AJAIR

AUSTRALIAN JOURNAL OF ARTIFICIAL INTELLIGENCE REVIEW
ISSN 2982-3323 | DOI prefix 10.67065
aaireview.org

REVIEW ARTICLE

Machine Learning-Based Worker-Safety Prediction in Construction Project Environments: A Systematic Literature Review and Risk-Control Framework

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ARTICLE INFORMATION

Published: August 2026
Volume/Issue: Vol. 2, No. 1

KEYWORDS

machine learning; construction safety; worker safety; accident prediction; computer vision; systematic literature review; risk-control framework

ABSTRACT

Construction safety has remained a major project risk because workers perform their activities in dynamic, temporary and equipment-intensive surroundings where the nature of hazards may change within a very short time. This paper reviews machine-learning-based worker-safety prediction in construction project environments and develops the reviewed findings into a practical risk-control framework. Using the verified coded Excel dataset as the authoritative evidence source, a PRISMA-informed systematic literature review was conducted. The final synthesis included 79 primary empirical or technical studies published during 2016–2026, while 10 background reviews and seven excluded or reclassified records remained outside the primary evidence base. The selected studies were coded according to bibliographic characteristics, AI/ML technique, specific algorithm, data source, modality, dataset, prediction or detection target, safety domain, outcome, availability of performance metrics, explainability method, major findings, safety implications, risk-control relevance and verification notes. The mapping findings show a clear concentration on computer vision and deep learning, particularly for PPE detection, monitoring of safety compliance, site-hazard detection, fall-related risk and worker–equipment interaction. However, traditional machine learning continues to be important for structured accident, injury and safety-indicator datasets. NLP, LLMs, wearable sensors, IoT-based analytics and multimodal approaches are also emerging for accident narratives, safety reports, physiological risk and contextual safety reasoning. The major limitations are related to data quality, class imbalance, small or customised datasets, weak cross-site validation, interpretability, privacy, workflow integration and incomplete extraction of full-text model-performance results. Since 73 included studies still need manual extraction of full-text metrics, this study is positioned as systematic mapping, thematic synthesis and framework development rather than a statistical meta-analysis. Therefore, the main contribution is a worker-safety prediction and risk-control framework that establishes a relationship among data acquisition, preprocessing, modelling, explainability, managerial decision-making, intervention and continuous learning.

1. Introduction

Construction projects represent a hazardous and continuously changing environment where workers, temporary works, mobile equipment, materials, subcontractors and weather conditions interact within spatial boundaries that change over time. Therefore, worker exposure does not arise from one isolated cause; rather, it develops from immediate task conditions together with the wider arrangements of a project. Accidents, injuries, near misses and unsafe activities may occur when production pressure, site layout, work at height, poor visibility, incomplete use of protective equipment or hazardous proximity between workers and equipment exist at the same time. Tixier et al. (2016a) considered construction injuries as patterns that could be predicted by using historical information, whereas Poh et al. (2018) extended this thinking towards safety leading indicators at construction sites. This development is significant because present construction safety management increasingly needs methods that can identify probable risk while work is being planned or is still under performance.

Traditional safety management has contributed to improved construction practice through regulations, training, inspection procedures, toolbox meetings, job-hazard analysis and accident investigation. However, these mechanisms remain partly reactive since many control activities begin after a violation, near miss or injury has already taken place. Such systems also depend strongly on manual observation and the subjective judgement of supervisors who may be required to control large, fragmented and rapidly changing work areas. Tixier et al. (2016b) showed that unstructured injury reports contain important safety precursors and outcomes, while Goh and Ubeynarayana (2017) similarly demonstrated the usefulness of classifying construction accident narratives. From these findings, it can be said that valuable safety knowledge often remains within records that are reviewed manually or only after an event. A fully retrospective approach is therefore insufficient for proactive risk control in project environments where conditions differ according to task, time and location.

The increasing availability of digital construction data has encouraged the movement towards predictive, automated and continuously updated safety-management systems. Machine learning can be applied to classify accident outcomes, estimate injury or severity risk, recognise repeated accident causes and determine leading indicators from structured as well as text-based records. For example, Cheng et al. (2020) applied hybrid supervised learning for the classification of accident narratives, while Nath et al. (2020) used deep learning for real-time PPE monitoring based on site images. Moreover, NLP and text-mining methods obtain patterns from safety narratives and regulatory documents, while wearable sensors and IoT devices generate time-series information concerning posture, fatigue, physiological stress and hazardous work-at-height activities. Thus, the studies reviewed in this paper address different dimensions of the safety-control problem instead of concentrating on one algorithmic task.

