolution, corresponding strategies and measures can be devised to address key cause nodes. Only by elucidating the reasons underlying events can we comprehensively grasp its development trend. Furthermore, an analysis of the event's repercussions reveals that the consequences of the Tangshan incident can be categorized into two distinct types: direct and indirect impacts. Among the direct impacts, the "Tangshan has negative news" includes "Tangshan was canceled as a civilized city" and "People's impression of Tangshan became bad". In the results of "Gender topic discussion", it was found that women pay more attention to this event and provide more emotionally charged feedback, leading to feelings of anger, unease, and fear among them, consequently shaping public opinion on the topic of sexual confrontation. At present, the regulatory authorities must take into account public sentiment and steer public opinion in a constructive direction. The incident has given rise to various sub-events, including discussions on injuries and punishments, which have been amplified by its aftermath. The sub-events encompass "A storm of anti-triad in various places", "Increasing the number of real-name reports", "Involving many similar cases", "Public lose sense of security", and "Government credibility declined".

This result illustrates the extensive impact of the incident and emphasizes the need for the relevant authorities to carefully manage each stage of its progression while formulating reasonable response strategies and measures. At this stage, it is imperative for the government and relevant departments to promptly declare their stance, undertake a thorough investigation of the case, and timely reveal the findings to the public to ensure information transparency and prevent potential exacerbations. Simultaneously, regulators should strive for precise and positive guidance to minimize any negative consequences.

Emergencies serve as catalysts for the transformation of social risks into public crisis, where the values, behavioral patterns, and social relations of different social groups intersect and clash, giving rise to the distinctive nature of emergencies. By conducting a scientific analysis of the motivations, exacerbating factors, and primary contradictions underlying public emergencies, it is possible to derive corresponding empirical knowledge that will help us better comprehend events in this field. Clarifying the evolutionary motivation of the Tangshan incident allows us to identify certain abnormal manifestations that exacerbate the situation and lead to a negative outcome throughout the evolutionary process of public emergencies. In this paper, these factors are collectively categorized as "inducing factors". Therefore, from a macro-perspective encompassing subjective conditions, external environments, and media dissemination, this paper summarizes the factors that transform public emergencies into public crisis, as illustrated in Fig. 12. A detailed exposition is presented below.

1) Subjective Condition - Abnormal Event Performance: The occurrence of emergencies is characterized by their suddenness, intensity, and destructiveness. These emergencies often do not develop as expected, and their evolutionary trend is difficult to predict. If an event fails to develop as anticipated or lacks timely communication about its progress, it may provoke speculation and conjecture among the public, thereby increasing attention towards the event itself. Therefore, it is necessary to understand the nature and impact of emergencies to take appropriate measures for the first time.

