Large Language Model-Based BIM-Design for Safety (DfS) Framework for Phase-Specific Safety Mitigation Recommendations during the Design Stage

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Abstract –

The construction industry exhibits a higher fatality rate compared to other industries, making proactive safety management essential for risk reduction. Existing safety management practices have primarily focused on post-accident responses, presenting challenges in implementing preventive measures. Therefore, this study proposes a framework that integrates the Design for Safety (DfS) concept with Building Information Modeling (BIM) for application during the design phase. While previous research analyzed only completed BIM models and relied on manual matching between DfS information and BIM elements, this study utilizes Large Language Models (LLMs) to automatically infer element information from 488 DfS reports and generates a knowledge graph consisting of 271 nodes and 780 relationships. The proposed system classifies construction progress into four phases based on Uniformat II (Excavation, Substructure, Superstructure, Finishing) and matches them with BIM models. Implemented as an add-in, it enables designers to access empirical data-based mitigation measures for phase-specific elements in real-time within the BIM environment without switching programs. This allows designers with limited DfS-related education or experience to immediately apply safety mitigation measures without interrupting their design workflow, thereby lowering barriers to DfS utilization and enhancing practical applicability in the design phase.

Keywords –

Design for Safety (DfS), Building Information Modeling (BIM), Knowledge Graph, Large Language Model (LLM), Construction Safety

1 Introduction

The construction industry exhibits higher fatality and injury rates compared to other industries [1–3], resulting in economic burdens, project delays, and reduced productivity [4,5]. Among various risk reduction strategies, identifying and mitigating hazards during the design phase is particularly important, as design decisions made early in a project can prevent numerous potential risks in subsequent construction phases [6,7]. Design for Safety (DfS) refers to systematic activities that identify, eliminate, and mitigate hazards during the design phase [8], studies have confirmed that over 40% of fatal accidents are associated with design defects [9–11].

Despite its recognized importance, the practical adoption of DfS remains limited. Designers often lack DfS knowledge, show passive attitudes, and receive insufficient training to systematically incorporate DfS into design workflows [12,13]. To tackle these challenges, investigations into the integration of DfS with Building Information Modeling (BIM) have been conducted. BIM is a collaborative tool applicable across design, construction, and maintenance phases, and BIM-DfS integration has attracted attention as an effective approach to directly utilize DfS during the design phase [14,15].

Existing BIM-based studies have limitations. Much of the existing research has focused on the design or construction stage using completed BIM models as analysis targets, failing to reflect how hazardous areas change with construction progress or synchronize with ongoing construction activities [16–18]. Additionally, while DfS reports are written in natural language centered on accident types and mitigation measures, BIM models have an information schema centered on building elements. This structural mismatch means that directly utilizing DfS information within a BIM environment requires manual interpretation, which introduces subjective judgment, reduces accuracy, and increases processing time.

Large Language Models (LLMs) can address these problems by leveraging their reasoning capabilities to analyze natural language in DfS reports and infer which building elements should have mitigation measures applied, even when such information is not explicitly stated [19–21]. This enables automated connection between natural language-centered information and building element-centered information.

This study targets fall accidents, which account for the highest fatality rate in construction [22], and proposes a BIM add-in framework that integrates DfS reports with BIM models through LLM-based knowledge graph generation. The framework classifies construction progress into four phases based on Uniformat II, automatically infers building element information from DfS reports using LLMs and converts it into a knowledge graph for automatic matching with BIM models. This enables designers to access empirical data-based mitigation measures for phase-specific elements in real-time within the BIM environment, allowing even those with limited DfS-related education or experience to apply appropriate safety measures without interrupting their design workflow.

2 Literature Review

2.1 Studies on Design for Safety

DfS is an activity to identify and mitigate risks early in the design phase, and numerous studies on its effectiveness exist. Gambatese et al. (2008) revealed that design defects account for 42% of fatal accidents and proposed that such accidents could be prevented through DfS utilization [22]. Goh et al. (2016) conducted a survey for practical application of the DfS concept and pointed out that while knowledge and education are important for DfS application, there is a lack of related materials and specific application method guidelines [13]. Hussain et al. (2026) and Xu et al. (2026) identified that competence-based capabilities such as education, knowledge, and skills remain the most critical factors for effective DfS regulatory enforcement [23,24]. Although the importance of DfS is clearly recognized, due to these limitations, practical DfS introduction requires specific application methods that practitioners can utilize during the design phase.

