Short Review of Intention Mining in Social Crisis Management through Automatic Technologies

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***Abstract*—In the current social environment, social crisis events occur frequently with significant impacts. Group intention mining through automatic technologies for managing social crises has gained extensive attention. This paper presents an overview of research on group intention mining in social crisis events, covering three areas: knowledge graph inference, intention attribution, and risk management. Knowledge graph inference facilitates the detection of group intention in crisis events. It is supported by the construction of crisis knowledge graphs, which organize crisis elements and inter-element relations into structured semantic knowledge. The interpretable semantics in the crisis knowledge graphs enables attribution of intention. Group intention mining consists of intention detection and intention attribution, serving the risk management of social crisis events. To gain insights into the process of group intention mining in social crises, the Covid-19 event is selected as a case study. Finally, the paper proposes future research directions to solve the limitations of existing intention mining methods in social crises.**

***Index Terms*—Social Crisis Events, Intention Mining, Intention Explanation, Risk Management**

I. Introduction

Social crises are complicated and dynamic events that threaten public safety and interest, influenced by various interconnected factors. The Covid-19 pandemic serves as a prime example of a global health crisis that has significantly disrupted the everyday lives of individuals. Exploring the formation and evolution of social crises is crucial to safeguard public safety. However, in the complex international environment, social crisis management is challenging for all countries.

The process of managing social crises consists of three stages: pre-crisis detection, real-time crisis response, and post-crisis review, as illustrated in Fig. 1. To effectively manage a crisis, it is crucial to mine the intention of groups involved, as it provides valuable insights into their behavior in a given situation. For example, tracking the public's sentimental intention during the Covid-19 pandemic can help restore social development. The model of group intention mining in social crisis events is defined as $I_{crisis}^{min} = \{I_{det}, I_{att}\}$, where I_{det} is intention detection, I_{att} indicates intention attribution. However, intention mining during social crises is challenging due to the unclear evolutionary trajectory and elusive precursors of such events. On the one hand, the vast amount of knowledge in social crises is both extensive and sparse, resulting in a semantic imbalance arising from long-tailed event information. On the other hand, the semantics of words may evolve over time, and new words or phrases keep emerging, making it difficult to analyze crisis-related data. Additionally, using unexplainable intention decision models in analyzing social crisis events involving life safety poses a risk.

This paper aims to address the issues related to group intention mining in social crises. It provides a comprehensive overview of current research in three closely related areas: knowledge graph inference, intention attribution, and risk management for social crisis events. Section II covers knowledge graph inference, which supports the identification of group intention in crisis events. Section III discusses intention attribution, which helps to determine the motivations and goals of crisis actors. Group intention mining, encompassing intention detection and attribution, plays a critical role in social crisis risk management, as discussed in Section IV. Section V presents a case study on Covid-19, demonstrating how the integration of knowledge inference and intention attribution can support risk management during a social crisis. Finally, the paper proposes improvements to overcome the limitations of existing research on intention mining in social crises.

II. Knowledge graph construction and inference for social crisis events

The extensive and sparse nature of social crisis data poses a challenge for effective knowledge representation. Knowledge graph offers a viable solution for organizing and integrating discrete semantic knowledge related to social crises. Using the constructed crisis knowledge graph for knowledge inference enables the detection of group intention.

Knowledge graph improves the agencies' ability to deal with crises in different areas. In counter-terrorism detection, to identify terrorist organizations, Bangerter et al. [1] constructed a knowledge graph from the Global Terrorism Database and trained graph neural network(GNN) by inductive link prediction technique. Yang et al. [2] utilized the co-occurrence matrix and relationship knowledge graph to sort out the development tendency of various topics in counter-terrorism intelligence. In public health domain, to identify and explain misleading Covid-19 statements on social media, Kou et al. [3] integrated the knowledge of both experts and non-experts to construct a Covid-19 knowledge graph. In environmental protection, Liu et al. [4] built a multi-source oil spill detection knowledge graph using rule reasoning and GNN

