Artificial Intelligence for Design for Safety in Construction: A Critical Review and Research Agenda

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Abstract –

Design for Safety (DfS) has gained increasing attention as a proactive strategy to reduce construction accidents, yet its practical implementation remains limited by manual, expertise-driven processes. Recent advances in artificial intelligence (AI), including rule-based reasoning, ontologies, natural language processing (NLP), machine learning, large language models (LLMs), and digital twins, offer new opportunities to automate hazard identification and enhance design-stage decision-making. This study conducts a systematic and critical review of 27 peer-reviewed studies to evaluate the current landscape of AI applications for DfS in construction. The results show substantial progress in BIM-integrated rule checking, ontology-based safety knowledge representation, NLP and deep learning applied to DfS documents, and simulation-driven DfS planning. However, key challenges persist, including fragmented datasets, limited interoperability, inadequate validation, workflow disruptions, and regulatory misalignment. Based on these findings, the paper proposes an integrated conceptual architecture comprising four components: (1) structured safety knowledge, (2) hybrid AI reasoning, (3) human–AI collaboration, and (4) governance and validation mechanisms. A research agenda is also outlined to guide future developments toward standardized datasets, explainable and trustworthy AI, and real-world deployment. The study provides a comprehensive foundation for advancing intelligent, scalable, and industry-ready DfS systems that can significantly improve construction safety outcomes.

Keywords –

Design for Safety (DfS); Artificial Intelligence; Construction Safety; Prevention through Design (PtD)

1 Introduction

Design for Safety (DfS), or Prevention through Design (PtD), is widely recognized as one of the most effective strategies for eliminating hazards at their source by integrating safety considerations directly into early design decisions [1]. Prior research consistently shows that many construction accidents originate from design-related factors, underscoring the need for proactive design-stage interventions [2–4]. Although regulatory frameworks such as Singapore's DfS Guidelines and the UK's Construction Design and Management (CDM) Regulations mandate early hazard mitigation, DfS practice in most regions still depends heavily on manual checklists and expert judgement, resulting in inconsistent outcomes and limited scalability [5].

Rapid developments in artificial intelligence (AI) offer new opportunities to overcome these limitations. AI has been widely applied in construction for tasks such as computer vision–based hazard detection, predictive incident modeling, and natural language processing (NLP) for extracting safety information from documents [3]. These developments highlight a growing momentum toward intelligent, automated safety management. Yet, when examined specifically through the lens of DfS/PtD, where safety interventions can have the greatest impact on preventing accidents, AI research remains scattered, heterogeneous, and often limited to conceptual prototypes or isolated case studies.

A key challenge is that DfS is fundamentally a design reasoning problem, requiring AI systems to interpret multi-modal design information, evaluate regulatory constraints, and explain how design choices create or mitigate hazards. Unlike site-level safety monitoring, where hazards are visible and sensor-detectable, design stage risks are abstract and embedded in BIM models, specifications, method statements, or construction sequences [6,7]. This demands AI systems capable of structured knowledge representation, semantic reasoning, and transparent decision logic to support designers and safety professionals effectively.

Existing reviews on AI in construction safety tend to emphasize computer vision, behavior monitoring, or predictive analytics, with limited attention to design-stage safety. Yet DfS requires tools that can anticipate future risks, integrate expert knowledge with data-driven insights, and produce traceable outputs suitable for regulatory review [5,8]. The distinct technical, organizational, and regulatory challenges associated with DfS therefore warrant a dedicated synthesis of AI-enabled approaches.

In response, this paper provides a critical review of AI applications developed specifically to support DfS processes in construction. The objectives of this review are to describe (1) the current landscape of AI-enabled DfS applications, (2) methodological and practical limitations of existing research, and (3) future research directions required to advance AI-supported design stage safety.

To guide the review, the following research questions are examined:

- RQ1: What AI applications have been developed to support Design for Safety (DfS) in construction?
- RQ2: What methodological and practical limitations exist in current AI-enabled DfS research?
- RQ3: What future research directions are needed to advance AI-supported design-stage safety?

