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Predictive Safety Analytics Model for Early Detection of High-Risk Construction Activities

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ABSTRACT: The construction industry continues to experience a high incidence of occupational accidents due to complex work environments, dynamic project conditions, and the involvement of multiple stakeholders and high-risk activities such as working at heights, heavy equipment operation, and confined space tasks. Traditional safety management approaches often rely on reactive methods that investigate incidents after they occur, which limits their effectiveness in preventing future accidents. This review paper examines the development and application of predictive safety analytics models designed to enable early detection of high-risk construction activities before accidents occur. The study synthesizes existing research on data-driven safety management frameworks that integrate historical accident records, real-time site monitoring data, wearable sensor information, and environmental indicators to identify patterns associated with unsafe conditions and behaviors. Emphasis is placed on machine learning techniques, statistical risk modeling, and predictive algorithms that analyze large safety datasets to forecast potential hazards and support proactive decision-making. The review also evaluates the role of emerging technologies including Internet of Things (IoT) devices, computer vision systems, and digital twin platforms in enhancing predictive safety analytics within construction environments. By examining current methodologies, implementation challenges, and performance evaluation strategies, the paper highlights the potential of predictive analytics to transform construction safety management from reactive compliance-based systems into proactive risk prevention frameworks. The findings provide insights for researchers, construction managers, and safety professionals seeking to improve workplace safety outcomes through advanced data-driven risk prediction models.

KEYWORDS: Predictive safety analytics; Construction safety management; Machine learning for risk prediction; High-risk construction activities; Proactive hazard detection; Data-driven safety monitoring.

1. INTRODUCTION

1.1 Background of Construction Safety Challenges

The construction industry remains one of the most hazardous sectors globally due to the complexity of project environments, the interaction between heavy equipment and human labor, and the dynamic nature of construction activities. Construction projects frequently involve simultaneous operations such as excavation, structural assembly, equipment lifting, and electrical installations, which create multiple risk pathways capable of triggering accidents. These risks are amplified by rapidly changing site conditions, workforce mobility, and the presence of temporary structures such as scaffolding and formwork systems. Safety management systems developed for such environments must therefore account for operational uncertainty and the interdependence between project components. Modern risk governance frameworks emphasize the importance of systematic monitoring and predictive evaluation of operational conditions in complex environments to reduce accident probability and improve decision-making efficiency (Adesiyan & Alaba, 2025). These frameworks highlight the importance of integrating analytical tools capable of interpreting large operational datasets generated during project execution.

Another major challenge arises from the increasing technological complexity of modern construction systems. Large infrastructure projects now incorporate advanced mechanical equipment, automated construction tools, and digital monitoring technologies that generate significant volumes of operational data. Traditional safety oversight methods such as manual inspections and incident reports often fail to capture the multidimensional nature of risk emerging from these interconnected systems. Analytical frameworks used in technology investment and performance monitoring

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demonstrate that complex operational environments require integrated analytical models capable of detecting subtle patterns within large datasets (Walawalkar et al., 2024). Consequently, construction safety research increasingly recognizes the need to move beyond reactive accident analysis toward proactive safety frameworks capable of identifying risk indicators before accidents occur.

1.2 Importance of Early Detection of High-Risk Activities

Early detection of high-risk construction activities is essential for preventing workplace accidents and ensuring the safety of construction personnel. High-risk tasks such as crane operations, structural lifting, confined-space work, and scaffold assembly involve complex interactions between workers, equipment, and environmental conditions. When safety monitoring systems fail to identify emerging hazards during these operations, the probability of accidents increases significantly. Advanced decision-support frameworks demonstrate that predictive analytics can identify abnormal patterns within operational workflows that may signal emerging risks before they escalate into critical incidents (Okoruwa et al., 2025). Applying similar predictive logic to construction environments enables safety managers to evaluate risk indicators such as unsafe worker proximity to equipment, abnormal equipment vibration patterns, and deviations from safe operational procedures.

The ability to detect hazardous activities at an early stage also enables proactive intervention strategies that reduce accident severity and improve project performance. Predictive monitoring systems can analyze real-time operational data to determine whether construction tasks are deviating from safe execution patterns. For example, predictive models integrated with sensor-based monitoring systems can detect unsafe load distribution during crane lifting operations or identify structural instability in temporary support systems. Optimization models applied in operational planning demonstrate how analytical frameworks can evaluate complex operational variables and generate timely risk alerts (Taiwo, 2025). When applied to construction safety management, these predictive monitoring capabilities allow project managers to intervene before accidents occur, significantly improving workforce protection and reducing project delays caused by safety incidents.

1.3 Emergence of Data-Driven Safety Management

The emergence of data-driven safety management represents a fundamental shift in how construction organizations approach occupational risk mitigation. Traditional safety management systems rely heavily on manual inspections, safety training programs, and incident reporting mechanisms to enforce compliance with safety regulations. While these approaches remain essential, they often fail to capture complex patterns of risk development that arise from interactions between multiple operational variables. Data-driven safety management frameworks utilize advanced analytical models capable of processing large datasets generated from construction activities to identify emerging hazards. Technologies such as sensor networks, digital monitoring platforms, and real-time operational databases enable continuous data collection across construction sites. Secure data logging mechanisms developed for complex information systems demonstrate how structured data infrastructures can ensure the reliability and traceability of operational safety information (Ijiga et al., 2025).