For the purpose of this review, worker-safety prediction has been defined broadly to cover accident and injury prediction, injury-severity modelling, hazard identification, PPE-compliance monitoring, unsafe-behaviour detection, fall-risk and work-at-height detection, near-miss identification, worker–equipment proximity monitoring, physiological-risk detection and site-risk assessment. This wider definition reflects how safety has been operationalised across the coded studies, as some papers investigate events already available in accident databases, including fatality, accident category and severity of workday loss, whereas other papers use images or video to identify safety-critical conditions before an injury happens. Koc and Gurgun (2022) provide an example of structured severity modelling, while W. Fang et al. (2018) demonstrate visual recognition for monitoring the use of safety harnesses. Therefore, this study examines the relationship among the model, its data and the resulting safety decision instead of considering predictive accuracy as the only important outcome.

The existing reviews generally discuss artificial intelligence in construction safety as a broad research field in which worker safety is combined with robotics, BIM, structural monitoring, productivity, general site management or the wider process of digital transformation. Although these reviews are useful for understanding the technological landscape, they do not sufficiently separate machine-learning-based worker-safety prediction from other construction AI applications. A more focused synthesis is required because worker-safety prediction contains specific considerations relating to human exposure, privacy, ethical monitoring, interpretability, alert fatigue, field validation and the conversion of model output into a practical safety control. Moreover, the literature has expanded rapidly since 2020, with recent studies introducing LLMs, vision-language models, few-shot learning, graph-based approaches, wearable-sensor analytics and integrated monitoring systems. From the above aspects, a domain-focused review can determine the present achievements, identify what remains experimental and explain the requirements for moving from technical prototypes towards field-ready safety support.

The objective of this paper is to perform a PRISMA-informed systematic literature review and thematic classification of machine-learning-based worker-safety prediction in construction project environments and, based on the findings, develop a worker-safety prediction and risk-control framework. Four research questions guide the study, where RQ1 asks: What machine learning, deep learning, computer vision, NLP, sensor-based and related AI techniques are used for worker-safety prediction and monitoring in construction project environments? RQ2 asks: How are model types, data sources, data modalities and prediction or detection targets aligned in the reviewed studies? RQ3 asks: What methodological, technical, ethical and implementation challenges limit deployment in construction safety management? Finally, RQ4 asks: How can the reviewed evidence be translated into a practical worker-safety prediction and risk-control framework? These research questions provide the structure for the method, findings and discussion presented in the following sections.

2. Materials and Methods

2.1. Data Sources

This review was prepared from the verified coded Excel workbook instead of using a new live database export. The workbook contained the README sheet, original search log, verification log, master verified records, final included coded studies, excluded or reclassified records, background reviews, verification issues, updated deduplication log, PRISMA counts, results-summary tables and the updated coding framework. According to the README, the final evidence consists of 79 included primary studies, 10 background review papers and seven records that were excluded or reclassified. The README further records that Scopus, Web of Science and Google Scholar were not accessed directly in Version 1 or Phase 2, and therefore the manuscript does not claim a direct search of these databases. The accessible evidence base was developed from publisher pages, DOI pages, index and reference metadata, together with official journal or conference pages where these were available.

The workbook recorded ScienceDirect and Elsevier pages, DOI metadata, ASCE Library, MDPI article pages, Emerald, Taylor & Francis, Wiley and IET pages, IEEE/DOI metadata, PubMed and DOI metadata, Frontiers, PeerJ, ITcon, Oxford Academic, institutional metadata and official journal pages as verification sources. Crossref was also identified in the deduplication notes for at least one record that had been consolidated, whereas publisher or reference metadata supported verification when full-text access was unavailable. Since these materials were applied for accessible-source verification and were not obtained from one database export, the study is described as a PRISMA-informed systematic mapping based on a verified dataset. This methodological distinction is important because it avoids an exaggerated claim regarding database coverage, while the screening, coding and synthesis activities remain transparent.

