

Integrating RAG-LLMs with BIM for Automated Fall Hazard Detection and Prevention in Building Design

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Abstract –

Falls from height (FFH) remain a leading cause of construction injuries and fatalities, necessitating proactive Design-for-Safety (DfS) approaches. While Building Information Modeling (BIM) facilitates safety checks, existing Automated Rule Checking (ARC) models rely on rigid, manual rule-coding and lack the spatial reasoning required to interpret complex safety regulations. This paper proposes a Retrieval-Augmented Generation (RAG) Large Language Model (LLM) pipeline integrated with BIM for automated FFH identification and prevention. The methodology incorporates a domain-specific ontology that maps unstructured regulatory constraints to BIM geometry, enabling the precise detection of spatial hazards. Additionally, the system automates the placement of preventive measures, such as Occupational Safety and Health Administration (OSHA)-compliant guardrails, directly within the design model. By bridging the gap between semantic regulatory interpretation and geometric analysis, this approach overcomes the spatial limitations of current LLM-BIM frameworks, empowering designers to eliminate fall hazards early in the project design.

Keywords –

Retrieval augmented generation; Large language models; Building information modeling; Automated rule checking; Design for Safety; Fall hazards

1 Introduction

The construction industry remains the most hazardous sector worldwide, despite safety improvements, legislation, and technological advancements [1]. Falls from height (FFH) are the leading cause of severe injuries and fatalities at construction sites [2]. Research shows that over 50% of construction accidents stem from design decisions [3],

and 60-90% can be prevented through decisions made during the design phase [4]. Consequently, there is a growing shift from reactive, site-based safety management to proactive Design-for-Safety (DfS) approaches that eliminate hazards before construction begins [5].

Building Information Modeling (BIM) offers an effective platform to implement DfS principles by enabling designers to visualize construction scenarios and identify spatial risks [6]. However, current BIM-based safety tools have key limitations, such as high initial costs and interoperability issues between software. It also relies on manual expertise, and designers lack safety knowledge. Similarly, Automated Rule-Checking (ARC) systems use rigid, manually created rules [7]. ARC systems can assess BIM models against safety requirements, but converting safety regulations from natural language to computer code requires extensive programming expertise and regular updates [8]. Furthermore, fall hazard identification is particularly challenging as regulations involve context-based judgments and semantic understanding. Terms like "unprotected edges" and "openings" are difficult to define in traditional logic-based systems. As a result, most existing ARC systems function primarily as post-design compliance checkers rather than adaptive decision-support tools.

Recent advances in Artificial Intelligence (AI), particularly Large Language Models (LLMs), offer new opportunities to address these challenges. LLMs can process complex regulatory texts and, when combined with Retrieval-Augmented Generation (RAG), dynamically reference safety standards. Studies have demonstrated the potential of LLM-based approaches for code compliance and rule extraction [9]. However, existing studies largely frame safety as a general management problem, focusing on guidance generation and inspections rather than specific prevention mechanisms. Current LLM approaches lack spatial reasoning capabilities and cannot accurately identify fall

hazards within building geometry without deep BIM integration. Consequently, FFH regulations, which rely heavily on spatial dependencies, remain inadequately addressed by existing AI-driven frameworks.

To bridge the gap between unstructured regulations and spatial hazard analysis, this paper proposes a RAG-LLM-augmented BIM pipeline for the automated identification and prevention of fall hazards in building design. The approach uses LLMs to interpret safety regulations and connects regulatory logic with BIM geometry to enable automated hazard analysis. By reducing manual rules encoding and providing early safety feedback, this method advances DfS and BIM-based safety automation.

2 Literature review

2.1 Embedding DfS rules in BIM

BIM serves as an effective platform for operationalizing DfS principles through its representation of geometric, semantic, and spatial information. Early research emphasized visualization and coordination for safety planning, while later studies explored embedding DfS knowledge to enable systematic hazard detection and prevention. Advanced implementations utilize rule-based reasoning engines to evaluate designs against encoded safety requirements. Safety ontologies further strengthen these systems by formalizing relationships between building components and risk categories [10]. Despite advances, embedding DfS into BIM faces limitations due to fragmented safety knowledge and rigid rule representations [11]. Most rule libraries are difficult to update or adapt across jurisdictions. Moreover, safety requirements are context-dependent, influenced by construction methods and temporary conditions, and are inadequately represented in static BIM models. Consequently, existing systems function primarily as post-design compliance checkers rather than adaptive decision-support tools.