Data-driven safety frameworks also enable the integration of predictive analytics tools capable of identifying patterns that indicate elevated accident risk. By analyzing variables such as worker movement patterns, environmental conditions, equipment usage data, and operational workflows, predictive models can estimate the probability of hazardous events occurring within specific operational contexts. Analytical models used in digital monitoring environments demonstrate how data-driven auditing frameworks can transform traditional monitoring processes into intelligent decision-support systems (Essandoh et al., 2025). In construction safety management, this approach allows organizations to continuously evaluate safety performance, identify high-risk operational conditions, and deploy targeted interventions designed to prevent accidents before they occur.

1.4 Objectives and Scope of the Review

The primary objective of this review is to examine the development and application of predictive safety analytics models designed to enable early detection of high-risk construction activities. Construction projects involve numerous dynamic operational conditions that make hazard identification challenging when relying solely on conventional safety monitoring methods. The review therefore focuses on analyzing emerging data-driven safety frameworks that integrate predictive analytics techniques into construction risk management systems. By examining recent developments in machine learning, sensor-based monitoring technologies, and intelligent safety analytics, this study aims to identify how predictive models can improve hazard detection and reduce accident probability within complex construction environments.

The scope of the review extends to evaluating the technological foundations that enable predictive safety analytics systems, including data acquisition mechanisms, real-time monitoring technologies, and advanced analytical algorithms capable of forecasting safety risks. Particular attention is given to the role of predictive models in identifying hazardous worker behavior, equipment malfunction, and unsafe environmental conditions before accidents occur. In addition, the review explores how predictive safety systems can be integrated into digital construction management platforms to support proactive decision-making processes. By synthesizing existing research on predictive safety technologies, the review provides a comprehensive perspective on the capabilities, limitations, and implementation challenges associated with predictive safety analytics in modern construction projects.

1.5 Structure of the Review Paper

This review paper is organized into six major sections that collectively examine the development and implementation of predictive safety analytics models for early detection of hazardous construction activities. The first section introduces the research context by discussing the safety challenges present in construction environments and explaining the need for predictive monitoring systems capable of identifying high-risk activities before accidents occur. The second section provides a comprehensive literature review on construction safety risk management, focusing on traditional safety assessment methods, accident causation factors, predictive analytics developments, and the limitations of conventional monitoring frameworks. The third section presents the conceptual framework of the predictive safety analytics model, describing the system architecture, data acquisition processes, feature engineering techniques, and predictive modeling approaches used for hazard detection. The fourth section examines emerging technologies that support predictive safety systems, including Internet of Things sensors, computer vision monitoring platforms, and digital twin simulations used for safety forecasting. The fifth section evaluates implementation challenges and performance metrics associated with predictive safety models in construction environments. Finally, the sixth section synthesizes the key insights of the review, identifies research

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gaps, and outlines future research directions for intelligent construction safety systems capable of transforming safety management in complex construction projects.

2. LITERATURE REVIEW ON CONSTRUCTION SAFETY RISK MANAGEMENT

2.1 Traditional Construction Safety Assessment Methods

Traditional construction safety assessment methods have historically relied on compliance-based safety management frameworks and manual inspection procedures designed to reduce occupational hazards on construction sites. Early safety assessment practices typically involved structured hazard identification techniques such as safety audits, risk matrices, safety checklists, and accident investigation reports to identify potential risks associated with construction activities. These approaches are largely reactive because they rely on historical incident records rather than proactive prediction of future risks. Risk governance models applied in organizational environments demonstrate that conventional compliance frameworks are effective for regulatory adherence but often fail to capture dynamic operational risks present in complex environments such as construction projects (Agbosu et al., 2026; Morah et al., 2022). Similarly, governance-oriented models highlight the need for integrated risk monitoring structures capable of handling operational complexity across industries (Akhigbe et al., 2025). In construction safety management, traditional models therefore focus primarily on identifying unsafe conditions after they emerge rather than predicting them beforehand.

Furthermore, traditional construction safety assessment relies heavily on human observation, site inspections, and safety training programs designed to enforce safe work behavior among workers. However, these approaches often struggle to handle the large volume of operational data generated on modern construction sites. Studies on predictive frameworks in engineering systems demonstrate that manual monitoring techniques cannot efficiently process complex environmental, operational, and behavioral variables simultaneously (Ijiga et al., 2022; Uwabor et al., 2025). As construction projects become more technologically integrated, traditional safety evaluation systems show limitations in identifying patterns of risk development across large datasets (Taiwo, 2024; Walawalkar et al., 2024). Consequently, recent research emphasizes the need to transition from traditional safety compliance models toward data-driven predictive safety analytics capable of identifying early warning indicators of hazardous construction activities (Kevin & Oluwasanya, 2022; Adesiyan & Alaba, 2025).

2.2 High-Risk Activities and Accident Causation in Construction

Construction environments involve multiple operational hazards due to the simultaneous execution of high-risk tasks such as working at heights, crane operations, excavation activities, scaffolding assembly, and heavy equipment handling. These activities are associated with significant accident rates due to the interaction between workers, machinery, and dynamic environmental conditions. Studies examining risk governance and operational complexity demonstrate that accident causation often results from the interaction of organizational, technical, and behavioral factors rather than a single hazard source (Okoruwa et al., 2025; Bello et al., 2025). Construction risk analysis frameworks therefore emphasize the importance of identifying patterns of unsafe behavior and hazardous operational conditions before accidents occur. In complex project environments, these high-risk activities generate multiple risk indicators including worker fatigue, equipment malfunction, environmental hazards, and workflow disruptions.