2.2. Search Strategy

The original search strategy combined construction-safety terminology with machine learning, artificial intelligence and terms relating to particular applications. The recorded search strings included “machine learning” AND “construction safety”, “machine learning” AND “construction worker safety”, “artificial intelligence” AND “construction safety”, “deep learning” AND “construction safety”, “computer vision” AND “construction safety”, “construction accident prediction” AND “machine learning”, “construction injury prediction” AND “machine learning”, “construction hazard detection” AND “deep learning”, and “PPE detection” AND construction AND “computer vision”. Further search strings considered unsafe behaviour, fall risk, near miss, safety-risk prediction, NLP, text mining, wearable sensors, IoT, explainable AI, SHAP and predictive analytics. Thus, the search process was intended to identify studies of structured prediction and real-time detection across different worker-safety applications.

The search and verification activities were completed through an iterative process in which earlier records were retained, deduplicated or reclassified following Phase 2 checking. At the same time, newer records were transferred from the needs-verification category when dependable publisher or DOI metadata justified their inclusion. A record was not retained simply for applying AI within construction, since it was required to address worker safety, prediction of accident or injury, PPE or safety compliance, hazard detection, unsafe behaviour, near miss, fall risk, physiological risk, site-risk assessment or another related safety-control outcome. Overlap among searches was expected because deep learning, computer vision, NLP and safety-prediction terms often produce the same papers. Therefore, duplicate-source results were resolved using the updated deduplication log before the final coding was performed.

2.3. Selection Criteria

The selection process screened the verified master records according to the scope of the review and its coding definitions. First, each record was assessed for bibliographic plausibility, peer-reviewed or technical status, relevance to construction-worker safety and the application of machine learning, deep learning, computer vision, NLP, LLMs, wearable sensors, IoT, multimodal AI or predictive modelling. Review papers were not treated as primary empirical or technical evidence; when relevant, they were transferred to the background-review sheet. Records were excluded or reclassified where construction-worker safety relevance was insufficient, the application concerned a non-safety area of construction AI or duplication remained unresolved. Table 1 presents the inclusion and exclusion criteria that produced the final group of primary studies.

Table 1.

Inclusion and exclusion criteria for the review.

Criterion type	Operational rule used in coding
Inclusion criteria	Publications from 2016 to 2026; English-language peer-reviewed empirical or technical journal/conference papers; construction worker-safety relevance; use of ML, DL, CV, NLP, LLM, wearable-sensor analytics, IoT-based analytics, multimodal AI or predictive modelling; focus on accident prediction, injury prediction, PPE detection, unsafe behaviour, hazard detection, fall risk, near miss, safety compliance or site risk assessment.
Exclusion criteria	General construction AI papers without a worker-safety focus; cost, schedule, productivity, BIM-only or sustainability papers without safety relevance; non-peer-reviewed items; editorials, opinion pieces, theses, reports and non-academic sources; review papers from the primary-study set; non-English publications; duplicate, unverified or reclassified records.
Treatment of review papers	Review and background papers were not included in the 79 primary studies. They were retained separately in the Background_Reviews sheet when useful for contextual framing.
Treatment of uncertain fields	Fields marked “Not available”, “Not reported”, “Reported in paper but not accessible from available source” or “Needs manual full-text check” were preserved rather than inferred.

After applying the selection criteria, the final evidence base contained 79 primary empirical or technical studies. In addition, the revised PRISMA count sheet identified 10 background review papers and seven excluded or reclassified records, while the pathway used for study selection is presented in Figure 1. The flow diagram makes a deliberate distinction among accessible-source identification, Phase 2 re-screening, storage of background reviews and final inclusion of primary studies. This distinction was necessary because the workbook was prepared through accessible publisher, DOI and index sources rather than a direct export from Scopus, Web of Science or Google Scholar.