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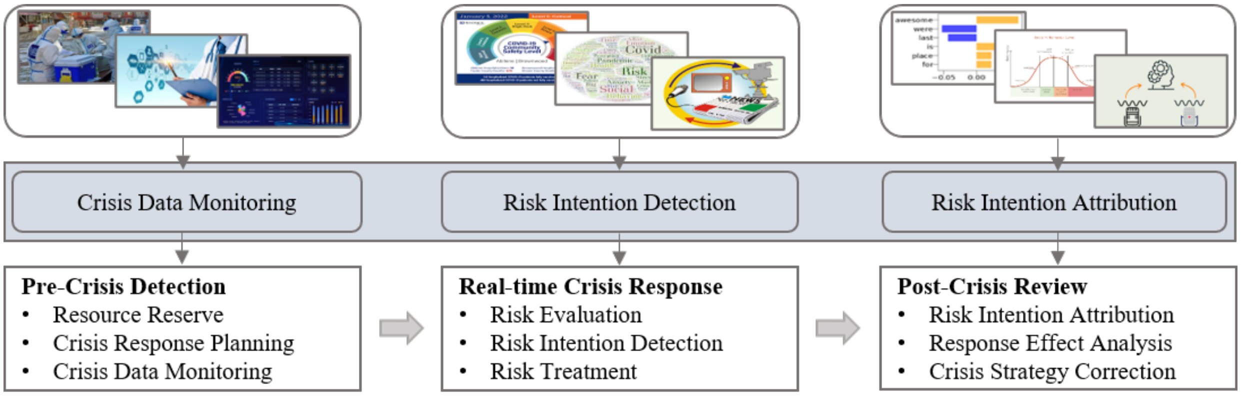

Fig. 1: Flowchart of Social Crisis Management

to address information isolation in oil spill detection. Pingle et al. [5] detected network threats by extracting semantic triples in cyber data. In climate change domain, Chen et al. [6] employed a knowledge graph-based meteorological risk analysis framework to visualize the hierarchical relationship between dangerous weather events and human activity events.

When utilizing knowledge graphs for crisis management, three steps must be taken, including knowledge extraction, fusion, and inference. To overcome challenges encountered during these stages, researchers have proposed several solutions. In the knowledge extraction stage, to solve the entity overlap problem during the triplet extraction, Wei et al. [7] regarded the triplet extraction as a discrete classification problem, extracting entities first and then identifying entity relation. Aiming at the long-term dependence problem of triples, Ye et al. [8] proposed a generative model to generate entity-relation-entity successively. Targeting the problem of missing part of the contextual information for extracted triples, Geng et al. [9] presented a convolutional recurrent neural network based on attention mechanism to jointly uncover entities and relations. In the knowledge fusion stage, Trisedya et al. [10] introduced an entity alignment model based on attribute-embedded characters and transitivity rule. Wu et al. [11] proposed a cross-lingual entity matching model named CLEM, which integrates multimodal information embedding matching entities based on a multi-perspective spatial learning method. In the stage of knowledge inference, given the incompleteness of knowledge graph, Lei et al. [12] proposed knowledge graph completion and reasoning based on symbolic methods and reinforcement learning. Niu et al. [13] presented a coding and decoding model based on GNN and high-dimensional structure weight. Knowledge graph has been applied in domain knowledge transfer, target recognition, and semantic tracing. The improvement of knowledge graph construction approaches promotes knowledge graph's application in social crisis management. Based on relevant research, the framework of knowledge graph construction and inference in social crises is shown in Fig. 2(a). Firstly, through the knowledge extraction, the triad of crisis elements is obtained as $KT = \{e_h, r, e_t\}$, where e_h is a header event element, e_t is a tail event element, and r denotes the relation between the above two elements. Secondly, the crisis knowledge graph CG is gained through the knowledge fusion, which is expressed as $CG = \{E, R\}$, where E is the set of crisis elements, R is the set of r. Finally, based on the crisis graph and the target event data, the group intention is derived by knowledge inference as $I_{det} = f(CG, D)$, where D is the target event data, f denotes the knowledge inference function. Knowledge graph as a way of structured representation have the ability to manage complex crisis data.

Current research on knowledge graph has made notable advancements in detecting intentions related to specific domains of risk. However, challenges arise when attempting to apply these approaches to cross-cutting social crises. These difficulties stem from the complexity and semantic co-reference of elements within crisis events. As a result, the constructed social crisis knowledge graph is often semantically sparse, failing to accurately capture the continuous scene semantics involved in social crisis events.

III. Intention Attribution and Explanation for Social Crisis Events

In recent years, deep learning has been applied in various public places to ensure public safety. However, the poor interpretability of deep models impairs their reliability and trustworthiness, especially in social crises involving the safety of people's lives and property. Therefore, it becomes imperative to explain and attribute public intention of social crises in a human-understandable way.

