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An Integrated Approach to Predicting and Preventing Scaffolding Accidents Using Bim, Machine Learning and AI Technologies

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ABSTRACT

Scaffolding operations and construction climbing remain one of the most hazardous activities in construction regarding their annual fall-from-height injuries and death rates worldwide. These accidents are predominantly driven by unsafe human behavior, management failures and the complex interactions between temporary structures, environmental conditions and other construction equipment like cranes. Traditional safety management approaches, which largely consist of inspections, checklists and post-accident investigations, are insufficient to address the indirect and dynamic nature of scaffolding risks.

The main objective of this study was to analyze scaffolding accidents, and to propose preventive measures that combine machine learning (ML), artificial intelligence (AI) and Building Information Modelling (BIM). This enables predictive risk identification, spatial risk analysis, scenario simulation and proactive accident prevention on construction sites.

Unsafe human behaviors were first analyzed across the following dimensions; physical factors, psychological factors, environmental factors; personal protective equipment, technical and procedural failures.

Corresponding preventive measures are then discussed including; certified personnel systems, education and training of site personnel, reward and punishment mechanisms and AI-assisted substitution systems. The framework further demonstrates how Building Information Modelling (BIM) intelligent monitoring platforms can detect risks before catastrophic failure occurs. Inclusive of; Online structural health monitoring systems and Integrated crane operations.

The proposed approach establishes a closed-loop safety system where scaffolding risks are detected early on, their causes and interactions analyzed, unsafe scenarios simulated in 3D environments, scaffolding accidents are prevented in real-time and continuous improvement of the systems over time in scaffolding management.

Key words: Scaffolding safety; Machine learning; Building Information Modelling; Artificial intelligence; Human factors; Crane integration; Structural health monitoring.

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I.Introduction

1.1Background

Scaffolding operations represent one of the most hazardous activities in the construction industry, accounting for a disproportionate share of fall-from-height injuries, fatalities, and structural collapse incidents worldwide [1], [2].

Investigations conducted by occupational health and safety agencies indicate that scaffolding accidents commonly occur during scaffold erection, modification and dismantling, where structural integrity is vulnerable to human error. Research demonstrates that these failures are rarely caused by structural deficiencies, rather by complex interactions between unsafe human behavior, environmental factors, organizational failures and equipment related hazards [3] [4]. Traditional safety management relies primarily on compliance with regulations, periodic inspections and post-accident investigations. While these measures are essential to preventing scaffolding accidents, they are often reactive, and are limited in their ability to capture the dynamic and complex interactions between human behavior, environmental factors, temporary structural conditions and other temporary construction equipment on site, such as cranes [5].

As such, most of the early warning signs of instability or unsafe behavior go undetected until an accident actually occurs. Advances in machine learning, AI, and BIM now enable transforming scaffolding safety from reactive to predictive and adaptive. 3D Building information modelling provides a digital representation of construction systems. This supports spatial risk visualization in real-time. 4D Building information Modelling enables simulation of construction sequences, thus enabling temporary risk visualization and evaluation. [8], [9]. These technologies enable project stakeholders to simulate hazards prior to implementation on site. Machine learning enables the analysis of large volumes of safety data and identify complex patterns associated with accident occurrence [6], [7]. Machine learning applications in the Architecture, Engineering and Construction industry such as PPE monitoring through computer vision and real-time wearable sensors, are often more effective than traditional methods of risk identification and ranking [10], [2], [7]. Artificial intelligence further enables real-time monitoring, anomaly detection and decision support through intelligent based systems and sensor integrations that can adapt and learn from new data [10], [11].

Scaffolding accidents often represent the complex interplay between human behavior, structural integrity and environmental influences. Recorded accident investigations consistently indicate that fall-from-height accidents remain the leading cause of scaffolding fatalities, followed by scaffold collapse and falling objects [3], [14]. Research by Dogan demonstrated that scaffolding failures frequently originate from improper assembly practices, inadequate supervision and poor safety training rather than structural deficiencies [15], [7].

Physical and ergonomic strain are significant contributors to scaffolding-related accidents. Scaffolding erection and dismantling operations involve repetitive lifting, manual alignment of structural components, and work at elevated heights, all of which impose substantial biomechanical stress on workers. Ergonomic fatigue reduces motor coordination, balance control, and hazard perception ability, thereby increasing fall and structural disassembly risks [17]. Studies investigating occupational fatigue in construction environments demonstrate that prolonged exposure to physically demanding tasks leads to decreased cognitive performance and increased error probability [4]. Wearable monitoring technologies have recently enabled the measurement of physiological fatigue indicators like heart rate, muscle activity, and worker posture, providing new opportunities for real-time fatigue risk assessment [17]. Psychological risk factors influence worker's decision making during scaffolding operations. Risk normalization happens when they repeatedly perform hazardous tasks without experiencing accidents, leading to reduced awareness and increased tolerance of unsafe practices. This phenomenon has been widely documented in construction safety culture research [18].

Furthermore, time pressure, noise exposure and environmental stressors also reduce worker awareness. Wind exposure has been identified as a primary environmental risk factor contributing to scaffold instability and worker balance loss [19]. Environmental conditions often influence scaffolding safety performance. Temporary scaffolding structures are particularly vulnerable to environmental loading because they lack permanent foundation stability [18]. Some environmental factors include thermal stress, heat and temperature variations, Dust, adverse weather. Research indicates that PPE misuse frequently results from discomfort, restricted mobility, and lack of training [3]. Work practices that involve bypassing PPE requirements during short duration tasks have also been identified as a common behavioral violation. Safety culture suggests that PPE compliance is strongly influenced by supervisory enforcement by safety managers. [18]. Ignoring standardized erection and dismantling procedures often results in incomplete load distribution and joint fastening errors. Unauthorized structural modifications, such as removal of bracing components to facilitate material movement, further compromise scaffold stability and frequently precede collapse accidents [7].