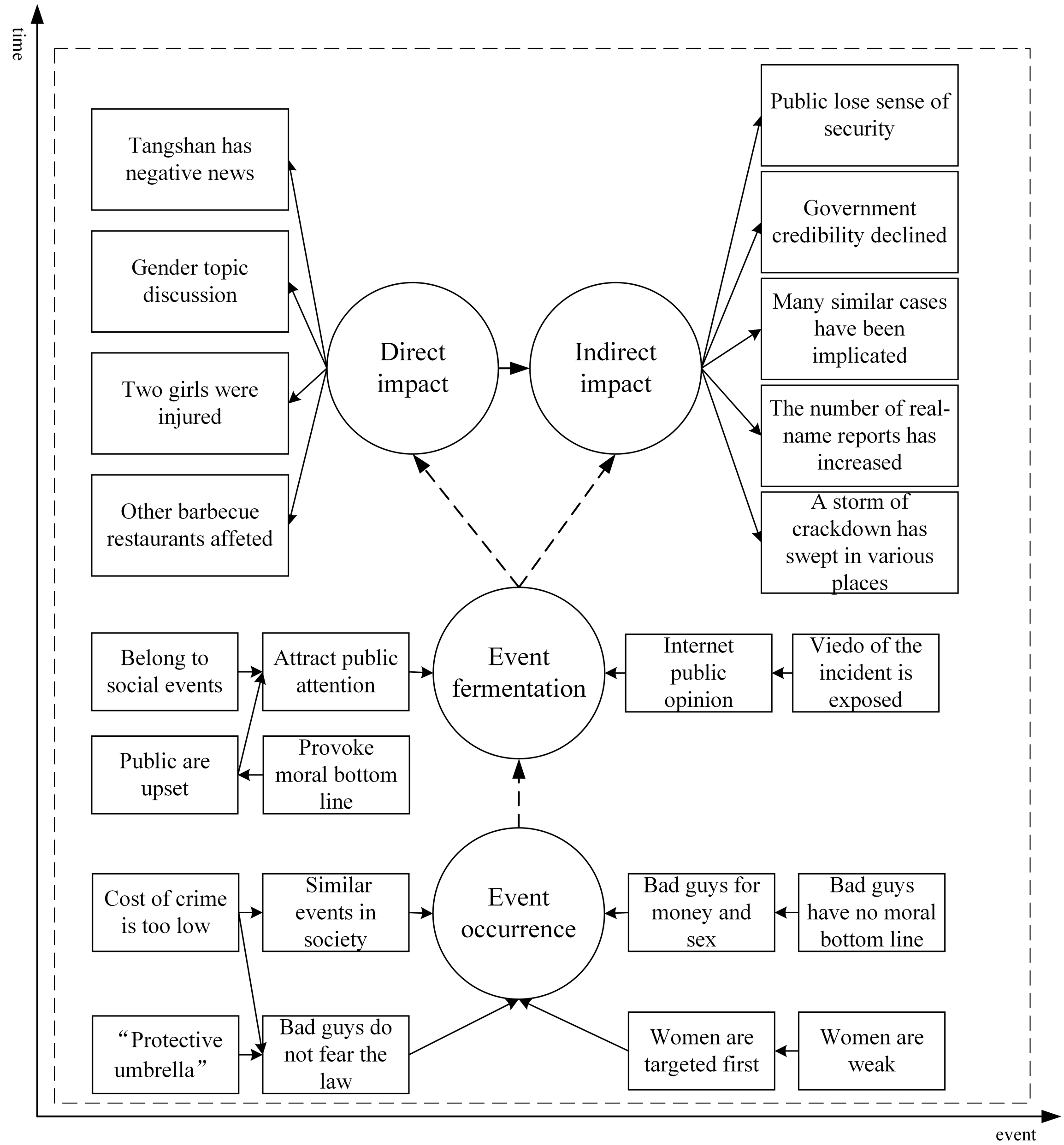

Fig. 11. The evolutionary motivation of the "Tangshan incident"