In different application domains, researchers have explored the interpretability of deep models. In the medical field, Assegie et al. [14] adopted LIME and SHAP to rank the importance of features and explain the model's output on whether a patient is diabetic or not. To provide clinical doctors with a clear understanding of the classification criteria utilized by GNN in Alzheimer's disease prediction, Anjomshoae et al. [15] proposed a single node classification explanation method. By scrutinizing the alterations in output arising from decomposed input values, the extent of input values' impact on predictions can be gauged. In the finance domain, Pisoni et al. [16] discussed how insurance companies provide cus-

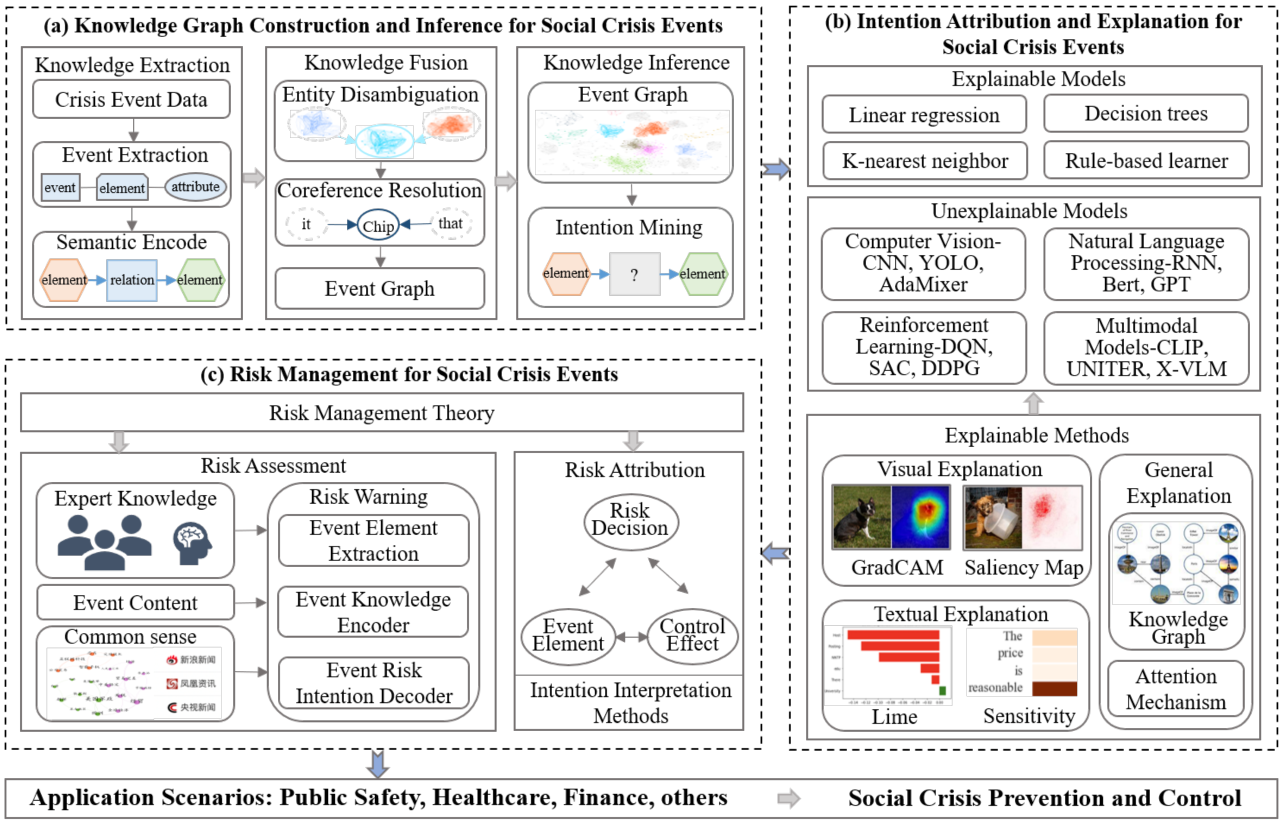

Fig. 2: Framework of Risk Management, Knowledge Graph Inference, and Intention Attribution for Social Crisis Events

tomers with suggestions and explanations on the recommended amount of insurance coverage. In the industrial area, Zhang et al. [17] utilized SHAP to identify salient features in predicting diagnostic faults in power transformers. In the environment area, Cilli et al. [18] employed random forest model with Shapley value to detect the driving factors that contribute to the occurrence of fires. In the sports field, to analyze the trend of NBA games, Wang et al. [19] applied random forest and feedforward neural network to build a prediction model. Then, they adopted the LIME model to explain the prediction.

