*sustainability*

MDPI

*Article*

# Achieving Sustainable Construction Safety Management: The Shift from Compliance to Intelligence via BIM–AI Convergence

**Heap-Yih Chong [1], Qinghua Ma [1], Jianying Lai [1,2,*] and Xiaofeng Liao [3,*]**

[1] School of Engineering Audit, Nanjing Audit University, Nanjing 211815, China; 270002@nau.edu.cn (H.-Y.C.); 15949137013@163.com (Q.M.)
[2] Jiangsu Key Laboratory of Public Project Audit, Nanjing 211815, China
[3] School of Civil and Hydraulic Engineering, Chongqing University of Science and Technology, Chongqing 401331, China
* Correspondence: 270399@nau.edu.cn (J.L.); lxf@cqust.edu.cn (X.L.)

**Abstract:** Traditional construction safety management, reliant on manual inspections and heuristic judgments, increasingly fails to address the dynamic, multi-dimensional risks of modern projects, perpetuating fragmented safety governance and reactive hazard mitigation. This study proposes an integrated building information modeling (BIM)–AI platform to unify safety supervision across the project lifecycle, synthesizing spatial-temporal data from BIM with AI-driven probabilistic models and IoT-enabled real-time monitoring for sustainable construction safety management. Employing a Design Science Research methodology, the platform's phase-agnostic architecture bridges technical–organizational divides, while the Multilayer Neural Risk Coupling Assessment framework quantifies interdependencies among structural, environmental, and human risk factors. Prototype testing in real-world projects demonstrates improved risk detection accuracy, reduced reliance on manual processes, and enhanced cross-departmental collaboration. The system transitions safety regimes from compliance-based protocols to proactive, data-empowered governance. This approach offers scalability across diverse projects. The BIM-AI intelligent fusion platform proposed in this study builds an intelligent construction paradigm with synergistic development of safety governance and sustainability through whole lifecycle risk coupling analysis and real-time dynamic monitoring, which realizes a proactive safety supervision system while significantly reducing construction waste and accident prevention mechanisms.

**Keywords:** BIM; AI; sustainable construction safety management; proactive; dynamic; prototype; project lifecycle

check for updates

Academic Editors: Yuanda Cheng, Wenzhuo Li and Zhipeng Deng

Received: 10 April 2025
Revised: 8 May 2025
Accepted: 12 May 2025
Published: 14 May 2025

**Citation:** Chong, H.-Y.; Ma, Q.; Lai, J.; Liao, X. Achieving Sustainable Construction Safety Management: The Shift from Compliance to Intelligence via BIM–AI Convergence. *Sustainability* **2025**, *17*, 4454. https://doi.org/10.3390/su17104454

**Copyright:** © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

## 1. Introduction

Construction safety supervision constitutes a critical determinant of project success, encompassing not only the preservation of human lives and structural integrity but also compliance with regulatory frameworks, economic viability, and societal trust [1]. As construction projects grow in scale and complexity, conventional safety management paradigms—reliant on manual inspections and heuristic judgments—increasingly prove inadequate in addressing dynamic, multi-dimensional risks [2,3]. This systemic inefficiency underscores an urgent need for data-driven methodologies capable of preempting hazards while ensuring cross-phase operational continuity.

Building information modeling (BIM), a transformative force in the construction industry's digitalization, offers unprecedented opportunities to reconceptualize safety

governance. By generating multi-dimensional digital twins that integrate spatial, temporal, and functional attributes, BIM transcends its traditional role as a visualization and collaboration tool [4]. BIM is rooted in three-dimensional (3D) building geometry, which now includes extended applications such as 4D (incorporating time-based scheduling), 5D (integrating cost management), and 6D (embedding sustainability metrics). These innovations have significantly enhanced workflow optimization and reduced design conflicts across construction and planning phases [5]. However, the latent potential of BIM-derived data remains underutilized in safety contexts, particularly in predictive risk analytics and cross-disciplinary decision support [6].

In parallel, artificial intelligence (AI) techniques have been increasingly applied to enhance the effectiveness and efficiency of safety checking. Methods such as rule-based reasoning (RBR), case-based reasoning (CBR), neural networks, and answer set programming (ASP) have been employed to improve the acquisition of safety knowledge and the identification of causation mechanisms for various safety risks [7–9]. For instance, Li et al. utilized RBR to learn safety checking rules and applied logical reasoning to analyze safety risk factors extracted from BIM models and sensor data [5]. Tian et al. integrated backpropagation neural networks with BIM and sensor data to assess risk factors for tunnel deformation in subway construction [7]. ASP, introduced by Schultz et al., has also been applied to conduct rule-based "Space–Time" safety checking [9]. Recent advancements, such as those mentioned in the International AI Safety Report 2025, also emphasize abstraction-guided verification frameworks to address vulnerabilities in neural networks, ensuring robustness in autonomous systems like construction and transportation [10]. These scholarly works emphasize two critical gaps. First, while BIM-AI convergence has been explored for discrete project phases (e.g., design clash detection or schedule optimization) [11–13], few studies address holistic, lifecycle-oriented safety ecosystems [14,15]. Second, existing technical implementations often prioritize algorithmic sophistication over practical interoperability, neglecting the organizational and procedural adaptations required for scalable deployment [16]. These limitations perpetuate reactive safety cultures, wherein risks are addressed post hoc rather than precluded through systemic design.

To address these challenges, this study proposes an integrated BIM-AI platform to unify safety supervision across all project phases—from planning to decommissioning for sustainable construction safety management. The proposed platform has three objectives, namely, (a) synthesizing BIM's spatial-temporal data with AI-driven probabilistic models to forecast hazards (e.g., structural instability); (b) leveraging IoT-enabled sensors and deep learning to monitor compliance and mitigate human-factor risks in real time, and (c) establishing a centralized repository for safety-related data, enabling continuous learning and regulatory alignment.

By bridging the technical–organizational divide, this research contributes to both theory and practice. Theoretically, it advances BIM-AI interoperability models through a phase-agnostic architecture that prioritizes scalability and user-centric design. Practically, it offers a replicable blueprint for transitioning from compliance-based safety regimes to proactive, data-empowered governance systems. Subsequent sections detail the platform's technical architecture, validation through case studies, and implications for construction digitalization.

## 2. Literature Review

The integration of BIM and AI in construction safety management has emerged as a transformative research frontier, with scholarly efforts converging on three principal research streams: (1) risk identification and predictive analytics, (2) real-time monitoring and behavioral governance, and (3) system integration and decision optimization. While

these domains have yielded significant methodological advancements, critical gaps persist in operationalizing theoretical innovations into holistic safety governance frameworks. This review systematically examines these thematic clusters, elucidating their interdependencies while foregrounding unresolved challenges that necessitate a paradigm shift toward lifecycle-integrated safety intelligence systems.

### *2.1. Risk Identification and Predictive Analytics*

In terms of risk identification and predictive analytics, researchers have constructed a multi-level early warning framework through multimodal data mining and machine learning models. For example, Zhang et al. extracted semantic features from accident reports based on text mining and natural language processing techniques to reveal potential patterns of accident causes [17], while Baker et al. utilized a deep learning model to automatically identify injury precursors and achieve dynamic prediction of high-risk scenarios [18]. The introduction of Random Forest [19] and Bayesian framework [20] further improves the robustness of the prediction models, especially when dealing with small samples and unbalanced data, showing strong generalization ability. In addition, the deep learning and text mining framework proposed by Zhong et al. achieves automatic identification and classification of hazardous topics in accident reports by combining the latent Dirichlet distribution (LDA) and a convolutional neural network (CNN) [21]. Notably, the graph convolutional network developed by Pan et al. constructed a dynamic map of risk propagation paths by correlating spatiotemporal features between accidents, providing a new perspective for systemic risk prediction [22]. Such studies not only validate the effectiveness of data-driven approaches but also emphasize the necessity of structured knowledge bases and interpretable models in complex environments. However, most of the existing studies focus on a single data source or specific scenarios, e.g., although Xiong et al. achieved a joint analysis of audio and visual data [23], their model is still limited to the identification of specific equipment noise and lacks a systematic integration of whole-lifecycle risk management, which leads to limits the cross-scenario generalization ability of the prediction model. A deeper contradiction is that the heterogeneous data from multiple sources (e.g., BIM models, IoT sensing data) on the construction site have not yet formed an effective knowledge fusion mechanism, which restricts the evolution of risk prediction models from "local optimization" to "global intelligence".