Certified competency verification is among one of the most effective strategies for reducing scaffolding accident risk. Mandatory scaffold certification programs ensure that workers possess the technical knowledge required for safe assembly, modification and dismantling operations [20]. Traditional scaffolding training relies heavily on classroom instruction and static safety manuals. These often fail to replicate the dynamic state of construction site hazards. Virtual reality (VR) and BIM-based simulation technologies provide immersive training that improve hazard recognition and decision making [12]. Behavioral safety research emphasizes the importance of reinforcing safety management strategies. Safety performance metrics linked to incentive systems encourage proactive safety compliance and improves the engagement of workers in safety programs [18]. Supervisor accountability mechanisms also strengthen the organizational safety culture by ensuring they consistently enforce safety regulation. Studies demonstrate that projects with strong safety leadership record lower accident rates Automated systems that monitor scaffold systems equipped with sensors provide real-time structural stability monitoring. This enables early detection of structural deformities or any load imbalance. [21]

1.2 BIM and Machine Learning and AI Application in Scaffolding

Supervised learning algorithms (Random Forests, Gradient Boosted Trees, Logistic Regression, and neural networks) are frequently used to predict incident likelihood, near-miss probability and component failure. Tree-based models are widely preferred for tabular construction data due to robustness, interpretability via feature importance, and minimal preprocessing. [22]. For time-series sensor data, deep learning architectures (LSTM, CNN) and hybrid models have been explored to forecast degradation. Recent studies applying machine learning to construction safety have demonstrated that behavioral variables, including training level, supervision quality, and work experience, often exhibit stronger predictive influence than purely technical variables [23]. Model interpretability techniques such as SHAP provide insight into variable importance, enabling targeted safety interventions [24].

Safety prediction tasks are often characterized by class imbalance (rare severe events). Metrics such as AUC, precision-recall curves, F1 score, and calibration (Brier score) are recommended. For rare events, precision-recall metrics provide a clearer view of predictive utility than accuracy. Cost-sensitive learning, resampling, and synthetic data generation (SMOTE) are common techniques to address imbalance [1]. A practical challenge for ML in safety is translating probabilistic outputs into deterministic operational actions (e.g., halt work, inspect). Decision thresholds should be chosen in the context of risk tolerance and verified by domain experts. Additionally, model explanations must be actionable (e.g.; Training level low and near-miss history highly recommend retraining and temporary reallocation). Label quality is paramount. Ambiguity in labels (e.g. what does ‘witness’ mean - near-miss vs injury?) undermines model validity. The literature emphasizes the need for standard ontologies for incident types, consistent severity grading, and standardized metadata (exposure time, role, environment). Without these, models learn idiosyncratic patterns that may not generalize [24].

Building Information Modeling has revolutionized construction planning by enabling digital representation of 3D building components, and visualizing operational constraints [6].

Collision detection identifies clashes between scaffolding elements and existing structures or temporary structures. By incorporating temporary works into BIM, planning teams can anticipate hazardous interactions and adjust sequences to reduce risk. [6].Safety managers can sequence the erection and dismantling scaffolding operations and are able to detect any potential risk activities and areas within the structure. [25]. In scaffolding applications, BIM enables visualization of scaffold configuration, load distribution, and access pathways, allowing safety managers to identify hazardous conditions prior to construction. Recent research has explored the integration of BIM with digital twin technologies, enabling real-time synchronization between digital models and physical construction environments [25].

Camera systems combined with deep learning models (object detection networks) can detect missing guardrails, unfastened harnesses, improper access, and PPE non-compliance. Practical challenges include variable lighting, occlusion, viewpoint constraints, and the need for high-quality labeled training datasets. AI-integrated wearable technologies linked to BIM platforms enable real-time worker location tracking and safety monitoring. This enhances hazard detection and enables emergency response time increase capability [17].

Despite strict safety regulations and standards, scaffolding accidents still occur at high rates, showing current safety management approaches don't fully address underlying causes. Specifically; Safety management in construction projects remains predominantly reactive, relying largely on routine inspections and post-accident investigations rather than proactive methods for identifying and mitigating risks in advance [5]. Such reactive approaches are often inadequate for addressing the complex and dynamic risks that arise from continuously changing construction activities and evolving scaffolding configurations [12]. In addition, unsafe human behavior is frequently underrepresented in safety models and is commonly treated merely as a compliance issue, rather than as a multidimensional and dynamic risk factor influenced by physical, psychological, environmental, and organizational conditions. Furthermore, temporary works are often poorly integrated into digital safety systems, with scaffolding frequently excluded from 3D Building Information Modeling (BIM)‑based modeling and spatial safety analyses [7] [8]. Another critical limitation is the insufficient attention given to crane‑scaffolding interactions, despite the fact that crane operations introduce dynamic loads, potential impact hazards, and additional operational uncertainties that may significantly affect scaffolding safety [6]. Additionally, the construction industry demonstrates limited capacity to systematically learn from near-miss incidents and operational data, which restricts opportunities for continuous improvement in safety performance.

These limitations reveal several important research gaps in the current body of knowledge. First, there is a clear absence of integrated predictive safety frameworks that combine behavioral safety theory with advanced machine learning analytics to anticipate and mitigate risks. Second, the integration between predictive safety models and BIM-based visualization platforms remains limited, reducing the practical usability of predictive insights in construction environments. Third, there is insufficient research focusing on real-time monitoring and structural detection within temporary scaffolding systems. Fourth, integrated modeling approaches that explicitly address the safety risks associated with crane scaffold interactions are lacking. Finally, there has been minimal development of adaptive, closed-loop learning safety management systems capable of continuously improving safety performance through feedback from operational data within construction environments.

1.3 Research Objective

Despite advances, research treats human behavior analysis, BIM safety visualization, and AI monitoring as separate, making scaffolding safety fragmented. An integrated framework linking unsafe behavior analysis, machine learning risk prediction, BIM simulation, and AI prevention is needed. External interactions like crane operations near scaffolding, often overlooked, also play a role in failures. This research proposes a cohesive framework where AI, ML, and BIM work together in a loop to predict, analyze, simulate, and prevent scaffolding accidents. The research is based on three key hypotheses: (i) unsafe human behaviors, while a major cause of scaffolding accidents, could be highly influenced by several environmental and organizational factors within a construction site, (ii) machine learning models that utilize the behavioral, technical, and contextual data of construction workers outperform customary methods in predicting scaffolding accident risks, and (iii) the integration of machine learning risk prediction tools with BIM data visualization, AI-based monitoring systems, and crane-scaffolding interaction models into a single safety framework will not only improve the early detection of construction site hazards but will also enable continuous improvement of construction safety management processes.

To achieve the research aim and explore present limitations of construction safety management approaches, the following research questions are addressed:

(1) Can Building Information Modeling (BIM) platforms improve the application and comprehension of machine learning-based safety risk predictions by easing spatial visualization, hazard simulation, and decision-support systems?

(2) How can AI-based smart monitoring systems using sensor data acquisition and analysis methods help in the automatic detection of early warning signs of scaffolding instability and unsafe operating conditions in the construction process?