2.2 Automated rule checking systems

ARC systematically evaluates BIM models against regulations using frameworks like CORENET X, FORNAX™, and Solibri Model Checker (SMC). Various studies have developed specific rule-checking algorithms for fall protection, job hazard analysis, and temporary structure assessment. Others have employed ontology-based schemas and voxelization techniques to enhance hazard detection. However, ARC effectiveness is constrained by reliance on manual rule creation, which requires domain expertise and programming skills. This dependency limits scalability, particularly for regulations involving qualitative descriptions. Fall protection

requirements, such as identifying "exposed edges," demand spatial and contextual understanding beyond logic-based models. The gap between unstructured natural language regulations and computational rules highlights the need for adaptive compliance verification methods.

2.3 LLM-Enhanced Compliance Checking

LLMs present a transformative solution to current ARC limitations. Their Natural Language Processing (NLP) capabilities allow for the interpretation of regulatory text and the creation of machine-readable formats without manual coding. When combined with RAG, LLMs can dynamically reference authoritative sources to ensure accuracy. Recent research demonstrates the potential of LLMs in this domain. Zheng et al. [12] and Madireddy et al. [13] developed frameworks for interpreting building codes and checking compliance. Chen et al. [14] and Du et al. [15] focused on rule extraction and code generation. Other studies have integrated knowledge graphs and visual language models to enhance safety monitoring. Despite these advancements, existing studies largely frame safety as a general management and inspection problem. A critical limitation is that current LLM approaches lack spatial reasoning capabilities and cannot accurately identify fall hazards without deep BIM integration. Consequently, FFH regulations involving implicit spatial dependencies remain inadequately addressed. This paper proposes a RAG-LLM-augmented BIM framework to bridge this gap by aligning semantic interpretation with BIM geometry for automated hazard prevention in building design.

3 Methodology

This study proposes a RAG-LLM-augmented BIM pipeline to integrate DfS principles into early design stages. As illustrated in [Figure 1](#), the framework formally bridges regulatory knowledge and BIM geometry through a domain-specific ontology. The workflow proceeds through five integrated phases: (1) collection of fall hazard rules and regulations; (2) fall hazard ontology development; (3) automated fall hazard identification and visualization; (4) rule-based fall prevention via OSHA-compliant guardrail generation; and (5) an intelligent advisory layer powered by RAG-LLM reasoning to provide context-aware safety decision support. The proposed framework employs deterministic, rule-based methods for fall hazard detection and guardrail generation to ensure reliable safety compliance, while the RAG-LLM component serves as an advisory layer providing regulatory knowledge and contextual guidance for user decision-making rather than directly generating geometric elements.

3.1 Fall hazard rules and regulations

To standardize safety requirements, this study analyzed fall hazard regulations from Hong Kong's Labour Department and China's Ministry of Housing and Urban-

Rural Development (MOHURD), classifying hazards into three categories: elevated works, openings, and access-related works (Table 1). Although numerous FFH rules exist, this study considered only those predefined in the BIM model, as they can be applied effectively.

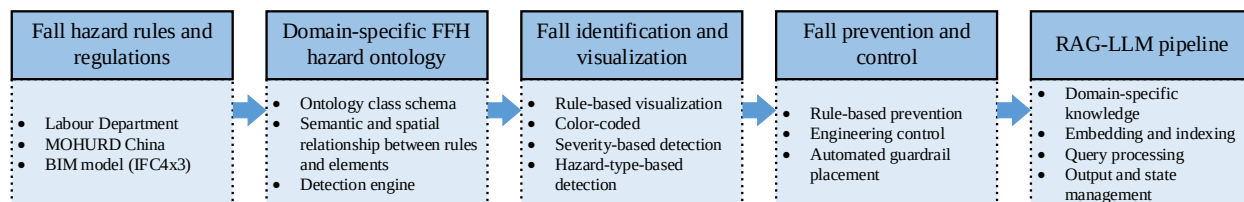


Figure 1. Overview of research methodology.

Table 1. Fall hazard rules and regulations.