### *2.2. Real-Time Monitoring and Behavioral Governance*

In the field of real-time monitoring and behavioral management, breakthroughs in computer vision technology provide a new paradigm for active safety management at construction sites. The intelligent helmet detection system developed by Mneymneh et al. realizes real-time monitoring of workers' personal protective equipment through convolutional neural networks (CNNs) [24], while the target detection algorithm proposed by Fang et al. effectively identifies the risk of spatial interaction between heavy-duty equipment and worker spatial interaction risks [25]. Recent studies have further extended to multimodal behavioral analysis for hazard detection system [3,26], while Jeelani et al. developed an emergency response mechanism through gesture recognition technology [27]. Notably, the transformer-based model significantly improves the recognition accuracy of unsafe actions through spatiotemporal feature fusion [28], while the successful application of the CenterNet real-time detection system proposed by Goh et al. in social distance surveillance of an epidemic exemplifies the potential of deep learning in complex dynamic scenes [29]. However, existing systems mostly rely on a single sensor or data source, e.g., the audio localization technique of Elelu et al. [30], while recognizing device proximity, and are unable to parse semantic relationships in complex scenes. More critically, the current behavioral anal-

ysis focuses on discrete action recognition and lacks continuous modeling of the operation process, such as the whole process of safety control of "loading–transportation–dumping" in earthmoving operations, which still relies on manual supervision. This fragmented monitoring method is difficult to capture the progressive risk evolution process, exposing the structural contradiction between the current technical system and the overall demand for construction safety management.

### *2.3. System Integration and Decision Optimization*

Research on system integration and decision optimization focuses on multi-technology fusion and automated decision support. Luo et al. combined computer vision and semantic reasoning to construct a heterogeneous data integration framework for construction sites [31], while Wang and El-Gohary achieved dynamic mapping and reasoning of safety specifications through knowledge graphs [32]. The proposal of a customized AutoML system [33] and a country-level, data-driven framework [34] marks a paradigm shift in construction safety management from a single technology application to systematic optimization. Notably, Chen et al. [35] developed a mixed reality system overlaying BIM models with real-time visual data to achieve augmented reality annotation of hidden hazards; however, the stability of this system under complex lighting conditions still needs to be improved. In addition, the machine learning decision support framework proposed by Gondia et al. [36] can output risk heat maps by integrating learning with SHAP interpretability techniques; however, it has not yet formed a closed loop with the decision-making process of the project management system.

The existing technological architecture exhibits three critical deficiencies across operational layers. At the data collection layer, insufficient integration of heterogeneous computing resources—specifically, the absence of synergistic edge-cloud computing architectures—results in suboptimal real-time data processing capabilities, primarily attributable to latency in distributed system coordination. Within the model development layer, the lack of domain-specific meta-learning frameworks impedes feature engineering adaptation across heterogeneous construction scenarios, thereby imposing prohibitive computational and annotation costs during cross-project knowledge transfer. At the application layer, the failure to institutionalize human-in-the-loop decision-making mechanisms creates a systemic disconnect between automated safety alerts and on-site operational protocols, particularly manifesting as implementation gaps in last-mile risk mitigation measures. This systemic fragmentation between technological innovation and organizational governance structures perpetuates a paradoxical scenario: despite algorithmic advancements achieving laboratory-level precision, their practical utility remains constrained by an inability to transcend proof-of-concept stages. Such disjuncture ultimately culminates in a misalignment between predictive analytics sophistication and tangible safety performance enhancements, underscoring the imperative for cyber-physical systems that concurrently address technical interoperability and socio-technical workflow integration.

Collectively, prior work establishes three critical lacunae: (1) Phase Fragmentation: Current BIM-AI implementations focus on isolated project stages (e.g., structural erection), lacking architectures for lifecycle-spanning safety intelligence. (2) Organizational Decoupling: Technical advancements rarely address how safety data should interface with managerial workflows. (3) Proactive Governance Deficit: Systems prioritize real-time hazard detection over upstream risk prevention. To bridge these gaps, this study posits a systems theory-informed framework that redefines safety governance as a closed-loop, lifecycle-integrated process.

## 3. Methodology

This study adopted a Design Science Research (DSR) methodology [37] to develop and evaluate an integrated BIM-AI platform for unified safety supervision across construction project lifecycles for sustainable construction safety management. The research followed a structured approach in the creation and evaluation of artifacts when addressing real-world problems. The DSR framework was structured into two iterative phases, namely, (a) framework development and design and (b) prototype platform and evaluation.

The first phase focused on synthesizing theoretical foundations and practical requirements to design the platform's architecture. The development and design processes were based on a holistic framework for understanding complex interactions within the construction project lifecycle. This approach was particularly relevant to construction safety supervision, as safety is an emergent property that could not be fully understood by examining individual components or phases of a project. The integrated BIM-AI platform was designed to address the complex, interconnected nature of safety risks across all project phases.

The second phase involved the agile, test-driven development of the prototype platform. The BIM models were developed using Autodesk Revit (Version 2023) [38], while IoT data were processed through Python (Version 3) [39] and TensorFlow (Version 2) [40] to enable machine learning-based pattern detection. Real-time communication between IoT-enabled sensors and the BIM platform leveraged the Message Queuing Telemetry Transport (MQTT) protocol, ensuring lightweight and efficient messaging across distributed systems. The evaluation emphasized holistic performance rather than isolated components: case studies on infrastructure projects evaluate how the entire system forecasts hazards (e.g., correlating BIM-derived load simulations with sensor-detected vibrations) and self-optimizes via the centralized repository. Case studies were tested on construction projects to evaluate the platform's efficacy as provided by the local government, as well as feedback from the actual users who used the prototype. By iterating between artifact refinement and empirical validation, this methodology ensured the platform addressed both theoretical gaps in BIM-AI integration and operational challenges in safety supervision.

## 4. Framework Development and Design

While the extant literature substantiates the technical feasibility of BIM-AI integration for discrete safety functions from predictive analytics to automated monitoring, these advancements remain circumscribed by their episodic and techno-centric orientations. The prevailing focus on algorithmic accuracy and phase-specific toolkits, though methodologically rigorous, inadvertently perpetuates the very silos that hinder holistic safety governance. This dissonance underscores a fundamental theoretical lacuna: current paradigms inadequately conceptualize safety as a systemic property emerging from the interplay of technological, procedural, and human factors across the project lifecycle.

To reconcile this divide, we anchor our framework in systems theory (Bertalanffy, 1968 [41]), which posits that complex systems cannot be understood through isolated components but require analysis of their interdependencies. By reconceptualizing construction safety as a socio-technical ecosystem (where BIM-derived data flows and AI-driven insights and human decision-making co-evolve), we transcend the reductionist "tool-first" approaches dominating prior research. The subsequent section operationalizes this lens, proposing a phase-agnostic architecture that embeds safety intelligence into every organizational layer, from strategic planning to frontline execution. Figure 1 illustrates the layers of the theoretical framework of this information integration platform. Below, we explore how each layer contributes to this holistic approach. This case study exemplified the integration of digital intelligence technologies such as big data, AI, and the IoT. Moreover, this case

highlights the collaborative potential of digital intelligence technologies across all stages of the building lifecycle, as illustrated in Figure 1. The integration of these technologies has significantly improved the building's operational efficiency, sustainability, and safety, making it an exemplary case of how digital intelligence can promote holistic and integrated approaches to building lifecycle management. This aligns well with the research objectives of identifying key technologies, analyzing integration mechanisms, and assessing their impacts on project efficiency, sustainability, and safety.