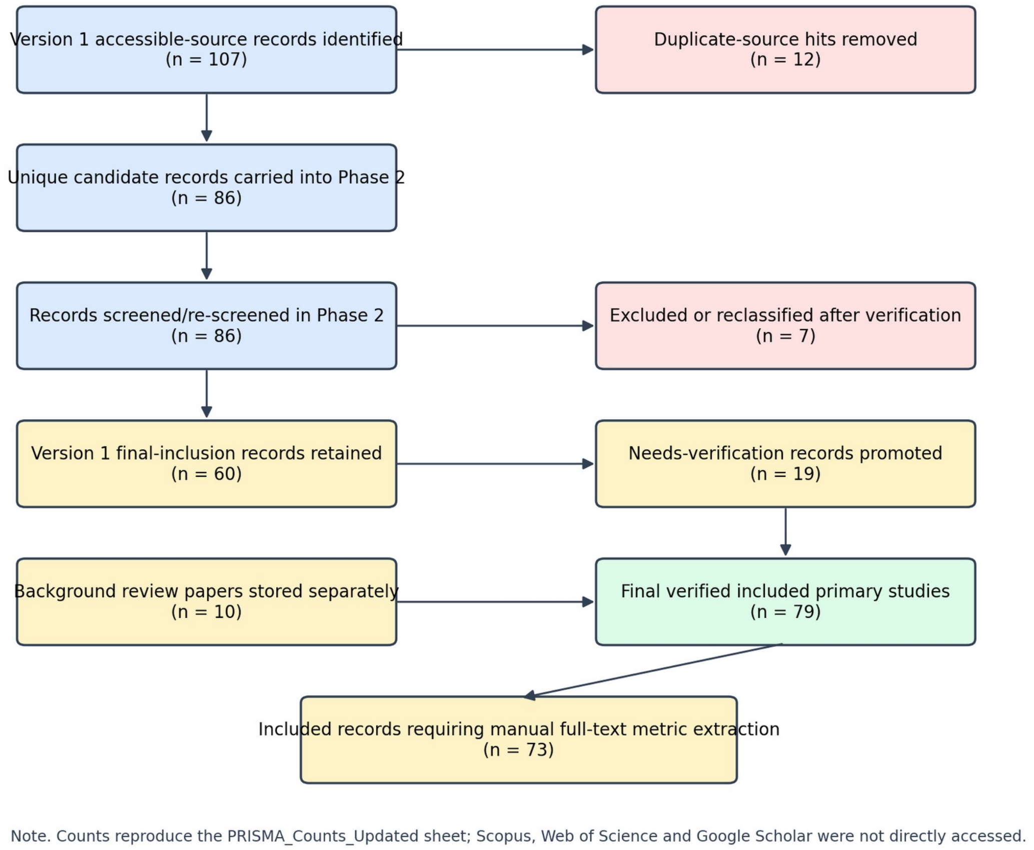

Figure 1. PRISMA flow diagram of the study selection process.

Figure 1 shows that duplicate-source consolidation, Phase 2 verification and reclassification were completed before developing the final synthesis. It also demonstrates that the primary-study dataset was separated from the background-review dataset. This separation has importance for the study because the principal purpose is to synthesise empirical and technical findings concerning worker-safety prediction. The broader AI reviews are therefore considered only for contextual support where this is appropriate.

2.4. Research Questions

The four research questions guided data extraction, descriptive mapping, thematic interpretation and development of the framework, where RQ1 identifies machine learning, deep learning, computer vision, NLP, sensor-based and related AI techniques applied to construction worker-safety prediction and monitoring. RQ2 examines the relationship among model types, sources of data, data modalities and prediction or detection targets. RQ3 reviews the methodological, technical, ethical and implementation-related barriers that restrict practical deployment in construction safety management. Finally, RQ4 transforms the reviewed evidence into a practical framework for worker-safety prediction and risk control.

2.5. Data Extraction and Coding

Every included study was coded according to the updated framework contained in the workbook. The extracted information covered record ID, title, authors, year of publication, publication type, journal or conference, publisher, DOI or stable URL, availability of the abstract, author keywords, country or context, construction-safety domain, AI or ML technique category, specific model or algorithm, data-source type, data modality, dataset or source, available sample size, prediction or detection target, outcome variable, reported performance metrics, best-performing model, explainability method, principal findings, practical safety implications, risk-control relevance, limitations, recommendations for future research, verification source, full-text access status and verification notes. Through this structure, the relationship nexus among technique, data source and safety application could be mapped for every study.