(3) How can crane and scaffolding operations be integrated into a computational safety framework that enables dynamic risk assessment and risk reduction for collision with other lifted and transported materials and dynamic interaction hazards?

(4) How can the suggested AI-ML-BIM safety framework enable adaptive closed-loop learning systems that systematically capture operational data and near-miss event evidence to continuously improve safety performance over the long term in construction projects?

II.Materials and Methods

2.1 Research method.

The methodology is designed to address the multidimensional nature of construction safety by combining behavioral safety theory, predictive analytics, digital construction modelling, and intelligent monitoring technologies.
The methodology consists of five primary stages:

I. Safety data acquisition and processing
II. Behavioral and environmental risk factor modelling
III. Machine learning predictive modelling
IV. BIM-based safety visualization and simulation
V. Intelligent monitoring and closed-loop safety learning validation

Research theoretical foundation

- HFACS-Based Behavioral Feature Structuring

The HFACS provides hierarchical categorization of human error across four major levels:

- Unsafe Acts
- Preconditions for Unsafe Acts
- Unsafe Supervision
- Organizational Influences

To systemize HFACS for machine learning modelling, each hierarchical category is translated into measurable quantitative features;
Let; B_i = Behavioral risk index for worker i

$$B_i = \sum_{j=1}^{n} w_j x_{ij}$$

Where;

- x_{ij} = behavioral variables derived from HFACS classification
- w_j = importance weights derived from ML feature importance score

- STAMP-based control loop modelling

The Systems-Theoretic Accident Model conceptualizes safety as a control problem involving feedback loops between controllers and controlled processes [31]. In scaffolding systems, control loops exist between:

- Site supervisors and site teams
- Crane operators and lifting planners
- Safety managers and operational workers

The control process is modelled as;

$$\bigcup(t) = C\big(E(t), S(t)\big)$$

Where;

- U(t) = safety control actions against time
- E(t) = environmental state
- S(t) = scaffold structural condition
- C = control decision function

STAMP is used to design feedback loops within the AI monitoring system to detect deviations from safe operational boundaries.

- Safety-II performance envelope modelling

Safety-II emphasizes understanding operational success boundaries rather than solely preventing failure. Scaffold stability is therefore modelled using safe performance envelopes:

$$\Omega = \{X | f(X)\} \leq \gamma$$

Where;

- X = operational parameters
- f(X) = risk evaluation function
- y = acceptable safety threshold

This envelope defines safe scaffold operation conditions across environmental and operational variables [13].

Research design framework and process

The research design follows a systems engineering methodology informed by STAMP systems safety theory and HFACS behavioral modelling. The methodology integrates predictive analytics and digital construction simulation to evaluate scaffolding safety risks. [27]

The overall research workflow is illustrated through the following sequential process:

- Data collection and classification
- Feature engineering and risk variable selection
- Predictive model development
- BIM integration and hazard simulation
- Monitoring platform development
- Model validation and performance evaluation

1.2 Data collection and sources.

2.2.1 Safety data acquisition

Safety data used in this research was obtained from multiple sources to capture the complex interactions influencing scaffolding accident risks. Multi-source data integration improves predictive model accuracy and enhances safety risk representation [27].

The safety data sets are categorized into four primary domains.

I. Accident and Incident Databases
   - OSHA accident reports
   - Corporate safety logs
   - Near-miss reporting systems

These datasets provide labelled outcomes for supervised ML training [3], [23]

II. Structural and environmental sensor data
   - Strain gauge measurements
   - Tilt sensor displacement
   - Accelerometer vibration data
   - Weather station wind speed and temperature

These sensors enable real-time monitoring of the scaffolding structural integrity. [28]

III. Wearable human monitoring

Wearable technologies collect physiological and motion data including:

- Worker posture angle
- Movement velocity
- Fatigue indicators (heart rate variability)

These measurements provide continual behavioral risk assessment. [27]

IV. Crane telemetry systems
   - Lift load magnitude
   - Boom radius
   - Swing velocity
   - Hook height and trajectory

Table 1. Safety data sources with their source type and purpose indicated

	Data Description	Source Type	Purpose
Historical Accident Reports	Incident cause analysis and accident frequency	Safety databases / industry reports	Training predictive ML models

Behavioural Safety Data	PPE compliance, worker training level, fatigue indicators	Site observations / wearable devices	Behaviour risk modelling
Environmental Monitoring	Wind speed, temperature, visibility, site congestion	Environmental sensors	External risk evaluation
Structural Monitoring	Strain, tilt, vibration, settlement	SHM sensors	Structural stability prediction
Crane Telemetry Data	Crane trajectory, load weight, load swing movement	Equipment monitoring systems	Crane‑scaffold interaction analysis

1.2.1 Data preprocessing

Collected data was subjected to cleaning, normalization and transformation to ensure modelling reliability. Missing data values were addressed using interpolation techniques while safety variables were encoded into numerical representations suitable for machine learning algorithms.

1.2.2 Behavioral risk factor modelling

Behavioral risk modelling was conducted using HFACS theory to classify unsafe worker behavior into five analytical categories:

- Physical factors
- Psychological factors
- Environmental factors
- PPE compliance factors
- Technical procedural factors

Table 2. HFACS behavioral risk feature variables

Behaviour Category	Variable	Measurement Method
Physical	Fatigue level	Wearable physiological sensors
Physical	Ergonomic strain	Posture monitoring systems
Psychological	Risk perception index	Worker safety surveys
Psychological	Time pressure indicator	Task scheduling metrics
Environmental	Wind exposure	Weather monitoring sensors
Environmental	Site congestion	BIM spatial density analysis
PPE Compliance	Harness anchoring status	Wearable compliance monitoring
Procedural	Assembly sequence adherence	BIM workflow comparison

1.2.3 Feature engineering to transform raw data into ML-compatible variables.

1.2.4 Behavioral risk metrics

Fatigue index is calculated as;

$$F_i = \propto H_i + \beta P_i + \gamma R_i$$

Where;

- H_i = Working hours
- P_i = Posture strain
- R_i = Rest interval

1.2.5 Environmental risk indicators

Wind load risk index is calculated as;

$$W_r = \frac{V^2 \, AC_d}{2}$$

Where;

- V = wind velocity
- A = Exposed scaffold area
- C_d = Drag coefficient

1.2.6 Crane interaction risk index

Crane risk index is calculated as;

$$C_r = \frac{L}{d_s} \times v_s$$

Where;

- L = Lifted load
- d_s = distance between crane hook and scaffold.
- v_s = swing velocity

1.3 Machine learning model development

Multiple machine learning algorithms were evaluated to determine optimal predictive accuracy. Ensemble learning techniques were selected due to their ability to model nonlinear relationships between safety variables [32].

