

DFBI 2026 aims to encourage the international exchange of innovative ideas between researchers from academia and industry. In addition to knowledge dissemination, the conference offers a valuable platform for professional networking, particularly benefiting university professors, graduate students, and postdoctoral researchers.

Research Article

Event Logic Graph Augmented Large Language Models for Fall Accident Risk Reasoning

Qiuyu Jin¹, Feng Xu¹, Yongshuang Li¹, Zhipeng Zhang¹

1. School of Ocean and Civil Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

Correspondence: F.Xu@sjtu.edu.cn

Copyright: Copyright: © 2026 by the authors. ISSN: 2979-1677

DFBI is an open-access proceedings distributed under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0). View this license's legal deed at <https://creativecommons.org/licenses/by/4.0/>



Abstract

Falls represent the most prevalent type of construction accident, emphasizing the critical importance of implementing effective risk management strategies. The advent of large language models (LLMs) has introduced novel perspectives to address this challenge. This paper presents an original methodology for enabling risk reasoning in fall accidents through the utilization of an event logic graph (ELG) to enhance LLMs. First, event relations and elements are extracted from accident reports to construct an ELG using semantic matching and deep learning techniques. Second, actual events are mapped to the ELG by applying a text similarity method. Then, accident casualties and corresponding medical procedures are identified to calculate loss values and risk metrics for fall accidents. Ultimately, the ELG augmented Qwen3-Max model is employed to generate risk assessments and operational recommendations based on relevant safety regulation provisions. This approach is validated through a real case. Results demonstrate that it effectively supports risk analysis and provides practical preventive recommendations for fall accidents.

Keywords: event logic graph; large language model; knowledge augmented generation; fall accident; construction safety management

Highlights

- Constructed an event logic graph (ELG) based on real fall accident reports.
- Leveraged ELG knowledge to augment the generation and reasoning of large language models (LLMs).
- Provided reliable risk assessments and operational recommendations for fall prevention and construction safety.

Cite this article:

Jin, Q., Xu, F., Li, Y., & Zhang, Z. (2026). Event logic graph augmented large language models for fall accident risk reasoning. *Proceedings of Digital Frontiers in Buildings and Infrastructure International Conference Series, Volume 2026*, 26337. <https://doi.org/10.66408/dfbi.2026.26337>

1 Introduction

Falls are the most prevalent safety accidents in construction and often result in severe casualties and substantial economic losses. Implementing effective risk analysis measures is therefore essential for preventing fall accidents and maintaining safe production.

Accident reports and safety regulations constitute important data sources for construction safety management. The former provides detailed records of accident development processes, while the latter specifies safety guidelines for construction activities. These data sources assist managers in assessing accident risks and implementing appropriate preventive measures. However, such data is typically documented in natural language text, presenting challenges of scattered, unstructured, and non-visual nature.

The advent of Large Language Models (LLMs) offers new insights for addressing these limitations. LLMs are language models with massive parameters and excellent learning capabilities, capable of processing, understanding, and generating natural language text. They have demonstrated outstanding performance in tasks such as document understanding and knowledge reasoning. Leveraging LLMs to interpret accident reports and safety regulations can provide intelligent support for management decisions regarding fall accidents.

Nevertheless, general-purpose LLMs struggle with highly specialized tasks that require domain expertise. Their training data has insufficient coverage of construction safety fields, lacking a deep understanding of professional knowledge such as safety regulations, causation theories, and accident mechanisms. On the other hand, general-purpose LLMs lack rule-based constraints and exhibit hallucination problems, which compromise the accuracy and reliability of generated content. When facing occupational safety and accident prevention, general-purpose LLMs cannot directly handle tasks requiring high reliability, and similarly need professional knowledge to constrain their generated content.

Event Logic Graph (ELG) is a structured event knowledge base that employs nodes to represent events, edges to represent event relations, and edge annotations to represent transition likelihoods, facilitating the visualization of logical relationships and evolutionary patterns between events (Ding et al., 2019). Extracting event knowledge from fall accident reports and constructing an ELG provides the benefits of centralized, structured, and visual knowledge. ELGs address the weakness of traditional accident reports in text format and help users analyze potential risks and evolutionary processes of fall accidents.

