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# Artificial Intelligence in Construction Safety: A Decade of Progress, Challenges, and Future Implications

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The construction industry is regarded as one of the riskiest industries in the world, due to the high accident rates and severe socio-economic implications. Technology has progressed incredibly in the last decade, with Artificial Intelligence (AI) based methods that offer the potential to advance safety within the construction sector through advanced hazard detection, prediction, and prevention. While there has been an undeniable surge in academic literature investigating AI in construction safety over the last decade, there remains a gap between the research level of AI tools and their deployment to support practical safety implementation, and no surface synthesis of common themes, emerging trends, methodologies, and contexts. This scoping review reports on 42 peer-reviewed empirical studies investigating AI in construction safety published from 2013 to 2025, following the PRISMA protocol. Overall findings exhibit deep learning as the primary method, and vision-based systems as the most prominent data type. Research largely remains in the domain of personal protective equipment (PPE) detection and compliance monitoring, including near-miss prediction, real-time deployment, and multi-sensor fusion. Most studies are conducted in Asia, with less emphasis on the presence of studies in developing countries. This review identifies technology, thematic, and contextual patterns and provides an integrated reference point for researchers and practitioners. It is noticed that an AI safety framework needs to be contextual, regionally adaptable, and co-developed. Future directions should favour AI systems that are real-time, multi-modal, and scalable, including conducting more relevant lab research that can be used practically in the field. A multi-stakeholder, interdisciplinary effort will enable full utilization of the potential of AI for safety outcomes in different types of construction work.

*Keywords*: Artificial Intelligence, Construction Industry, Safety and Risk Management, Predictive Analytics

## 1. Introduction

Considerable global attention is focused on ensuring workplace safety in high-risk sectors like the construction industry (Mistikoglu et al., 2015; Son et al., 2024). Relying on numerous safety protocols and training initiatives, injuries, casualties, and property damage continue to occur at alarming rates (Erkal et al., 2024; Tixier et al., 2016). In recent years, artificial intelligence (AI) has fundamentally shifted the paradigm and can play a role in addressing historical safety challenges through proactive risk identification, real-time tracking, and predictive analytics (Kim et al., 2022; Ajayi et al., 2020). With the rapid growth of AI technologies, there are new channels for accident prevention using machines to observe and recognize hazardous behaviors and independently act upon visual stimuli (Park et al., 2022; Yang et al., 2022). Consequently, researchers and practitioners are finding AI-based systems to be more prevalent and useful for applications such as detecting personal protective equipment, identifying hazards, predicting near-miss incidents, and analyzing behavioral patterns on worksites (Delhi et al., 2020; Aria et al., 2014). Although more studies have reported positive applications of AI for occupational safety, little knowledge has been synthesized across fields, sectors, and geographical regions (Li & Wu, 2023; Alateeq et al., 2023). Reviews relevant to the work of the safety domain mostly describe either technical advances without artefacts or developments associated with safety outcomes, or they focus on specific applications (e.g., helmet detection or fatigue recognition) (Zhao et al., 2023; Jiao et al., 2025). Additionally, there are many different forms of data, algorithmic choices, and areas of implementation, making it difficult to draw broader conclusions or build common research pathways (Koc et al., 2023; Toğan et al., 2022).

However, though there have been scoping reviews on occupational health and safety, there has been no systematic scoping review that has mapped and classified the Application of AI for occupational safety, including the machine learning methods used, types of data used, safety outcomes, or geography in which the research occurred (Mohajeri et al., 2022; Hjemgård, 2024). Significant knowledge gaps have been exposed in this review process, such as understanding where the developed world is with AI deployment in the real world, utilization of longitudinal data, and how research has incorporated representation from developing countries (Demirkesen, 2024; Hjemgård, 2024). Initial screening of more recent publications provides an incentive to be optimistic about the growing number of deep learning-based models, particularly the latest models that are trained on images and video data captured using a static or wearable camera (Akinsemoyin et al., 2023; Sharifzada et al., 2025). Nonetheless, there are relatively few studies focusing on real-time applications and multi-sensor fusion approaches (Liu et al., 2024; Lung et al., 2025). In addition, while there is evidence of global contributions, the bulk of the research activity appears to be based in Asian countries (Kim et al., 2024; Yoo et al., 2024). The research also indicates that it is mostly visible in ecological and applied contexts, with limited understanding of regional safety issues or constraints to technology adoption in underrepresented situations (Shuang & Zhang, 2023; Demirkesen, 2024).