2.2 BIM for Safety Management

BIM is a collaborative tool that facilitates data management throughout the construction lifecycle [25]. As LOD levels increase from 100 to 500, information about object locations, materials, and design details becomes richer, enabling hazardous area identification, hazard detection, and quantity takeoff for project coordination and decision-making.

BIM-based safety management research has focused on physical hazard identification. Zhang et al. (2013) and Tamanaeifar and Shahhosseini (2025) proposed methods to identify fall hazard areas using BIM object information and verify safety facility installation [16,17]. Recent studies evolved toward regulatory compliance verification. Yang et al. (2023) converted regulations into knowledge graphs combined with BIM models for systematic compliance verification [26], while Goh et al. (2024) demonstrated design-phase compliance verification using building element details [27]. Uniformat II has been adopted in prior BIM-integrated studies as a standard framework for linking building elements to construction stages. Jung et al. (2024) proposed a model that automatically maps construction schedule activities to Uniformat II categories to enable 4D BIM integration [28], and Pishdad and Onungwa (2024) utilized Uniformat classification codes to link BIM model objects to construction phase activities for cost estimation and control [29].

However, previous research has limitations. First, hazard detection targeted only completed models without reflecting how hazardous areas change with construction progress—excavation edges during substructure phases versus slab edges during superstructure phases. Second, knowledge graph construction depends on manual expert rule generation, introducing subjectivity and requiring significant processing time. Third, compliance verification research lacks integration with field-collected data, limiting its practical applicability to real construction sites.

2.3 Knowledge Graph for Construction

Knowledge graphs are structured representations of domain knowledge in which nodes denote entities and edges denote semantic relationships, enabling logical inference and scalable knowledge integration [30]. In the construction safety domain, knowledge graphs have been increasingly adopted to organize and utilize safety-related information. Jiang et al. (2021) developed a knowledge graph of construction safety standards to enable systematic knowledge retrieval and standards planning through ontology-based semantic querying and inference [31]. Zhu and Luo (2022) proposed a condition-based knowledge graph comprising a Rule Knowledge Graph and an Association Knowledge Graph, using NLP to automatically extract safety rules from construction regulations for automated safety violation identification [32]. Lee and Lee (2024) utilized BERT and graph models to automatically extract risk-assessment knowledge from unstructured construction safety data, supporting automated knowledge management for construction risk assessment [33]. Despite these advances, knowledge graph construction has largely relied on manual rule encoding, limiting scalability and practical applicability.

2.4 Research Gap and Contribution

Building on the limitations identified in the previous section, this study proposes a mitigation measure recommendation methodology using DfS reports and LLMs that divides construction progress into four phases based on Uniformat II, automatically extracts building element information and mitigation measure relationships using LLMs and implements them as a BIM add-in for practical applicability. The novelty lies in implementing a system that automatically recommends empirical data-based mitigation measures by integrating DfS reports, LLM-based knowledge graphs, and stage-specific BIM models, which enables automated linking between DfS recommendations and specific BIM elements without manual interpretation, where the LLM-based inference addresses missing element specifications in DfS reports. Unlike previous research focused on regulation-based compliance, this study provides mitigation measures based on actual accident cases and enables designers with limited DfS-related education or experience to apply specific and stage-appropriate mitigation measures through LLM automation.

3 Framework

This study aims to effectively provide risk reduction measures during the design phase by extracting and inferring building elements related to hazards from DfS reports, converting them into knowledge graph form, and integrating them with BIM models. To achieve this, the framework of this study is divided into three main stages: (1) Mapping to Uniformat II, (2) LLM-based knowledge graph generation, and (3) Application development.

3.1 Mapping to Uniformat II

This study divides project progress stages into four phases—Excavation, Substructure, Superstructure, and Finishing—based on the Uniformat II classification system. Uniformat II is a standard system for construction project specifications and cost estimation, consisting of Level 1 (major groups) and Level 2 (system classification) [34].