In summary, to address the aforementioned limitations, this paper combines ELG with LLM technology to present a risk reasoning approach for fall accidents. This approach specifically involves:

First, event relations and event elements are extracted from fall accident reports to construct an ELG based on semantic matching and deep learning techniques. Second, a text similarity method is employed to map actual construction site events to the ELG. Corresponding Casualties event elements and relevant medical procedures are identified to calculate the loss values and risk values of fall accidents. Finally, LLMs are used to match applicable safety regulation clauses. On this basis, pertinent content from ELGs, accident risks, and safety regulations is utilized as external knowledge bases to enhance LLM content generation. This process outputs fall accident risks according to actual construction site events and provides support for on-site safety management.

The proposed fall risk reasoning approach using ELG augmented LLMs represents event knowledge in accident reports through structured graph formats and leverages the exceptional language capabilities of LLMs to interpret event knowledge and safety regulations. Fall risk reasoning content generated by LLMs is therefore enhanced, and simultaneously, ELGs also serve as constraint rules to avoid hallucination issues. This approach combines the advantages of ELGs and LLMs, providing a new solution for fall accident risk management.

2 Related Works

2.1 Event Logic Graph Methods in Accident Analysis

Traditional analysis based on accident reports requires manual efforts to understand the unstructured management knowledge involved. Structured and visualized ELGs built upon authentic historical data addressed this limitation of manual analysis and have attracted extensive attention.

Shi (2022) targeted construction safety accidents and used deep learning methods to extract event knowledge from accident reports. An event logic graph was thus constructed and integrated with computer vision technology to further estimate the accident risk at construction sites. Ma et al. (2024) developed an event graph based on ship collision reports, and analyzed the contribution degree of different causes and accident conduction paths in ship collision accidents. Xu (2024) proposed an accident analysis framework combining case reasoning with an event logic graph. By constructing event logical structures and leveraging disaster chains, this framework enhanced the identification, understanding, and handling of sudden fire accident events. Zou et al. (2024) designed a multilayer knowledge graph architecture consisting of an event knowledge layer, object-state layer, attribute layer, and relationship layer, and employed the constructed knowledge graph in the evolutionary analysis of urban rainstorm disasters. N. Chen et al. (2025) created an industrial explosion accident-emergency ontology grounded in event ontology, which facilitated the construction of an eventic graph. This eventic graph enabled the development of a question answering system and provided emergency decision support for industrial explosion accidents.

Nonetheless, existing ELGs still demand specialized knowledge and expertise to interpret their internal event knowledge. To employ ELGs in construction management decision support, researchers have utilized natural language processing (NLP) techniques to extract semantic information from ELGs and implemented information retrieval and question answering systems. While LLMs have demonstrated superior performance in both information retrieval and question answering tasks, this paper therefore proposes an integrated approach that combines ELGs with LLMs to further enhance their application in construction accident analysis and decision support.

2.2 Large Language Model Applications in Construction Risk Management

In light of the advancement in artificial intelligence, LLMs have been widely utilized in construction risk management because of their versatility in handling diverse risk assessment tasks and providing intelligent decision support.

Aladağ (2023) decomposed risk management into multiple subtasks and investigated ChatGPT's performance on different subtasks. According to expert assessments, ChatGPT showed limited effectiveness in risk identification yet demonstrated considerable strength in risk response. Wong et al. (2024) focused on the contract review process in construction projects and proposed an approach of identifying construction contract risks by LLMs. Specifically, LLMs' capabilities were enhanced with expert knowledge about construction contracts, and results demonstrated their solid performance. Zhang and Ge (2025) introduced a prompt-based LLM chatbot agent for defining and analyzing Off-Site Construction risk factors. This agent achieved a 99.95% accuracy rate in risk definition queries and an 88.6% accuracy rate in analysing risk factors from interview transcripts, which effectively assisted users in risk management without requiring extensive expert experience. Oral et al. (2025) conducted a comparative study involving 10 domain experts and ChatGPT, tasking both groups with risk assessment across 12 work items. Using a modified Manhattan distance metric for quantitative comparison, their findings revealed that the LLM demonstrated performance similar to human experts in both risk scoring and precaution selection. G. Chen et al. (2026) presented a Change to Mitigate framework leveraging large language models. In their framework, LLMs were employed to refine the classification of risk categories and provide tailored management strategies in transportation projects.