Therefore, this scoping review intends to provide a systematic and thematic overview of AI-based safety research in the construction industry, highlighting the following key factors:

- Identifying different machine learning methods and their applications in construction safety
- Investigating the types of data, ML tasks and methodological innovations and discussing the patterns, challenges, and future implications

The ultimate objective of this paper is to provide a systematic and evidence-based overview of AI-based safety research to inform future studies, notify practitioners, and provide evidence for policy intervention for smarter and safer workplaces.

## 2. Method

This scoping review was conducted using a systematic process, in accordance with PRISMA criteria, to provide a clear and comprehensive method of synthesising the existing literature. The methods included two basic steps: (i) Search strategy and eligibility criteria, (ii) screen and selection process.

### 2.1. *Search strategy and eligibility criteria*

A comprehensive search of the literature was conducted on 23rd July 2025 through two major multidisciplinary citation databases: ‘Scopus’ and ‘Web of Science’. These databases had been chosen for their broad coverage of peer-reviewed journals in the areas of engineering, construction management, safety, and computer science. The search string, which was constructed in an iterative process, attempted to identify studies at the intersection of construction safety, machine learning applications, and acute occupational incident analysis. The boolean (AND, OR), proximity operators (W/3), and truncation operators (*) were used to optimize the recall and precision. The search string is depicted below:

*(TITLE-ABS-KEY( construction W/3 (safety OR accident* OR incident* OR injury OR "near miss*" OR hazard*) ) OR TITLE-ABS-KEY( "construction worker*" )) AND (TITLE-ABS-KEY( "machine learning" OR "deep learning" OR "neural network*" OR "convolutional neural network*" OR "recurrent neural network*" OR "transformer*" OR "LSTM" OR "GRU" OR "random forest" OR "gradient boosting" OR "support vector machine*" OR "computer vision" OR "YOLO" )) AND (TITLE-ABS-KEY( accident* OR incident* OR injury OR "near miss*" OR "unsafe behavior" OR "PPE compliance" OR "hazard detection" OR "fall detection" )) AND NOT (TITLE-ABS-KEY( maintenance OR durability OR seismic OR earthquake OR bridge OR tunnel OR pavement OR railway OR traffic OR evacuation OR "structural health" OR "asset management" OR "chronic exposure" OR musculoskeletal OR ergonomics OR silicosis OR vibration )) AND ( PUBYEAR > 2012 ) AND ( LANGUAGE = English )*

### 2.2 *Screening and Selection Process*

To maintain methodological rigor and basic consistency, the research used pre-defined inclusion and exclusion criteria. All eligible studies referred to as empirical studies developed machine learning (ML) algorithms to address issues related to construction safety, specifically acute occupational safety events like accidents, near misses, unsafe behaviors, or hazard detection. Only studies that focused on real field, collection, or historical data of the construction industry in peer-reviewed journals and in English from 2013 to 2025 were included. Excluded studies were reviews, theories, abstracts from conferences, or based only on artificial, simulated, or laboratory-made datasets; studies with diversified industry analyses, with no construction-specific results; and studies examining chronic exposure, ergonomic hazards, or long-term health effects. This selective approach made it possible for the review to aggregate high-quality, construction-specific evidence and reflect practical implementation of AI-enabled safety interventions, while excluding studies without empirical basis or construction relevance.

