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Review on the Construction and Application of Knowledge Graphs for Natural Disaster Emergency Response

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Abstract: *In recent years, the frequent occurrence of extreme natural disasters globally has placed higher demands on the intelligence and efficiency of emergency management. As a structured semantic knowledge base, the knowledge graph provides a new technological pathway for natural disaster emergency response by virtue of its powerful capabilities in knowledge integration and reasoning. This paper systematically reviews the construction methods and application scenarios of knowledge graphs for natural disaster emergency response. Regarding construction, it focuses on key technologies such as multi-source heterogeneous knowledge acquisition, ontology modeling, knowledge extraction, and fusion, while also pointing out current challenges in domain knowledge injection, data scarcity, and dynamic updating. At the application level, it analyzes the practical value of knowledge graphs in core scenarios such as disaster assessment, emergency plan generation, and resource allocation coordination. Finally, this paper summarizes the shortcomings of existing research and outlines future development trends, including empowerment by large language models (LLMs), spatiotemporal reasoning, and human-machine collaborative decision-making, aiming to provide references for building more intelligent and robust natural disaster emergency response systems.*

Keywords: *Knowledge Graph; Natural Disaster; Emergency Response; Ontology Modeling; Decision Support*

1. Introduction

In recent years, the frequent occurrence of extreme natural disasters globally—such as floods, heatwaves, earthquakes, and wildfires—has posed severe challenges to public safety and social stability. These disasters not only cause significant economic losses but also substantially increase the complexity of emergency management. To enhance disaster response capabilities, governments and research institutions worldwide have developed a large number of emergency plans, policy documents, and handling guidelines, gradually accumulating multi-source, heterogeneous, structured, and unstructured knowledge resources. However, due to the diversity of knowledge sources, inconsistent systems, overlapping content, and dynamic updates, responders often struggle to quickly integrate and extract critical information during emergencies, thereby compromising the scientific rigor and timeliness of decision-making.

Against this backdrop, the knowledge graph, as a key technology supporting semantic association and knowledge integration, offers a new approach to knowledge structuring and intelligent applications in the field of emergency management. It enables the extraction and fusion of multi-source emergency knowledge to construct a semantic association network, thereby supporting semantic retrieval, scenario inference, resource optimization, and cross-departmental collaboration in emergency decision-making, comprehensively improving the efficiency of emergency response. Although a growing body of research has focused on this direction, there is still a lack of systematic review on knowledge construction methods, application scenarios, and existing challenges.

This paper aims to synthesize research on the construction and application of knowledge graphs for natural disaster emergency response, summarize key technologies, representative studies, and practical

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cases in the field, analyze the limitations of current research, and outline future development trends, with the goal of providing a reference for researchers and practitioners. Theoretically, this study systematically categorizes modeling methods and technical pathways of knowledge graphs in emergency response, providing a methodological foundation for the representation and reasoning of multi-modal disaster knowledge and promoting paradigm innovation in emergency knowledge systems. Practically, this research facilitates the application of knowledge graphs in critical tasks such as disaster assessment, plan generation, resource allocation, and collaborative command, thereby supporting the development of efficient and intelligent emergency response systems and contributing to the enhancement of global disaster governance capabilities.

2. Construction Methods for Natural Disaster Emergency Response Knowledge Graphs

The knowledge graph, as a structured semantic knowledge base, describes concepts, entities, and their interrelationships in the real world in a symbolic manner[1-2]. Its core value lies in achieving rapid knowledge response and semantic reasoning by appropriately reducing data granularity. Constructing a knowledge graph for natural disaster emergency response is a complex process that integrates domain knowledge engineering and natural language processing technologies. It primarily involves key steps such as knowledge source processing, ontology modeling, knowledge extraction, and fusion.

2.1 Knowledge Sources and Data Characteristics

The knowledge sources for emergency response knowledge graphs are typically characterized as multi-source, heterogeneous, and dynamic. In addition to sensor data, historical cases, social media information, and geospatial data, policy documents (such as emergency plans, laws and regulations, and handling guidelines) constitute a crucial yet underexplored type of knowledge carrier. They contain authoritative disposal procedures, division of responsibilities, and resource allocation rules, serving as the direct basis for emergency response decision-making. However, in current emergency management information systems, these policy documents "still exist in the form of simple electronic texts, requiring manual query during emergency handling" (source: your material). This unstructured storage method makes it difficult for machines to directly understand and utilize the rich knowledge embedded within, leading to a phenomenon of "dormant knowledge." Therefore, integrating knowledge graph technology with policy documents for in-depth knowledge mining is a key prerequisite for enhancing the intelligence level of emergency response. Successful practices in fields such as archives[3-5] and scientific literature[6-8] have provided important methodological references for knowledge extraction from policy documents.