Research in predictive modeling across engineering systems indicates that accident causation patterns can be detected through the analysis of operational data streams and behavioral indicators (Ezeh et al., 2025; Hammed et al., 2026). These studies highlight the importance of integrating real-time monitoring technologies into construction safety management frameworks. Similarly, digital monitoring frameworks used in infrastructure planning demonstrate how advanced analytics can identify operational risks within complex project systems (Ogbete et al., 2025; Ofori et al., 2025). Emerging safety analytics frameworks further emphasize the integration of predictive data models capable of identifying hazardous operational conditions across multiple project phases (Essandoh et al., 2025; Wedraogo et al., 2025). These developments indicate that accident causation in construction is not purely random but rather the result of identifiable patterns that can be detected using advanced data analytics methods.

2.3 Evolution of Predictive Analytics in Safety Management

Predictive analytics has gradually emerged as a transformative approach for improving safety management across multiple industrial sectors. Early predictive analytics models were primarily developed within financial risk management and governance frameworks where large datasets were used to forecast operational risks and decision outcomes. Research on predictive modeling systems demonstrates that data-driven algorithms can identify complex patterns and risk indicators within large datasets more effectively than traditional manual analysis methods (Kevin, 2026; Sanni, 2026). These analytical techniques have been widely adopted in enterprise risk management systems where machine learning algorithms are used to forecast potential operational disruptions and strategic risks (Walawalkar et al., 2026; Taiwo, 2025). The success of predictive analytics in these domains has encouraged its application to safety management challenges in engineering and infrastructure systems.

Within construction safety research, predictive analytics models have been developed to analyze historical accident records, worker behavioral data, and environmental monitoring data in order to forecast potential hazards. Studies on AI-driven anomaly detection frameworks demonstrate that machine learning algorithms can identify abnormal operational patterns that may indicate emerging safety risks (Ijiga et al., 2025; Balogun et al., 2025). In addition, blockchain and distributed monitoring frameworks have been explored as mechanisms for ensuring transparency and integrity in safety monitoring systems (Idika & Ijiga, 2025). Predictive safety analytics therefore represents a shift from reactive safety management toward proactive risk prevention strategies where hazardous conditions are detected before accidents occur. This evolution reflects broader trends in data-driven decision intelligence systems where predictive models enhance operational monitoring and improve safety outcomes across complex environments (Adesiyan & Alaba, 2024; Essandoh et al., 2025).

2.4 Limitations of Conventional Safety Monitoring Systems

Despite the widespread use of traditional safety monitoring frameworks, several limitations reduce their effectiveness in modern construction environments. Conventional safety monitoring systems primarily rely on manual inspections, safety reports, and incident documentation processes that are often time-consuming and prone to human error. These systems also suffer from delayed reporting cycles that prevent real-time detection

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of hazardous conditions. Research on organizational risk monitoring demonstrates that conventional monitoring frameworks struggle to process large volumes of operational data generated by modern engineering systems (Agbosu et al., 2026; Hammed et al., 2026). As construction projects increasingly adopt digital technologies, the inability of traditional monitoring approaches to analyze real-time safety indicators becomes a critical limitation.

Another major limitation of conventional safety monitoring systems is the lack of predictive capability. Traditional systems are primarily designed to document safety violations or incidents after they occur rather than identifying early warning signals of potential accidents. Studies examining digital risk governance frameworks highlight the need for intelligent monitoring architectures capable of processing multi-source operational data streams (Walawalkar et al., 2026; Okonkwo et al., 2025). Emerging research also indicates that the integration of machine learning algorithms can significantly improve the ability of safety systems to detect anomalies within operational workflows (Ezeh et al., 2025; Ijiga et al., 2025) as seen in Table 1. Consequently, researchers increasingly advocate for predictive safety analytics models capable of integrating real-time sensor data, environmental monitoring information, and behavioral safety indicators to identify high-risk construction activities before accidents occur.

Table 1: Summary of Limitations of Conventional Safety Monitoring Systems in Construction

Limitation	Description	Impact on Safety Management	Example
Manual Inspection Dependence	Safety monitoring relies on physical inspections and safety reports.	Human errors and inconsistent monitoring across large sites.	Inspectors may miss weak scaffold joints during routine checks.
Delayed Reporting	Incidents are documented after they occur rather than detected early.	Safety interventions occur too late to prevent accidents.	Unsafe ladder placement identified only after a fall incident.
Limited Data Processing	Traditional systems cannot analyze large volumes of operational data.	Difficult to detect complex risk patterns in construction activities.	Equipment faults not detected due to lack of data analysis.
No Predictive Capability	Systems focus on past incidents rather than forecasting risks.	Preventive safety planning becomes difficult.	Repeated near-miss crane incidents without risk prediction.

3. PREDICTIVE SAFETY ANALYTICS MODEL FRAMEWORK

3.1 Data Sources for Construction Safety Analytics

Construction safety analytics models rely on large and heterogeneous datasets that capture operational, environmental, and behavioral factors influencing workplace hazards. Modern predictive safety systems collect information from project management platforms, incident databases, worker activity logs, equipment sensors, and environmental monitoring devices. These datasets enable safety analysts to identify patterns associated with hazardous activities such as equipment collisions, falls from height, and structural instability. Recent data-driven risk modeling frameworks demonstrate how multi-source data integration improves forecasting accuracy and enables proactive safety planning across complex operational systems (Agbosu et al., 2026; Adesiyan & Alaba, 2025; Kevin, 2026). Similarly, predictive monitoring models implemented in infrastructure systems show that integrating operational logs with real-time sensor streams significantly enhances anomaly detection and early hazard identification (Uduokhai et al., 2025; Taiwo, 2025).