In this study, Services, Equipment & Furnishings, and Special Construction & Demolition from Uniformat's Hierarchy were excluded due to low relevance to fall accidents. Additionally, phases were separated according to detailed work content even within the same hierarchy. For example, in A20 Basement Construction, excavation work was assigned to the Excavation phase, and basement wall construction was assigned to the Substructure phase. Detailed classification results are shown in Table 1.

DfS reports include information on title, work type, accident type, mitigation measures, human hazards, and physical hazards. In this study, the title, accident type, physical hazards, and mitigation measures were extracted and utilized. Each report was analyzed and assigned a phase according to the classification criteria in Table 1.

BIM IFC (Industry Foundation Classes) is an international standard format for BIM models containing information about each element's class, properties, and location [35]. This study utilized IFC 4.3 version and targeted only IfcBuiltElement components (IfcSlab, IfcColumn, IfcBeam, IfcWall, etc.) representing actual physical elements rather than conceptual entities.

To assign phase information to each element in the BIM model, the following process was performed. First, Phase was initially assigned by matching Uniformat Hierarchy with IFC Entity types. Second, since Substructure and Superstructure can include the same IFC Entities, level information and ground height were utilized to assign underground structures to Substructure and above-ground structures to Superstructure. Finally, the assigned phase information was added as a property of each element in the IFC file. As this phase assignment represents a deterministic decomposition of a completed BIM model into construction phases based on predefined Uniformat II criteria, rather than a predictive classification task, no pre-existing ground truth exists for accuracy evaluation.

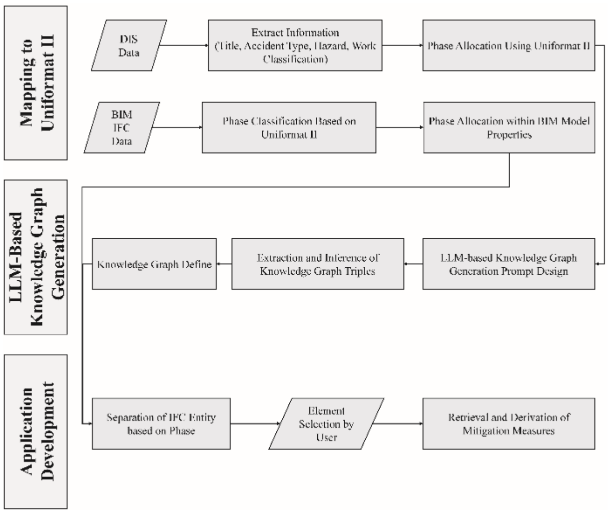

Figure 1. Research framework

Table 1. Uniformat Classification by Construction Phase

Phase	UNIFORMAT LEVEL 1	UNIFORMAT LEVEL 2
Excavation	A(Substructure)	A20 Basement Construction (Excavation)
	G(Building Sitework)	G10 Site Preparation
Substructure	A(Substructure)	A10 Foundations
		A20 Basement Construction (Walls)
Superstructure	B(Shell)	B10 Superstructure
Finishing	B(Shell)	B20 Exterior Enclosure
		B30 Roofing
	C(Interiors)	C10 Interior Construction
		C20 Stairs
		C30 Interior Finishes

3.2 LLM-based Knowledge Graph Generation

The LLM-based knowledge graph generation process consists of IFC entity extraction, deduplication, and knowledge graph construction. First, Claude 3.5 Sonnet was used to extract IFC entities, which represent building element information, from DfS reports. DfS reports are written in natural language and, in most cases, do not explicitly describe IFC entity information. LLM can be effective in addressing such low-quality documents [19]. Therefore, this study utilized LLM's inference function to infer and extract IFC entities based on information such as accident type, physical hazards, and mitigation measures.

The prompt was structured in three parts: role definition, input data schema, and output format. In role definition, the LLM was defined as an expert in construction safety and building element classification to ensure appropriate context understanding. In the input data schema, the structure of DfS reports (accident type, physical hazard, mitigation measure, etc.) was explained in detail. In output format, both explicit entity extraction and inferred entity reasoning were requested. The prompt was applied in a single execution to generate results without iterative refinement. Table 2 shows the prompt example used for entity extraction.