In conclusion, while substantial research has explored LLM applications in construction risk management, studies specifically focusing on safety risk management remain relatively limited. Besides, general LLMs often struggle with highly specialized risk management tasks due to domain knowledge limitations and inherent hallucination issues when operating without appropriate constraints. As a result, external knowledge augmentation has emerged as a promising research direction. Thus, this paper presents a novel approach that leverages ELGs to augment LLMs through two key mechanisms: knowledge enrichment with safety domain knowledge and hallucination reduction through grounded reasoning, thereby enhancing their application in construction safety risk management.

3 Event Logic Graph Construction

Event logic graph (ELG) construction forms the foundation of the proposed fall accident risk reasoning approach. This paper collected 75,654 occupational injury reports from 2015 to 2024 published by the U.S. Occupational Safety and Health Administration (OSHA, 2024). Furthermore, 2,174 fall accident reports in the construction industry were selected as the data source for subsequent work. Building upon the graph construction methodology proposed by Li et al. (2024), the ELG was constructed following the steps of event definition, event extraction, likelihood calculation, and graph generation.

3.1 Event Definition

An event definition targeted at fall accidents is introduced, which includes two key components: event element and event relation. Referring to the event element definitions proposed in ACE2005 (Walker et al., 2006), this paper uses seven categories of event elements for the structured representation of events in fall accidents, as shown in Equation (1). These event elements are represented as distinct nodes in the ELG.

$$I = [E_1; E_2; E_3; E_4; E_5; E_6; E_7] \quad (1)$$

In Equation (1), let I denote one of the events in the evolution of a fall accident. Let $E_1, E_2, E_3, E_4, E_5, E_6, E_7$ denote the Subject, Predicate, Object, Time, Location, Fall Height, and Casualties of event I , respectively.

In addition, the abstract semantic relationships between events are classified into four categories, namely, four types of event relations: Sequential, Causal, Contrast, and Coreferential. These are denoted as different edges in the ELG.

3.2 Event Extraction

The semantic matching and deep learning methods are integrated in this paper in order to extract four categories of event relations and seven categories of event elements from the unstructured accident report texts, according to the aforementioned event definition.

First, based on the 28 key phrases shown in Table I, the event relations within the report texts were identified. Regular expression patterns were then applied to match the text segments surrounding these event relations, converting the report texts into a list formatted as “text segment, event relation, text segment”.

Table I. Key phrases and regular expression patterns for event relation extraction.

Relation	Key phrase	Regular expression pattern
Sequential	afterwards, eventually, later, next, subsequently, then	$r'(?p<before>)\{kp\}s+(?p<after>)'$
	after, following, when, while	$r'(?p<after>)\{kp\}s+(?p<before>)'$
Causal	allowing, as a result, causing, resulted in, resulting in, so, so that	$r'(?p<cause>)\{kp\}s+(?p<result>)'$
	because, because of, due to, for, in an effort to, in order to	$r'(?p<result>)\{kp\}s+(?p<cause>)'$
Contrast	but, however, yet	$r'(?p<part>)\{kp\}s+(?p<counter>)'$
	even though, though	$r'(?p<counter>)\{kp\}s+(?p<part>)'$

Second, 500 entries were randomly selected from the 2,174 items, and event elements within the text segments were labelled to create a training dataset. The BERT-base-NER pre-trained model was adopted as the base model, with Cross Entropy Loss specified as the loss function and AdamW as the optimizer. Through a semi-supervised learning approach, the model was fine-tuned on the training dataset.

After 7 epochs of iteration, the converged Modified-BERT-NER model was obtained, achieving weighted averages of Precision=0.907, Recall=0.906, and F1 Score=0.905. The model's performance evaluation is visualized in Figure 1: (a) shows the F1 Score – Epoch curve; (b) shows the F1 Score per element category. As a result, a total of 9,487 event relations, 11,671 events, and 33,985 event elements were extracted from the 2,174 accident reports.