By addressing these questions, this paper clarifies the current state of AI-enabled DfS, identifies critical research gaps, and provides a foundation for developing next-generation tools that can meaningfully improve safety performance through design.

2 Methodology

This study applies a structured review approach informed by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The methodology ensures transparency and replicability in identifying literature on artificial intelligence (AI) applications for Design for Safety (DfS) and Prevention through Design (PtD) in construction.

2.1 Data Sources and Search Strategy

A comprehensive search was conducted across two major electronic databases commonly used in construction and engineering research: Scopus and Web of Science (WoS). These platforms were selected to ensure broad coverage of peer-reviewed journal articles, conference papers, and emerging AI-enabled design safety studies. Search terms were developed iteratively to capture the intersection between DfS/PtD, construction, and artificial intelligence. Boolean operators and controlled vocabulary (when supported by databases) were used to increase precision and reduce irrelevant results. Key search terms included "design for safety", "DfS", "prevention through design", "PtD", "safety-in-design", "design stage safety", "hazard prevention through design", "Construction Design and Management", "Safety by Design", "Design for Construction Safety", "Design risk management", "construction", "artificial intelligence", "AI", "machine learning", "deep learning", "natural language processing", "NLP", "large language model", "Large Language Models (LLMs)", "rule-based", "expert system", "knowledge graph", "ontology".

2.2 Inclusion and Exclusion Criteria

To ensure relevance and methodological consistency, explicit eligibility criteria were applied. Table 1 summarizes the criteria.

Table 1 Inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal articles and conference papers	Non-peer-reviewed sources with unverified findings
Studies addressing DfS, PtD, design-stage hazard identification, design risk management, constructability safety	Studies about site-level safety monitoring, computer vision on site, or safety behavior detection without links to design
Publications written in English	Insufficient methodological transparency
Studies published up to 2025	Duplicated studies across databases

2.3 Study Selection

The PRISMA approach guided the selection process through three stages:

- Identification: All search results from Scopus and WoS were exported. Duplicates were removed using EndNote.
- Screening: Titles and abstracts were screened against the inclusion/exclusion criteria. Articles unrelated to design-stage safety or lacking AI relevance were excluded.
- Eligibility: Full-text review of remaining studies. Studies were retained if they explicitly applied AI to DfS/PtD functions such as rule checking, risk evaluation, hazard extraction, or design decision support.

A PRISMA flow diagram (presented in Figure 1) summarizes the numbers at each stage.