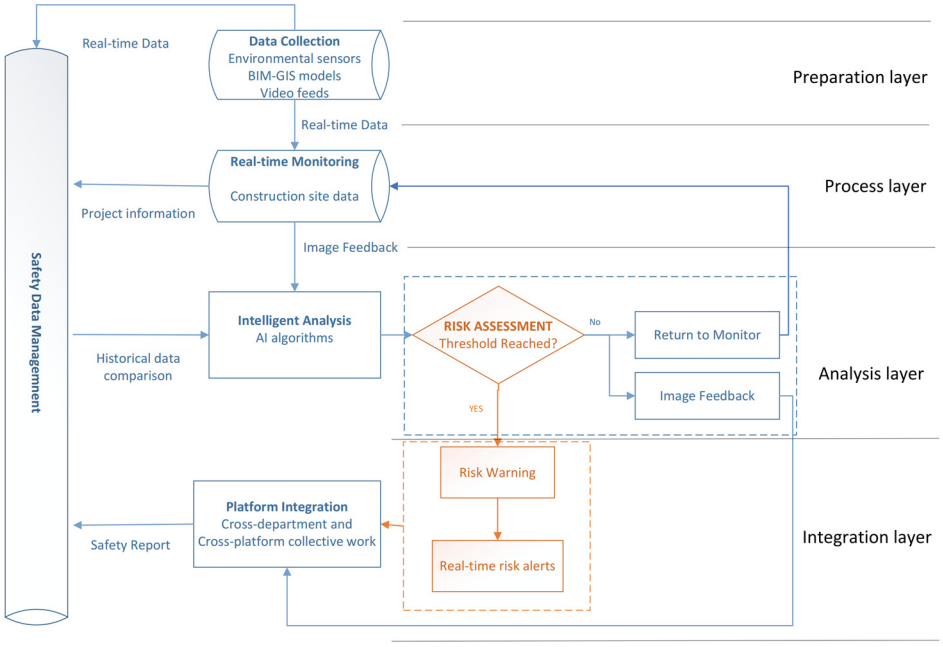



**Figure 1.** Theoretical framework.

### *4.1. Preparation Layer*

This layer functions as the system's sensory apparatus, capturing the multifaceted realities of the construction environment. Analogous to a nervous system attuned to its surroundings, this layer assimilates heterogeneous data streams—ambient conditions captured by environmental sensors, spatial geometries encoded in BIM models, and behavioral patterns discerned from video analytics. Its mandate extends beyond passive data aggregation; it constructs a living digital twin of the physical site, continuously updated to reflect real-time dynamics. For instance, the spatial intelligence embedded in BIM models contextualizes sensor data, enabling the system to distinguish between routine vibrations from machinery and anomalous tremors indicative of structural instability. By prioritizing data integrity and temporal fidelity, this layer grounds subsequent analyses in an accurate, holistic representation of site conditions. This perceptual fidelity is critical, as it forms the empirical bedrock upon which the entire safety ecosystem operates.

### *4.2. Process Layer*

Building upon this sensory foundation, the monitoring layer operates as the system's cognitive engine, perpetually parsing data streams to identify deviations from normative states. Its function parallels the human capacity for situational awareness, albeit augmented by machine precision and tirelessness. Through continuous surveillance of variables such as equipment performance thresholds, environmental tolerances, and personnel compliance, the layer detects nascent risks, such as a crane operator exceeding safe lifting parameters, particulate concentrations, breathing air quality thresholds, or workers bypassing geofenced hazard zones. Upon detection, it triggers a cascading feedback

mechanism: visual dashboards illuminate risk hotspots, mobile alerts ping responsible supervisors, and automated protocols temporarily immobilize compromised equipment. This real-time closed loop—"detect, alert, act"—collapses the temporal gap between hazard emergence and mitigation, transforming safety management from a retrospective audit into a preemptive discipline.

### *4.3. Analysis Layer*

The third layer embodies the system's higher-order cognitive faculties, synthesizing disparate data modalities into actionable intelligence. Here, spatially tagged BIM metadata, temporally sequenced sensor logs, and semantically annotated incident reports converge within an analytical crucible. The layer discerns latent patterns and causal linkages invisible to human analysts. For instance, it identifies correlations between subcontractor turnover rates and safety violations, as well as cyclical spikes in accidents during post-lunch productivity surges. Leveraging these insights, it projects risk trajectories, predicting, for example, how schedule compression might elevate fall hazards during roofing phases or how seasonal rainfall could destabilize excavation sites.

Drawing on Hollnagel's system safety theory and digital twin paradigms [42], this study proposes a Multilayer Neural Risk Coupling Assessment (MNRA) that redefines safety governance through three core computational mechanisms during the analysis: structural degradation ($S_{str}$), environmental perturbation ($S_{env}$), and human error ($S_{hum}$). As established in risk metric research, this interdependence necessitates a composite evaluation function:

$$R = \Phi(S_{str} + S_{env} + S_{hum}) \quad (1)$$

where $\Phi$ denotes the coupling operator.

The following is an explanation of each evaluation indicator:

- Structural Component (GNN): Graph Neural Networks process BIM-derived adjacency matrices (A) and node features (X) [43] through spectral graph convolution. The GAT architecture enables adaptive attention to critical structural relationships, quantifying material fatigue and connection vulnerabilities via message passing between BIM elements [44].
- Environmental Component (LSTM): Bidirectional LSTM networks [45,46] model sensor time series $S_t$ through gated memory cells. The temporal attention mechanism dynamically weights meteorological, vibration, and acoustic inputs, capturing nonstationary environmental patterns preceding structural failures.
- Human Factor Component (BNN): Bayesian Neural Networks [47,48] process operational logs O1:t using Monte Carlo dropout. The probabilistic weights quantify epistemic uncertainty in worker behavior patterns, enabling adaptive learning from sparse near-miss data through variational inference [49].

Based on the above derivation of the components, the proposed composite risk evaluation function (CREF) integrates multi-source data as follows:

$$R(t) = \alpha \times GNN(, X) + \beta \times LSTM(S_t) + \gamma \times BNN(O_{1:t}) \quad (2)$$

All parameters in the composite risk evaluation framework are bounded within rigorously defined ranges to ensure system stability; structural risk indicators ($S_{str}$) and environmental risk factors ($S_{env}$) are normalized to [0, 1] through min–max scaling based on historical failure thresholds. Human error probabilities ($S_{hum}$) are constrained to [0, 1] via sigmoid activation, reflecting cumulative near-miss observations. Weight coefficients ($\alpha$, $\beta$, $\gamma$) are softmax-normalized to [0, 1] with $\alpha + \beta + \gamma = 1$, ensuring interpretable risk contribution ratios.

This analysis layer and its feedback loop can improve safety management from static rule-based compliance into a dynamic, knowledge-driven science. By continuously refining risk projections, the system reduces latent vulnerabilities and fosters resilience in complex construction environments.

### *4.4. Integration Layer*

#### 4.4.1. Safety Data Management

The fourth layer serves as the system's institutional memory, archiving and structuring safety-related knowledge into retrievable, reusable formats. It transcends mere record-keeping; through ontological categorization of incidents, root-cause taxonomies, and compliance benchmarks, it transforms raw data into organizational wisdom. Automated reporting tools generate regulatory submissions, internal audit summaries, and stakeholder briefings, each tailored to distinct epistemic communities—regulators demand compliance metrics, insurers seek risk exposure profiles, while site supervisors require actionable remediation checklists. Furthermore, by mapping historical data onto current operations, the layer identifies chronic vulnerabilities: recurring scaffolding defects, persistent PPE noncompliance among specific subcontractors, or lagging response times to electrical hazards. These insights empower strategic interventions, such as targeted training programs or revised procurement specifications. In essence, this layer ensures that safety knowledge transcends individual projects, becoming a transferable asset that fortifies the entire enterprise.

#### 4.4.2. Platform Integration

As the top-level design of the system, the platform integration undertakes the core functions of integrating heterogeneous systems, optimizing resource allocation, and realizing cross-departmental synergy. Through standardized interfaces and protocols, this layer achieves seamless integration with heterogeneous platforms such as project management systems, equipment management systems, and human resources systems, effectively breaking the problem of information silos prevailing in traditional safety management. The design concept of this layer emphasizes the interoperability and functional complementarity between subsystems and adopts a microservice architecture to achieve modular deployment and flexible expansion while optimizing task allocation and execution efficiency through the Workflow Engine. In addition, this layer introduces a multi-party collaborative governance mechanism and builds a collaborative governance network covering construction units, supervisory units, and construction units through a process design and data sharing strategy with clear authority and responsibility. The ultimate goal is to optimize resource allocation and maximize safety management efficiency, providing system-level support for construction safety supervision.

## 5. Prototype Testing and Evaluation

In order to verify the feasibility and practical application value of the proposed theoretical framework and MNRA, a prototype system was developed with the technical support of the partner technology companies. The prototype was field-verified in some projects under construction with the support of application scenarios provided by local governments. Based on the principle of intellectual property protection on some restricted commercially sensitive information, Figure 2 shows the brief technical implementation framework of the prototype system.