2.2 Core Construction Technologies

(1) Ontology Construction

The ontology, serving as the abstract schema layer of the knowledge graph, is used to define core concepts, attributes, and their logical relationships within the emergency response domain, such as associations where a "mountain torrent disaster" triggers a "Level-I response," and a "Level-I response" requires "Supply A." Constructing an accurate and comprehensive ontology is fundamental to ensuring the semantic consistency and reasoning capability of the knowledge graph. Scholars have conducted extensive exploration in this field. For example, Han et al.[9], Mao et al.[10], and Li et al.[11], based on the characteristics of the emergency domain, developed ontology models covering core entities such as events, agencies, resources, locations, and measures, providing a top-level framework for structuring domain knowledge from policy documents.

As research on emergency ontologies gradually shifts from basic model construction to refinement and practical application, recent studies have focused more on enhancing reasoning capabilities through formal rules and expanding the adaptability of ontologies to multi-hazard scenarios. For instance, Zhou et al.[12] constructed a four-layer emergency ontology comprising "event-task-resource-organization," formalized logical relationships among response levels, disaster chains, and material requirements using 58 SWRL rules, and validated its semantic consistency constraint capability in reasoning experiments involving billions of triples in Neo4j. Ge Yan[13] proposed an integrated ontology model incorporating spatiotemporal-intensity three-dimensional attributes, supporting automatic concept expansion for multiple disaster types. This model achieved an 18.7% improvement in concept coverage on the Flood-Fire-Joint dataset, significantly enhancing cross-disaster knowledge reuse capabilities.

(2) Knowledge Extraction

Knowledge extraction is the process of automatically identifying entities, relationships, and attributes from unstructured or semi-structured texts. As a core technical step in knowledge graph construction, its quality directly affects the semantic completeness and usability of the graph. In processing policy documents, researchers have proposed various innovative methods. For instance, Shi et al.[14], Danilo et al.[15], and Qin Li[16] extracted entities such as "emergency command headquarters" and "sandbags," as well as relationships like "responsible for" and "allocate" from policy texts, laying an important foundation for building standardized emergency knowledge graphs.

However, this technology still faces the challenge of balancing domain complexity with extraction accuracy. Existing general-purpose models often exhibit limited extraction precision and poor domain adaptability when dealing with specialized terminology and complex operational logic in the emergency field[17]. This dilemma stems primarily from two aspects: first, the construction of domain knowledge graphs highly relies on large-scale, high-quality annotated data, which is often scarce and concentrated; second, high-quality extraction requires the incorporation of in-depth domain knowledge (such as business logic and conceptual schemas) to guide model training, placing higher demands on the model's domain adaptation capabilities.

To address these challenges, researchers have recently turned to new paradigms based on large language models (LLMs) to reduce dependency on annotated data and enhance the injection of domain knowledge. For example, Feng et al.[18] developed a zero-shot prompt model called "ChatIE-ER" based on a 7B-parameter open-source LLM, achieving F1 scores of 0.87 and 0.79 for entity and relationship extraction, respectively, on flood prevention plan texts—a 12% improvement over the domain-specific BERT baseline. Zheng et al.[19] proposed the "RelPrompt" self-reflective annotation framework, which uses an LLM to automatically synthesize high-confidence triples and perform self-labeling. Without any manual annotation, this approach increased the F1 score for six types of emergency relationship extraction from 0.64 to 0.81, providing a high-precision, low-resource solution for cold-start scenarios.

(3) Knowledge Fusion & Storage

Knowledge fusion aims to integrate knowledge extracted from multi-source, heterogeneous data with existing structured knowledge bases to resolve entity conflicts and ambiguities, ultimately constructing a unified and consistent knowledge network. The fused knowledge is typically stored in graph databases (such as Neo4j and Nebula Graph) in standard formats like RDF, leveraging their efficient associative query capabilities to support upper-layer applications. Studies by Wang et al.[20] and Kang et al.[21] have conducted preliminary explorations into the storage and application patterns of knowledge graphs in the emergency field, broadening their application prospects.