1.3.1 Random forest risk prediction model

Random forest constructs multiple decision trees;

$$RF(X) = \frac{1}{T} \sum_{t=1}^{T} h_t(X)$$

Where;

- T= number of trees
- h_t (X) = individual decision tree prediction

Random Forest provides strong performance in safety classification tasks due to its robustness to noise and ability to capture non-linear relationships. [1]

1.3.2 Gradient boosting (XGBoost)

XGBoost sequentially optimizes prediction error;

$$y_i = \sum_{k=1}^{K} f_k(x_i)$$

Where;

- f_k = boosting tree functions.

This improves the predictive accuracy while controlling the model complexity. [33].

1.3.3 Model training and performance evaluation

Feature engineering involved transforming raw safety data into predictive modelling variables using normalization and dimensionality reduction techniques. Principal Component Analysis (PCA) was used to reduce data redundancy while maintaining predictive variable significance [23].

Training datasets were divided into:

- 70% model training
- 15% validation dataset
- 15% testing dataset

Cross-validation techniques were used to prevent model overfitting and improve predictive generalization.

Table 3. Model evaluation metrics

Metric	Description
Accuracy	Overall prediction correctness
Precision	True positive accident prediction rate
Recall	Hazard detection sensitivity
F1 Score	Combined precision and recall performance
ROC-AUC	Overall classification reliability

1.4 BIM Based risk visualization

Figure 1 below shows the integrated digital safety management system approach to scaffold risk prediction at construction sites based on building information modeling (BIM), ML, and AI technologies. The system collects behavioral, sensor, and crane operation data from the construction site and feeds it into the machine-learning-based risk-prediction system, which processes the data for risk assessment. The forecasts are connected to the BIM model and tagged within the digital construction environment with likely hazard areas, such as fall risks, unsafe working zones and crane-scaffold interferences. This allows for predictive hazard detection, virtual 4D sequencing to assess for safety, real-time safety observation, improved safety communication and data-based safety decision-making to be performed.

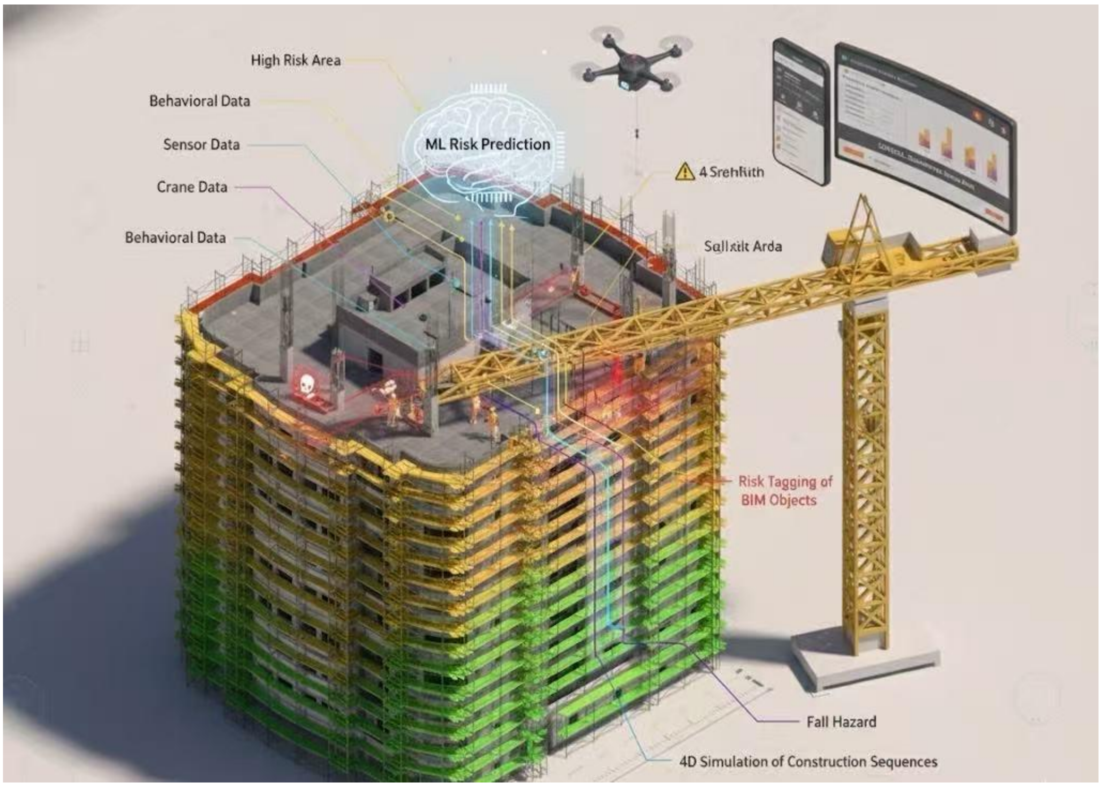

Figure 1. AI-ML-BIM Integrated Framework for Predictive Scaffolding Safety Management

A building information model was used to integrate predictive safety analytics into a 3D construction model environment.

Figure 1. 3D scaffolding model to integrate predictive safety analytics (Illustration by Author)

BIM simulations were conducted to;

- Detect scaffold structural clashes
- Simulate erection sequence hazards
- Visualize spatial risk distribution
- Integrate crane operation modelling

Collision detection algorithms identified structural conflicts between scaffolding and building elements, supporting proactive safety planning. [34].

4D BIM modelling enabled temporary simulation of scaffold erection and dismantling stages, revealing structural instability risks at the different stages of the construction process.

An evaluation criterion was developed as shown below;

Table 4. BIM visualization color risk interpretation

Risk Level	BIM Visualization Colour	Risk Interpretation
Low Risk	Green	Safe structural condition
Moderate Risk	Yellow	Monitoring required
High Risk	Orange	Preventive action required
Critical Risk	Red	Immediate intervention required

1.4.1 Intelligent monitoring platform development.

1.4.2 Structural health monitoring integration

Sensor-based SHM systems were integrated with BIM models to monitor scaffold structural stability. With specifications as outlined;

Table 5. Structural monitoring sensor specifications

Sensor Type	Monitoring Purpose
Strain Gauges	Load distribution monitoring
Tilt Sensors	Scaffold displacement detection
Settlement Sensors	Foundation stability monitoring
Vibration Sensors	Dynamic structural behaviour monitoring

1.4.3 Crane-scaffold interaction simulation

Crane telemetry data was integrated with BIM simulations to analyze dynamic crane‑scaffold interactions.