Fall hazard category	Specific type	Definition	Threshold (mm)	Regulation
Elevated work hazards	Falls from height	Risk of falling from elevated work areas	≥ 2000	JGJ80-2016
	Unprotected sides and edges	Edges of floors, roofs, or platforms without fall protection	≥ 1800	Reg. 38B, CSSR Part VA
Opening hazards	Floor openings (Horizontal)	Uncovered holes or openings in floors	≥ 500	GB10000-88
	Wall openings (Vertical)	Uncovered holes or openings in walls	≥ 500	GB10000-88
Access hazards	Stairways	Use of stairways without adequate safety measures	≥ 760	Reg. 38C-F, CSSR Part VA

3.2 Fall hazard ontology development

This study uses an ontology-based approach to represent regulatory knowledge and establish semantic and spatial relationships between FFH rules and BIM elements, enabling automated reasoning. A domain-specific ontology was developed through regulatory analysis, BIM-IFC mapping, and rule-based spatial-logic encoding.

By mapping fall hazards to IFC entities (e.g., IfcSlab, IfcOpeningElement, IfcStair), semantic relationships were established through IFC property sets, aggregation hierarchies, and filling relationships. Spatial relationships were derived from bounding-box analysis and perimeter-edge detection. The ontology defines these hazard classes and executes detection through a ten-stage pipeline: IFC file loading, geometry extraction, unit normalization, opening classification, protection analysis, edge detection, stair-railing spatial analysis, threshold comparison, severity assignment, and result export. The pipeline generated JSON output containing OntologyID,

SpecificHazard, DetectedValue_mm, Threshold_mm, Severity, Location coordinates, ElementContext, and Notes, supporting visualization, prevention planning, and LLM-based reasoning.

3.3 Fall identification and visualization

The fall hazard identification workflow comprises three steps: data parsing, IFC coloring, and report generation. This approach integrates ontology-driven hazard data (stored in JSON) with the IFC model to produce a color-enriched representation that enables intuitive interpretation of fall risks during design review and construction planning.

First, the hazard visualization controller processes input JSON files containing semantic and geometric attributes, including hazard type, severity, and spatial location. Second, the IFC-based colorizer embeds hazard information by classifying risks by their physical and representational characteristics within IFC. Element-based hazards (e.g., slabs, walls) are visualized through surface styles, while void-based hazards (e.g., floor

openings) are represented using proxy-based 3D markers. Finally, hazard integration is executed using IfcOpenShell for hierarchical element identification. For hazards requiring independent markers, the system generates extruded geometry as IfcBuildingElementProxy objects linked to the building's spatial hierarchy. The outputs include a color-enriched IFC model and JSON and text-based reports summarizing visualization success rates, hazard distributions, marker creation statistics, and IFC-based coloring limitations. These outputs support visual inspection and systematic assessment of fall hazards, meeting automation-focused construction research requirements.

3.4 Fall prevention

Following FFH identification and visualization, the system prioritizes engineering controls by automatically generating OSHA-compliant guardrail systems at detected and identified hazard locations. The prevention system implements three layers: 1) data, 2) logic, and 3) output, using Python libraries: IfcOpenShell for IFC analysis, NumPy for geometric computation, and SciPy for boundary extraction. For stairways, walking edges are identified to place continuous top and mid rails at 1100 mm and 550 mm heights. For elevated slabs, a wall-aware safety classification evaluates edges, and guardrails are installed only where adjacent walls are insufficient (<1070 mm). Components are created as IfcRailing objects with safety coloring and proper storey assignment, enabling proactive BIM-based safety planning.

3.5 Integrated RAG-LLM pipeline

To address the limitations of rigid rule checking, this study proposes a RAG-LLM system that introduces a knowledge-augmented reasoning layer combining BIM hazard data with expert reasoning.

Since current LLMs struggle to interpret complex regulatory requirements outside their pretraining scope, a specialized knowledge base was developed where hazard instances are converted into regulatory standards, prevention best practices, and case-based documents. The hazard instances are structured into five fall hazard types, unprotected sides and edges, floor openings, wall openings, stairways, and FFH, which are derived from regulatory classifications (Table 1) and consistently used across the ontology development, detection, and prevention stages. These knowledge base documents are transformed into dense 384-dimensional vector representations using the *all-MiniLM-L6-v2* model and stored in an in-memory vector database for real-time access.

Upon receiving a user query, the system computed

semantic relevance using cosine similarity to retrieve the top-k (k=5) documents. Subsequently, the system utilizes prompt engineering to integrate these retrieved contexts with a BIM-derived hazard summary, comprising hazard frequencies, severity distributions, and geometric measurements. The final structured prompt incorporates role-specific instructions, regulatory guidelines, best practices, case-based knowledge, BIM hazard context, conversation history, and the user query. The system interfaces with a DeepSeek-based LLM via an OpenAI-compatible API, utilizing a temperature setting of 0.7 to balance analytical precision and interpretability. By functioning as a processor of retrieved safety knowledge rather than an independent source, this architecture ensures regulatory compliance and substantially reduces the risk of hallucination during safety advisory interactions. The system maintains conversation continuity by storing user-assistant exchanges in a JSON-based history.