To increase trust in deep models across diverse domains, it is crucial to continuously enhance intention attribution techniques. Automated approaches like dependency graphs, feature engineering, and alternative models have been developed for intention explanation. Semantic barriers exist between different modal data, targeted attribution algorithms have been proposed to verify diverse data attributes. For image data, various visual interpretation methods have been introduced, including LIME, GRAD-CAM, and RISE. The SIDU method [20], addressed salient region localization by creating pixel similarity difference and uniqueness masks extracted from the last convolutional layer of the convolutional neural network. For textual data, to tackle the problem of interpretable information retrieval, Chen et al. [21] introduced structured knowledge graph that record interpretable relationships between entities into various steps of the retrieval process. For speech data, to predict and explain the sentiment in speech, Zhang et al. [22] proposed the RexNet model and the XAI perceptual processing framework inspired by the perceptual process of cognitive psychology, in which contrast salience, counterfactual synthesis, and contrast cue interpretation are treated as interpretation methods. Of course, there are also many interpretable tactics for multimodal data. To help non-expert end users understand the decision-making process of intelligent agents, Muñoz et al. [23] utilized a success probability-based approach to construct a humanoid explanation that visually displays the state of the autonomous robot after taking an action. To explain the driving route of autonomous vehicles in complex environments, Zhang et al. [24] propose a Multimodal Trajectory Prediction Transformer model to retrieve the influencing factors of the prediction. Based on related research, the research framework for group intention explanation is shown in Fig. 2(b). For example, based on the interpretable crisis community knowledge graph, the interpretation of group intention I_{det} is gained as $I_{att} = g(CG, I_{det})$, where g is the knowledge graph-based attribution method. The enhancement of attribution techniques has facilitated their utilization in various vertical domains.

Existing intention attribution methods are effective in providing understandable explanations. However, the presence of fuzzy crisis elements and the complex mechanisms of action among these elements present a notable obstacle in identifying the factors that determine group intention and behavior.

IV. Risk management for social crisis events

Social crisis data involves numerous risk elements, with intricate interdependencies among them. Intelligent technologies equipped with robust data analysis capabilities exhibit superior efficacy in identifying and mitigating social crises compared to human operators. These technologies leverage advanced techniques such as machine learning, data mining, and natural language processing to analyze vast amounts of data, identifying patterns and insights that might otherwise be missed by humans.

Organizations responsible for crisis management rely on a combination of management theory and intelligent technology to detect and respond to social crises. Mcgowran et al. [25] utilized a disaster risk detection method and portfolio theory to analyze the overall response approach. Wei et al. [26] developed an intelligence model for social crisis early warning based on the intelligence production chain. Liu et al. [27] fused information collection, epidemic monitoring, and risk assessment theories of epidemic risk to enhance the public health emergency response system's capacity. Yan [28] proposed the establishment of an efficient mechanism for sharing crisis response information among international actors to address abrupt environmental crises across various regions. Simpson et al. [29] identified forms of interactions that generate risks and subsequently integrated corresponding response strategies into a climate change risk framework to enhance decision-making.

In response to the increasing demand for risk management, there has been a growing interest in the development of automatic technologies. Researchers have proposed numerous data analysis methods to tackle crisis events. Zhu et al. [30] utilized K-means to construct an anti-crime information system to predict potential crime hazards. Deng et al. [31] developed a spatiotemporal hotspot-factor model to study the temporal and spatial locations of unusual crime events. Guo et al. [32] used video reconstruction to locate security threats. Zhong et al. [33] developed a security risk assessment system for sporting events using neural networks. Li et al. [34] studied public risk perception and emotion expression during the Covid-19 pandemic to assist in managing public health risks. To normatively organize various multi-source heterogeneous mass event information, Ren et al. [35] extracted event elements from mass event data based on the BiLSTM-CRF model, constructed a mass event knowledge graph reflecting the correlations among the event elements. Based on the comprehensive related research, the framework of social crisis risk management is shown in Fig. 2(c). In this framework, data analysis methods such as knowledge graph are applied to encode crisis data and decode group intention. At the same time, interpretable semantic information in the knowledge graph provides support for risk intention attribution.

Previous research has shown success in solving crisis events within specific fields through various methods. However, social crisis events are complex, encompassing diverse domains. Current methods lack the ability to comprehensively incorporate complex event element clues and multi-source semantic knowledge, leading to a one-sided and incomplete treatment of social crisis-related information processing.