Table 2. Prompt for LLM-based knowledge graph generation

```
// IFC Entity Inference Prompt
You are an expert in construction safety and BIM.
Given accident report information:
- Title: {accident_title}
- Hazard: {hazard_description}
- Phase: {phase}
- Mitigation: {mitigation}
IFC entities by phase:
- EXCAVATION: IfcSpace, IfcPile, IfcFooting
- SUBSTRUCTURE: IfcFooting, IfcPile, IfcWall, IfcSlab
- SUPERSTRUCTURE: IfcSlab, IfcBeam, IfcColumn, IfcWall
- FINISHING: IfcRailing, IfcRoof, IfcStair, IfcDoor, IfcWindow
Task: Identify IFC elements involved in this accident.
Output: Comma-separated list (max 3), IFC 2x3 format.
Example: IfcSlab, IfcBeam, IfcColumn
// Knowledge Graph Generation Prompt
You are an expert in Neo4j knowledge graphs.
Input: Safety reports with project title, accident type, hazard, mitigation, phase, IFC elements.
Generate Neo4j Cypher script with:
Nodes: AccidentType, IfcEntity, Phase, Mitigation
Relationships:
- (Phase)-[:Contains]->(IfcEntity)
- (IfcEntity)-[:Causes {source}]->(AccidentType)
- (IfcEntity)-[:Mitigated_by]->(Mitigation)
- (Mitigation)-[:ForPhase]->(Phase)
Requirements:
1. Create indexes on name properties
2. Use MERGE to prevent duplicates
3. Add source attribute ("explicit"/"inferred")
4. Handle comma-separated values
Output: Single executable .cypher file
```

Through this process, not only explicitly mentioned entities in DfS reports but also implicitly related entities were extracted. For example, when 'deck plate work' appears, not only IfcSlab but also IfcBeam, IfcColumn, and IfcOpening could be inferred. The extracted IFC entities were categorized as 'explicit' or 'inferred' according to their source, and this information was utilized in knowledge graph relationship generation.

Next, duplicate removal work was conducted on the extracted IFC entities. In this process, different expressions referring to the same entity were standardized to IFC standard names (e.g., standardizing various expressions such as 'wall', 'retaining wall', 'basement wall' to 'IfcWall'). Additionally, when multiple mitigation measures targeting the same entity existed, they were integrated to maintain data consistency.

Finally, prompts were utilized to build a Neo4j-based knowledge graph. Neo4j is a graph database platform that facilitates the creation, querying, and updating of knowledge graphs. LLM generated Cypher queries using classified DfS report data and IFC entity information as input to build the knowledge graph. The knowledge graph consists of four types of nodes (AccidentType, IfcEntity, Phase, and Mitigation) and their relationships (Contains, Causes, MitigatedBy, and ForPhase). In particular, the Causes relationship included a source attribute ('explicit' or 'inferred') to distinguish whether the entity was explicitly mentioned or inferred. Table 2 shows the prompts for building the knowledge graph.

3.3 Application Development

For practical utilization of IFC data with assigned phase information and knowledge graphs constructed through LLMs, a Revit add-in based on C# programming language was developed. Main functions are as follows.

- Phase Classification: Automatically classifies and assigns phase to all building elements using IFC entity type, level information, and ground height
- Visualization: When users select a specific phase, only building elements belonging to that stage are visually highlighted. This supports designers in focusing on stage-specific hazards.
- Mitigation Measure Inquiry: When users click on a building element in the BIM model, mitigation measures related to that element are queried. Mitigation measures are retrieved by sending cypher queries to the knowledge graph through the Neo4j API.

When users click on a building element, the selected phase and IFC entity type of the clicked element are input into the knowledge graph. The knowledge graph retrieves mitigation measures applicable to that element and stage based on (Phase)-[:Contains]->(IfcEntity), (IfcEntity)-[:MitigatedBy]->(Mitigation), and (Mitigation)-[:ForPhase]->(Phase) relationships. The queried mitigation measures are displayed in list form on the Revit add-in UI panel, enabling users to identify building elements by phase within the BIM model and immediately check specific safety mitigation measures based on empirical data for each element.

4 Case Study and Results

4.1 DfS Report Description

In this study, 1,413 DfS reports written in actual construction projects were collected from the Korea Authority of Land and Infrastructure Safety and construction companies' internal records. Each report contains information on work type, title, human hazards, hazard factors (physical hazards), and mitigation measures. After removing missing values from the collected 1,413 data and filtering only fall accident-related data, 488 DfS reports were finally selected as analysis targets.