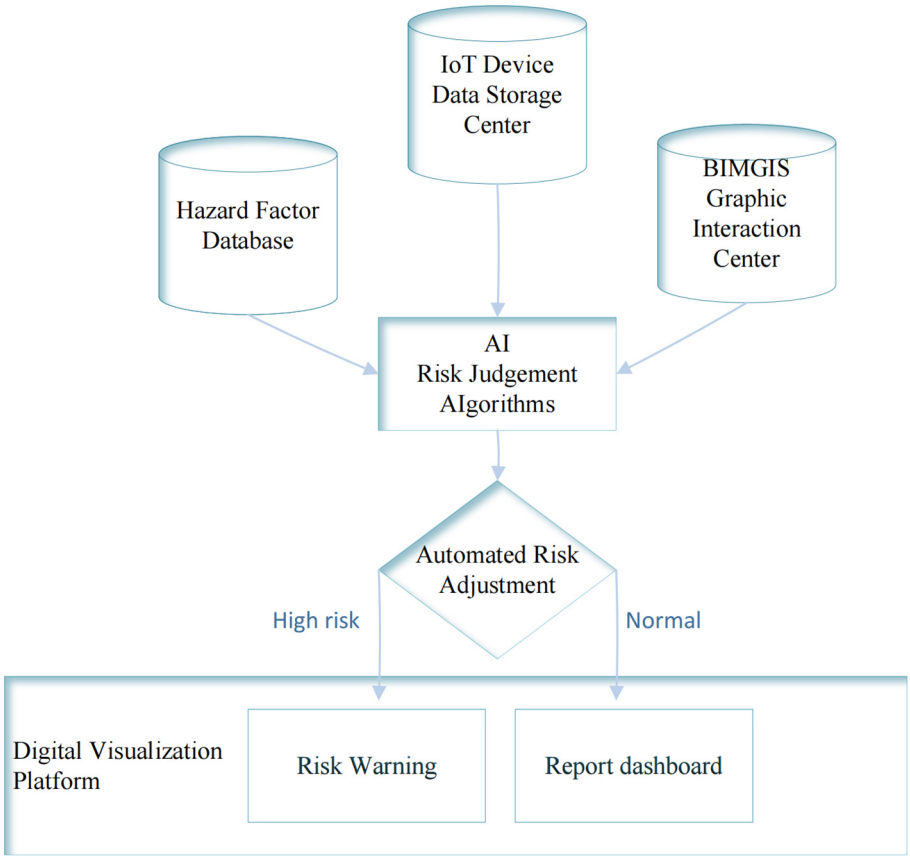



**Figure 2.** Technological route.

### *5.1. Data Sensing*

Through the BIM-GIS graphic interaction center and the inspection equipment data storage center, the platform achieved comprehensive data collection and integration, ensuring efficient and dynamically responsive safety monitoring. Furthermore, by integrating IoT and AI technologies, the platform enabled dynamic risk assessment and intelligent early warning, significantly enhancing safety levels on construction sites.

In the process of data collection and integration, two core components played a crucial role: the BIM-GIS graphic interaction center and the inspection equipment data storage center. These two elements worked together to ensure that safety monitoring was comprehensive, efficient, and responsive to the dynamic nature of construction sites.

The collection and integration of BIM data constituted the foundational layer for intelligent safety supervision. The process commenced with developing ISO-compliant coding protocols for construction components, ensuring data consistency across geometric properties, material specifications, and regulatory attributes. These standardized codes enabled the creation of a semantically enriched BIM model that encapsulated both structural semantics and safety-critical metadata. Figure 3 illustrates the BIM model of a sports park, which was developed using Autodesk Revit and subsequently imported into the risk management platform through Industry Foundation Classes (IFC) format conversion. This interoperability process preserved parametric relationships and material properties while enabling cross-platform data continuity. The model's synchronization with the safety supervision platform established a bidirectional data ecosystem: geometric modifications in BIM dynamically recalibrated safety parameters (e.g., structural load thresholds, spatial clearance requirements), while IoT-derived telemetry (e.g., strain gauge measurements, vibration spectra) continuously annotated risk vectors within the evolving digital twin. This cyber-physical integration achieved sub-15-s latency in model-to-reality alignment through

edge computing architectures, enabling near real-time hazard topology mapping. Furthermore, domain-specific safety ontologies were embedded within BIM families, incorporating structural fatigue coefficients, environmental exposure limits, and PPE compliance checklists, which transformed passive 3D representations into proactive risk prediction engines.

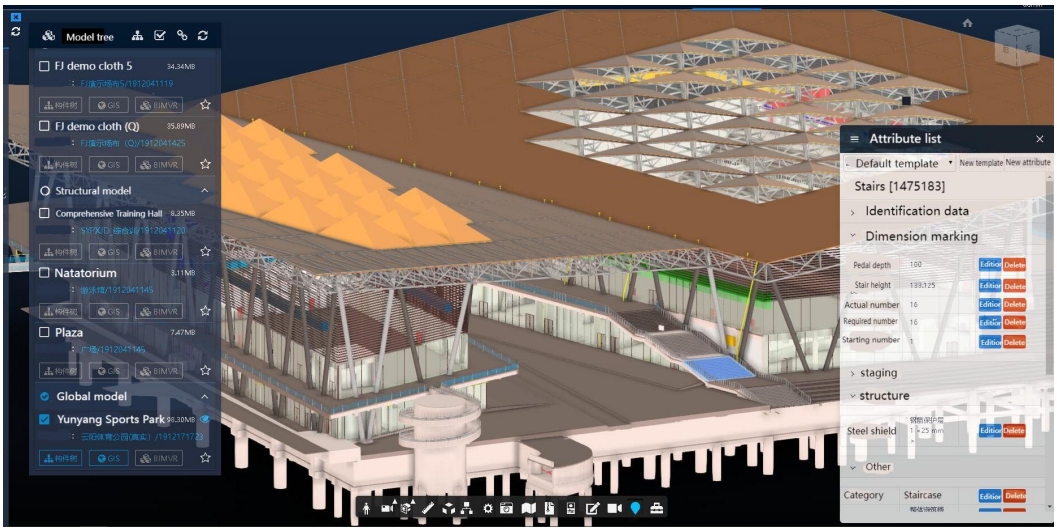



**Figure 3.** BIM center console.

Furthermore, GIS technology was used to import geographic location information of the construction site, helping to analyze the potential impact of environmental conditions on construction safety. For instance, unstable soil conditions or geological weaknesses may pose risks to the foundation of a building. By incorporating GIS data, safety supervisors could assess these risks and implement preventive measures before construction started. Furthermore, IoT sensing devices, such as temperature and humidity sensors, meteorological monitoring tools, and environmental detectors, dynamically collect data that provide insights into on-site, changing conditions. This continuous data collection served as a critical component of decision-making, allowing supervisors to respond proactively to environmental factors that may compromise safety.

In addition to environmental monitoring, IoT devices deployed at construction sites play a key role in real-time data collection related to operational safety. Figure 4 shows some of the devices. In the technical route of equipment and model data connection, the digital foundation was first laid through the model construction stage, and the 3D model of the overall line and parameterized model library of inspection equipment were established based on BIM technology, covering the geometric attributes, functional parameters, and installation rules of the equipment. The classification and coding standard of "equipment type + spatial coordinate" was adopted to give a unique identification code to each model. At the same time, the "equipment type + spatial coordinates" classification and coding standard was used to give each model a unique identification code for the topological relationship between equipment and the main structure of the network. It should be noted that the technical solutions described in this paper only show part of the dimensions of the system capabilities. As the relevant core technology has entered the patent application process (involving the integration of building information modeling and Internet of Things), some of the proprietary algorithm modules and multimodal data synergy mechanisms are not fully disclosed for the time being. The depth of the current technical realization covers the edge intelligent computing framework, adaptive building information interaction protocol, and other patent protection systems, and the specific technical route will be gradually released through subsequent industry–university research cooperation.