The system implements comprehensive monitoring for evaluation and optimization. Key performance indicators include response latency, token usage, response length, and retrieval efficiency, with data logged per query and aggregated across sessions. The evaluation framework comprises test cases covering hazard prioritization, regulatory compliance, and mitigation strategies, enabling systematic comparison of embedding models, retrieval parameters, and LLM configurations. To assess classification performance, the system utilizes confusion matrix metrics (precision, recall, and F1 score) across five fall hazard types corresponding to those in the BIM model. True Positives (TP) represent fall hazards correctly identified and categorized, False Positives (FP) indicate elements incorrectly classified as fall hazards, and False Negatives (FN) represent fall hazards in the BIM model that were either unidentified or misclassified. The metrics are defined by Eqs. (1)-(3).

$$\text{Precision} = \frac{TP}{TP + FP} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (2)$$

$$\text{F1 - score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

4 Results

4.1 Fall detection engine

The system employs an ontology-driven detection engine that analyzes IFC-based BIM geometry through spatial reasoning. Fall hazards are identified using bounding box analysis, elevation stratification, proximity detection, and semantic validation of protection elements.

The ontology encodes safety regulations as machine-interpretable constraints, enabling hazard classification based on regulatory non-compliance rather than purely geometric analysis. This approach successfully detects unprotected openings, exposed edges, stair hazards, and multi-story fall risks while excluding protected elements. The results demonstrate that ontology-guided spatial logic effectively formalizes and detects fall hazards, enabling automated safety assessment during the design phase.

After running the ontology, the processing statistics showed a geometric success rate of 97.7%, with a total of 115 hazards identified. These included 75.7% elevated work hazards, 20.8% opening hazards, and 3.5% access hazards. The total processing time was 0.68 s. As illustrated in Figure 2, the total number of fall hazards was 85 for unprotected sides and edges, 16 for wall openings, 8 for floor openings, 4 for stairways, and 2 for FFH. These hazards were stored in a JSON file, and the subsequent phases, such as fall identification, fall prevention, and LLM reasoning advisory, were based on this JSON file. For fall identification, the extracted hazards were further visualized using a color-coded scheme to clearly distinguish different fall-risk categories.

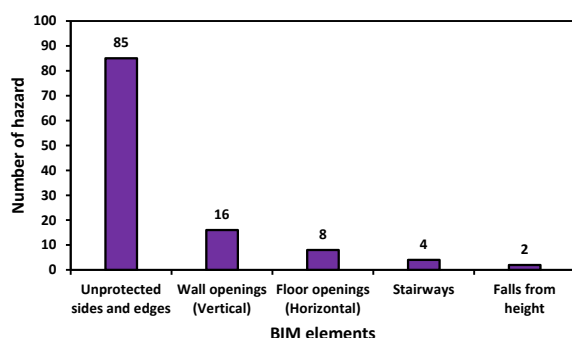


Figure 2. Element-based detection.

4.2 Fall identification and visualization

The results demonstrate that the proposed ontology-driven and BIM-based framework effectively identifies, classifies, and visualizes fall hazards in construction environments. The results support fall hazard identification through color-coded visualization, as shown in Figure 3. Each detected hazard is mapped to its corresponding IFC element or spatial location and rendered using a predefined hazard-based color scheme. Solid building components like slabs, stairways, and structural elements are colored directly, while void-related hazards (floor and wall openings) are represented using 3D markers to overcome IFC visualization

limitations. This visual differentiation allows users to distinguish between unprotected edges, openings, stair-related risks, and FFH scenarios within the 3D model, transforming abstract hazard data into interpretable spatial information.

From a safety prevention perspective, the results enable proactive decision-making by making fall risks visible during design and planning stages rather than during construction. The results indicate the potential of automated hazard identification and visualization to support improved coordination and reduce reliance on manual inspections. Although these aspects are not quantitatively evaluated in this study, color-coding indicates each hazard type associated with BIM elements, allowing stakeholders to easily identify the hazard type, its location, the responsible element, and prevention measures. The color-coded BIM model provides a shared awareness platform for designers, planners, and safety officers, enabling earlier design revisions, clearer safety briefings, and informed construction sequencing. The results confirm that the proposed approach achieves accurate fall hazard identification while strengthening safety prevention strategies and supporting data-driven construction management practices.