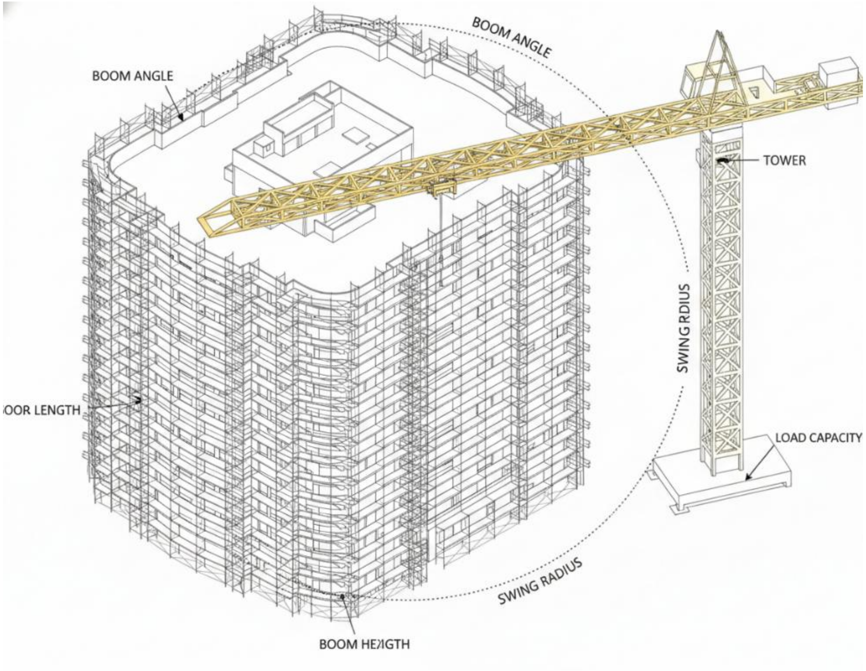

Figure 2. Crane boom angle and swing radius (Illustration by Author)

Table 6. Crane monitoring variables

Variable	Purpose
Crane boom angle	Movement trajectory prediction
Load weight	Structural load risk analysis
Load swing velocity	Collision hazard detection
Crane position	Operational safety envelope modelling

1.4.4 Anomaly detection using autoencoders

Autoencoders detect structural anomalies by reconstructing normal behavior patterns:

$$L = \|X - \hat{X}\|^2$$

Large reconstruction errors indicate abnormal scaffold behavior. [28]

Autoencoder neural network models were used to detect abnormal structural behavior and unsafe worker movement patterns. These models enable early hazard detection before accident occurrence.

The research incorporated ethical considerations regarding decision control to ensure AI outputs support, rather than replace human judgement. Data privacy measures were taken to ensure anonymity and encryption.

3 Results and discussions

3.1 Over view of analytical outputs

To provide a structured understanding of the framework's capabilities, the analytical findings were organized into four distinct primary domains, each addressing a critical layer of site safety. Behavioral risk identification and classification. This domain focuses on the human element, systematically categorizing risky actions and identifying the root psychological or environmental triggers that lead to site hazards. Machine learning predictive performance. Here, the focus shifts to the data-driven intelligence of the system, evaluating how accurately the algorithms can forecast potential failures or accidents before they occur. BIM-based risk visualization and construction sequencing simulation. This involves the spatial and temporal aspects of the project, using 3D modeling to visualize risks in real-time and simulate the step-by-step construction process to catch hazards in the planning phase. Intelligent monitoring and crane interaction risk detection. This specialized domain addresses high-stakes mechanical movements, specifically tracking crane activity to prevent collisions or structural stresses during complex maneuvers.

3.2 Behavioral risk identification and analysis.

3.2.1 Dominant behavioral risk factors

Upon examination of the incident data, factors that are correlated with scaffolding collapse include; Improper scaffold assembly, Unauthorized structural modifications, Production pressure and deviation from procedure

Furthermore, the integration of wearable monitoring data provided a new dimension of insight through the fatigue index. Beyond internal site dynamics, the research highlighted that environmental variables, most notably wind velocity and thermal stress, play a decisive role in both the structural stability of the scaffold and the physical performance of the workers. Rather than acting as static background conditions, these factors serve as dynamic stressors that can rapidly alter the safety of a construction site.

3.3 Machine learning predictive performance.

3.3.1 Model accuracy and predictive reliability

The research utilized a suite of ensemble machine learning models, which demonstrated consistently high predictive performance across a diverse range of evaluation metrics.

Random Forest Models: These models achieved a high degree of classification accuracy. Their primary strength lay in their inherent ability to map and capture complex, nonlinear relationships between behavioral triggers, environmental stressors, and technical structural variables. Gradient Boosting (XGBoost): Specifically, XGBoost demonstrated an exceptional sensitivity to rare accident events. This is a critical factor in safety analytics, as it resulted in superior recall performance, ensuring that low-frequency but high-impact hazards were not dismissed as statistical noise. Model Interpretability via SHAP: Perhaps most importantly, the integration of SHAP (SHapley Additive exPlanations) analysis transformed the framework to a transparent decision-support tool. By quantifying the specific contribution of each variable to a risk prediction. This approach allows for a more nuanced understanding of site risk, moving beyond simple observation to provide a sophisticated, predictive toolkit for real-time safety intervention.

3.3.2 Predictive risk scoring and threshold analysis

The framework’s core utility lies in its ability to translate complex data into actionable intelligence through a probabilistic risk-scoring engine. This engine generates raw likelihood values for potential accidents, which are then systematically mapped into four intuitive safety categories to facilitate rapid onsite decision-making: Low Risk, Moderate Risk, High Risk and Critical Risk

3.4 BIM-based risk visualization and simulation

3.4.1 3D spatial risk mapping

Embedding machine learning-derived risk scores into BIM environments enabled spatial visualization of hazard concentration zones. Color-coded scaffold components highlighted high-risk structural regions, allowing safety managers to identify hazardous work areas before actual construction occurred.