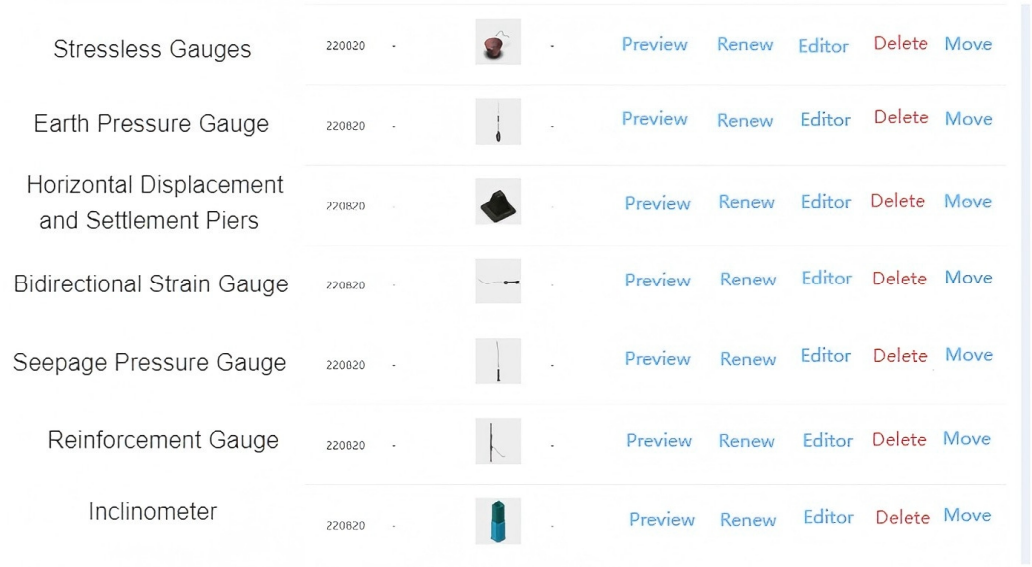


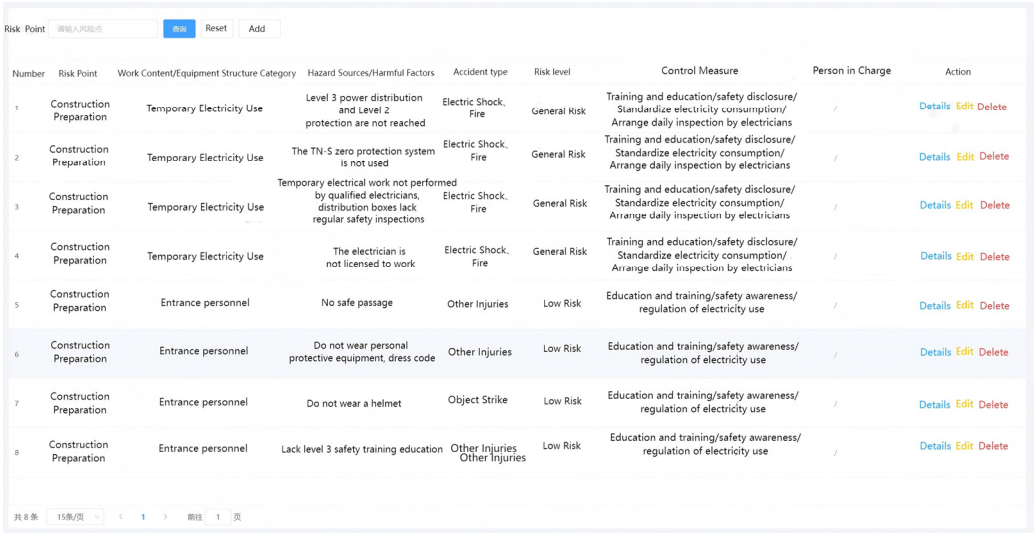

**Figure 4.** IoT device information.

The deployment phase extended from the design process to the implementation process by automatically extracting the standard installation coordinates, codes, and type parameters of the inspection equipment by analyzing the CAD plan schematic. It generated the three-dimensional spatial positioning benchmarks and installed the physical equipment at key nodes, such as the concrete pouring position and the steel structure connection point, in the context of the construction progress. Moreover, mobile scanning code technology was used to bind the equipment code and the model ID in real time. The wireless sensing terminal and edge computing unit were deployed synchronously to build an automated data acquisition network covering pressure, displacement, and other parameters to ensure the high-frequency encrypted transmission of measurement data.

Next, the data processing stage focused on the in-depth integration of data and model, where the monitoring data table uploaded by the field equipment was matched with the model code in the cloud. It relied on the spatiotemporal indexing technology to align the equipment installation location, measurement timestamps, and model attributes, generating structured time-sequence data sets through the data cleaning process of outlier elimination, unit unification, etc., with a dynamic mapping relationship library of equipment code-model unit-monitoring data. Ultimately, in the visualization stage, the prototype system realized the closed loop of interaction between reality and reality, based on the three-dimensional visualization platform, to dynamically bind the BIM model and real-time monitoring data. This was achieved through the color mapping and data-driven animation intuitive presentation of the state of the equipment (such as the displacement trend, stress exceeding the limit of the early warning area), the integration of the data interaction model and the early-warning algorithms, the formation of the construction inspection from the model to retrieve, data parsing, visualization, and the early warning of the construction risk of the intelligent closed loop. It also supported cross-terminal multi-dimensional data drilling analysis and decision-making responses, which comprehensively improve the transparent supervision of the construction process and risk pre-control capability.

To enhance construction safety risk management, the prototype system was connected with a comprehensive database of risk factors (Figure 5). This database was built beforehand using information from various sources, including industry safety standards, historical accident records, and regulatory guidelines. By compiling and structuring this database, it could access a wide range of risk categories, such as unsafe worker behaviors, equipment malfunctions, environmental hazards, and deficiencies in construction planning. Through

the integration of MNRA, historical data can be automatically analyzed to identify high-frequency risk factors. MNRA helped to optimize the classification of hazardous elements and determined their relative impact on overall site safety with risk scores based on potential harm levels. These assessments helped define safety thresholds, which triggered preemptive safety measures when exceeded.


Risk Point 请输入风险点 查询 Reset Add

| Number | Risk Point | Work Content/Equipment Structure Category | Hazard Sources/Harmful Factors | Accident type | Risk level | Control Measure | Person in Charge | Action |
|---|---|---|---|---|---|---|---|---|
| 1 | Construction Preparation | Temporary Electricity Use | Level 3 power distribution and Level 2 protection are not reached | Electric Shock, Fire | General Risk | Training and education/safety disclosure/ Standardize electricity consumption/ Arrange daily inspection by electricians | / | Details Edit Delete |
| 2 | Construction Preparation | Temporary Electricity Use | The TN-S zero protection system is not used | Electric Shock, Fire | General Risk | Training and education/safety disclosure/ Standardize electricity consumption/ Arrange daily inspection by electricians | / | Details Edit Delete |
| 3 | Construction Preparation | Temporary Electricity Use | Temporary electrical work not performed by qualified electricians, distribution boxes lack regular safety inspections | Electric Shock, Fire | General Risk | Training and education/safety disclosure/ Standardize electricity consumption/ Arrange daily inspection by electricians | / | Details Edit Delete |
| 4 | Construction Preparation | Temporary Electricity Use | The electrician is not licensed to work | Electric Shock, Fire | General Risk | Training and education/safety disclosure/ Standardize electricity consumption/ Arrange daily inspection by electricians | / | Details Edit Delete |
| 5 | Construction Preparation | Entrance personnel | No safe passage | Other Injuries | Low Risk | Education and training/safety awareness/ regulation of electricity use | / | Details Edit Delete |
| 6 | Construction Preparation | Entrance personnel | Do not wear personal protective equipment, dress code | Other Injuries | Low Risk | Education and training/safety awareness/ regulation of electricity use | / | Details Edit Delete |
| 7 | Construction Preparation | Entrance personnel | Do not wear a helmet | Object Strike | Low Risk | Education and training/safety awareness/ regulation of electricity use | / | Details Edit Delete |
| 8 | Construction Preparation | Entrance personnel | Lack level 3 safety training education | Other Injuries Other Injuries | Low Risk | Education and training/safety awareness/ regulation of electricity use | / | Details Edit Delete |

共 8 条 15条/页 1 前往 1 页

**Figure 5.** Database of risk factors.

### *5.2. Computing Process*

The prototype system integrated data from BIM, GIS, and IoT systems, performing comprehensive analyses of various safety-related parameters. Through continuous data evaluation, it could detect emerging safety risks and initiate timely alerts. For instance, when the system identified abnormal gas concentrations in a specific area or detected instability in structural support elements, it could immediately activate a warning mechanism. This capability ensured that potential dangers were addressed before they posed a significant threat to workers and equipment.

To enhance risk communication and ensure that safety measures were effectively implemented, AI-driven safety supervision systems incorporated beacon technology and sensor base stations. These devices, strategically placed around construction sites, provided real-time updates on risk levels based on the results of MNRA. If a hazardous situation was detected, the system dynamically adjusted the risk classification according to the predefined algorithms. This information was then visualized in the BIM field model, displaying high-risk zones within the construction site in a clear and accessible manner (Figure 6). By linking this real-time risk assessment to the broader safety supervision platform, automated risk mitigation strategies could be deployed. Adjustments to construction workflows, the implementation of additional safety measures, or targeted alerts to site managers could all be triggered through the system, ensuring a rapid and effective response to evolving risks.