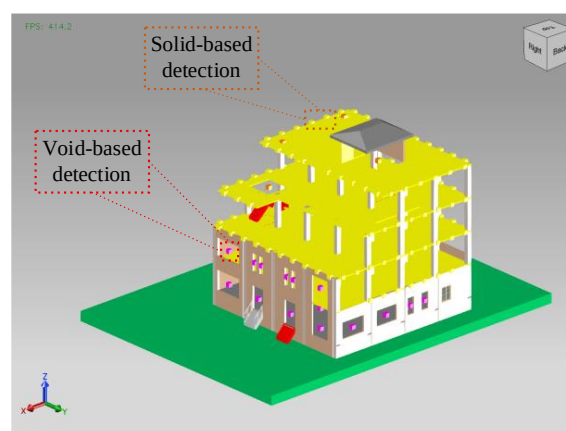


Figure 3. Rule-based fall hazard visualization.

4.3 Fall prevention

The guardrail placement demonstrates that fall prevention measures can be automatically generated and embedded into BIM models in an OSHA-compliant manner. Guardrails were placed at locations identified as unsafe or partially protected, including stair flights without railings, elevated slab perimeters, and floor openings. The placement logic evaluated existing protective elements and skipped compliant locations to avoid redundant safety

components, explaining why guardrails appear only along unprotected areas. The correctness and compliance of generated guardrails are ensured through a rule-based validation mechanism, where OSHA safety requirements, such as guardrail height, mid-rail placement, and edge protection conditions, are explicitly encoded into the system. Guardrail geometries are directly derived from these regulatory constraints, ensuring that all generated elements conform to predefined safety standards without requiring additional manual validation.

As illustrated in Figure 4, the system placed guardrails using geometric and semantic reasoning from the IFC model. For stairs, the code analyzed step geometry across elevations, identified edges, and generated continuous top and mid rails with posts at OSHA-specified spacing. For slabs, the algorithm extracted perimeter and opening loops, classified edges based on adjacent wall height relative to OSHA's 1070 mm parapet threshold, and generated guardrails where needed. Wall-aware inset logic offset guardrails to prevent clashes, reflecting constructability requirements. The results demonstrate fall prevention operationalization in construction sites. By enclosing unprotected edges, openings, and stairways with properly dimensioned guardrails, the system blocks fall paths and reduces height-related hazards. This approach translates detected risks into preventive controls, bridging hazard analysis and mitigation. The BIM integration enables safety strategy review and communication before construction.

From a management perspective, automated guardrail generation improves consistency, efficiency, and traceability. Safety measures are applied uniformly according to rules rather than manual modeling or subjective judgment, reducing missed hazards. The BIM model serves as a digital safety plan supporting inspections, method statements, and stakeholder coordination. Integration of hazard detection and prevention strengthens proactive safety management. However, these guardrail placement methods are hard-coded, rule-based, and deterministic, making them time-consuming to develop, error-prone when conditions deviate from assumptions, and difficult to generalize, motivating the need for an LLM-based approach to overcome these limitations.



Figure 4. Rule-based guardrail placement.

4.4 RAG-LLM reasoning advisor

This section evaluates the advisory and reasoning stage using confusion matrix analysis. As shown in Figure 5, a 5×5 confusion matrix assessed fall hazard classification accuracy against ontology-identified ground truth labels across five categories: unprotected edges, floor openings, wall openings, stairways, and FFH. The ground truth labels are generated through an ontology-based hazard detection process, where regulatory rules and spatial logic are explicitly encoded to deterministically classify fall hazards. These ontology-derived classifications serve as a rule-based reference for evaluating the consistency of predicted hazard categories. Strong diagonal dominance confirmed high classification consistency and validated the ontology-based hazard extraction and rule-based reasoning. Overall performance achieved precision, recall, and F1-score of 0.940 based on 113 true positives, 2 false positives, and 2 false negatives. Classification was achieved for floor openings (0.934), wall openings (0.940), and stairways (0.960), while unprotected edges (0.941) showed minimal misclassification. Compared to recent LLM-based ARC studies [13, 16], which primarily focus on regulatory text interpretation and rule extraction, the proposed approach demonstrates comparable classification performance while introducing a key advancement through integrating ontology-driven spatial reasoning with BIM geometry. Unlike prior works that treat compliance checking as a text-based or post-processing task, this framework directly links semantic regulatory understanding with geometric hazard detection and extends functionality to automated prevention (e.g., guardrail generation). This integration enables spatially grounded hazard identification and mitigation within the BIM

environment.