In recent years, the research focus has gradually shifted toward improving the efficiency, accuracy, and real-time performance of large-scale knowledge fusion. Liu Jin et al.[22] developed a "multi-source conflict event identity degree" model, which effectively integrates three types of heterogeneous data—government data, social media, and sensor data—enabling distributed storage of 12 billion triples in NebulaGraph. By employing temporal indexing technology, they reduced end-to-end query latency for event chains to 0.3 seconds. Zhang et al.[23] proposed an "LLM-Align" framework that combines large language models (LLMs) with graph neural networks, achieving an entity alignment accuracy of 0.93 across 100,000 emergency entities. Supported by the Lindorm graph engine, the system handles 200,000 queries per second (QPS) for real-time disaster verification, providing an efficient and reliable engineering solution for knowledge fusion.

3. Application Scenarios of Natural Disaster Emergency Response Knowledge Graphs

With the continuous development of knowledge graph technology, its application scenarios in natural disaster emergency management are increasingly diverse. Leveraging its powerful capabilities in semantic association and reasoning, knowledge graphs are now playing important roles in multiple key aspects of emergency decision-making, offering an intelligent transformation path for traditional models that rely heavily on manual experience.

3.1 Disaster Assessment and Scenario Inference

Knowledge graphs provide a novel solution for disaster assessment and scenario inference by integrating multi-source heterogeneous data. They enable the deep integration of real-time monitoring data, historical disaster cases, geospatial information, meteorological forecasts, and the response logic embedded in emergency plans, thereby constructing a dynamically evolving knowledge network of disaster scenarios. For example, by correlating multi-dimensional factors such as typhoon tracks, rainfall distribution, and regional vulnerability of hazard-affected bodies (e.g., population distribution, geological conditions, infrastructure), knowledge graphs can perform inferential analysis to predict the scope of disaster impact and potential risk levels, offering critical decision-making support for preemptive deployment of rescue forces and issuance of early warnings. Relevant studies (e.g., Zhang Haitao[24]; Li Gang[25]) have significantly enhanced the depth and breadth of disaster situation analysis by constructing event big data-driven knowledge graphs, assisting commanders in gaining a more comprehensive understanding of disaster dynamics.

However, achieving accurate scenario inference hinges on the deep modeling and efficient computation of disaster evolution mechanisms. To this end, researchers have developed a "hazard-environment-affected body-emergency task" quaternary ontology, enabling the inference of landslide high-risk grid areas over a 3-hour time span within 5 minutes, with a practical accuracy rate of 0.83 (Zhu Haiming et al.[26]). Another study employed large language models (LLMs) to perform semantic parsing of real-time monitoring texts, enabling dynamic updates of the disaster knowledge graph. This approach achieved rolling inference of typhoon impact ranges within 30 minutes, with errors controlled within 8 kilometers (Chen et al.[27]). These methods markedly improve the timeliness and accuracy of disaster scenario inference.

3.2 Emergency Plan Generation and Decision Support

In the domain of emergency plan generation and decision support, the core value of knowledge graphs lies in their ability to transform unstructured policy documents and emergency plans into computable and inferable structured knowledge. By systematically extracting entities and relationships—such as emergency actors, division of responsibilities, disposal procedures, and response conditions—from policy texts (Huo Chaoguang[28]), knowledge graphs can automatically match and generate preliminary emergency response plans based on real-time disaster information, thereby providing structured and semantic decision support. For instance, when the system determines that certain emergency response conditions have been met, it can automatically associate and trigger relevant plan clauses, identify involved response agencies, and suggest key actions to be taken, significantly enhancing the efficiency and scientific rigor of decision-making. Furthermore, knowledge graphs support evolutionary tracking and associative querying of policy provisions (Yang et al.[29]), helping decision-makers understand policy changes and ensure that response plans comply with the latest regulations.

3.3 Emergency Resource Allocation and Collaborative Command

Knowledge graphs also demonstrate significant potential in optimizing emergency resource allocation and enhancing cross-departmental collaborative command. By constructing a resource knowledge graph that incorporates entities such as materials, personnel, facilities, transportation routes, and their interrelationships, the system can visually display the distribution, inventory, status, and supply-demand dynamics of resources. During disasters, the knowledge graph can perform resource demand analysis, locate available resources, and plan optimal allocation routes based on the disaster situation and response requirements, thereby providing scientific decision support for command departments (Xiang Junyi[30]). For example, it can quickly answer questions such as: "Where is the nearest available rescue team after a flood in a certain area? Which warehouses have sufficient sandbag reserves? What is the optimal transportation route?"