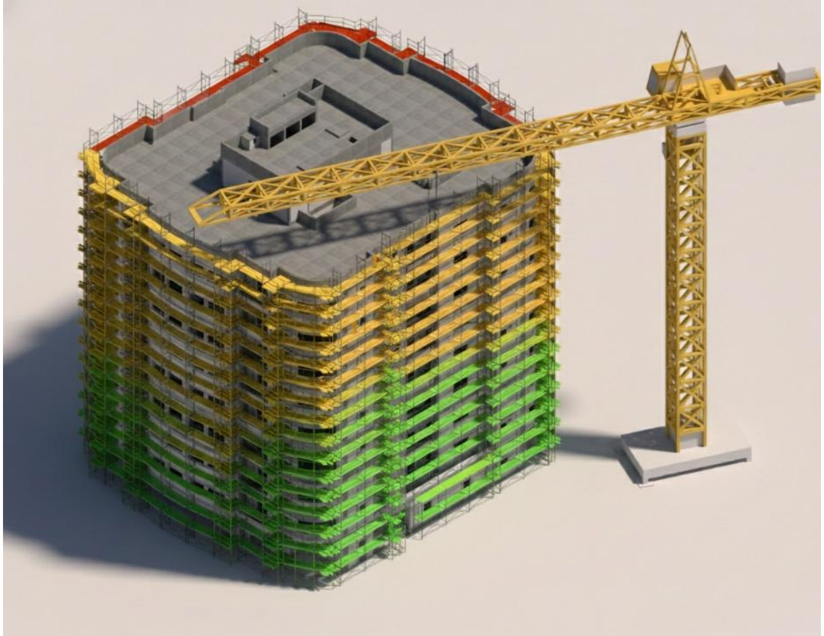

Figure 3. Color coded heatmap to show scaffold risk regions, with color codes from Green (low risk) to Red (High risk) (Illustration by Author)

This spatial contextualization addresses a critical limitation of standalone machine learning safety models, which often fail to provide actionable site-level guidance [35].

3.4.2 4D construction sequence simulation

The use of 4D Building Information Modeling (BIM) simulations offered a temporal perspective that 3D modeling could not achieve, specifically identifying the enhanced vulnerability of transitional scaffold configurations. These simulations demonstrated that the most hazardous periods usually occur during scaffold erection and dismantling, when the structure remains in a transitional state and has not attained its intended rigidity. During these intervals, the scaffold displays significantly increased structural instability because load-bearing paths are often incomplete or temporarily compromised.

Figure 4. 4D sequencing of scaffolding construction illustrations, to show the erection and dismantling sequences (Illustrations by Author)

According to the results obtained from the BIM 4D model, the benefits are:

I. A good platform to generate a time schedule free from hazards.
II. Choose the necessary safety equipment.
III. Increase safety communication.
IV. A good tool uses as training program for workers.

The 4D model can help make complex construction projects more visible and easier to safety managers and thus the identification of hazards will be easier than relying on 2D drawings.

3.4.3 Crane scaffold interaction risk detection

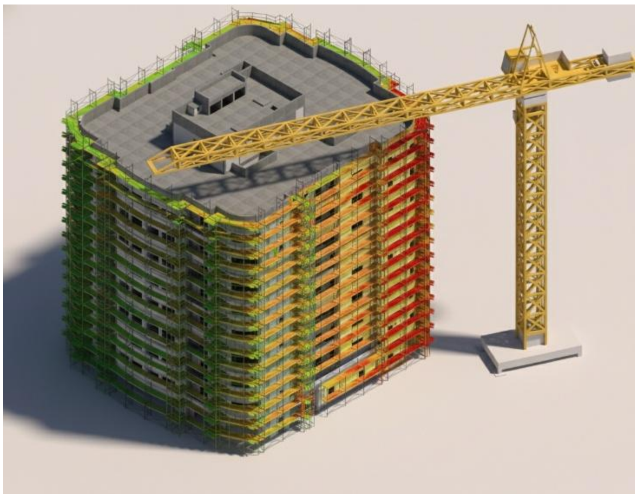

Figure 5. Color coded heatmap to show areas with high risk of crane-scaffolding clashes, with color codes from Green (low risk) to Red (High risk) (Illustration by Author)

To move beyond simple proximity detection, the framework utilized automated clash detection within the BIM environment to analyze the some of the forces at play in the 3d environment. The results demonstrated that dynamic crane loading, specifically the centrifugal forces generated during swinging operations, exerted higher levels of structural stress on the scaffold than static loads. By integrating crane telemetry directly into a 3d-BIM-based monitoring system, the data was fused in order to allow automation and real-time enforcement of risk exclusion zones identified.

3.5 Intelligent monitoring and structural health monitoring

To manage the influx of data, the framework utilized Autoencoder-based anomaly detection algorithms. Unlike traditional systems that rely on rigid, pre-set limits, these deep-learning models were trained to understand the baseline or normal structural behavior of the scaffold. By recognizing even slight deviations from this learned equilibrium, the algorithms could trigger early-warning alerts. This capability is a cornerstone of the proposed framework, as it transforms safety management from a reactive post-incident investigation into a predictive intervention strategy, allowing for structural reinforcement or site evacuation before a catastrophic failure can occur. [13].

3.6 Limitation and future research

While the proposed framework offers a significant advancement in safety management, several critical limitations must be addressed to ensure its successful transition from a controlled research environment to a dynamic construction site: The Data Dependency Constraint: The predictive power of any machine learning model is inherently tied to the quality, volume, and consistency of the input data. In the construction industry, data availability can vary wildly between projects depending on the digital maturity of the firm. Logistical Hurdles in Temporary Works: Unlike permanent buildings, scaffolds are constantly being erected, modified, and dismantled. Ensuring that sensors remain calibrated, powered, and securely attached throughout these rapid transitions is a significant logistical undertaking. For a real-time system to function effectively, it requires a robust technological backbone including high-speed onsite connectivity and a centralized BIM coordination unit. Organizational Resistance and Commitment: Success of this framework depends greatly on organizational commitment beyond technical needs. Transitioning from manual inspections to an AI-driven Safety-II approach demands a cultural change in management.

The framework methodological approach is to use a data-driven analysis to convert behavioral, structural , and operational construction data into safety-related indicators. It also builds interpretable machine learning algorithms to characterize the marginal and interaction effects of several risk factors in predictive model outputs. Finally, it integrates machine learning with BIM-based spatial information environments to visualize the predictive model outputs in digital construction environments. Not only can it improve the explain ability of the ML algorithms used, but also the feasibility and usability of all the results of the performed analyzes for engineers, safety managers and the project decision-makers. The hybrid AI-ML-BIM framework developed can efficiently assess scaffolding safety risks in more complicated construction scenarios with different site activities and structural conditions , and thus reduce the dependence on manual safety assessments alone.