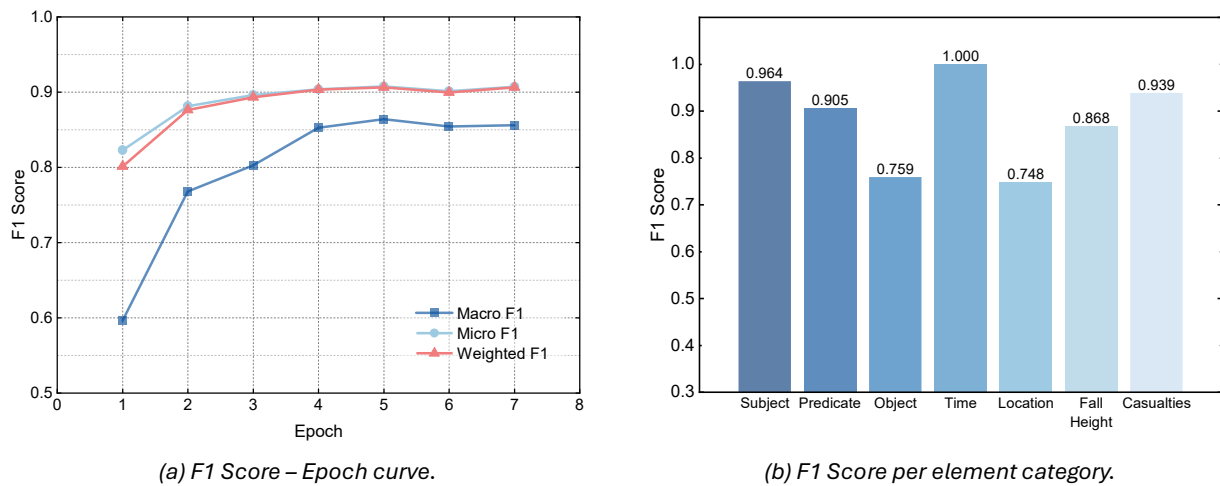


Figure 1. Performance evaluation of the fine-tuned Modified-BERT-NER model.

3.3 Likelihood Computation

Completing the extraction of event relations and event elements, based on Bayes' Theorem, this paper used transition likelihood $P_{1 \rightarrow 2}$ to represent the confidence level of an event relation. The specific values were calculated by counting event occurrence frequencies, as shown in Equation (2).

$$P_{1 \rightarrow 2} = P(I_2 | I_1) = \frac{P(I_1, I_2)}{P(I_1)} = \frac{N_{1,2}}{N_1} \quad (2)$$

In Equation (2), let $P(I_2 | I_1)$ denote the likelihood of I_2 occurring given that I_1 has occurred. Let $P(I_1, I_2)$ denote the likelihood of I_1 and I_2 occurring simultaneously. Let $P(I_1)$ denote the likelihood of I_1 occurring. Let $N_{1,2}$ denote the frequency of I_1 and I_2 occurring simultaneously. Let N_1 denote the frequency of I_1 occurring.

3.4 Graph Generation

Following the storage of event relations, event elements, and transition likelihoods in CSV files, the Import Model function in the Neo4j graph database platform was utilized to generate the ELG for fall accidents. Events and event elements were therefore represented as nodes, event relations as edges, and transition likelihoods were annotated on the corresponding edges. Figure 2 shows a partial view of the constructed ELG.