First, the retrieved records from the databases were exported to an Excel-based review management sheet, and duplicates were excluded before screening. The selection consisted of two stages: (1) title and abstract screening, in which each study is screened based on its relevance to machine learning (ML) and deep learning (DL) applications on construction safety, with unrelated studies being excluded, and (2) full-text Screening, where remaining articles are screened in full-text based on predefined inclusion and exclusion criteria. Any ambiguity in terms of eligibility was resolved by repeated cross-reference of the full text. The preliminary search retrieved 200 records. After reviewing titles and abstracts, 46 articles were retrieved for complete review. Of them, 4 were omitted due to reasons such as being based on synthetic data, cross-sector (rather than construction-specific) focus, or lack of ML techniques, which led to a final 42 articles as our dataset for analysis. A structured data extraction table was used to facilitate uniform charting of important details from each study. For each included article, the following components were extracted: bibliographic (DOI, year and publication) information, methodological (types of specific ML algorithms used), data information (type of dataset, that is accident logs, images or videos, textual narratives, or sensor readings), safety focus (e.g., PPE compliance detection, hazard identification, accident severity prediction, fall risk monitoring) and geographic (country or region of dataset source). This compiled database is the basis of the thematic and methodological synthesis provided in subsequent sections. The process for screening and selection of studies is reported in a PRISMA Flow Diagram (Fig. 1).

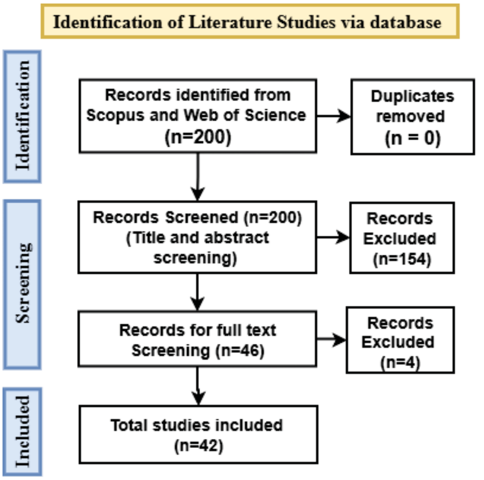

Fig 1. PRISMA Flowchart (Moher et al., 2009)

## 3. Bibliometric and Temporal Distribution

### 3.1 Early Foundations of Machine Learning Framework (2014–2017)

Between the years 2014–17, mostly foundational ML applications in construction safety took place that focused on accident narratives and tabular data. Tixier et al. (2016a; 2016b) as well as Goh & Ubeynarayana (2017) employed NLP and supervised ML to categorize injury causes collected from OSHA logs. However, support vector machine (SVM) and decision trees (DT) were used to predict the risk, but such methods are constrained by small and skewed datasets (Lee et al., 2020; Mistikoglu et al., 2015). The results demonstrated ML's advantages over manual approaches in incident classification and identified persistent problems of data imbalance and heterogeneity related to construction safety analytics.

### 3.2 Expansion into deep learning and vision-based safety (2018–2020)

Construction safety research saw the emergence of deep learning and vision-based analytics between 2018 and 2020. Kumar et al. (2024) combined CNNs and LSTMs to detect unsafe behavior in video streams in real time. However, mixed methods combining deep learning and neural networks improved narrative classification (Zhang et al., 2019; Zhang et al., 2020). Moreover, Lee et al. (2020) presented tools such as ensemble learning with visualizations. Furthermore, SMOTE has later been the benchmark for dealing with rare-event prediction (Koc et al., 2023). On the other hand, Delhi et al. (2020) conducted vision-based studies, and other researchers have employed YOLO and Faster R-CNN to enforce PPE compliance using images and footage (Akinsemoyin et al., 2023; Alateeq et al., 2023). This period witnessed a shift to multimodal deep learning and near real-time safety monitoring.

### 3.3 Towards sophistication, multi-tasking, and cross-modality (2021–2022)

From 2021–2022, exploration was focused on advanced ML workflows, AutoML, and multimodal data blending. For instance, Koc et al. (2023) and Toğan et al. (2022) enhanced accident predictions based on resampling and AutoML pipelines. Vision systems, such as Safety-MobileNet and optimized YOLO and Faster R-CNN, enabled real-time and explainable safety monitoring (Park et al., 2022). Site images, structured data, and IoT streams are increasingly being included in work, but full multimodal fusion is still limited. Interpretability in explainable AI methodologies such as SHAP and feature importance (Yoo et al., 2024; Park et al., 2022) emerged and increasingly manifested as interpretable, decision-supportive safety analytics.