Furthermore, the framework provides a proof-of-concept for sensor-enabled data streams and AI-based analytics for real-time safety supervision and hazard anticipation by continuous assessment of the dynamic responses, activity, and behavior of structures, construction sites, and workers to identify detrimental behavior patterns of scaffolding instability, unsafe worker behavior, and crane-movement and scaffolding-interaction hazards to enable construction safety management systems to progress from reactive monitoring or post-hazard analysis to predictive and adaptive safety-engineering. In particular, these approaches would be less reactive and responsive to changes on fast-changing construction sites.

These limitations suggest that scaffolding safety in contemporary construction worksites is a function of the dynamic interactions of human factors, structural conditions, and work processes, and can be adequately modeled in an integrated computing platform. The modeling approach proposed in this study adds to the foundational knowledge of the complex web of construction safety risk formation through machine learning prediction, BIM-enabled spatial visualization, and AI-enabled monitoring. Safety interventions should be technology-enabled and data-driven, leveraging predictive analytics, digital modeling, and clever monitoring to improve hazard visibility, construction activity coordination, and risk management, supporting the shift to proactive safety approaches.

Future studies could apply bigger multi-project datasets and emerging sensing technologies and digital twin-based construction monitoring environments to the proposed framework to improve its predictive and operational outcomes. Furthermore, comparative validation of the proposed framework in different construction environments, contexts, and project scales could reinforce its robustness and extend its potential application of smart safety management systems in digital construction engineering.

The evolution of intelligent construction safety management necessitates further exploration in several key areas: Large scale empirical validation for live construction projects Evolution from correlation to causality. Where the shift of the research is focused on understanding the why behind the accident and Optimizing human-AI interaction in safety decision making. The construction industry has traditionally faced high accident rates, with scaffolding being a common cause of serious injuries and deaths. Conventional safety approaches, based on manual inspections and post-incident reviews, fall short in handling the complex and ever-changing environments of current worksites. This study fills this gap by creating an integrated AI‑ML‑BIM framework that shifts safety management from a reactive.

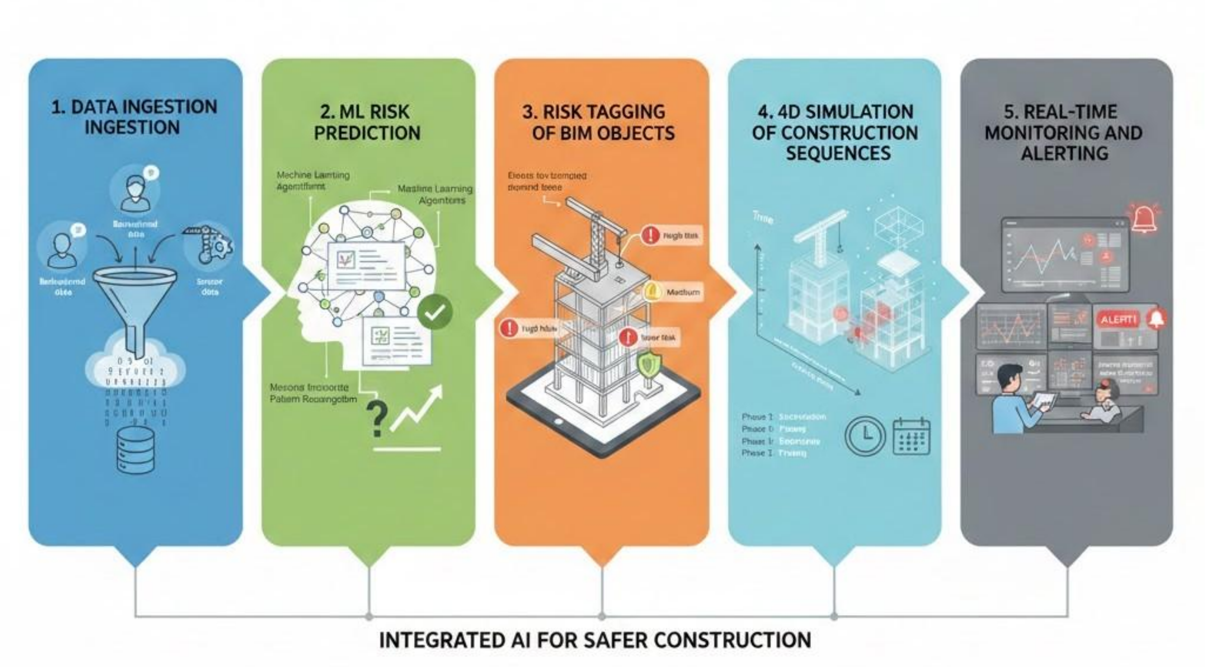

Figure 6. Proposed AI-ML-BIM framework workflow sequence (Illustration by Author)

4 Conclusions

This study develops a scaffolding safety risk pre-evaluation framework integrated with Building Information Modeling (BIM), machine learning, and artificial intelligence (AI) to evaluate scaffolding safety risk in complex construction systems. The proposed system integrated behavioral safety analysis (BSA), digital construction modeling (DCM), predictive machine learning, and AI-based smart monitoring technologies to identify and evaluate scaffolding safety risk in complex construction systems. This guides the development of computational modeling and digital construction technologies to translate and structure diverse safety-relevant data into interpretable systemic indicators that ease proactive management of safety risks. Furthermore, it includes the integration of AI-based monitoring models and visualization environments that leverage BIM-based technologies aimed at improving the understanding and usage of predictive safety information. Accordingly, construction safety conditions are modeled as a set of interacting concepts that capture the relationship between scaffolding, crane, and activity states at the construction site. The framework also allows the evaluation of the safety of potential hazards in isolation or within the larger operational system including the dynamic interaction between structural and behavioral factors, providing a more realistic and operationally relevant way of looking at safety management of scaffolding and its various components.

The results indicate that unsafe human behavior remains the primary source of scaffolding accidents. By utilizing machine learning to rank these risks by importance, the data consistently showed that training quality, procedural compliance and the state of onsite supervision were the factors that mostly influenced the safety outcomes. This provides a critical shift in perspective in that; scaffolding safety is not merely about the technical design and implementation, but rather inclusive of organizational and management of the construction site. When scaffolding fails, the root cause is most likely found in the boardroom or training center before it actually manifests on the construction site. This research also significantly advances the body of construction safety literature by proving that abstract safety theories can be harmonized with high-tech, data-driven frameworks. By bridging the gap between social science (behavioral theory) and engineering (AI/BIM), this study offers several transformative contributions: Operationalizing Safety Theory, From Abstract Predictions to Visual Intelligence, Closing the Crane‑Structure Research Gap and Enabling Proactive Intervention:

The method integrates multimodal behavioral, structural and operational data to identify systematic variations in scaffolding safety risk between construction sites and to identify interactions between human behavior, temporary structures and the construction process. The computational framework uses machine learning prediction models to cope with the complex interdependences between risk factors, and is augmented by a building information modeling (BIM) enabled spatial visualization to enable the contextualization of the prediction results with a 3D model of the construction site. This provides a more holistic, data-informed characterization of safety within construction than customary approaches that rely on inspections, codes, and standards, by integrating computational predictive data with spatial and operational context.