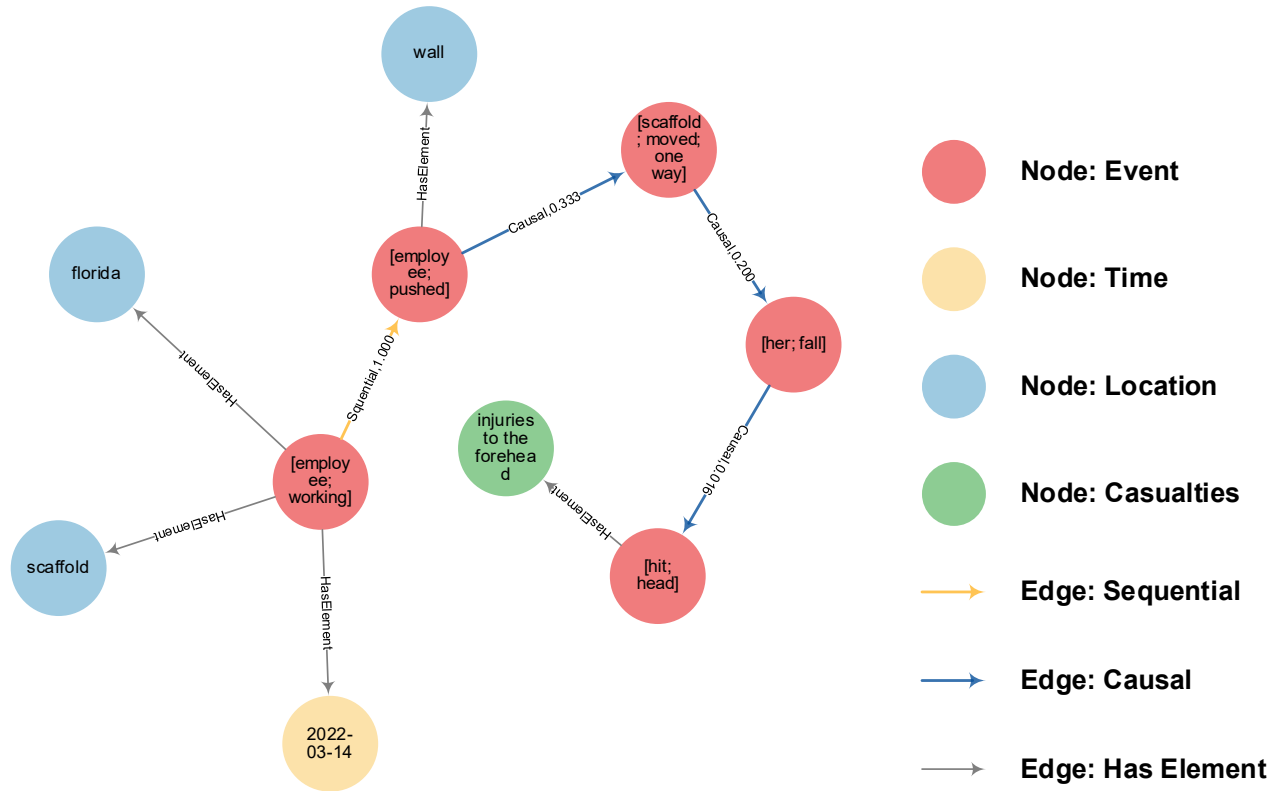


Figure 2. Partial view of the event logic graph.

4 Event Mapping and Risk Reasoning

Upon completion of the ELG construction, a text similarity method was employed to map actual construction site events to the ELG. Using the event knowledge within the graph, potential paths and risk levels of fall accidents at the construction site were thus predicted.

In the text similarity method, a pre-trained model first converted natural language events into numerical embeddings that captured the semantic information in a vector space. Specifically, this paper employed the text-embedding-v4 model, which is trained on the Qwen3 large language model, to transform text events into vectors encoding semantic features, as presented in Equation (3).

$$\mathbf{v} = \text{Embedding}(I) = \text{Embedding}[E_1; E_2; E_3; E_4; E_5; E_6; E_7] \quad (3)$$

In Equation (3), let $\mathbf{v}$ denote the embedding vector of event I . Let $E_1; E_2; E_3; E_4; E_5; E_6; E_7$ denote the seven elements of event I .

Cosine similarity metrics were utilized to quantify the relatedness between different events. Specifically, the similarity between the actual event I_1 and each event I_i in the constructed ELG was calculated according to Equation (4). Events with higher similarity scores were considered semantically closer. Through setting an appropriate similarity threshold, the most relevant event pairs were identified and retained, facilitating the faithful representation of actual construction site conditions within the ELG.

$$S = \frac{\mathbf{v}_1 \cdot \mathbf{v}_i}{\|\mathbf{v}_1\|_2 \cdot \|\mathbf{v}_i\|_2} \quad (4)$$

In Equation (4), let $\mathbf{v}_1$ denote the embedding vector of actual event I_1 . Let $\mathbf{v}_i$ denote the embedding vector of each event I_i in the constructed ELG. Let $\|\mathbf{v}_1\|_2, \|\mathbf{v}_i\|_2$ denote the Euclidean norms of $\mathbf{v}_1, \mathbf{v}_i$.

The event [Employee; is installing pipes; roof] was taken as an example to further illustrate the event mapping process. The similarity threshold was set to 0.8, and the graph mapping results are shown in Table II.

Table II. Event similarity scores for the selected actual event.