V. Case Study and Analysis: the Covid-19 event

The Covid-19 event is treated as a case to mine sentimental intention of group in social health crisis events. Specifically, the public opinion knowledge graphs are constructed to organize the sentiment information in the crisis event, and the potential group sentimental intention is detected through knowledge inference. The identified sentiment is further explained through the distribution of feature words within corresponding knowledge graphs of different communities. The implementation process of the Covid-19 event consists of three parts: data source, public opinion knowledge graph construction, and group intention analysis.

a) Data source: The data of the Covid-19 incident was obtained by crawling official news media reports from January to July 2020 and from April to August 2021. After preprocessing, a total of 26,192 news samples were collected.

b) Public opinion knowledge graph construction of the Covid-19 event: Firstly, the adjectival words in the corpus reflecting sentiment are extracted using Jieba[1]. Secondly, Word2Vec[2] is used to train the public opinion word vectors. For a public opinion word x, its word vector $\boldsymbol{t_{pow}} \in \mathbb{R}^{dim}$ is

$$\boldsymbol{t_{pow}} = \boldsymbol{W_{em}} \boldsymbol{w_{pow}} \tag{1}$$

where dim is vector dimension, $\boldsymbol{W_{em}}$ is embedding matrix, and $\boldsymbol{w_{pow}}$ denotes the one-hot vector of x. Cosine similarity method is employed to compute inter-word similarity. For two public opinion word vectors $\boldsymbol{t_{pow_1}}$ and $\boldsymbol{t_{pow_2}}$, their similarity is shown below,

$$sim(\boldsymbol{t_{pow_1}}, \boldsymbol{t_{pow_2}}) = \frac{\sum_{i=1}^{dim} t_{pow_1}^i t_{pow_2}^i}{\sqrt{\sum_{i=1}^{dim} t_{pow_1}^i} \sqrt{\sum_{i=1}^{dim} t_{pow_2}^i}} \tag{2}$$

Finally, based on the word vectors and inter-word similarity, the public opinion knowledge graphs are obtained using Gephi[3]. Fig. 3 displays several month-level graphs, each with representative opinion words shown underneath. These opinion words serve as explanation I_{att} for group intention.

c) Group intention analysis of the Covid-19 event: Firstly, Sentiment score of public opinion words being positive or negative is calculated utilizing a Bayesian model:

$$P(pos|x) = \frac{P(x|pos) \cdot P(pos)}{P(x|pos) \cdot P(pos) + P(x|neg) \cdot P(neg)} \tag{3}$$

when $P(pos|x) > 0.5$, the word is positive, otherwise it is negative. Then, the positive and negative sentiment intensity for that month was gained based on the frequency of positive or negative words in the month-level corpus data:

$$s_{pos} = \frac{count(pos)}{count(pos) + count(neg)} \tag{4}$$

[1] https://pypi.org/project/jieba

[2] https://pypi.python.org/pypi/word2vec

[3] https://gephi.org

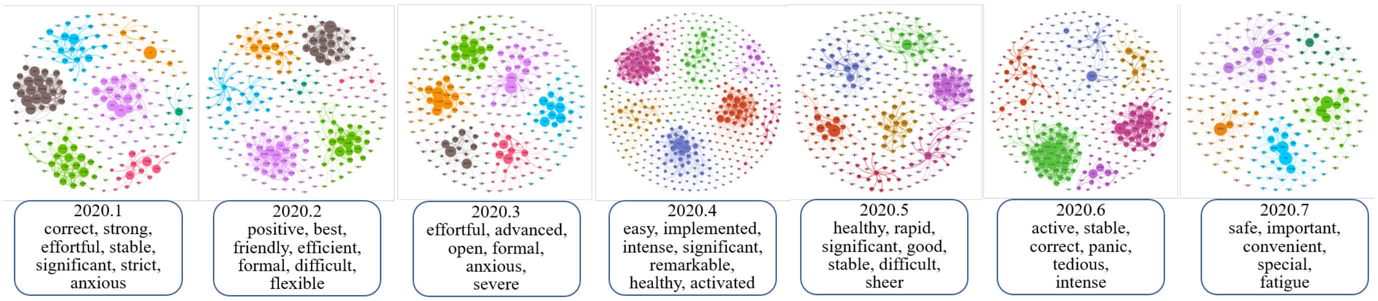

Fig. 3: Sentiment depression intention(2020.1-2020.7)