4.2 Results of Knowledge Graph Generation

As a result of duplicate removal and knowledge graph generation using LLMs, 271 nodes and 780 relationships were created, with an example shown in Figure 2. The knowledge graph includes relationships among AccidentType, IFC Entity, Mitigation, and Phase, and it confirmed their relationships. Through this, mitigation measures related to building elements by phase within the BIM model can be queried and presented.

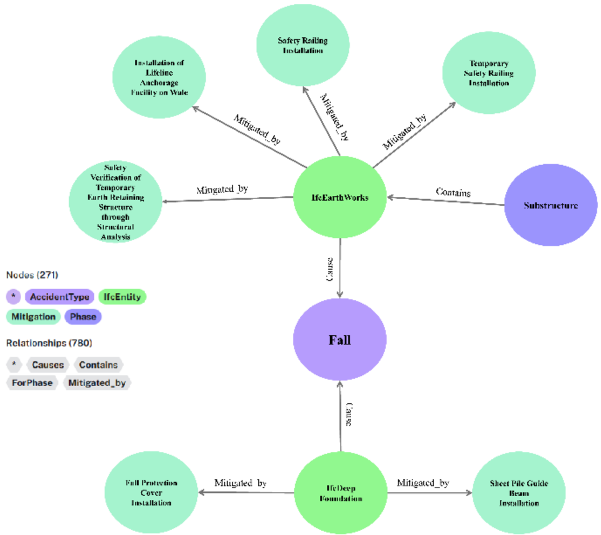

Figure 2. Knowledge graph generation results

4.3 Results of application development

To confirm the applicability of the proposed methodology, a sample project provided in Revit was analyzed. Phase classification was conducted for 4,039 builtElements corresponding to BuildingElement in the sample project. As a result of classification (Figure 3), no elements were classified as Excavation, 60 elements were classified as Substructure, 3,307 elements were classified as Superstructure, and 672 elements were classified as Finishing. The reason no elements correspond to the Excavation stage is that the sample project is a building model that does not include excavation and earth retaining-related elements.

Next, visualization by Phase was conducted for elements with assigned Phase, and the visualization results for Substructure, Superstructure, and Finishing, excluding the Excavation stage where no IFC Entities exist, are shown in Figure 4. In the Substructure Phase, mainly Beam, Column, Slab, and Wall elements were identified, and in the Superstructure Phase, Beam, Column, Plate, Ramp, Roof, Slab, Wall, and Stair elements were identified. In the Finishing Phase, elements such as Railing, CurtainWall, Window, and Door were identified.

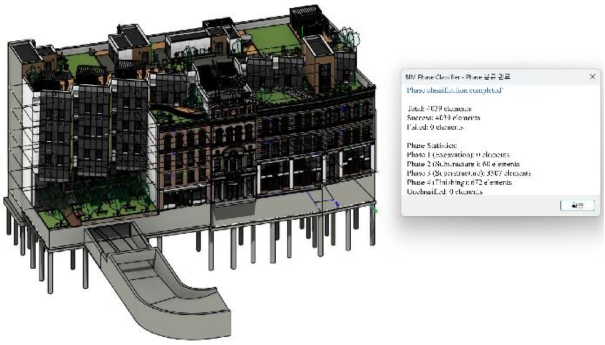

Figure 3. Results of classification by phase

It can be seen that the Pile structure visible in Figure 3 is not identified in Figure 4. This is because the Pile is not defined as an IFC entity but modeled as a separate Assembly and thus not included in the BuiltElement scope. In such cases, it may be excluded from Phase classification targets depending on modeling methods, and when applied in practice, it can be resolved by using standard elements defined as IFC entities or adding to the classification system.