During coding, uncertainty was retained rather than completing missing information through inference, as several rows included statements such as "reported in paper but not accessible from available source", "reported in paper; not extracted in this datasheet" and "needs manual full-text check". Such entries were not changed into exact measures of performance, and for this reason algorithms were not ranked by pooled accuracy, F1 score or mean average precision. Exact values are reported only when they were already available in the verified workbook; otherwise, cautious expressions are used for model application, performance and practical relevance. This approach maintains alignment with the verified dataset and reduces the possibility of creating unsupported paper-level findings.

2.6. Synthesis Strategy

The synthesis was conducted by combining descriptive statistics, systematic mapping, thematic synthesis and framework development, where descriptive statistics summarised year of publication, outlet, technique category, safety domain and type of data source. Systematic mapping then established relationships among models, data modalities and safety targets, while thematic synthesis was applied to interpret common problems, including data quality, imbalance, generalisability, shortage of benchmarks, real-time processing, annotation burden, interpretability, privacy and workflow integration. Finally, framework development transformed the findings into a risk-control pathway that connects data acquisition, preprocessing, prediction, explainability, human validation, managerial action and feedback. A meta-analysis was not performed because exact metrics and limitations were incomplete in many studies and considerable differences existed in data type, task definition, validation environment and maturity of deployment. Thus, the method follows the reporting logic of PRISMA 2020 with necessary adaptation for the accessible-source workbook applied in this study (Page et al., 2021).

3. Results

3.1. Overview of the selected studies

The final included dataset consisted of 79 primary empirical or technical studies, and most of this evidence was published as journal articles, comprising 76 journal papers and three conference papers. The publication pattern shows that the research field developed gradually after 2016 and expanded more rapidly after 2020, mainly because of the growth of deep-learning visual monitoring and data-driven modelling of construction accidents. Figure 2 presents the yearly distribution of the selected studies, where the highest publication frequency was found in 2023, followed by 2022, whereas 2024 and 2026 each provided eight coded studies. The inclusion of records from 2025 and 2026 reflects the updated accessible-source verification within the workbook, and therefore these frequencies should be considered within the stated range of the dataset rather than interpreted as the output of a live bibliometric search.

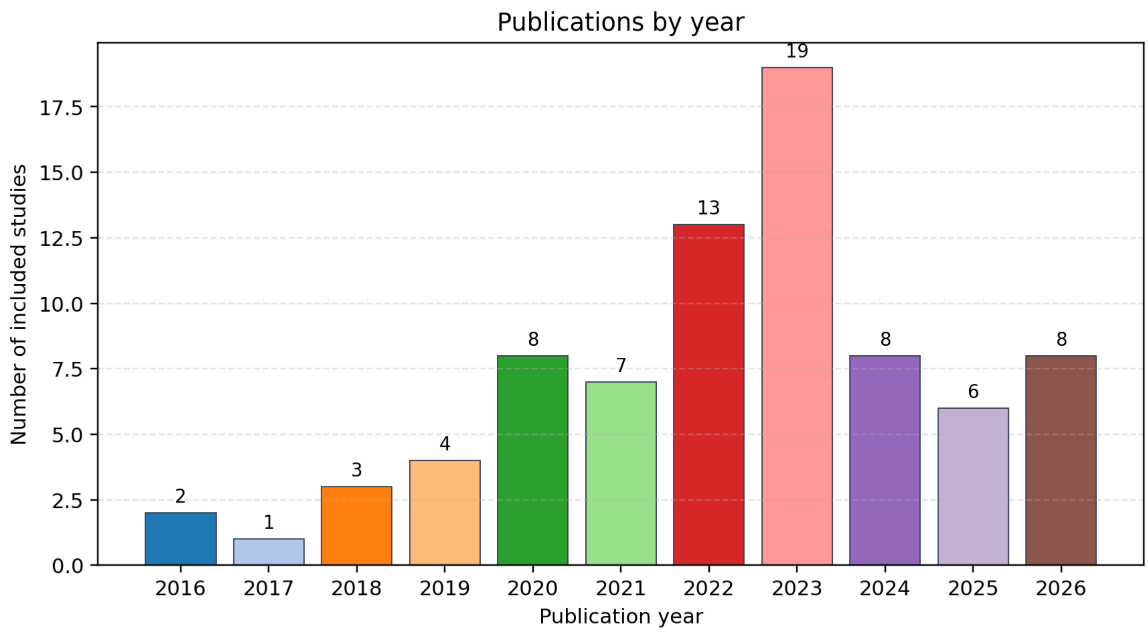

Figure 2. Publications by year.