ID	Event	Similarity
2597	[employee; installing; pipes]	0.8539
3304	[employee; performing; roof]	0.8379
2962	[employee; installing; drip edge; roof eave]	0.8284
3540	[employee; installing; roofing material; flat roof; 7-8 feet]	0.8158
1106	[install; pipe]	0.8064
550	[employee; installing; ridge cap roof]	0.8036

This paper introduced the accident loss values based on casualties caused by fall accidents. Specifically, the number and severity of casualties resulting from fall accidents were determined using the Casualties event elements stored in the ELG. According to the medical procedure cost list provided by the Orthopaedic Surgery Center, the large language model Qwen3-Max was employed to identify appropriate medical procedures for different casualty scenarios. Then the total cost of these procedures was adopted as the loss values for fall accidents.

Within the constructed ELG, the six events shown in Table II corresponded to eight event chains, representing eight evolution paths leading to fall accidents. Accident loss values for these eight event chains were calculated with the aforementioned method. Combined with the transition likelihoods of event relations in these chains, the fall accident risk value for the [Employee; is installing pipes; roof] event was derived using Equation (5). Table III shows the top five fall accident evolution paths with the highest risk values, along with their accident loss values and risk values.

$$R = \prod_i P_i \cdot L \quad (5)$$

In Equation (5), let R denote the risk value of the event chain. Let P_i denote the transition likelihood of each event relation in the event chain. Let L denote the loss value of the event chain.

Table III. Top five fall accident evolution paths ranked by risk value.

ID	Accident evolution path	Likelihood	Loss	Risk
1205	[employee; performing; roof]→[wind; blown; insulation; edge]→[he; retrieve; insulation]→[it; caught; wind]→[he; pulled off; roof]→[falling; ground; 30 feet]→[he; hospitalized; fractures to his wrists, two broken fingers, cracked disks in his spinal column]	0.0208	5324	110.92
2131	[employee; working; 25/5/2022 9:00 am]→[they; unloading; shingles; roof]→[employees; utilizing; crane]→[employee; installing; ridge cap roof]→[foot; slipped]→[employee; slid; roof; 10 feet]→[employee; suffered; a fractured T12 vertebra, a fractured left heel, and a spinal cord injury]	0.0033	13327	43.84
1320	[employee; installing; roofing material; flat roof; 7-8 feet]→[he; stepped; board]→[lost; balance]→[falling; concrete patio; 8 feet; fracturing his left elbow]→[he; hospitalized]	0.0051	6930	35.00
906	[employee; installing; pipes]→[descending; ladder]→[it; gave way]→[him; fall; ground]	0.0133	2222	29.63
322	[employee; climbing; ladder]→[install; pipe]→[hand; slipped; ladder rung]→[him; fall; second floor; 6-8 feet; fracturing his left arm and breaking three ribs]	0.0028	9152	26.07

5 EEG Knowledge Augmented LLM Generation

After the above graph mapping and risk reasoning steps, this paper implemented the API of the Qwen3-Max model based on the OpenAI framework to achieve the augmented generation of LLMs with an ELG. The generation content aims to provide preventive measures for fall accidents and enhance safety at construction sites.

In the process of knowledge augmented generation, this paper refers to two regulations and standards: the *Occupational Safety and Health Standards* and the *Safety and Health Regulations for Construction*. Original documents were retrieved from the U.S. National Archives and Records Administration (NARA,

2025) database, specifically under Title 29 Labor, Subtitle B Regulations Relating to Labor, Chapter XVII Occupational Safety and Health Administration, Department of Labor.

Subsequently, the role of the LLM was defined as: “You are a construction accident investigation expert with extensive knowledge of construction safety.” Key information was stored in TXT file format, encompassing construction conditions, actual events, safety regulations, event chains, and accident risks derived from the ELG. This TXT file was read as embedded knowledge for Qwen3-Max, enabling the LLM to automatically generate safety recommendations for fall accidents following a fixed template as follows:

Event Background

At a construction site, an employee was involved in the installation of pipes on the roof. Recent incident data analysis from an event logic graph highlights recurring fall hazards associated with roof work, particularly during material handling, ladder use, and balance loss on unstable surfaces.