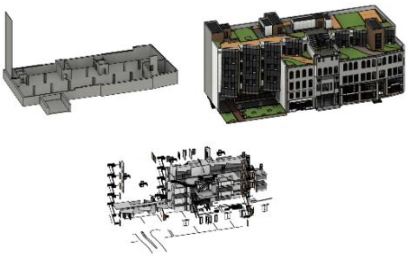

Figure 4. Results of visualization by phase

Next, to verify the mitigation measure inquiry function, results were derived using Substructure Phase as an example, with specific details shown in Figure 5. Figure 5 shows the mitigation measure inquiry results when Slab is selected in the Substructure and Superstructure Phases, respectively. The system window displays the selected IFC entity name and corresponding Phase, and related mitigation measures retrieved from the knowledge graph are provided in list form. Specifically, mitigation measures such as jack support installation were derived for Substructure, while structural safety review of system supports, and preparation of assembly drawings were derived for Superstructure. In the case of Slab, which is a component that can be applied in both Substructure and Superstructure, some overlapping design improvement measures were derived, but it was also confirmed that unique improvement measures for each Phase were derived. These mitigation measure recommendations are empirical data-based information extracted from actual DfS reports, automatically retrieved through the knowledge graph. Through this, it was confirmed that DfS-based mitigation measure recommendations according to BIM model Phase classification are operating effectively.

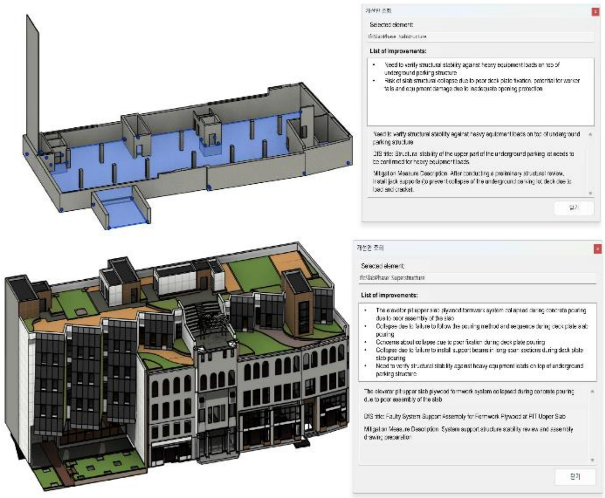

Figure 5. Results of mitigation measure recommendation

5 Conclusion and Discussion

This study proposed an approach that can effectively support design safety management during the design phase in the construction industry by utilizing BIM model information and DfS report content. By converting DfS reports into knowledge graphs using LLMs and developing an add-in program that can be utilized by combining them with BIM IFC format information, the main objectives were achieved by enabling effective utilization even by designers with low DfS-related education levels or those who have not received education.

The Revit-based case study results show that already completed BIM models can be separated by each phase within general construction process categories, enabling presentation of appropriate design mitigation measures according to risk changes following construction progress. Additionally, through the knowledge graph method using LLMs, inference of insufficient information can work effectively, demonstrating that LLM model inference capabilities can be a sufficient alternative when utilizing low-quality DfS reports.

This study has the following contributions. First, from a technical contribution perspective, a method was proposed to infer unstated building elements from large volumes of DfS reports using LLMs, generate knowledge graphs, and combine them with BIM models. Second, from an industry perspective, a practical approach for introducing the DfS concept was presented, enabling support for more effective safety design concept introduction during the design phase. Through this, it can be an effective solution for personnel lacking experience and education.

The limitations of this study are as follows. First, when matching DfS reports and BIM IFC information, attribute information that could consider mutual context was not considered. For more accurate matching, reflection of more diverse attributes such as exterior walls, interior walls, and materials is necessary. Second, for LLMs, logic writing is needed to identify hallucination problems and infer correct results. Third, as this study primarily proposes a proof-of-concept framework for integrating DfS reports with BIM models, formal validation of the LLM outputs was not conducted. The accuracy of IFC entity extraction was not evaluated against a ground truth dataset using standard metrics, and the reasonableness of inferred entities was not systematically assessed. Future work should establish a ground truth corpus through expert annotation and evaluate LLM performance using quantitative metrics to ensure the reliability of the proposed approach. Finally, when recommending multiple mitigation measures, there is a need to assign priorities using additional indicators such as risk level or occurrence frequency.

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References

[1] L. Kumi, J. Jeong, J. Jeong, Data-driven automatic classification model for construction accident cases using natural language processing with hyperparameter tuning, Autom. Constr. 164 (2024). https://doi.org/10.1016/j.autcon.2024.105458.

[2] J. Jeong, J. Jeong, Quantitative Risk Evaluation of Fatal Incidents in Construction Based on Frequency and Probability Analysis, Journal of Management in Engineering 38 (2022). https://doi.org/10.1061/(asce)me.1943-5479.0000998.