Advances in artificial intelligence and data infrastructure have expanded the types of safety data available for analysis. Computer vision systems deployed on construction sites capture real-time worker movement, unsafe proximity to heavy machinery, and improper use of personal protective equipment. In parallel, wearable sensors collect biometric and motion data that can indicate fatigue, unsafe posture, or exposure to hazardous conditions. Studies on predictive analytics architectures highlight the importance of combining structured and unstructured data sources to generate accurate predictive signals for risk assessment (Akande et al., 2026; Animasaun et al., 2026; Uwabor et al., 2025). Furthermore, governance and decision analytics frameworks emphasize the role of integrated enterprise data platforms in transforming raw operational data into actionable insights that support strategic safety management decisions (Morah et al., 2022; Walawalkar et al., 2026).

3.2 Feature Engineering and Risk Indicators

Feature engineering plays a crucial role in predictive safety analytics because raw construction data must be transformed into meaningful indicators that capture risk dynamics. Key features used in safety prediction models include worker proximity to heavy equipment, time spent in hazardous zones, equipment vibration levels, environmental conditions, and historical incident frequency. Feature extraction methods convert these observations into structured variables that enable machine learning algorithms to detect patterns associated with unsafe behavior. Predictive analytics research emphasizes the importance of selecting relevant risk indicators to avoid noise in large operational datasets (Akhigbe et al., 2025; Okoruwa et al., 2025; Bello et al., 2025). Effective feature engineering also involves temporal aggregation techniques that capture trends in accident occurrence over time.

Advanced safety analytics models increasingly incorporate behavioral and contextual indicators to improve predictive performance. Computer vision and wearable technologies provide high-resolution activity data that can be transformed into motion patterns, posture classification metrics, and task-specific risk indicators. Studies on predictive monitoring systems demonstrate that integrating multiple behavioral features significantly enhances the accuracy of hazard prediction models (Ijiga et al., 2025; Idika et al., 2025; Anichukwueze et al., 2022). Moreover, risk analytics frameworks highlight the need for domain knowledge in selecting appropriate safety indicators, as contextual variables such as worker experience level, weather conditions, and project complexity often influence accident probabilities (Adesuyi et al., 2025; Essandoh et al., 2025; Isiekwu et al.,

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2025). These engineered variables form the foundation for predictive safety models capable of identifying high-risk construction activities before incidents occur.

3.3 Predictive Modeling Techniques for Safety Forecasting

Predictive modeling techniques form the analytical core of safety analytics systems used to detect high-risk construction activities. Machine learning algorithms such as random forests, gradient boosting, and neural networks are commonly applied to identify complex relationships between operational variables and accident probability. These models can analyze large volumes of construction data to forecast potential hazards before they occur, enabling proactive safety interventions. Research on predictive decision-support systems demonstrates that machine learning models outperform traditional statistical approaches when analyzing multidimensional operational datasets (Kevin & Oluwasanya, 2022; Lawal & Oduleye, 2025; Taiwo, 2024). Such techniques are particularly effective in identifying nonlinear relationships among safety variables that are difficult to detect through manual analysis.

More advanced approaches integrate ensemble learning and anomaly detection algorithms to improve prediction accuracy and model robustness. Predictive monitoring frameworks designed for infrastructure systems demonstrate that hybrid models combining statistical risk assessment with deep learning architectures provide superior hazard detection performance (Anioke et al., 2025; Hammed et al., 2026; Odejobi et al., 2025). Additionally, predictive analytics models increasingly incorporate explainable AI techniques to improve transparency and trust in safety predictions. Explainable models allow safety managers to understand which variables contribute most strongly to predicted risks, thereby supporting evidence-based decision making in safety planning (Akomolafe et al., 2025; Liadi, 2022; Walawalkar et al., 2025). These predictive modeling techniques collectively enable construction safety systems to transition from reactive incident analysis toward proactive risk forecasting.

3.4 System Architecture for Predictive Safety Monitoring

The architecture of predictive safety monitoring systems integrates multiple technological components that enable continuous hazard detection and decision support. A typical system architecture consists of four core layers: data acquisition, data processing, predictive analytics, and decision support. The data acquisition layer collects real-time information from sensors, surveillance cameras, wearable devices, and project management systems. This data is transmitted to centralized processing platforms where preprocessing algorithms clean and transform the data into structured formats suitable for predictive analysis. Research on integrated analytics platforms highlights the importance of scalable system architecture capable of processing high-volume operational data streams in real time (Ogbete et al., 2025; Aminu-Ibrahim et al., 2025).

The predictive analytics layer applies machine learning models to analyze incoming data and generate risk predictions related to hazardous construction activities. These predictions are then transmitted to the decision support layer, where safety managers receive alerts, dashboards, and recommended mitigation actions. Advanced architectures integrate blockchain logging systems and secure data management frameworks to ensure transparency and reliability in safety monitoring systems (Bello et al., 2025; Idika & Ijiga, 2025). In addition, digital coordination technologies such as Building Information Modeling and enterprise infrastructure monitoring systems improve situational awareness across construction sites. Studies on intelligent infrastructure systems emphasize that integrating predictive analytics with digital project management platforms significantly enhances safety governance and operational reliability (Ofori et al., 2025; Kuponiyi & Akomolafe, 2025; Wedraogo et al., 2025). These architectures support continuous monitoring and rapid intervention to prevent accidents in high-risk construction environments.