### 3.4 Integrative, real-time, and next-generation Approaches (2023–2025)

From 2023 until 2025, researchers simultaneously made advancements toward more vibrant and multimodal safety systems. Studies' horizons of research also transitioned from forecasting to causal analyses (Shuang & Zhang, 2023), early warning systems (Zhao et al., 2023), and integrated cross-methodologies (unsupervised learning, association rule mining) (Mohajeri et al., 2022). Large databases established sufficient stability across sites (Yoo et al., 2024; Hjemgård, 2024). Moreover, real-world implementations in Norway, Turkey, and Korea showed successful UAV-assisted YOLOv8, CNN, and DNN PPE and behavior detection systems (Kim et al., 2024; Yoo et al., 2024; Akinsemoyin et al., 2023; Jiao et al., 2025; Demirkesen, 2024). At the same time, emerging testbeds adopted IMUs and other wearable sensing systems for the discovery of near-miss predictions (Hjemgård, 2024; Aria et al., 2014). Additional innovations included attention-based fusion networks, hybrid GRU-LSTM, and closed-loop IoT, vision, and interpretable AI systems (Zhao et al., 2023; Lung et al., 2025).

## 4. Findings

### 4.1 Types of Data and Incidents Addressed

The data modalities used in the studies reviewed are varied when conducting construction safety analysis. Structured datasets are mostly based on national and institutional report systems and continue to dominate severity and risk prediction with serious injury and fatality (SIF) exposure, categories of accidents, and time to recovery as possible predictors (Erkal et al., 2024; Kim et al., 2024; Yoo et al., 2024; Koc et al., 2023; Son et al., 2024; Demirkesen, 2024). Descriptive reports, which are being processed more and more by natural language processing (NLP) and deep learning, provide the ability to classify the nature of incidents, infer their causes, and extract leading indicators that do not have any structured representation (Tixier et al., 2016b; Bugalia et al., 2022; Zhang et al., 2019; Zhang et al., 2020; Li & Wu, 2023). Visual data from CCTV, UAV imagery, and wearables are widely leveraged in unsafe act detection, PPE compliance, and hazardous behavior monitoring, with well-performing CNN, YOLO, and Faster R-CNN in the field (Delhi et al., 2020; Park et al., 2022; Akinsemoyin et al., 2023; Zhao et al., 2019; Zhao et al., 2023; Jiao et al., 2025; Kumar et al., 2024; Alateeq et al., 2023). Nowadays, IoT and physiological sensors (IMUs, EEG, eye tracking) are utilized in real-time fall detection and risk state monitoring (Hjemgård, 2024; Aria et al., 2014).

### 4.2 ML tasks and analytical approaches

There is continued attention to accident and severity prediction by means of ensemble models (Random Forest, XGBoost), DNNs, and AutoML frameworks (Erkal et al., 2024; Yoo et al., 2024; Koc et al., 2023; Kim et al., 2022; Toğan et al., 2022; Toptancı et al., 2023). Incident type and cause mining takes advantage of multi-class and hierarchical classification, which may be further complemented by feature selection (Kim et al., 2024; Yoo et al., 2024; Shuang & Zhang, 2023; Zhang et al., 2019; Zhang et al., 2020). Vision-based monitoring is the prevalent detection method of hazards, empirically verifying PPE compliance and unsafe acts (Park et al., 2022; Akinsemoyin et al., 2023; Zhao et al., 2023; Kumar et al., 2024; Alateeq et al., 2023). Descriptive and diagnostic techniques such as clustering, association rules, and visualization tools are employed to identify patterns in temporal databases that may contain hidden causes (Lee et al., 2020; Mohajeri et al., 2022).

### 4.3 Methodological innovations

Significant developments are observed in terms of class imbalance treatment with SMOTE, sampling, and cost-sensitive learning, model explainability with SHAP, permutation importance, and saliency mapping, and cross-site field validation to guarantee general rightness (Erkal et al., 2024; Yoo et al., 2024; Koc et al., 2023; Park et al., 2022; Akinsemoyin et al., 2023). Vision and sensor-directed systems are more and more targeted at real-time site-based warning, to allow proactive risk reduction (Park et al., 2022; Akinsemoyin et al., 2023; Zhao et al., 2023; Lung et al., 2025).