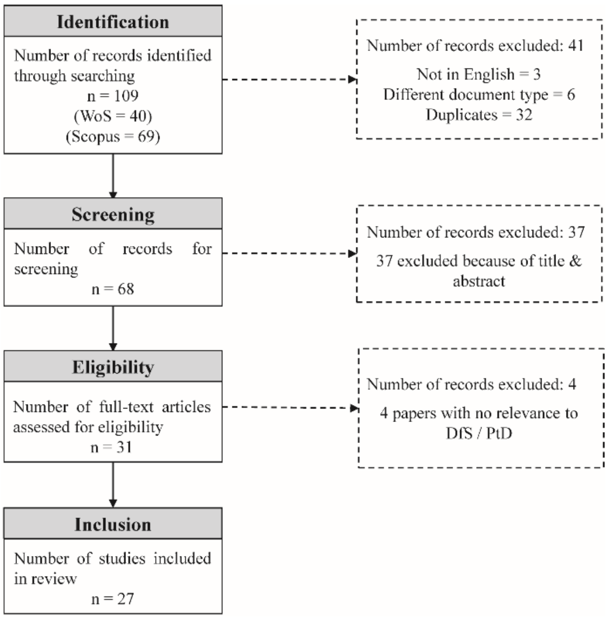

Figure 1. PRISMA flow diagram for the study selection

2.4 Data Analysis

The data analysis employed a structured coding framework for extracting comparable information from included studies, focusing on both descriptive mapping and critical evaluation. Descriptive coding systematically recorded attributes for each study, including its publication year, methodological type, the DfS/PtD stage supported (concept, detailed, temporary works, maintenance), the AI technique employed (ML, LLM, ontology, rule-based, hybrid), data inputs (BIM models, engineering drawings, textual specifications, rulesets), safety function (hazard identification, rule checking, risk ranking, mitigation generation), level of system integration (stand-alone prototype, BIM-integrated, semi-automated workflow), and evaluation methods (case study, experiment, simulation, expert panel). Subsequently, a qualitative thematic synthesis was performed to identify recurring themes, compare the role and maturity of different AI methods across design stages, and evaluate methodological and practical limitations. The results of this thematic synthesis were further used to derive a conceptual architecture and research agenda.

3 Landscape of AI Applications for DfS/PtD in Construction

This section presents the results of the systematic review of 27 studies, structured around the main ways in which artificial intelligence and related computational approaches have been used to support Design for Safety (DfS) and Prevention through Design (PtD) in construction. The findings are organized into five themes: (1) BIM and rule-based systems for design stage safety checking, (2) ontologies and safety risk libraries for knowledge representation and reuse, (3) data-driven and NLP/ML approaches applied to DfS documentation and accident data, (4) digital twins, 4D models, and agent-based simulation for PtD/P, and (5) emerging LLM-based and decision-support tools for hazard identification and design decision-making.

3.1 Overview of Included Studies

The final sample covers publications from 2007 to 2025, with a marked increase from 2013 onwards as BIM and AI technologies matured. Early work is dominated by knowledge-based and rule-based decision-support systems, evolving into BIM-integrated automated safety checking [9–11], followed by ontology-based safety knowledge models [12–15]. More recent studies increasingly incorporate NLP, machine learning, deep learning, recommender systems, digital twins, agent-based simulation, and LLMs [16–21]. Most studies are journal articles, complemented by conference papers that often introduce prototype systems or benchmarks [11,15,22,23]. The dominant application context is BIM-enabled building and infrastructure projects, though some works focus specifically on metro stations [6], residential construction with panelized walls [24], or corporate PtD deployment [25]. To provide a concise synthesis of the reviewed literature, Table 2 presents a comparative overview of the dominant AI application themes for DfS.

Table 2 Comparative overview of AI applications for DfS

Theme	AI Techniques	Input Data	DfS Function	Strengths	Limitations
BIM + Rule-based	Rule engines, BIM plugins	BIM models, schedules	Hazard detection, compliance checking	High interpretability, direct regulatory mapping	Manual rule encoding, BIM dependency
Ontologies & Risk Libraries	Ontologies, knowledge graphs	Structured safety knowledge	Knowledge reuse, semantic querying	Standardization, interoperability potential	Limited adoption, complex modeling
NLP / ML / DL	CNN, LSTM, NLP	Text (reports, regulations)	Hazard extraction, classification	Scalable, reduces manual effort	Data dependency, limited explainability
Digital Twins & Simulation	Agent-based, DT, 4D BIM	BIM + sensor + schedule	Dynamic risk analysis, exposure modeling	Captures temporal risk	High complexity, integration issues
LLM & Decision Support	LLMs, recommender systems	Text + multimodal	Hazard ideation, design assistance	High usability, improves cognition	Reliability, hallucination risk

3.2 BIM and Rule-based Systems for Design Stage Safety Checking

A major theme is the use of BIM combined with rule-based reasoning to automatically identify safety hazards and non-compliant design features at the design or planning stage. Early work by Zhang et al. [9] demonstrated automated safety checking of BIM models and schedules, particularly for fall hazards, while Melzner et al. [10] extended this approach to support configurable compliance checking across different regulatory standards.

Subsequent studies further integrated rule-based logic within BIM environments. Guo et al. [11] and Hossain et al. [2] developed systems linking design elements with safety rules and risk knowledge, enabling automated identification of unsafe design conditions. Yuan et al. [26] implemented a BIM-based plug-in for automated rule checking and risk feedback, while Tang et al. [6] extended BIM-based safety design to evacuation planning in metro stations.