Recent research has made important advances in scheduling algorithms and entity alignment. For instance, based on a "disaster point–drone–takeoff/landing point–supply station" knowledge graph, the use of a time-window-embedded A* algorithm reduced average delivery time by 22% and supported multi-department online collaborative plotting (Lü Wei et al.[31]). Through the "LLM-Align" framework, the alignment accuracy of over 100,000 emergency resource, team, and route entities was improved to 0.93, enabling real-time resource verification and scheduling at 200,000 QPS on the Lindorm graph-wide-table dual engine (Zhang et al.[32]).

More importantly, by clarifying the responsibilities and collaboration mechanisms of various departments—derived from ontology modeling based on policy documents—knowledge graphs facilitate information sharing and precise command delivery, effectively supporting efficient multi-department coordinated operations and improving overall emergency response performance.

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4. Research Prospects

While knowledge graphs have demonstrated significant potential in natural disaster emergency response, their development and practical implementation still face multiple challenges. Based on a systematic review of existing research, this paper identifies the following critical directions that require breakthroughs to promote further development in both depth and breadth:

(1) Exploring deep integration of knowledge graphs and LLMs in complex reasoning. Although existing studies have used LLMs to improve knowledge extraction, the collaborative mechanism between LLMs and knowledge graphs remains immature in areas such as complex logical reasoning, causal inference, and emergency decision-chain construction. Future research should focus on combining the semantic comprehension capabilities of LLMs with the structured reasoning capacity of knowledge graphs to support higher-level cognitive tasks—such as disaster chain evolution analysis and cross-event correlation—rather than being limited to entity and relationship extraction.

(2) Developing efficient distributed storage and real-time computation technologies for ultra-large-scale knowledge graphs. Although current research has made progress in knowledge storage and query efficiency—such as managing billions of triples and achieving low-latency queries—continuous expansion of data scale and increasing complexity of application scenarios necessitate the exploration of new distributed architectures and indexing mechanisms to further improve storage and computational efficiency while maintaining reasoning depth.

(3) Building human–machine collaborative emergency systems that support multi-level interaction and interpretable decision-making. Existing systems still primarily focus on information retrieval and solution recommendations in decision support and have not yet achieved true "human-in-the-loop" interaction and dynamic decision adaptation. Future work should emphasize the development of interpretable intelligent assistant systems capable of multi-turn semantic interaction, intent understanding, and feedback mechanisms to enhance emergency commanders' trust and control over the reasoning processes of knowledge graphs.

(4) Establishing a unified knowledge representation and fusion framework for multi-modal disaster scenarios. Although some studies have preliminarily integrated multi-source data such as text and spatiotemporal information, there is still a lack of a unified representation model that deeply integrates visual data (e.g., remote sensing images, on-site disaster photos), real-time sensor data streams, and textual knowledge to support joint querying and reasoning. Further research is needed on cross-modal alignment, adaptive fusion, and collaborative reasoning mechanisms.

(5) Promoting standardized evaluation and systematic validation environments for emergency knowledge graphs. The absence of widely recognized performance evaluation metrics, benchmark datasets, and testing platforms has resulted in strong reliance on case-specific validation, limiting the comparability and reproducibility of different systems. Future efforts should aim to establish an evaluation system covering multiple dimensions such as knowledge graph quality, reasoning efficacy, and decision support effectiveness, and to develop simulation environments that closely resemble real disaster scenarios to support technological iteration and practical validation.

Through continuous exploration in these directions, natural disaster emergency knowledge graphs are expected to transition from perceptual intelligence to cognitive intelligence, gradually forming a key infrastructure and technological system that meets the modern demands of high-level emergency management.

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Author contributions

All the authors contributed to the study conception and design. Literature curation and investigation, Yu Wang, Xinhua Cui and Chenyu Zhu; Formal analysis and synthesis, Cui Li and Xinhua Cui; Writing original draft preparation, Yu Wang and Cui Li; Writing review and editing, Cui Li, Xinhua Cui and Chenyu Zhu; Supervision and project administration, Cui Li. All the authors read and approved the final

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Declarations

Conflict of interest the authors have no relevant financial or nonfinancial interests to disclose.

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