Risk Assessment

Based on the event logic graph, the following high-risk fall scenarios and corresponding risk scores have been identified:

- [employee; performing; roof]→[wind; blown; insulation; edge]→[he; retrieve; insulation]→[it; caught; wind]→[he; pulled off; roof]→[falling; ground; 30 feet]→[he; hospitalized; fractures to his wrists, two broken fingers, cracked disks in his spinal column] | **Risk Score: 110.92**
- [employee; working; 25/5/2022 9:00 am]→[they; unloading; shingles; roof]→[employees; utilizing; crane]→[employee; installing; ridge cap roof]→[foot; slipped]→[employee; slid; roof; 10 feet]→[employee; suffered; a fractured T12 vertebra, a fractured left heel, and a spinal cord injury] | **Risk Score: 43.84**
- [employee; installing; roofing material; flat roof; 7-8 feet]→[he; stepped; board]→[lost; balance]→[falling; concrete patio; 8 feet; fracturing his left elbow]→[he; hospitalized] | **Risk Score: 35.00**
- [employee; installing; pipes]→[descending; ladder]→[it; gave way]→[him; fall; ground] | **Risk Score: 29.63**
- [employee; climbing; ladder]→[install; pipe]→[hand; slipped; ladder rung]→[him; fall; second floor; 6-8 feet; fracturing his left arm and breaking three ribs] | **Risk Score: 26.07**

Operational Recommendations

According to regulations, *Occupational Safety and Health Administration, Department of Labor §1926.25(a), §1926.501(b), §1926.502(d), §1926.502(j), §1926.1053(b)*, the following preventive measures and operational recommendations have been formulated in response to the identified risks:

- Require the use of a personal fall arrest system, guardrail system, or safety net system for all employees working on any roof or elevated surface with an unprotected edge that is 6 feet (1.8 m) or more above a lower level, including during emergency roof repairs or retrieval of materials near the edge.
- When using personal fall arrest systems, ensure anchorages are independent of material-handling equipment (e.g., crane-mounted boom trucks), capable of supporting at least 5,000 pounds per employee, and installed under the supervision of a qualified person; also ensure systems limit free fall to no more than 6 feet and prevent contact with lower levels.
- Secure all portable ladders at the top to a rigid support or equip them with a grasping device (e.g., grabrail) when used for access to a roof or elevated surface, and ensure side rails extend at least 3 feet above the landing surface; additionally, inspect ladders before each use and immediately remove from service any ladder with structural defects such as cracked rails, missing rungs, or instability.

- Prohibit employees from carrying tools, materials, or objects (including insulation boards or shingles) while ascending or descending ladders if doing so compromises balance or requires both hands off the ladder; require use of tool belts, hoisting equipment, or alternative material-handling methods.
- Implement daily housekeeping protocols to remove loose debris, unsecured materials (e.g., blown insulation), and tripping hazards from all roof and elevated work areas, particularly within 6 feet of unprotected edges.

6 Conclusions

Based on accident reports and safety regulations, this paper focused on construction fall accidents, developed an ELG, and proposed an ELG augmented LLM generation approach for fall accident risk reasoning. The main contributions are as follows:

- Event relations were extracted from accident reports by integrating key phrases and regular expression patterns. A Modified-BERT-NER model was then obtained through fine-tuning to extract event elements, thereby converting event knowledge into a structured and visual ELG.
- The text-embedding-v4 model trained on Qwen3, was utilized to generate event embedding vectors. A text similarity method was then applied to map actual construction events to the ELG. In addition, accident losses were identified based on Casualties event elements and corresponding medical procedure costs. Losses were subsequently integrated with event relation transition likelihoods to calculate risk values for different accident evolution paths within the ELG.
- The ELG, accident risks, and safety regulations were embedded as external knowledge to the Qwen3-Max large language model, enhancing the generation of risk assessments for construction fall accidents. Besides, operational recommendations for accident prevention were provided based on relevant safety regulation content.