These studies highlight the value of rule-based reasoning for improving consistency and reducing manual effort, although they remain constrained by manual rule encoding and BIM model completeness.

3.3 Ontologies and Safety Risk Libraries for Knowledge Representation and Reuse

Another strong theme is the development of ontologies and structured safety risk libraries to formalize and reuse DfS/PtD knowledge. Zhang et al. [12] introduced an ontology-based safety knowledge model linking product, process, and hazard information, while Farghaly et al. [13] aligned safety ontologies with IFC standards to improve interoperability. Johansen et al. [14] and Johansen et al. [15] focused on hazard ontology and benchmark models for PtD/P, targeting falls-from-height and struck-by falling object hazards. They created a 4D BIM-based benchmark model and safety ontology to enable standardized performance assessment of automated PtD tools and later extended this work in the SafeConAI framework. Johansen et al. [16]'s automated performance assessment of PtD/P strategies formalizes quantitative indicators such as soundness, completeness, and spatial correctness, providing a way to objectively compare automated safety assessment approaches. Collinge et al. [7] introduced a BIM-based Safety Risk Library that organizes risk scenarios and treatments into a seven-stage ontology to support designers in PtD decision-making. Osorio-Sandoval et al. [27] published a data paper describing the underlying dataset of characterized safety risks and associated treatments, which was iteratively built through focus groups, pilot projects, and accident report analysis. Collinge and Osorio-Sandoval [28] subsequently reported on the deployment of the Safety Risk Library in real projects, capturing practitioner feedback, barriers, and alignment with industry standards such as PAS 1192-6.

These efforts demonstrate that ontologies form a semantic foundation for advanced AI-enabled DfS.

3.4 Data-driven and NLP/ML approaches applied to DfS documentation and accident data

More recent studies move beyond hand-coded rules toward data-driven AI methods, particularly in processing textual safety information and accident records. Tixier et al. [29] applied NLP and data mining to identify unsafe attribute combinations from accident reports, supporting design-stage risk awareness. Zhou et al. [17] developed an NLP-based framework to extract and structure safety regulations for automated BIM-based compliance checking. Kumi et al. [18] developed a deep learning–based classification framework for DfS reports, using Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and hybrid CNN–LSTM models to classify reports by accident type, facility type, and work type. The CNN model showed the best performance, enabling automated, large-scale analysis of DfS reports and supporting proactive hazard identification and risk prioritization. Kumi et al. [19] proposed a multimodal recommender system for DfS, combining textual and image data and using cosine similarity to suggest tailored DfS recommendations via a web application. Expert evaluation results indicate that recommender systems can help bridge the gap between DfS theory and practice.

These studies illustrate how data-driven AI can complement rule-based approaches by automating pattern discovery from real-world safety data.

3.5 Digital twins, 4D models, and agent-based simulation for PtD/P

Another emerging direction involves the use of digital twins, 4D BIM, and simulation to support dynamic risk assessment in design and planning. Hong and Teizer [30] introduced a digital twin framework integrating BIM, rule-based checking, and Real-Time Kinematic Global Navigation Satellite Systems (RTK-GNSS) data for proactive safety monitoring. Johansen et al. [31] developed a spatio-temporal approach to quantify worker exposure to hazards, supporting design and planning decisions. Similarly, Sorbi et al. [20] proposed an agent-based simulation framework integrated with 4D BIM to estimate risk and visualize hazard exposure. Hoeft and Trask [8] provided a broader mapping review and practitioner focus group study on the occupational health and safety potential of BIM-based digital platforms throughout the building lifecycle. While not focused on a single algorithm, they identify use cases such as rule-based checking, site layout planning, real-time monitoring, and digital twins, underscoring the strategic potential of these technologies for DfS/PtD.