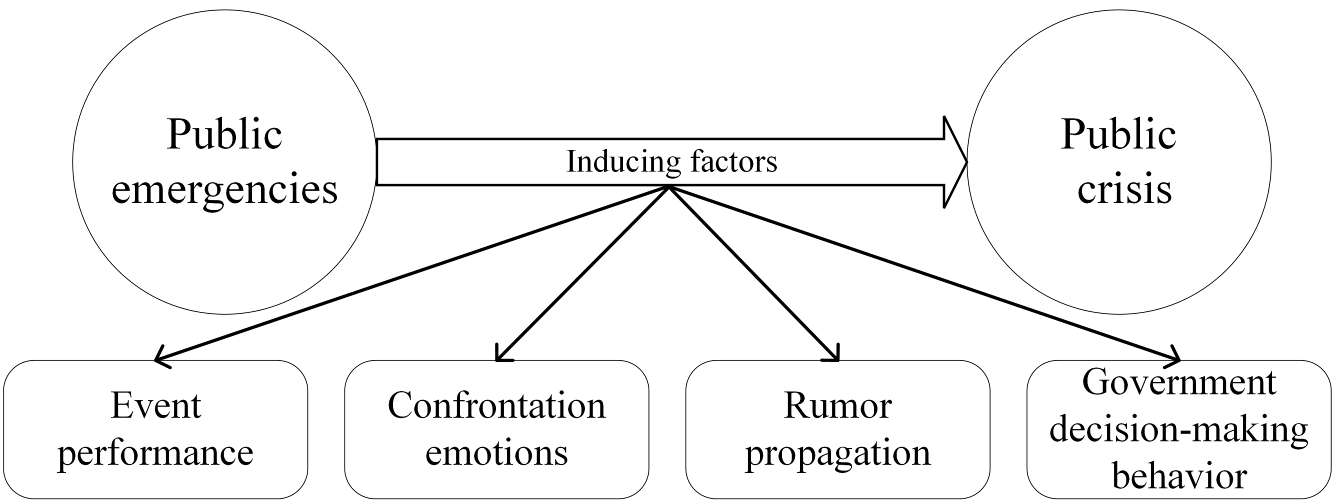

Fig. 12. Inducing factors of public emergencies

2) External Environments - Threat Transference Generates Confrontation Emotions: The state of threat transference refers to the fact that social power and social welfare are closely related to every member of society. When the causes of events are unrelated to bystanders but share similar characteristics with vulnerable parties, bystanders may associate these events with their potential vulnerability, giving rise to a sense of “associative threat”. Because group behavior is infectious, homogeneous, and illogical, it can lead to the formation of conflictual emotions among members of the group due to psychology, which will further intensify public crisis.

3) External Environments - Improper Government Decision-making Behavior: The government decision-making behavior plays a pivotal role in effectively managing public emergencies. When confronted with public crisis, local governments and officials may display restricted options for action, a delayed response, and imperfect response mechanisms. These flaws not only prevent the crisis from being resolved but also exacerbate and amplify it. Public emergencies set off a chain reaction of negative emotions once they ferment and propagate online. Negative emotions spread quickly when these messages are not promptly prevented or verified, which exacerbates the crisis. To effectively handle public crisis, relevant departments must coordinate active participation from both online and offline parties while achieving collaborative governance that fully integrates and utilizes internal and external crisis management resources.

4) Media Dissemination - Rumor Propagation as a Catalyst: Rumors possess a potent mobilizing and stimulating effect, capable of directing people’s attention to specific issues. Rumors frequently cause uninformed netizens to question and misunderstand the government or the veracity of the situation at hand, transitioning from support to opposition. Consequently, this negative shift exacerbates social contradictions and contributes to public crisis.

V. Conclusion

To elucidate the evolutionary mechanism of public emergencies, this paper proposes a comprehensive analysis framework for the evolutionary logic of public emergencies based on the research idea of “event-relationship-logic”. Additionally, this paper further focuses on the causal relationship and proposes the construction process of ELG, which lays a foundation for the visualization graph. In terms of method innovation, this paper transforms the task of causality extraction into a sequence labeling problem and proposes a multi-structured convolutional neural network model that integrates word position features. Furthermore, compared with the template matching method, the effectiveness and precision of the model are further proved.

Based on the empirical analysis of the ELG of public emergencies, the study reveals several key findings: Firstly, the formation logic of public emergencies is highly intricate and influenced by various factors. Simultaneously, the evolutionary path of causal event chains is relatively short, with many of them having a length of 1. Secondly, there are three types of important nodes in the evolutionary process of public emergencies: key nodes, central nodes, and intermediate nodes. These modes often steer the direction of event evolution and serve as turning points in its development. Therefore, regulatory authorities should focus more on them. Lastly, this paper reveals several triggering factors that promote the transformation of public emergencies into public crisis. Specifically, there are abnormal event performance, threat transference generates confrontation emotions, improper government decision-making behavior, and rumor propagation as a catalyst. By constructing an ELG of public emergencies, this paper offers a novel perspective for studying the evolution of such emergencies and provides targeted governance suggestions and measures for emergency management departments to effectively address them.

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