## 5. Discussion

### 5.1 Emerging trends in ML and DL

In the previous ten years, the technologies of machine learning (ML) and deep learning (DL) have advanced in construction safety applications (Tixier et al., 2016a; Tixier et al., 2016b; Zhang et al., 2019; Goh & Ubeynarayana, 2017; Mistikoglu et al., 2015; Hjemgård, 2024). Early studies investigated safety data reporting that was tabular and textual in nature and drawn from institutional datasets (e.g., KOSHA, OSHA) and standard ML algorithms were emplyed (Tixier et al., 2016a; Tixier et al., 2016b; Zhang et al., 2019; Goh & Ubeynarayana, 2017; Toptancı et al., 2023; Mistikoglu et al., 2015). Most recent studies appear to emphasize using multi-modal methods which combine structured data and objects, images, sensors, and physiological models to improve analytics for construction safety (Ajayi et al., 2020; Park et al., 2022; Liu et al., 2024; Akinsemoyin et al., 2023; Lung et al., 2025; Sharifzada et al., 2025; Aria et al., 2014). Systems based on computer vision and deep convolutional neural networks (CNNs) are contributing to real-time visualization, and monitoring and hazard detection (Delhi et al., 2020; Park et al., 2022; Liu et al., 2024; Akinsemoyin et al., 2023; Zhao et al., 2019; Zhao et al., 2023; Wójcik et al., 2023; Jiao et al., 2025; Yang et al., 2022; Sharifzada et al., 2025; Kumar et al., 2024; Dzeng et al., 2024).

### 5.2 Methodological shifts: from feature engineering to end-to-end learning

The initial models reviewed manually engineered features that greatly impacted their scalability and adaptability (Tixier et al., 2016a; Tixier et al., 2016b; Zhang et al., 2019; Goh & Ubeynarayana, 2017; Mistikoglu et al., 2015). The transition to end-to-end learning architectures, which learn to automatically extract features from raw inputs and minimize preprocessing efforts, has made scalable and more flexible models (Kim et al., 2022; Ajayi et al., 2020; Zhang et al., 2019; Zhang et al., 2020; Park et al., 2022; Liu et al., 2024; Zhao et al., 2019; Li & Wu, 2023; Yang et al., 2022). However, model performance and explainability may remain important to comply with regulations or can offer practitioners trust in their use of AI models (Toğan et al., 2022; Shuang & Zhang, 2023; Ayhan & Tokdemir, 2020; Mohajeri et al., 2022; Mohammadian et al., 2022).

### 5.3 From retrospective analysis to predictive and prescriptive systems

The field has moved from retrospective incident analysis to predictive modeling and prescriptive safety solutions (Tixier et al., 2016a; Tixier et al., 2016b; Zhang et al., 2019; Goh & Ubeynarayana, 2017; Toptancı et al., 2023; Mistikoglu et al., 2015; Hjemgård, 2024). Finally, frameworks created using RNNs and TCNs are increasingly being applied to time-series sensor data to forecast hazardous events, allowing for preventive steps to be made before the occurrence of the unsafe event (Ajayi et al., 2020; Park et al., 2022; Zhao et al., 2019; Lung et al., 2025; Sharifzada et al., 2025; Aria et al., 2014; Dzeng et al., 2024).

### 5.4 Addressing class imbalance in rare events

Rare safety occurrences have the potential to create class imbalance issues (Koc et al., 2023; Toğan et al., 2022; Shuang & Zhang, 2023; Mohammadian et al., 2022; Bilim & Çelik, 2023; Demirkesen, 2024). Early studies used standard forms of resampling for the data, while more recent studies have used cost-sensitive learning, SMOTE, and GAN-based data augmentation to improve the sensitivity of detection, all while minimizing the rate of false-positive results (Koc et al., 2023; Toğan et al., 2022; Shuang & Zhang, 2023; Mohammadian et al., 2022; Bilim & Çelik, 2023; Toptancı et al., 2023)

### 5.5 Generalizability and practical deployment

Field testing requires sound validation and compact models (Toğan et al., 2022; Ajayi et al., 2020; Liu et al., 2024; Akinsemoyin et al., 2023; Lung et al., 2025; Sharifzada et al., 2025). There are methodologies such as leave-one-project-out cross-validation (LOPO-CV) that evaluate generalizability across different sites (Erkal et al., 2024; Koc et al., 2023; Toğan et al., 2022; Hjemgård, 2024). While using AutoML and simpler architectures allow real-time and in-field use, explainability remains crucial for field use (Toğan et al., 2022; Ayhan & Tokdemir, 2020; Ajayi et al., 2020; Mohajeri et al., 2022; Mohammadian et al., 2022).