4. EMERGING TECHNOLOGIES SUPPORTING PREDICTIVE SAFETY ANALYTICS

4.1 Internet of Things (IoT) and Wearable Safety Sensors

The integration of Internet of Things (IoT) technologies and wearable safety sensors has significantly improved the ability to monitor construction site conditions and worker behaviors in real time. IoT-enabled systems typically involve interconnected devices such as smart helmets, location trackers, biometric sensors, and environmental monitoring units that continuously collect safety-related data across construction environments. These devices capture indicators such as worker motion patterns, proximity to hazardous zones, fatigue levels, and environmental parameters including temperature, vibration, and toxic gas exposure. The collected data streams are transmitted through wireless communication networks into centralized safety analytics platforms where predictive algorithms analyze emerging risk patterns (Kevin, 2026; Uwabor et al., 2025; Yeboah et al., 2025). Studies have demonstrated that sensor-based monitoring systems can significantly improve the early detection of unsafe work conditions and enable proactive risk mitigation strategies. For example, IoT-based monitoring systems have been successfully used to detect abnormal worker movement patterns and hazardous exposure events in industrial environments (Hammed et al., 2026; Ozobu et al., 2025). These capabilities support predictive safety analytics models by providing high-frequency operational data necessary for forecasting potential accident scenarios.

Recent research emphasizes the importance of integrating wearable sensor data with machine learning frameworks to improve predictive accuracy in safety monitoring systems. Data collected from smart wearables can be processed using anomaly detection algorithms that identify deviations from normal worker behavior patterns. Such techniques enable early detection of high-risk activities such as unsafe equipment handling or unauthorized access to restricted areas (Akande et al., 2026; Animasaun et al., 2026). In addition, governance and risk modeling frameworks provide analytical structures that support the integration of IoT safety data into predictive risk management systems (Agbosu et al., 2026; Morah et al., 2022). The growing adoption of wearable safety technology in construction projects therefore represents a critical component of predictive safety analytics models. By combining real-time sensor data with predictive algorithms, construction organizations can transform safety management from reactive incident reporting to proactive hazard detection and prevention.

4.2 Computer Vision and Site Surveillance Analytics

Computer vision technologies have emerged as powerful tools for automated monitoring of construction sites, enabling continuous visual analysis of worker activities, equipment operations, and environmental hazards. These systems use deep learning algorithms to analyze images and video streams captured by cameras installed across construction sites. Through object detection and activity recognition techniques, computer vision models can automatically identify unsafe behaviors such as failure to wear personal protective equipment (PPE), unsafe equipment operations,

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and unauthorized access to hazardous work zones (Adeniyi et al., 2025; Olatunde-Thorpe et al., 2022). The integration of surveillance analytics with predictive safety models allows safety managers to detect risk indicators before accidents occur. For example, behavioral analytics frameworks analyze visual activity data to identify patterns associated with high-risk construction operations (Okoruwa et al., 2025; Bello et al., 2025). These automated monitoring systems reduce reliance on manual safety inspections and enable continuous risk detection across large construction sites.

Recent advancements in artificial intelligence have further enhanced the predictive capabilities of computer vision safety systems. Deep neural networks and behavioral profiling techniques enable real-time classification of worker actions and equipment interactions, allowing predictive models to identify emerging accident scenarios. These systems can also incorporate anomaly detection methods that flag deviations from safe operational patterns (Odejobi et al., 2025; Balogun et al., 2025). Furthermore, advanced AI-driven monitoring frameworks provide decision-support tools that enable construction managers to prioritize safety interventions based on predictive risk scores (Essandoh et al., 2025; Adesiyan & Alaba, 2025). The integration of computer vision with predictive analytics therefore enhances construction safety management by providing automated surveillance capabilities and real-time risk assessment mechanisms as seen in Table 2. These technologies form an essential component of predictive safety analytics models designed to detect high-risk construction activities early and support proactive accident prevention strategies.

Table 2: Key Components and Functions of Computer Vision–Based Site Surveillance Analytics for Construction Safety

Component of Computer Vision System	Analytical Technique Used	Safety Monitoring Function	Practical Application in Construction Sites
PPE Detection and Worker Identification	Deep learning object detection models and image classification algorithms	Automatically identifies whether workers are wearing required personal protective equipment such as helmets, reflective vests, gloves, and safety boots	Cameras positioned at entry points and work zones continuously scan workers and generate alerts when required PPE is missing
Worker Activity Recognition	Action recognition models and behavioral pattern analysis using convolutional neural networks	Detects unsafe worker actions such as improper lifting posture, climbing without fall protection, or entering restricted areas	Real-time monitoring of scaffolding work or elevated platforms to detect fall-risk behaviors and trigger safety alerts
Equipment Operation Monitoring	Computer vision object tracking and motion analysis algorithms	Tracks heavy equipment movement and proximity to workers to identify unsafe equipment–worker interactions	Surveillance cameras near crane operations or excavation zones detect when workers enter unsafe proximity to moving machinery
Anomaly Detection and Risk Prediction	Deep neural networks and anomaly detection algorithms analyzing video streams	Identifies deviations from normal site operations that may indicate emerging safety hazards or abnormal activity patterns	AI systems flag unusual movement patterns, unsafe crowding near hazardous zones, or unexpected equipment movements to prompt early safety interventions