[3] G.M. Waehrer, X.S. Dong, T. Miller, E. Haile, Y. Men, Costs of occupational injuries in construction in the United States, Accid. Anal. Prev. 39 (2007). https://doi.org/10.1016/j.aap.2007.03.012.

[4] M. López-Alonso, M.P. Ibarrondo-Dávila, M.C. Rubio-Gámez, T.G. Munoz, The impact of health and safety investment on construction company costs, Saf. Sci. 60 (2013). https://doi.org/10.1016/j.ssci.2013.06.013.

[5] B. Estudillo, J.M. Carretero-Gómez, F.J. Forteza, The impact of occupational accidents on economic Performance: Evidence from the construction, Saf. Sci. 177 (2024). https://doi.org/10.1016/j.ssci.2024.106571.

[6] A.C.P. Frijters, P.H.J.J. Swuste, Safety assessment in design and preparation phase, Saf. Sci. 46 (2008). https://doi.org/10.1016/j.ssci.2007.06.032.

[7] A.F. Waly, W.Y. Thabet, A Virtual Construction Environment for preconstruction planning, Autom. Constr. 12 (2003). https://doi.org/10.1016/S0926-5805(02)00047-X.

[8] Workplace Safety and Health Council, Workplace Safety and Health Guidelines : Design for Safety, 2016.

[9] A. Gibb, R. Haslam, S. Hide, D. Gyi, The role of design in accident causality, in: University of Oregon Press, Eugene, OR, 2004: pp. 11–21.

[10] M. Behm, Linking construction fatalities to the design for construction safety concept, Saf. Sci. 43 (2005). https://doi.org/10.1016/j.ssci.2005.04.002.

[11] J.A. Gambatese, M. Behm, J.W. Hinze, Viability of Designing for Construction Worker Safety, J. Constr. Eng. Manag. 131 (2005). https://doi.org/10.1061/(asce)0733-9364(2005)131:9(1029).

[12] C.K.I. Che Ibrahim, S. Belayutham, P. Manu, A.M. Mahamadu, C.M. Cheung, Knowledge, attitude and practices of design for safety (DfS): A dynamic insight between academics and practitioners in Malaysia, Saf. Sci. 146 (2022). https://doi.org/10.1016/j.ssci.2021.105576.

[13] Y.M. Goh, S. Chua, Knowledge, attitude and practices for design for safety: A study on civil & structural engineers, Accid. Anal. Prev. 93 (2016). https://doi.org/10.1016/j.aap.2015.09.023.

[14] Y. Zhou, J. She, Y. Huang, L. Li, L. Zhang, J. Zhang, A Design for Safety (DFS) Semantic Framework Development Based on Natural Language Processing (NLP) for Automated Compliance Checking Using BIM: The Case of China, Buildings 12 (2022). https://doi.org/10.3390/buildings12060780.

[15] M.A. Hossain, E.L.S. Abbott, D.K.H. Chua, T.Q. Nguyen, Y.M. Goh, Design-for-Safety knowledge library for BIM-integrated safety risk reviews, Autom. Constr. 94 (2018). https://doi.org/10.1016/j.autcon.2018.07.010.

[16] S. Zhang, J. Teizer, J.K. Lee, C.M. Eastman, M. Venugopal, Building Information Modeling (BIM) and Safety: Automatic Safety Checking of

Construction Models and Schedules, Autom. Constr. 29 (2013). https://doi.org/10.1016/j.autcon.2012.05.006.

[17] M.H. Tamanaeifar, V. Shahhosseini, Automated fall hazard analysis in the design stage using Building Information Modeling (BIM), Civil Engineering and Environmental Systems (2025) 1–28. https://doi.org/10.1080/10286608.2025.2524412.

[18] S. Jiang, J. Zhang, J. Shi, Y. Wu, Adaptive information retrieval for enhanced building safety management leveraging BIM, Engineering, Construction and Architectural Management 33 (2026). https://doi.org/10.1108/ECAM-08-2024-1018.

[19] J. Zhou, Z. Ma, Named entity recognition for construction documents based on fine-tuning of large language models with low-quality datasets, Autom. Constr. 174 (2025) 106151. https://doi.org/10.1016/j.autcon.2025.106151.