3.6 LLM-based and other decision-support tools for PtD and DfS

Finally, several studies explore LLM-based tools and decision-support systems that indirectly support DfS/PtD through improved hazard recognition, ergonomics, or competence assessment. Uddin et al. [21] conducted a randomized controlled experiment to evaluate ChatGPT as an intervention in Construction Hazard Prevention through Design (CHPtD) sessions. Participants using ChatGPT identified about 40% more hazards than those without AI assistance, demonstrating that LLMs can meaningfully enhance hazard recognition during early design and hazard brainstorming sessions. Earlier, Nussbaum et al. [24] developed a decision support system for residential construction with panelized walls, focusing on ergonomic risk and productivity. The system allows designers to assess musculoskeletal disorder risks at early design stages. Yu et al. [23] developed a knowledge-based decision-support system for health and safety competence assessment under CDM regulations. Sinha et al. [25] reported a corporate-level case study on PtD implementation at Tata Steel, describing the adoption of practices such as virtual design and construction, 3D modelling, prefabrication, and AI-based CCTV surveillance within a PtD program. While not detailing specific AI algorithms, it highlights how digital and AI-enhanced tools can be embedded within broader PtD strategies in large organizations.

4 Critical Analysis: Limitations, Risks, and Barriers

The reviewed studies demonstrate substantial progress in applying artificial intelligence to Design for Safety (DfS), yet several limitations continue to constrain their maturity and industry uptake. A persistent challenge is the fragmentation of datasets used to train and validate AI models. Many studies rely on project-specific information or manually curated datasets, such as the Safety Risk Library [7,27] or DfS report collections [18], while early work on accident data extraction [29] similarly depends on localized sources. Although hazard ontologies and benchmark models have begun to address comparability [14,15], there remain no standardized or openly shared datasets that enable cross-study evaluation. This lack of common data inhibits replication, limits generalizability, and slows development of robust machine learning and NLP models suitable for diverse design contexts.

Another technical limitation concerns the dependence on complete and semantically rich BIM models and the laborious encoding of safety rules. Automated checking systems require consistent object definitions, parameterization, and model completeness to function reliably [9–11,26]. In practice, BIM models rarely contain the level of detail or attribute structure required for effective automated reasoning. Moreover, translating regulatory requirements into computable rules remains a time-consuming and expertise-intensive process, even in frameworks supported by NLP or ontologies [13,17]. Interoperability challenges further limit scalability, as many semantic, BIM-based, and simulation-driven systems function as isolated prototypes rather than integrated components of established design and project management platforms [12,20,30].

Beyond technical issues, organizational and human factors present significant barriers. Several studies highlight designers' limited construction safety knowledge and difficulty interpreting AI-generated outputs [2,8,26]. This challenge is compounded by low AI literacy, which reduces confidence in automated recommendations and limits effective human–AI collaboration. The introduction of new DfS platforms often disrupts existing workflows, especially when they require additional modeling effort or early-stage safety tasks, contributing to resistance to adoption [28]. Conversely, studies exploring LLM-based assistance, such as ChatGPT-supported hazard recognition [21] and multimodal recommender systems [19], demonstrate improved hazard identification yet introduce risks of over-reliance, where designers may defer excessively to AI suggestions without adequate critical review.

At the regulatory and industry level, AI-enabled DfS systems remain misaligned with formal compliance frameworks such as CDM, OSHA PtD, and Singapore's DfS process. Existing regulations assume human accountability and do not formally recognize automated safety assessment as part of statutory design stage obligations. Consequently, AI tools, whether rule-based or ML-driven, are generally treated as advisory. Ethical concerns also arise due to potential bias embedded in training datasets, curated risk libraries, or pretrained language models, which may lead to systematic under-recognition of certain hazards [7,21]. Moreover, few studies discuss governance mechanisms for model validation, update cycles, auditability, or accountability when AI influences design decisions, issues that are critical for safety-critical applications. Without clear governance structures, organizations may be reluctant to rely on AI-assisted DfS tools in practice.