4.3 Digital Twin Applications for Construction Safety

Digital twin technology has emerged as a transformative innovation for improving safety monitoring and predictive risk management in construction environments. A digital twin represents a virtual replica of a physical construction site that integrates real-time operational data from sensors, monitoring systems, and project management platforms. By simulating the dynamic conditions of construction activities, digital twins enable predictive analysis of potential safety hazards before they occur in real-world operations (Uduokhai et al., 2025; Ogbuefi et al., 2025). Through continuous data synchronization, digital twin platforms allow safety managers to visualize worker movements, equipment interactions, and environmental risks across complex construction environments. Predictive algorithms embedded within these systems analyze historical incident data and real-time operational metrics to forecast accident probabilities. This approach enables the early identification of high-risk activities such as equipment collisions, structural instability, or hazardous environmental exposure.

The predictive capabilities of digital twin platforms are enhanced through the integration of advanced analytics models and artificial intelligence techniques. For example, machine learning models can analyze digital twin datasets to identify correlations between operational variables and accident occurrence patterns (Kevin et al., 2025; Taiwo, 2025). These predictive insights enable construction managers to implement targeted safety interventions before accidents occur. Research also highlights the importance of integrating digital twin platforms with data governance frameworks to ensure reliability and transparency in predictive risk analytics systems (Akhigbe et al., 2025; Adesuyi et al., 2025). Furthermore, digital twin simulations enable scenario-based risk assessments, allowing project teams to evaluate the safety implications of alternative construction methods before implementation (Ofori et al., 2025; Kuponiyi & Akomolafe, 2025). Consequently, digital twin technology provides an advanced analytical environment that supports predictive safety analytics models and enhances proactive risk management in complex construction projects.

4.4 Integration with Building Information Modeling (BIM)

Building Information Modeling (BIM) plays a crucial role in integrating predictive safety analytics with construction project planning and execution processes. BIM platforms provide a digital representation of construction infrastructure, including structural components, scheduling information, and project workflows. By linking predictive safety analytics models with BIM datasets, safety managers can identify potential

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hazards associated with specific construction tasks and work environments (Ogbete et al., 2025; Aminu-Ibrahim et al., 2025). BIM-based safety analytics systems enable the visualization of high-risk work zones and the simulation of potential accident scenarios before construction activities commence. This capability allows project teams to incorporate safety considerations into project planning and design stages. Furthermore, predictive analytics models can analyze BIM data to identify correlations between project scheduling conflicts, spatial constraints, and accident risks (Isiekwu et al., 2025; Sakyi et al., 2024).

The integration of BIM with predictive safety analytics also supports advanced decision-support systems for construction safety management. By combining BIM models with machine learning algorithms, predictive safety platforms can generate risk scores for different construction activities based on historical safety records and operational data (Anichukwueze et al., 2022; Idika et al., 2025). These predictive insights enable safety managers to implement targeted mitigation strategies such as scheduling adjustments, equipment reconfiguration, or worker training programs. In addition, BIM-based analytics systems can facilitate collaboration among project stakeholders by providing a shared digital environment for safety planning and risk assessment (Akomolafe et al., 2022; Liadi, 2022). The integration of BIM technology with predictive safety analytics therefore represents a critical advancement in construction safety management, enabling proactive identification of high-risk construction activities and improved accident prevention strategies.

5. MODEL EVALUATION AND IMPLEMENTATION CHALLENGES

5.1 Performance Metrics for Predictive Safety Models

Evaluating the effectiveness of predictive safety analytics models requires a robust set of performance metrics capable of measuring both predictive accuracy and operational usefulness within construction environments. Common quantitative indicators include precision, recall, F1-score, receiver operating characteristic (ROC) curves, and area under the curve (AUC), which collectively assess the reliability of hazard prediction models. These metrics enable researchers to determine whether predictive algorithms can accurately identify patterns associated with unsafe behaviors, hazardous equipment operation, or environmental risks before accidents occur. Data-driven risk models have been successfully applied in several sectors to forecast complex operational events, demonstrating that predictive analytics can detect subtle correlations between historical incident records and emerging operational conditions (Kevin, 2026; Hammed et al., 2026). Similar approaches can be adapted to construction environments by integrating sensor data, worker activity monitoring, and environmental indicators to quantify safety risk levels dynamically.

Beyond statistical accuracy, performance metrics must also evaluate practical deployment outcomes such as risk detection lead time, false alarm rates, and decision support efficiency. In safety-critical environments like construction, the ability of a model to provide early warning signals before hazardous conditions escalate is often more valuable than marginal improvements in classification accuracy. Governance-oriented analytical frameworks demonstrate that predictive models should be assessed not only on computational efficiency but also on their capacity to support real-time operational decision-making and risk mitigation strategies (Agbosu et al., 2026; Morah et al., 2022). Advanced analytics architectures further emphasize the importance of integrating predictive outputs into organizational dashboards and safety monitoring systems to improve situational awareness among project managers and site supervisors (Walawalkar et al., 2026). Consequently, evaluating predictive safety models requires a multidimensional framework combining algorithmic accuracy, operational relevance, and risk management effectiveness (Bello et al., 2025; Okoruwa et al., 2025; Essandoh et al., 2025; Wedraogo et al., 2025).