To evaluate practical usability, a query table (Table 2) tested structured safety-related questions about critical hazards, fall prevention recommendations, and mitigation priorities. The queries successfully retrieved hazard instances from the JSON-based repository and combined them with regulation-informed guidance from the knowledge base. This shows the system can translate visualized, color-coded fall hazards and implemented guardrail measures into actionable safety insights. Combined with previous results on automated hazard detection and preventive modeling, these findings confirm that the framework identifies and mitigates fall hazards while supporting safety decision-making and construction safety management. However, the evaluation of LLM-generated advisory responses is limited to structured query-based testing and does not include validation against expert judgment, robustness analysis under varying prompts or model parameters, or detailed error analysis. These limitations will be addressed in future work to further assess the reliability and robustness of the RAG-LLM advisory module.

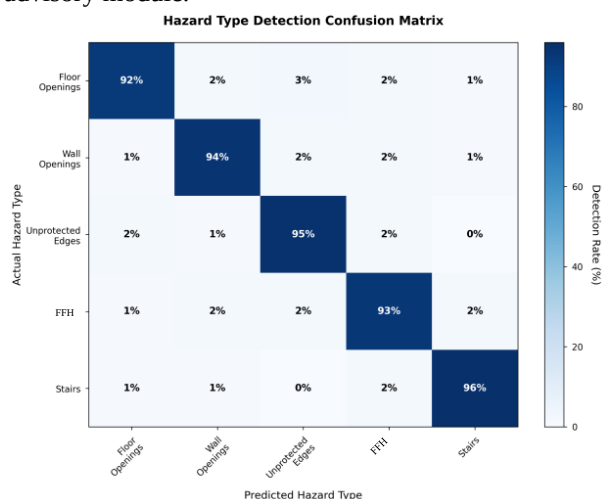


Figure 5. Confusion matrix for fall hazard classifications.

Table 2. RAG-LLM safety-related questions.

Role: How many hazards do I have?

Content: User uploaded hazard report: 115 hazards detected.

Role: How many high-risk hazards do I have to cover?

Content: Based on the information provided in your hazards summary, you have 75.7% elevated wor hazard. This number is specifically categorized under elevated work hazards.

Role: How do I fix slab opening hazards according

to fall rules?

Content: To address slab opening hazards in compliance with Hong Kong Labour Department and MOHURD rules, you must follow specific guidance to ensure worker safety and prevent falls through guardrails.

5 Conclusion

This study proposes a RAG-LLM-augmented BIM pipeline for automated identification and prevention of fall hazards in building design, advancing DfS beyond traditional rule-based approaches. By integrating BIM geometry with a domain-specific ontology and enhancing it through a RAG-enabled LLM, the framework bridges unstructured safety regulations and spatial building data. This integration enables precise, context-aware detection of fall hazards, like unprotected edges, floor and wall openings, and stairway risks, within BIM environments. The system demonstrates effectiveness through three functions: (1) ontology-driven hazard detection with 97.7% geometric processing success, (2) color-coded visualization of hazards within the BIM model, and (3) automated generation of OSHA-compliant guardrails at identified hazard locations. The RAG-LLM layer provides dynamic, knowledge-augmented safety advice, reducing reliance on rule coding and delivering regulation-aware recommendations.

The contributions are threefold. First, the study introduces a semantic-spatial ontology that translates safety regulations into machine-interpretable logic linked to IFC entities. Second, it operationalizes prevention by connecting hazard detection with real-time guardrail placement. Third, it incorporates RAG-LLM as an adaptive reasoning layer to enhance regulatory compliance and support proactive safety decisions.

The study identifies key limitations affecting its applicability. Validation on a single BIM case limits generalizability across diverse project types and scales. Guardrail placement relies on deterministic, rule-based methods that cannot adapt to complex geometries or regulatory changes. The ontology and LLM knowledge base derive primarily from Hong Kong and Chinese safety standards, restricting broader applicability. Future directions include expanding the regulatory knowledge base to international standards, enhancing LLM spatial reasoning through BIM-specific fine-tuning, incorporating sensor data for real-time construction-phase monitoring, and developing generative design approaches for hazard-free alternatives.

This research presents a scalable framework that shifts BIM-based safety checking from compliance verification to proactive hazard prevention. By combining semantic regulatory understanding, geometric analysis, and LLM-augmented reasoning, the pipeline

supports earlier design decisions and advances automated, human-centric safety management in digital construction.

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