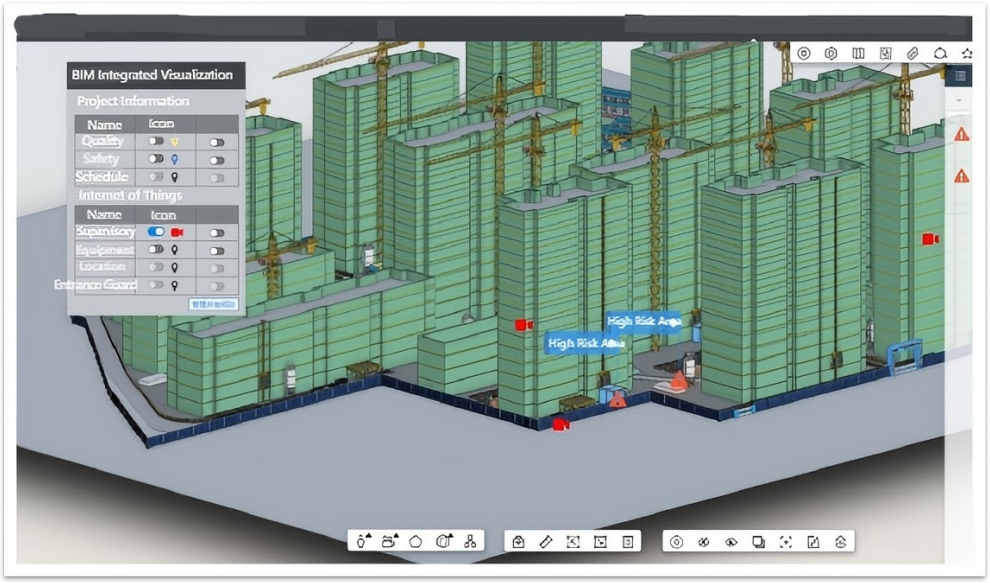



**Figure 6.** Automated risk adjustment.

### *5.3. Decision Output*

Data recording and analysis played an essential role in ongoing safety improvements. The system continuously logged risk events, compiling them into a structured construction safety log. These logs served as a valuable resource for analyzing trends in safety incidents, identifying recurrent hazards, and refining risk management strategies over time, as illustrated in Figure 7. Additionally, the system adapted to changing conditions by adjusting safety inspection schedules based on risk patterns. High-risk areas may require more frequent monitoring, while lower-risk zones could be inspected at standard intervals. By dynamically optimizing inspection frequency, safety managers could allocate resources efficiently, focusing on areas that demanded the most attention.

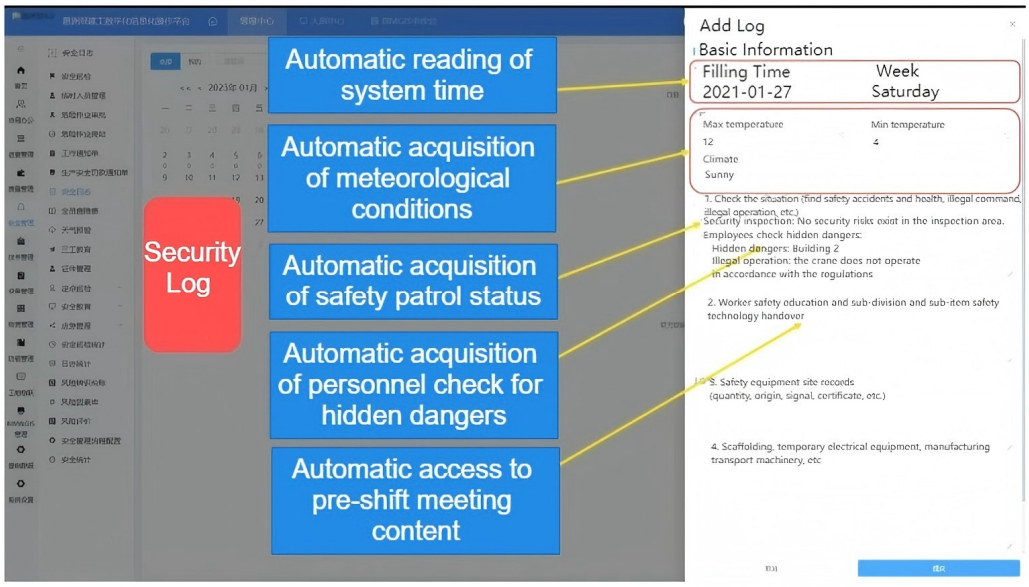



**Figure 7.** Security log.

### *5.4. Feedback from Users*

To further assess the applicability and user acceptance of the prototype, the research team conducted a mixed-methods evaluation in a regional pilot application. Feedback was collected from 44 construction practitioners through semi-structured interviews combined

with a questionnaire, resulting in 36 valid responses (81.8% response rate). The quantitative data in Table 1 were specifically derived from in-depth interviews with 12 key participants selected based on their leadership roles and technical expertise, including five project managers from general contractors (36.1%) and seven senior engineers from professional service providers (63.9%). All interviewees possessed over 8 years of industry experience, with nine holding professional certifications in BIM or safety management, ensuring the representativeness of their evaluations.

**Table 1.** Results of the prototype evaluation.

| Evaluation Variables | Mean | Interpretation |
|---|---|---|
| Information input/output friendliness | 4.2 | Satisfied |
| Risk warning timeliness | 3.8 | Satisfied |
| Optimization of safety inspection tasks | 4.0 | Satisfied |
| Impact of improving the safety of construction projects | 4.1 | Satisfied |

Participants' backgrounds spanned general contractors (13, 36.1%) and professional service providers (23, 63.9%), both strategic decision-makers (e.g., construction directors) and frontline implementers, with 86.1% of respondents (31) having more than 5 years of industry experience. The interview protocol focused on contextualizing user experiences through scenario-based discussions about the prototype's application in actual construction workflows. User satisfaction with the prototype's functionality was assessed using a 5-point Likert scale (0 = very dissatisfied; 5 = very satisfied), with interview transcripts undergoing thematic analysis to triangulate quantitative ratings with qualitative insights.

The results of the survey show that users were generally positive about the core functional modules of the prototype, especially in terms of the clarity of the information interaction logic, the timeliness of the risk warning prompts, and the completeness of the safety management data, which were highly rated. Most interviewees believed that the interface design of the prototype was in line with the operating habits of engineering management scenarios, and the visual presentation of safety risks was intuitive and easy to understand, which can provide differentiated information support for decision makers at different levels. At the level of practical effectiveness, user feedback indicated that the implementation of the prototype effectively improved the standardization and coverage of daily safety inspections, and at the same time assisted the project team in identifying a number of potential risk factors through the trend analysis function of historical data, so as to strengthen on-site control measures in a targeted manner. It is worth noting that some interviewees put forward suggestions for improvement from the perspective of function expansion, including enhancing the automated cleaning capability of multi-source heterogeneous data, developing customized safety management report generation modules, and optimizing the interactive experience of mobile devices, etc. These suggestions provided an important reference direction for the subsequent iteration and upgrading of the system.

## 6. Discussions

In the course of project implementation, it was observed that at the initial stage of introducing the prototype system, the tested pilot projects generally had problems such as loose security management mechanism and weak risk prediction capability; however, with the continuous deepening of the application of the prototype's functions, the project team gradually built up a systematic risk management and control system. Especially in the middle and late stages of the platform's operation, the safety management capability of the pilot units has shown significant improvement, and all the projects had effectively avoided the occurrence of major safety accidents during the construction cycle, which confirmed

the practical value of the platform at the level of risk prevention and control. Through stakeholder interviews and feedback analysis, the prototype enhances safety management by visualizing real-time data and automating risk alerts, reducing reliance on manual processes. Its knowledge-sharing mechanism breaks information silos, enabling the faster adaptation of proven strategies across projects, optimizing efficiency and decision-making.

This research has two major theoretical contributions. The proposed prototype addresses a critical gap in existing BIM-AI integration research by extending its application beyond isolated project phases to a lifecycle-oriented safety governance system. Traditional approaches have focused on specific stages, such as design clash detection or schedule optimization, but fail to address the interconnected nature of risks across planning, construction, and decommissioning [15,16]. By adopting a systems theory perspective, this study demonstrates how BIM's spatial-temporal data can be combined with AI-driven probabilistic models to create a unified architecture that supports risk prediction and mitigation throughout the project lifecycle. This approach aligns with calls for holistic frameworks that transcend phase-specific toolkits and prioritize interoperability [11]. For instance, while prior work has leveraged BIM for fall hazard identification [1], the proposed platform extends this capability by integrating real-time IoT data and AI analytics to predict risks such as structural instability during dynamic construction phases. This lifecycle perspective not only enhances predictive accuracy but also fosters resilience in complex environments by enabling continuous learning from historical data and cross-project knowledge transfer. By harmonizing data flows, algorithmic outputs, and human oversight, the prototype establishes a unified safety ecosystem that dynamically adapts to project lifecycle complexities, thereby resolving the phase fragmentation endemic to prior BIM-AI implementations.