From Figure 2, it is observed that worker-safety prediction became more diversified with the introduction of computer vision, object detection, accident-severity models, LLM-based report classification and sensor-based recognition of activities. The earlier papers were more dependent on structured datasets, accident narratives and text-mining procedures, whereas later research increasingly used site images, video, pose-estimation methods, graph models and real-time monitoring of compliance. Thus, the time-based pattern reflects a wider transition from post-accident analysis towards automated risk detection and safety-related decision support.

The reviewed papers were published across the areas of construction automation, safety, computing, management and applied engineering. Table 2 presents the major publication outlets available in the coded dataset. Automation in Construction was found as the dominant outlet, which reflects the important position of automation, computer vision, machine learning and digital monitoring of construction sites within this field. The other studies were distributed among construction engineering, applied sciences, safety science, sustainability, computing and conference publications. From this distribution, worker-safety prediction can be identified as a multidisciplinary research area rather than a topic belonging to one journal community.

Table 2.

Main publication outlets represented in the reviewed studies.

Publication outlet	Count	Interpretation in the reviewed dataset
Automation in Construction	27	Main outlet for CV, ML, NLP, accident modelling and integrated site monitoring.
Journal of Construction Engineering and Management	6	Construction safety prediction, injury/severity modelling and safety-management applications.
Applied Sciences	5	Applied AI, safety analytics, PPE/compliance and risk-prediction studies.
Engineering, Construction and	4	Specialised computing, informatics or engineering venue

Publication outlet	Count	Interpretation in the reviewed dataset
Architectural Management		represented in the coded set.
Sustainability	4	Applied AI, safety analytics, PPE/compliance and risk-prediction studies.
Buildings	3	Applied AI, safety analytics, PPE/compliance and risk-prediction studies.
Safety Science	3	Applied AI, safety analytics, PPE/compliance and risk-prediction studies.
Sensors	2	Specialised computing, informatics or engineering venue represented in the coded set.
Advanced Engineering Informatics	2	Specialised computing, informatics or engineering venue represented in the coded set.
Journal of Computing in Civil Engineering	2	Specialised computing, informatics or engineering venue represented in the coded set.
Other journals and conference venues	21	Single-study or low-frequency outlets; full coded list appears in Appendix A.

Table 2 reveals a publication pattern that is concentrated but not exclusive. The leading journal indicates the strong automation and digital-monitoring direction of the research field. However, the long distribution of remaining outlets shows that construction worker-safety prediction has a relationship with safety science, engineering informatics, computer vision, management and mobile or intelligent systems. Therefore, a synthesis comparing techniques and their safety functions is required instead of depending only on classification by publication venue.

3.2. RQ1: AI and machine-learning techniques used for construction worker-safety prediction

RQ1 examines the techniques applied to predict, identify or monitor worker safety within construction project environments, and the coded findings show that computer vision and deep learning are dominant, with 45 and 42 coded occurrences respectively. These frequencies do not suggest that every study used one technique only, as several papers were placed in more than one category because visual monitoring commonly integrates deep learning with object detection, tracking, pose estimation or semantic reasoning. Q. Fang et al. (2018) demonstrate the application of visual models for detecting non-hardhat use, while Nath et al. (2020) show the use of deep learning for real-time PPE monitoring. The distribution of the major technique categories is summarised in Figure 3.