### 5.7 Safety data paradox

While enhanced safety processes result in fewer occurrences of accidents, effective ML models rely on large amounts of incident data. The safety data paradox identifies this tension between achieving zero accident incidents and having viable data for training models (Fig. 2). Most incidents provided for modelling are limited, biased, or local and so, researchers have employed resampling, synthetic data augmentation, or cost-sensitive methods to deal with biases in training data (Toğan et al., 2022; Hjemgård, 2024). While the construction industry is typically moving toward fewer accidents through improved safety (e.g., enactment of safety regulations), the reduction in the generation of real-world data presents a significant hindrance to progressing AI-based approaches to improve safety processes in construction.

Fig. 2 Safety-Data paradox in construction

### 5.7 Overall challenges

The ML technology in construction safety specifically involves various complex issues that are tightly connected. Primarily, data quality is a key concern, since biased and poor datasets will limit model generalization, whereas incomplete or unrepresentative information can result in unsafe predictions (Tixier et al., 2016a; Lee et al., 2020; Koc et al., 2023; Hjemgård, 2024). Moreover, integration problems are faced by data engineers where they struggle to integrate structured and unstructured data sources, as well as video footage, written safety reports, and sensor information. These data may be incompatible or incomplete; that is why significant up-front preprocessing is frequently required (Zhang et al., 2019; Bugalia et al., 2022; Park et al., 2022; Liu et al., 2024; Sharifzada et al., 2025). Additionally, model performance issues such as overfitting and underfitting are a particular problem, as sometimes it may be hard to define when trained machine learning models perform poorly in new site conditions or other dynamic contexts, especially related to limited or imbalanced data (Mistikoglu et al., 2015; Toğan et al., 2022; Shuang & Zhang, 2023; Mohammadian et al., 2022; Bilim & Çelik, 2023). Lastly, operational issues (e.g., high cost, lack of time, stale data) hinder the effective use of AI-powered solutions at various levels in the industry, particularly for real-time deployment and scalability (Akinsemoyin et al., 2023; Erkal et al., 2024; Lung et al., 2025; Hjemgård, 2024). Therefore, these interacting issues must be addressed holistically so that meaningful AI solutions can be developed for site safety in construction.

## 6. Conclusion

This review has highlighted a significant transformation regarding machine learning (ML) and deep learning (DL) applications in construction safety, specifically a move from retrospective statistical analyses to active, real-time, and contextualized decision-support systems. Multi-modal data sets and architectures will allow for different ways to identify hazards, predict risks, and manage safety in a rapidly changing environment in construction. From a practical perspective, AI-enabled safety tools can enable more proactive hazard identification, streamline processes in inspections, and support real-time decisions to continue to mitigate accidents and enable more efficient operations. Despite this promise, there are ongoing barriers to large-scale deployment, including regular data management, data integration, operational procedures, and professional uncertainty. Realizing the promise of ML for safety will require even more collaboration between academia and industry; for example, creating benchmarks for the development of ML systems, sharing of data, and creating usable models that are fair, accountable, and robust. From a theoretical perspective, the results of this scoping review emphasize the importance of moving beyond static, siloed models to an embrace of adaptive, explainable, and ethically aligned AI systems; these matters relate to broader discussions about the use of AI in high-stakes domains that emphasize the capacity for trust and transparency rather than technical performance.

Hence, future research must focus on data collection efforts regionally, fairness-aware learning algorithms, and evaluation protocols that are cross-domain. In addition, future research must also prioritize multi-modal fusion, IoT, and integrating human-centered safety systems, to ensure the advancement in a socially aware and practically responsive way.

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