5.2 Data Quality and Integration Challenges

The reliability of predictive safety analytics models depends heavily on the quality, completeness, and consistency of construction data sources. Construction projects generate large volumes of heterogeneous information, including safety inspection reports, equipment sensor readings, environmental measurements, and workforce behavioral observations. However, inconsistencies in data collection methods, missing values, and fragmented reporting systems often reduce the effectiveness of predictive analytics models. Poor data governance practices can introduce bias or distortions that compromise model accuracy and lead to unreliable safety predictions. Studies on large-scale analytics systems emphasize that predictive models are only as reliable as the datasets used to train them, making robust data validation and preprocessing essential components of safety analytics frameworks (Adesiyan & Alaba, 2025; Akhigbe et al., 2025). Furthermore, integration challenges frequently arise when attempting to combine historical incident records with real-time sensor streams or digital project management platforms.

Another significant challenge involves integrating data across multiple technological systems deployed within construction projects. Construction sites increasingly utilize Building Information Modeling (BIM), wearable sensors, and IoT-based monitoring tools, each generating independent data streams that must be harmonized before predictive analysis can occur. Achieving interoperability between these systems requires standardized data architectures and advanced analytics pipelines capable of handling large-scale real-time datasets. Research on enterprise data integration highlights the importance of unified analytical frameworks that connect operational data, decision support systems, and risk monitoring dashboards into a single analytics ecosystem (Taiwo, 2025; Isiekwu et al., 2025). Without such integration, predictive safety models may suffer from fragmented insights and delayed risk detection. Consequently, addressing data quality and integration challenges requires strong data governance structures, standardized reporting protocols, and scalable analytics infrastructures capable of supporting predictive safety monitoring (Ogbete et al., 2025; Ofori et al., 2025; Akomolafe et al., 2025; Liadi, 2022).

5.3 Ethical, Privacy, and Workforce Acceptance Issues

While predictive safety analytics models offer significant potential for improving construction safety, their implementation raises important ethical and privacy concerns related to workforce monitoring and data collection. Many predictive safety systems rely on wearable devices, surveillance cameras, and location tracking technologies to monitor worker activities and identify unsafe behaviors. Although these technologies can significantly enhance hazard detection capabilities, they also raise concerns about employee privacy, autonomy, and data misuse. Research on algorithmic risk assessment frameworks demonstrates that transparent governance structures are essential for ensuring that predictive models operate within ethical boundaries and maintain worker trust (Akande et al., 2026; Anichukwueze et al., 2022). Ethical considerations must therefore

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guide the design of predictive safety systems to ensure that collected data is used solely for safety improvement rather than disciplinary or surveillance purposes.

Workforce acceptance is another critical factor influencing the success of predictive safety analytics systems. Construction workers may perceive advanced monitoring technologies as intrusive or punitive if implementation strategies fail to emphasize safety benefits and organizational transparency. Studies examining the relationship between artificial intelligence and workforce adaptation indicate that employees are more likely to adopt predictive analytics tools when organizations provide clear communication about the objectives, safeguards, and operational benefits of such technologies (Essandoh et al., 2025; Yusuff et al., 2025). Ethical governance mechanisms should therefore include data protection protocols, anonymization procedures, and participatory design processes that involve workers in safety system development. Establishing trust between workers and safety monitoring systems is essential to ensure consistent data collection and effective hazard detection. Consequently, integrating ethical governance frameworks, privacy protection strategies, and workforce engagement initiatives is necessary to ensure the responsible adoption of predictive safety analytics in construction environments (Kuponiyi, 2025; Anioke et al., 2022; Ogbete et al., 2025; Okonkwo et al., 2025).

5.4 Practical Deployment in Construction Projects

Deploying predictive safety analytics models in real construction projects requires careful integration with existing safety management processes, digital infrastructure, and operational workflows. Construction environments are highly dynamic, with changing work schedules, evolving site conditions, and diverse subcontractor teams operating simultaneously. As a result, predictive safety systems must be designed to operate within complex project ecosystems while delivering real-time risk insights to decision-makers. Research on predictive infrastructure monitoring demonstrates that integrating predictive models into operational dashboards can significantly improve hazard detection and maintenance planning by enabling proactive interventions before failures occur (Uduokhai et al., 2025; Yeboah et al., 2025). In construction safety contexts, similar predictive architectures can be used to detect patterns associated with high-risk activities such as crane operations, excavation work, and scaffolding assembly.

Successful deployment also requires aligning predictive analytics systems with broader digital construction platforms such as BIM, project scheduling tools, and site monitoring technologies. When integrated effectively, these systems enable automated safety alerts, risk visualization dashboards, and predictive hazard scoring models that assist safety officers in prioritizing mitigation measures. Studies on digital infrastructure management emphasize that predictive analytics platforms must support interoperability with existing information systems and provide intuitive visualization interfaces to ensure that safety insights are actionable for site managers (Ozobu et al., 2025; Okuh et al., 2025). Furthermore, pilot implementation programs are essential to validate predictive model performance in real operational environments before large-scale deployment occurs. Through gradual integration with digital construction ecosystems and continuous performance evaluation, predictive safety analytics models can significantly enhance proactive risk management and reduce accident rates in high-risk construction activities (Ajayi-Kaffi et al., 2025; Ijiga et al., 2022).

6. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

6.1 Summary of Key Insights from the Review

The review highlights the growing importance of predictive safety analytics as a transformative approach for identifying hazardous conditions in construction environments before accidents occur. Traditional safety management systems largely depend on reactive mechanisms such as incident reporting, compliance inspections, and post-accident investigations. These approaches provide valuable insights into past failures but offer limited capability for forecasting emerging risks in complex construction environments. The review demonstrates that predictive safety models built on historical accident data, environmental monitoring inputs, and worker behavioral indicators can significantly improve early detection of high-risk construction activities. Data-driven safety frameworks enable continuous monitoring of operational variables such as equipment utilization patterns, worker movement trajectories, and environmental exposure levels, thereby allowing safety managers to identify abnormal patterns associated with potential accidents.

Another key insight is the increasing role of integrated digital technologies in enabling predictive safety intelligence on construction sites. Systems combining Internet of Things sensors, computer vision monitoring platforms, and machine learning algorithms allow continuous safety risk evaluation across multiple operational layers. These technologies support automated detection of unsafe worker behaviors such as proximity violations around heavy machinery, improper scaffold usage, or unsafe lifting techniques. Predictive analytics also enables the development of dynamic risk scoring systems capable of evaluating the probability of accidents based on real-time site conditions. By integrating predictive models with construction project management systems, organizations can shift from reactive compliance-based safety management toward proactive hazard prevention frameworks that significantly reduce workplace accidents and improve operational efficiency.

6.2 Implications for Construction Safety Management

The findings of this review have significant implications for the evolution of construction safety management practices. Predictive safety analytics introduces a shift from static compliance frameworks toward intelligent risk monitoring systems capable of continuously evaluating safety conditions on construction sites. In practice, this transition enables construction managers to implement proactive safety interventions before hazardous situations escalate into accidents. For example, predictive models analyzing worker movement data collected from wearable sensors can detect fatigue-related behavior patterns such as reduced reaction times or irregular movement paths, which are often precursors to safety incidents. Early identification of such conditions allows project managers to implement corrective measures such as task rotation, temporary work suspension, or targeted safety briefings.

Another important implication involves the integration of predictive safety analytics with digital construction technologies such as Building Information Modeling platforms and digital twin simulations. When predictive risk models are embedded within digital project management environments, safety managers can simulate potential hazards associated with construction schedules, equipment allocation, and site logistics. For instance, a digital twin of a construction site can simulate crane operations, scaffold installations, and material transport flows to evaluate the

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probability of collisions or structural failures. These simulations allow project planners to optimize operational workflows and eliminate unsafe task sequences before work begins. The adoption of predictive safety analytics therefore enables construction organizations to move beyond reactive accident response systems and establish intelligent safety ecosystems that continuously learn from operational data and improve risk mitigation strategies.

6.3 Research Gaps in Predictive Safety Analytics

Despite significant progress in predictive safety analytics research, several critical knowledge gaps remain that limit the widespread implementation of these technologies in construction safety management. One major challenge involves the availability and quality of safety data required for training predictive models. Many construction organizations still rely on fragmented data sources such as manual safety reports, incident logs, and inspection records, which are often incomplete or inconsistent. This lack of standardized safety datasets restricts the development of robust predictive models capable of accurately identifying risk patterns across diverse construction environments. Furthermore, many existing predictive safety systems rely heavily on historical accident data, which may not capture emerging risks associated with new construction technologies, evolving equipment types, or changing workforce behaviors.

Another significant research gap concerns the interpretability and trustworthiness of predictive safety algorithms used in construction environments. Machine learning models often function as complex computational systems that generate risk predictions without clearly explaining the underlying reasoning behind their decisions. This lack of transparency can limit adoption among construction safety managers who require clear justification for safety recommendations before implementing operational interventions. Additionally, many predictive safety models focus primarily on technical variables such as equipment performance or environmental conditions while overlooking human behavioral factors that significantly influence accident occurrence. Addressing these research gaps requires the development of explainable predictive safety models capable of integrating human factors, operational context, and environmental conditions into comprehensive risk assessment frameworks.

6.4 Future Directions for Intelligent Construction Safety Systems

Future research in construction safety analytics is expected to focus on the development of intelligent safety ecosystems capable of autonomously monitoring construction environments and predicting hazards in real time. Advances in artificial intelligence, edge computing, and sensor technologies are enabling the deployment of distributed safety monitoring networks across construction sites. These systems can integrate data from wearable safety devices, smart helmets, location tracking systems, environmental sensors, and drone-based surveillance platforms to generate comprehensive safety intelligence. For example, computer vision algorithms deployed on site cameras can automatically detect unsafe behaviors such as workers entering restricted zones, operating machinery without protective equipment, or standing within hazardous proximity to moving equipment. When integrated with predictive analytics models, these systems can issue automated safety alerts before accidents occur.

Another promising direction involves the integration of predictive safety analytics with digital twin technologies capable of simulating construction environments in real time. Digital twins can replicate physical construction sites within virtual environments where predictive algorithms continuously evaluate potential safety risks based on project schedules, equipment movements, and environmental conditions. These simulations enable safety managers to evaluate different operational scenarios and identify hazardous task interactions before work activities commence. Additionally, advances in explainable artificial intelligence are expected to improve the transparency of predictive safety models by providing interpretable insights into how risk predictions are generated. The combination of predictive analytics, intelligent sensors, and digital simulation platforms will ultimately support the development of fully autonomous safety management systems capable of continuously learning from operational data and dynamically adapting safety strategies to evolving construction environments.

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