The second critical contribution lies in redefining safety governance as a dynamic, closed-loop process enabled through the integration of BIM, AI, and IoT. Existing research often prioritizes real-time hazard detection over upstream risk prevention, perpetuating reactive safety cultures [9,13]. This study introduces and applies MNRA that synthesizes structural, environmental, and human factors into a composite risk evaluation function. It quantifies interdependencies between risk variables, such as material fatigue (modeled via graph neural networks) and environmental perturbations (modeled via bidirectional LSTMs). This approach advances prior work that focused on single-factor risk analysis (e.g., Zermane et al. [19]; Wu et al. [20]) by emphasizing causal linkages and systemic feedback. For example, the platform's ability to correlate subcontractor turnover rates with safety violations highlights how organizational dynamics can be systematically integrated into risk assessments, thereby bridging the gap between technical and organizational dimensions of safety governance.

Practically, the proposed prototype offers construction firms a replicable blueprint for transitioning from reactive safety regimes to proactive, data-driven governance. By integrating real-time IoT monitoring, predictive risk analytics, and centralized data repositories, the system reduces dependency on manual inspections, minimizes latency in hazard response, and enhances compliance transparency. Project managers gain actionable insights through visualized risk heatmaps and automated alerts, enabling targeted resource allocation. Furthermore, the platform's scalability allows adaptation to diverse project types, from infrastructure megaprojects to residential builds, fostering industry-wide safety standardization. By mitigating latent risks early, the system not only safeguards worker well-being but also curtails cost overruns and delays, ultimately strengthening public trust in construction practices.

## 7. Conclusions

This study demonstrates that integrating BIM and AI into a unified platform significantly enhances construction safety governance by proactively addressing lifecycle-wide risks through data-driven methodologies for sustainable construction safety management. Using a Design Science Research approach, the developed system synthesizes multi-phase spatiotemporal data from BIM models with AI-driven probabilistic analytics and IoT-enabled edge computing, establishing a closed-loop safety ecosystem that spans the planning, construction, and operational phases.

Key findings reveal that the platform's phase-agnostic architecture effectively resolves fragmentation across project stages through its four-layer framework—Preparation, Process, Analysis, and Integration layers—that enables continuous data capture via BIM-GIS digital twins, real-time behavioral monitoring through computer vision, and dynamic risk coupling analysis using the Multilayer Neural Risk Coupling Assessment (MNRA) framework. User evaluations (mean score 4.1/5) confirmed improvements in cross-departmental collaboration and regulatory compliance transparency, underscoring the system's practical value.

Importantly, these innovations foster resilience in complex construction environments by establishing self-optimizing safety protocols, including automated equipment lockdown in overload conditions and AI-generated hazard heatmaps for optimized resource allocation. Beyond improving immediate safety outcomes, the integrated BIM-AI platform establishes a transformative framework that simultaneously elevates construction safety governance and advances sustainable engineering practices. By unifying lifecycle-oriented safety supervision with AI-driven dynamic risk prediction, the system shifts safety management from fragmented compliance checks to proactive, systemic governance—a critical foundation for both worker protection and sustainable project delivery. The platform's real-time hazard mitigation capabilities not only prevent accidents but inherently reduce resource waste and carbon emissions by avoiding safety-related delays, rework, and material overconsumption. Through continuous environmental monitoring and BIM-optimized resource allocation, it further minimizes ecological impacts while maintaining stringent safety standards, creating a synergistic loop where enhanced safety protocols directly reinforce sustainability objectives. This dual focus on human-centric safety resilience and environmentally conscious efficiency positions the platform as a cornerstone for modern construction ecosystems, driving operational excellence that aligns with global safety imperatives and sustainable development goals.

## 8. Research Limitations and Future Directions

However, some limitations warrant consideration. First, the prototype's validation relied on limited case studies, potentially underrepresenting diverse project contexts. Second, the current system exhibits inherent data dependency constraints. While BIM-IoT integration provides rich contextual information, its effectiveness presupposes the comprehensive digitalization of construction processes. Traditional construction sites with fragmented paper-based workflows or limited sensor coverage may experience data integrity degradation, potentially compromising risk prediction accuracy. Third, organizational resistance to workflow changes and training demands was not fully explored, highlighting implementation challenges. Addressing these gaps could strengthen future scalability and adoption.

While addressing these technical and organizational challenges presents opportunities for system enhancement, future research should prioritize three directions. First, expanding the platform's adaptability to low-resource environments through edge computing optimization and lightweight AI models could democratize access for regions with limited digital infrastructure. Meanwhile, developing hybrid intelligence frameworks that synergize human expertise with machine learning, particularly through explainable AI

interfaces and collaborative decision protocols, may mitigate organizational resistance while preserving human oversight. Moreover, longitudinal studies across diverse project types (e.g., underground engineering, smart cities) could establish domain-specific risk ontologies and validate the framework's generalizability. Emerging technologies like digital twins and blockchain-enabled safety traceability systems present promising avenues for enhancing data veracity and accountability in safety governance.

**Author Contributions:** Conceptualization, H.-Y.C. and X.L.; methodology, X.L.; software, X.L.; validation, Q.M. and J.L.; formal analysis, J.L.; investigation, Q.M.; resources, X.L.; data curation, X.L.; writing—original draft preparation, H.-Y.C.; writing—review and editing, H.-Y.C. and Q.M.; visualization, X.L.; supervision, H.-Y.C.; project administration, J.L. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by Jiangsu Provincial Department of Education Fund of Philosophy and Social Science grant number 2023SJYB0338; and Jiangsu Provincial of Education Science Planning Project Funding grant number C/2023/01/30.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data generated and analyzed during this research are available from the corresponding author upon reasonable request.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## References

1. Zhang, S.; Sulankivi, K.; Kiviniemi, M.; Romo, I.; Eastman, C.M.; Teizer, J. BIM-based fall hazard identification and prevention in construction safety planning. *Saf. Sci.* **2015**, *72*, 31–45. [CrossRef]
2. Zhou, C.; Yang, J. Develop an Intelligent System of Construction Safety Management Using BIM and Multi-Sensor. In Proceedings of the 2023 International Conference on Computer, Vision and Intelligent Technology, Paris, France, 2–3 October 2023; pp. 1–12.
3. Kim, D.; Yoo, T.; Tran, S.V.-T.; Lee, D.; Park, C.; Lee, D. Automated Safety Risk Assessment Framework by Integrating Safety Regulation and 4D BIM-Based Rule Modeling. *Buildings* **2024**, *14*, 2529. [CrossRef]
4. Volk, R.; Stengel, J.; Schultmann, F. Building Information Modeling (BIM) for existing buildings—Literature review and future needs. *Autom. Constr.* **2014**, *38*, 109–127. [CrossRef]
5. Li, M.; Yu, H.L.; Jin, H.Y.; Liu, P. Methodologies of safety risk control for China's metro construction based on BIM. *Saf. Sci.* **2018**, *110*, 418–426. [CrossRef]
6. Pan, Y.; Zhang, L.M. Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Autom. Constr.* **2021**, *122*, 103517. [CrossRef]
7. Tian, W.; Meng, J.; Zhong, X.J.; Tan, X. Intelligent early warning system for construction safety of excavations adjacent to existing metro tunnels. *Adv. Civ. Eng.* **2021**, *2021*, 8833473. [CrossRef]
8. Li, B.; Nielsen, R.O.; Johansen, K.W.; Teizer, J.; Larsen, P.G.; Schultz, C. Towards digital twins for knowledge-driven construction progress and predictive safety analysis on a construction site. In *International Symposium on Leveraging Applications of Formal Methods*; Springer: Cham, Switzerland, 2021; pp. 153–174.
9. Schultz, C.; Bhatt, M.; Suchan, J.; Wałęga, P.A. Answer set programming modulo 'Space-Time'. In *Rules and Reasoning*; Springer: Cham, Switzerland, 2021; pp. 318–326.
10. UK Government. International AI Safety Report: The International Scientific Report on the Safety of Advanced AI. 2025. Available online: https://assets.publishing.service.gov.uk/media/679a0c48a77d250007d313ee/International_AI_Safety_Report_2025_accessible_f.pdf (accessed on 1 April 2025).
11. Pan, Y.; Zhang, L. Integrating BIM and AI for smart construction management: Current status and future directions. *Arch. Comput. Methods Eng.* **2023**, *30*, 1081–1110. [CrossRef]
12. Moshtaghian, F.; Noorzai, E. Integration of risk management within the building information modeling (BIM) framework. *Constr. Archit. Manag.* **2023**, *30*, 1951–1977. [CrossRef]
13. Khan, A.A.; Bello, A.O.; Arqam, M.; Ullah, F. Integrating Building Information Modelling and Artificial Intelligence in Construction Projects: A Review of Challenges and Mitigation Strategies. *Technologies* **2024**, *12*, 185. [CrossRef]
14. Zabin, A.; González, V.A.; Zou, Y.; Amor, R. Applications of machine learning to BIM: A systematic literature review. *Adv. Eng. Inform.* **2022**, *51*, 101474. [CrossRef]