[20] Y. Fujiwara, T. Tuchida, R. Miyata, H. Washizaki, N. Ubayashi, LLM-Based Automated Mitigation and Assurance Case Generation Against Threats to AI Systems, in: Proceedings - 2025 IEEE Conference on Artificial Intelligence, CAI 2025, 2025. https://doi.org/10.1109/CAI64502.2025.00160.

[21] S. Baek, C.Y. Park, W. Jung, Automated safety risk management guidance enhanced by retrieval-augmented large language model, Autom. Constr. 176 (2025). https://doi.org/10.1016/j.autcon.2025.106255.

[22] J.A. Gambatese, M. Behm, S. Rajendran, Design's role in construction accident causality and prevention: Perspectives from an expert panel, Saf. Sci. 46 (2008). https://doi.org/10.1016/j.ssci.2007.06.010.

[23] A. Hussain, C.K.I. Che Ibrahim, S. Belayutham, P. Manu, C. Cheung, Exploring regulatory capabilities for design for safety in construction: the case of Malaysia, Built Environment Project and Asset Management (2025). https://doi.org/10.1108/BEPAM-03-2025-0077.

[24] D. Xu, K. Agyekum, P. Manu, C. Cheung, C.K.I. Che Ibrahim, A.M. Mahamadu, P.A. Perez, Design for safety (DfS) implementation in the construction industry: a study of design professionals in Northern China, Journal of Engineering, Design and Technology (2025). https://doi.org/10.1108/JEDT-11-2024-0694.

[25] C. Boton, L. Rivest, O. Ghnaya, M. Chouchen, What is at the Root of Construction 4.0: A Systematic Review of the Recent Research Effort, Archives of Computational Methods in Engineering 28 (2021). https://doi.org/10.1007/s11831-020-09457-7.

[26] M. Yang, Q. Zhao, L. Zhu, H. Meng, K. Chen, Z. Li, X. Hei, Semi-automatic representation of design code based on knowledge graph for automated compliance checking, Comput. Ind. 150 (2023). https://doi.org/10.1016/j.compind.2023.103945.

[27] W. Goh, J. Jang, S.I. Park, B.-H. Choi, H. Lim, G. Zi, Automated Compliance Checking System for Structural Design Codes in a BIM Environment, KSCE Journal of Civil Engineering 28 (2024) 4175–4189. https://doi.org/10.1007/s12205-024-1121-5.

[28] Y. Jung, J. Hockenmaier, M. Golparvar-Fard, Transformer language model for mapping construction schedule activities to uniformat categories, Autom. Constr. 157 (2024). https://doi.org/10.1016/j.autcon.2023.105183.

[29] P. Pishdad, I.O. Onungwa, ANALYSIS OF 5D BIM FOR COST ESTIMATION, COST CONTROL, AND PAYMENTS, Journal of Information Technology in Construction 29 (2024). https://doi.org/10.36680/j.itcon.2024.024.

[30] S. Ji, S. Pan, E. Cambria, P. Marttinen, P.S. Yu, A Survey on Knowledge Graphs: Representation, Acquisition, and Applications, IEEE Trans. Neural Netw. Learn. Syst. 33 (2022). https://doi.org/10.1109/TNNLS.2021.3070843.

[31] Y. Jiang, X. Gao, W. Su, J. Li, Systematic knowledge management of construction safety standards based on knowledge graphs: A case study in China, Int. J. Environ. Res. Public Health 18 (2021). https://doi.org/10.3390/ijerph182010692.

[32] Y. Zhu, X. Luo, A Knowledge Graph for Automated Construction Workers' Safety Violation Identification, in: Proceedings of the International Symposium on Automation and Robotics in Construction, 2022. https://doi.org/10.22260/isarc2022/0044.

[33] W. Lee, S. Lee, Development of a Knowledge Base for Construction Risk Assessments Using BERT and Graph Models, Buildings 14 (2024). https://doi.org/10.3390/buildings14113359.

[34] ASTM, Standard Classification for Building Elements and Related Sitework — UNIFORMAT II, 2020.

[35] BuildingSMART, IFC4 Documentation, (n.d.). https://standards.buildingsmart.org/IFC/RELEASE/IFC4/ADD2_TC1/HTML/ (accessed December 13, 2025).