Overall, the findings suggest that scaffolding safety in modern construction is innately related to human, structural and management behavior and can be represented in an integrated digital modeling process. Scaffolding safety management should be proactive, predictive, tech-enabled and data-driven, rather than purely reactive and compliance-focused, to provide a governing system of operational scaffolding safety management . The proposed AI-ML-BIM framework can act as a basis for scalable analytics-based smart construction safety management and digital transformation of safety management practices in the construction industry.

4.1 Practical industry contributions

From an industrial perspective, the developed AI-ML-BIM framework can provide the construction organizations with advanced technology-enabled safety management that is proactive and overcomes most of the limitations of the existing construction safety management practices, which are compliance-driven, inspection-focused, and reactive to incidents and accidents after they occur on construction sites. However, these typically reactive methods are relatively ineffective at predicting risks that may occur in complex and dynamic construction sites. The risk management framework proposed in this study can be considered as a proactive framework that combines artificial intelligence and machine learning with a building information model (BIM) to identify, assess and interpret risks before an accident occurs.

For example, one potential use of the framework is in predicting scaffold accident risk before the erection of scaffolding. Predictive algorithms using historical safety data, behavioral indicators, environmental variables, and structural attributes can identify patterns indicative of high hazard situations in scaffolding operations, easing proactive measures to reduce risks. This prediction aids the PM, safety officer and site engineers in predicting possible hazards in the construction process through the planning and design stages and allows for the safety procedures to be implemented.

A second contribution is safety communication through risk prediction-based BIM visual hazard simulation. If the predicted risk is included in the BIM model, safety information can be visualized directly in the 3D model of the construction site. Such a capability can help communicate spatial hazards such as scaffold layout, crane movement and hazardous site conditions to engineers, supervisors and workers. It can also help visualize these hazards to aid in risk understanding, assist in risk communication and safety training, and ease project team collaboration towards project objectives.

The framework also allows real-time safety monitoring tools to be used, such as clever sensors and monitoring tools based on artificial intelligence, to be installed on scaffolding or parts of the structure itself. These tools can monitor real-time structural and operational parameters of construction such as load distribution, displacements, vibrations, and environmental conditions. Machine learning could be used for real-time analysis. It may be possible to detect abnormal patterns or precursors to conditions which can lead to structural problems or unsafe working conditions in a way that prevents scaffolding collapses and other incidents.

Furthermore, it could also be applied to better coordinate the scaffold systems with the cranes that generate many hazards at construction sites, which could create dynamic loads, uncertain motions, and collisions that negatively affect the stability and safety of the existing scaffold systems that support the workers. By customizing the variables which define the crane operation and feeding them to the BIM system with other means of spatial analysis, it is possible to identify the areas of risk that may result from cranes and scaffolding interacting, and make decisions about optimized paths with safe distances to avoid impact and disturbance of elements.

Finally, the process of empowering data driven safety decision making in construction organizations by continuous data collection and conversion of raw site data into information. Safety managers can use these insights for risk analysis and prioritization, implementing risk control measures, and for improving their knowledge base about the continuous improvement of safety programs and policies over time at the organizational level. The framework seeks to contribute towards the digital transformation of construction safety management by using predictive analytics, clever monitoring systems and BIM-based visualization to ease the shift in the construction industry from a compliance-based safety approach towards a predictive, adaptive and data-driven safety engineering management approach. The framework has the potential to improve safety performance and reduce scaffolding related accidents on a modern construction site by increasing risk awareness, communication between parties involved in scaffolding, and helping in decision making.

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Appendices

Table 7. Classification of unsafe human behavior variables (HFACS-aligned)

HFACS Level	Category	Variable Name	Description	Data Source
Unsafe Acts	Skill-based error	Improper scaffold assembly	Incorrect placement of braces, planks, or ties	Inspection reports

Unsafe Acts	Violation	PPE non-compliance	Failure to wear harness or helmet	Wearables / audits
Preconditions	Physical	Fatigue index	Composite score based on hours worked and posture	Wearables
Preconditions	Psychological	Risk normalization	Frequency of repeated exposure without incident	Safety logs
Preconditions	Environmental	Wind exposure	Wind speed exceeding safe thresholds	Weather sensors
Supervision	Supervisory failure	Inadequate inspection	Missed or delayed scaffold checks	Management records
Organization	Organizational climate	Training deficiency	Absence of valid certification	HR databases

Table 8. Mapping unsafe behaviors to preventive measures

Unsafe Behavior	Root Cause	Preventive Measure	Digital Support
Unauthorized modification	Time pressure	Permit-to-modify system	BIM access control
PPE non-use	Comfort / culture	Incentive & enforcement	AI wearables
Improper erection	Skill gap	Certification requirement	BIM-based training
Fatigue-induced errors	Long shifts	Shift optimization	ML scheduling
Crane proximity risk	Poor coordination	Digital exclusion zones	BIM + AI crane control

Table 9. Machine learning algorithms and parameters

Model	Purpose	Justification
Random Forest	Baseline risk prediction	Robust to noise, interpretable
XGBoost	High-accuracy prediction	Handles nonlinear interactions
LightGBM	Real-time inference	Fast training and inference
Autoencoder	Anomaly detection	Identifies unseen failure patterns

Table 10. Example feature set for Machine learning training.

Feature Group	Feature	Type
Physical	Work duration (hrs)	Continuous
Physical	Posture deviation	Continuous
Psychological	Experience level	Ordinal
Environmental	Wind speed (m/s)	Continuous
PPE	Harness usage	Binary
Technical	Modification frequency	Discrete
Crane	Load proximity index	Continuous

Table 11. BIM object and safety parameters embedded

BIM Object	Safety Attribute	Description
Scaffold bay	Risk score	ML-generated probability
Access ladder	Fall risk	PPE + geometry-based
Tie connection	Stability index	Sensor-derived
Crane zone	Collision risk	Dynamic envelope
Work platform	Load limit	Real-time monitoring