15. Chowdhury, M.; Hosseini, M.R.; Edwards, D.J.; Martek, I.; Shuchi, S. Comprehensive analysis of BIM adoption: From narrow focus to holistic understanding. *Autom. Constr.* **2024**, *160*, 105301. [CrossRef]
16. Jin, R.; Hancock, C.M.; Tang, L.; Wanatowski, D. BIM investment, returns, and risks in China's AEC industries. *J. Constr. Eng. Manag.* **2017**, *143*, 04017089. [CrossRef]
17. Zhang, F. A hybrid structured deep neural network with Word2Vec for construction accident causes classification. *Int. J. Constr. Manag.* **2022**, *22*, 1120–1140. [CrossRef]
18. Baker, H.; Hallowell, M.R.; Tixier, A.J.P. Automatically learning construction injury precursors from text. *Autom. Constr.* **2020**, *118*, 103145. [CrossRef]
19. Zermane, A.; Mohd Tohir, M.Z.; Zermane, H.; Baharudin, M.R.; Mohamed Yusoff, H. Predicting fatal fall from heights accidents using random forest classification machine learning model. *Saf. Sci.* **2023**, *159*, 106023. [CrossRef]
20. Wu, L.; Mohamed, E.; Jafari, P.; AbouRizk, S. Machine Learning–Based bayesian framework for interval estimate of unsafe-event prediction in construction. *J. Constr. Eng. Manag.* **2023**, *149*, 04023118. [CrossRef]
21. Zhong, B.; Pan, X.; Love, P.E.D.; Ding, L.; Fang, W. Deep learning and network analysis: Classifying and visualizing accident narratives in construction. *Autom. Constr.* **2020**, *113*, 103089. [CrossRef]
22. Pan, X.; Zhong, B.; Wang, Y.; Shen, L. Identification of accident-injury type and bodypart factors from construction accident reports: A graph-based deep learning framework. *Adv. Eng. Inform.* **2022**, *54*, 101752. [CrossRef]
23. Xiong, W.; Xu, X.; Chen, L.; Yang, J. Sound-Based Construction Activity Monitoring with Deep Learning. *Buildings* **2022**, *12*, 1947. [CrossRef]
24. Mneymneh, B.E.; Abbas, M.; Khoury, H. Vision-based framework for intelligent monitoring of hardhat wearing on construction sites. *J. Comput. Civ. Eng.* **2019**, *33*, 4018066. [CrossRef]
25. Fang, W.; Ding, L.; Zhong, B.; Love, P.E.D.; Luo, H. Automated detection of workers and heavy equipment on construction sites: A convolutional neural network approach. *Adv. Eng. Inform.* **2018**, *37*, 139–149. [CrossRef]
26. Park, M.; Tran, D.Q.; Bak, J.; Park, S. Small and overlapping worker detection at construction sites. *Autom. Constr.* **2023**, *151*, 104856. [CrossRef]
27. Jeelani, I.; Asadi, K.; Ramshankar, H.; Han, K.; Albert, A. Real-time vision-based worker localization & hazard detection for construction. *Autom. Constr.* **2021**, *121*, 103448.
28. Yang, M.; Wu, C.; Guo, Y.; Jiang, R.; Zhou, F.; Zhang, J.; Yang, Z. Transformer-based deep learning model and video dataset for unsafe action identification in construction projects. *Autom. Constr.* **2023**, *146*, 104703. [CrossRef]
29. Goh, Y.M.; Tian, J.; Chian, E.Y.T. Management of safe distancing on construction sites during COVID-19: A smart real-time monitoring system. *Comput. Ind. Eng.* **2022**, *163*, 107847. [CrossRef]
30. Elelu, K.; Le, T.; Le, C. Collision Hazard detection for construction worker Safety using audio surveillance. *J. Constr. Eng. Manag.* **2023**, *149*, 04022159. [CrossRef]
31. Luo, H.; Wang, M.; Wong, P.K.Y.; Cheng, J.C.P. Full body pose estimation of construction equipment using computer vision and deep learning techniques. *Autom. Constr.* **2020**, *110*, 103016. [CrossRef]
32. Wang, X.; El-Gohary, N. Deep learning-based relation extraction and knowledge graph-based representation of construction safety requirements. *Autom. Constr.* **2023**, *147*, 104696. [CrossRef]
33. Gan, T.; Mostofi, F.; Ayözen, Y.E.; Tokdemir, O.B. Customized AutoML: An automated machine learning system for predicting severity of construction accidents. *Buildings* **2022**, *12*, 1933. [CrossRef]
34. Koc, K.; Ekmekcioğlu, Ö.; Gurgun, A.P. Developing a National Data-Driven Construction Safety Management Framework with interpretable fatal accident prediction. *J. Constr. Eng. Manag.* **2023**, *149*, 04023010. [CrossRef]
35. Chen, H.; Hou, L.; Zhang, G.K.; Wu, S. Using context-guided data augmentation, lightweight CNN, and proximity detection techniques to improve site safety monitoring under occlusion conditions. *Saf. Sci.* **2023**, *158*, 105958. [CrossRef]
36. Gondia, A.; Ezzeldin, M.; El-Dakhakhni, W. Machine learning-based decision support framework for construction injury severity prediction and risk mitigation. *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part A Civ. Eng.* **2022**, *8*, 04022024. [CrossRef]
37. Hevner, A.R. A three cycle view of design science research. *Scand. J. Inf. Syst.* **2007**, *19*, 4.
38. Autodesk Inc. Autodesk Revit 2024. Autodesk Official Website. 2024. Available online: https://www.autodesk.com/products/revit/ (accessed on 2 February 2025).
39. Python Software Foundation. Python 3.11: A High-Level Programming Language for General-Purpose Programming. Python Official Website. 2023. Available online: https://www.python.org/ (accessed on 2 February 2025).
40. Abadi, M.; Barham, P.; Chen, J.; Chen, Z.; Davis, A.; Dean, J.; Devin, M.; Ghemawat, S.; Irving, G.; Isard, M.; et al. TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems. 2015. Available online: https://www.tensorflow.org/ (accessed on 2 February 2025).
41. von Bertalanffy, L. *General System Theory: Foundations, Development, Applications*; Braziller: New York, NY, USA, 1968.
42. Woods, D.D. *Resilience Engineering: Concepts and Precepts*; Hollnagel, E., Woods, D.D., Leveson, N., Eds.; Ashgate Publishing, Ltd.: Farnham, UK, 2006.

43. Scarselli, F.; Gori, M.; Tsoi, A.C.; Hagenbuchner, M.; Monfardini, G. The graph neural network model. *IEEE Trans. Neural Netw.* **2008**, *20*, 61–80. [CrossRef]
44. Graves, A. Long short-term memory. In *Supervised Sequence Labelling with Recurrent Neural Networks*; Springer Nature: Dordrecht, The Netherlands, 2012; pp. 37–45.
45. Gers, F.A.; Schmidhuber, J.; Cummins, F. Learning to forget: Continual prediction with LSTM. *Neural Comput.* **2000**, *12*, 2451–2471. [CrossRef]
46. Sutskever, I.; Vinyals, O.; Le, Q.V. Sequence to sequence learning with neural networks. *Adv. Neural Inf. Process. Syst.* **2014**, *27*, 3104–3112.
47. Neal, R.M. *Bayesian Learning for Neural Networks*; Springer Science & Business Media: Berlin, Germany, 2012.
48. Yarin, G.; Ghahramani, Z. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. In Proceedings of the International Conference on Machine Learning, New York, NY, USA, 19–24 June 2016.
49. Blundell, C.; Cornebise, J.; Kavukcuoglu, K.; Wierstra, D. Weight uncertainty in neural network. In Proceedings of the International Conference on Machine Learning, Lille, France, 6–11 July 2015.


**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.