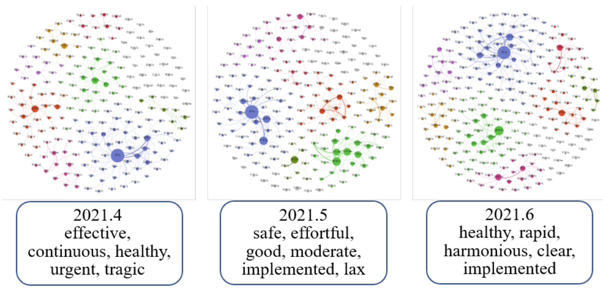

Fig. 4: Sentiment optimism intention(2020.7-2021.6)

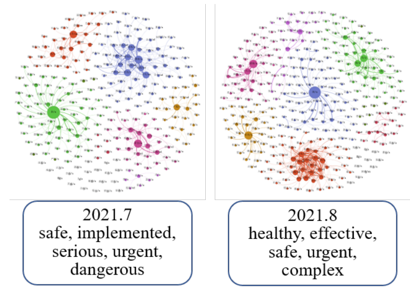

Fig. 5: Sentiment fallback intention(2021.6-2021.8)

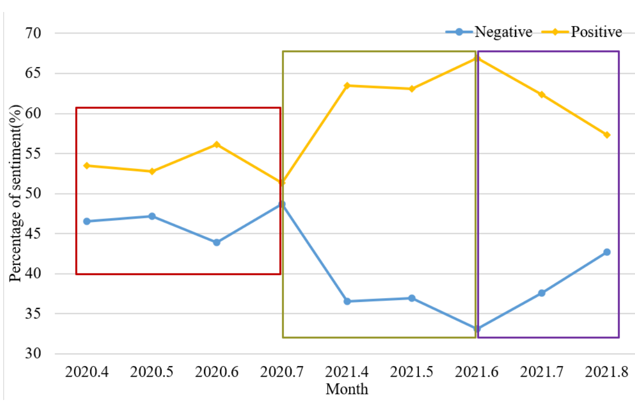

Fig. 6: Sentiment intensity of the Covid-19 event

$$s_{neg} = 1 - s_{pos} \tag{5}$$

where $count(pos)$, $count(neg)$ are the word frequencies of positive and negative words respectively, s_{pos}, s_{neg} are the sentiment intensity of positive and negative feelings respectively. Finally, the sentiment intensity of the Covid-19 event is represented in Fig. 6. It can be observed that group intention I_{det} is classified into three categories: sentiment depression, sentiment optimism, and sentiment fallback intention. The corresponding opinion knowledge graphs for each of these categories are presented in Fig. 3, Fig. 4, Fig. 5, respectively.

Sentiment depression intention(2020.1-2020.7): Covid-19 outbreak caused an increase in pneumonia cases and global fear. Rapid response of the government controlled overall public opinion. Sentiment optimism intention(2020.7-2021.6): effective epidemic prevention measures and good deeds led to peak in positive sentiment intensity. Sentiment fallback intention(2021.6-2021.8): negative sentiment increased due to mutant strain and economic downturn, but still remained below the level of positive sentiment.

In general, through collaborative efforts between governmental authorities and media outlets, the public's outlook on the coronavirus has progressively improved, resulting in a proactive resumption of their daily routines.

VI. Conclusion and Future Research

Group intention mining is a crucial aspect of managing social crises effectively. This paper presents a comprehensive overview of current research on group intention mining, including knowledge graph inference, intention attribution, and risk management. However, current methods still exhibit limitations that require further investigation in the future.

To address the challenge of managing the all-round and multifaceted risk information in social crisis events, crisis knowledge graphs can be constructed based on distributed representation. This involves treating noun semantic clusters as entities and verb semantic clusters as relations, resulting in a crisis knowledge graph that utilizes adaptive synonymous semantic expressions.

To tackle the challenge of identifying comprehensive group intention in social crises with diverse and obscure elements, event information and crisis knowledge graphs are fused to mine potential group intention. Different encoders encode event descriptions, background knowledge, and common sense, followed by an attention-based intention decoder for intention extraction.

To solve the difficulty of tracing the evidence for determining group intention due to the complex action mechanism between crisis elements, the attribution and reflection of group intention are realized based on explainable methods such as knowledge graph. The reverse optimization process of model is designed to maximize the current intention, and reflection method is utilized for intention re-determination.

Social crises endanger the overall well-being and common interests of the entire society. This paper utilizes interpretable knowledge graph and intention mining techniques to analyze the process of group intention mining in social crisis management. It is hoped that our research provides constructive insights for social crisis management agencies.

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