5 Proposed Conceptual Architecture and Research Agenda

This review identifies the need for an integrated approach that connects structured safety knowledge, multiple AI techniques, human decision-making, and regulatory alignment. To address the limitations outlined in Section 4, a conceptual architecture is proposed to guide future development of AI-enabled Design for Safety (DfS) systems.

The architecture consists of four interrelated layers, as illustrated in Figure 2.

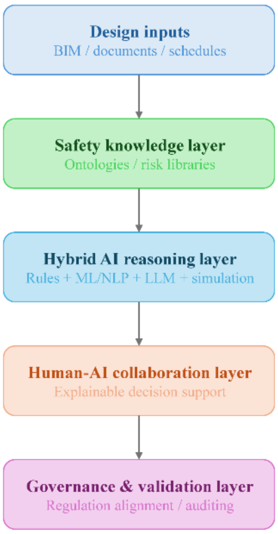

Figure 2. Conceptual architecture of AI-enabled DfS systems

The Safety Knowledge Layer provides structured, machine-readable representations of hazards, rules, and risk scenarios through ontologies, risk libraries, and benchmark datasets.

The Hybrid AI Reasoning Layer integrates multiple AI paradigms, combining rule-based compliance checking with data-driven methods such as ML, NLP, LLMs, and simulation-based approaches to support both static and dynamic risk assessment.

The Human-AI Collaboration Layer ensures that AI outputs are interpretable and actionable, supporting designers through explainable recommendations and interactive decision-making interfaces rather than replacing professional judgment.

The Governance and Validation Layer addresses critical requirements for safety-critical systems, including transparency, auditability, regulatory alignment, and lifecycle management of AI models and data.

Together, these layers form an integrated ecosystem supporting automated hazard identification, design evaluation, risk reasoning, and proactive intervention throughout the design and planning stages.

Building on this conceptual architecture, several research priorities emerge. First, there is a need for standardized and openly accessible datasets to enable reproducible AI research in DfS. Second, future work should focus on hybrid and multi-modal AI systems that integrate textual, geometric, schedule, and sensor data. Third, the development of explainable and trustworthy AI is essential to enhance user acceptance and reduce over-reliance. Fourth, stronger alignment between AI tools and regulatory frameworks is required to support industry adoption. Finally, longitudinal and real-world validation studies are needed to evaluate the impact of AI-enabled DfS systems on safety performance and project outcomes.

This conceptual architecture and research agenda provide a structured pathway for advancing AI-enabled DfS from experimental prototypes toward scalable, industry-ready solutions.

6 Conclusions

This paper presented a critical review on the application of artificial intelligence to Design for Safety (DfS) in construction. The findings show that AI has progressed from early rule-based systems and safety ontologies to advanced NLP, machine learning, recommender systems, and digital twin–enabled DfS analysis. These technologies demonstrate strong potential for automating hazard identification, improving design stage decision support, and strengthening the integration of safety considerations into BIM and 4D planning environments.

However, the review also reveals persistent challenges. Data fragmentation, limited interoperability, incomplete validation, and insufficient explainability continue to restrict the robustness and adoption of current AI-enabled DfS tools. Organizational barriers, such as low safety and AI literacy among designers, workflow disruptions, and concerns about accountability, further constrain implementation. In addition, regulatory frameworks lag behind technological developments, leaving AI-assisted safety assessments without formal recognition in compliance processes.

To address these issues, a conceptual architecture was proposed that integrates structured safety knowledge, hybrid AI reasoning, human–AI collaboration, and governance mechanisms. A research agenda was also outlined, emphasizing the need for standardized datasets, explainable and multi-modal AI models, regulatory alignment, and longitudinal real-world evaluations.

AI offers a promising pathway for transforming how safety is embedded in design. Realizing this potential will require coordinated efforts across research, industry, and regulatory bodies to develop trustworthy, interoperable, and practice-ready AI systems. Such advancements can significantly enhance early hazard mitigation and ultimately contribute to a safer construction industry.

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