The proposed method in this paper transforms scattered and unstructured event knowledge in accident reports into a visual graph structure, namely the ELG. This ELG is then input as external knowledge to LLMs, leveraging their powerful knowledge understanding and content generation capabilities to perform reliable risk reasoning and strategy recommendations for fall accidents. While avoiding the hallucination problem of LLMs, this method also provides credible support for highly specialized tasks such as effective risk management of construction fall accidents. However, this paper still has the following limitations and potential improvements:

- This paper constructed an ELG specifically for falls, and the subsequent work was also based on this foundation. Therefore, the risk reasoning capability and adaptability for other accident types are relatively restricted.
- Due to prompt length limitations of LLMs, only core chapters were considered when matching relevant safety regulation clauses. Future research can further expand the external knowledge base of LLMs.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- Aladağ, H. (2023). Assessing the Accuracy of ChatGPT Use for Risk Management in Construction Projects. *Sustainability*, 15(22), 16071. <https://doi.org/10.3390/su152216071>
- Chen, G., Jaselskis, E. J., Tamer, A., & Folz, A. (2026). Using an LLM-Powered Framework for Automatic Risk Identification and Mitigation from Past Claims and Supplemental Agreements. *Journal of Computing in Civil Engineering*, 40(2), 04025151. <https://doi.org/10.1061/JCCEE5.CPENG-6754>
- Chen, N., Du, P., Liu, T., & Li, P. (2025). Construction and application of an industrial explosion eventic graph for emergency decision support. *Geomatics, Natural Hazards and Risk*. <https://www.tandfonline.com/doi/abs/10.1080/19475705.2025.2598667>
- Ding, X., Li, Z., Liu, T., & Liao, K. (2019). *ELG: An Event Logic Graph* (No. arXiv:1907.08015). arXiv. <http://arxiv.org/abs/1907.08015>
- Li, Y., Xu, F., Zhang, Z., & Mei, X. (2024). *Construction Behavior Safety Risk Identification Based on Knowledge Graph and Large Language Model*. Computing in Civil Engineering 2024.
- Ma, J., Wang, Y., Wang, L., Xu, L., & Zhao, J. (2024). Construction of Event Graph for Ship Collision Accident Analysis to Improve Maritime Traffic Safety. *Complexity*, 2024. <https://doi.org/10.1155/2024/4998195>
- NARA. (2025). 29 CFR Chapter XVII, Occupational Safety and Health Administration, Department of Labor. <https://www.ecfr.gov/current/title-29/subtitle-B/chapter-XVII>
- Oral, M., Alboga, Ö., Aydınli, S., & Erdis, E. (2025). Usability of large language models for building construction safety risk assessment. *Engineering, Construction and Architectural Management*. <https://doi.org/10.1108/ECAM-08-2024-1143>
- OSHA. (2024). *Occupational Safety and Health Administration Inspection Data*. <https://www.osha.gov/data#inspections>
- Shi R. (2022). *Identification of Construction Safety Risks Based on Event Logic Graph and Image Semantics* [Master Dissertation, Dalian University of Technology]. <https://doi.org/10.26991/d.cnki.gdllu.2021.000149>
- Walker, C., Strassel, S., Medero, J., & Maeda, K. (2006). *ACE 2005 Multilingual Training Corpus* (p. 1572864 KB) [Dataset]. Linguistic Data Consortium. <https://doi.org/10.35111/MWXC-VH88>
- Wong, S., Zheng, C., Su, X., & Tang, Y. (2024). Construction contract risk identification based on knowledge-augmented language models. *Computers in Industry*, 157–158, 104082. <https://doi.org/10.1016/j.compind.2024.104082>
- Xu, K. (2024). Pathway and Empirical Study of Fire Accident Intelligence Support Based on Case Reasoning and Event Logic Graph. *2024 20th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*, 1–6. <https://doi.org/10.1109/ICNC-FSKD64080.2024.10702290>
- Zhang, L., & Ge, Q. (2025). Offsite construction risk management agent – a GPTs based analysis model. *Engineering, Construction and Architectural Management*. <https://doi.org/10.1108/ECAM-05-2024-0624>
- Zou, Y., Huang, Y., Wang, Y., Zhou, F., Xia, Y., & Shen, Z. (2024). The Construction of Urban Rainstorm Disaster Event Knowledge Graph Considering Evolutionary Processes. *Water*, 16(7), 942. <https://doi.org/10.3390/w16070942>

Disclaimer/Publisher's Note

The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and do not reflect the views of the Architecture, Buildings, Construction and Cities (ABC2) Journal and/or its editor(s). DFB Journal and/or its editor(s) disclaim any responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.