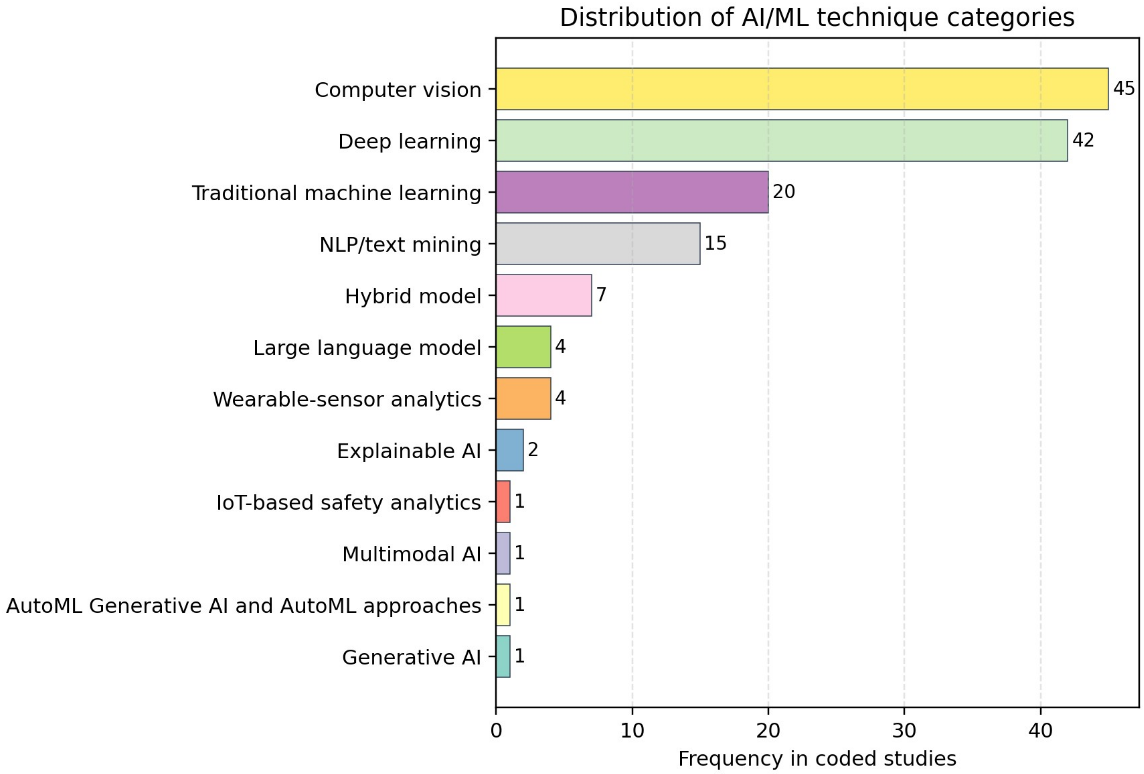

Figure 3. Distribution of AI/ML technique categories in the reviewed studies.

The dominance of visual methods can be explained by the observable nature of many construction hazards and the availability of image or video information from fixed cameras, drones and site-surveillance systems. Deep-learning approaches, including convolutional neural networks, YOLO-based detectors, Faster R-CNN, graph convolutional networks and pose-estimation models, are applied to identify safety objects, worker conditions and spatial relationships. Such methods are particularly appropriate for PPE compliance and visual safety monitoring because the target can generally be represented as an observable class or relation. Han and Zeng (2022) illustrate multi-scale detection of safety helmets, whereas Park et al. (2024) extend visual monitoring to the detection of struck-by hazards from far-field surveillance videos. Within the coded evidence, this research area appears to have reached greater maturity than deeper causal prediction since its data, labels and outputs are comparatively easier to determine.

Traditional machine learning also represents an important research strand, with 20 coded occurrences. These studies employ structured accident records, national occupational-accident datasets, safety indicators, exposure measures and engineered features to predict injury occurrence, fatality, accident severity, post-accident disability, safety risk or accident outcome. Unlike visual detection, the principal purpose of these models is often to support planning and risk prioritisation before or after an accident instead of identifying an unsafe image in real time. Choi et al. (2020) developed a machine-learning model for fatal accidents, while Koc et al. (2021) investigated post-accident disability through structured safety information. Therefore, the continuing importance of traditional ML is related to its suitability for tabular administrative data and its relatively interpretable nature compared with black-box visual models.

NLP and text mining were identified in 15 coded occurrences and were applied to accident narratives, injury reports, case retrieval, safety precursors, extraction of important information and the relationship between accidents and activities. This research has importance because a considerable amount of construction safety knowledge remains in textual form rather than in structured labels. Goh and Ubeynarayana (2017) evaluated the classification of accident narratives, and T. Kim and Chi (2019) used NLP for accident-case retrieval and further analysis. Moreover, Park (2026) and Wang et al. (2025) expand this direction by comparing conventional machine learning with language-model-based classification and reasoning from reports. The findings indicate future promise; however, the workbook also confirms that several exact performance measures and validation procedures continue to depend upon manual checking of full texts.

The categories with lower frequencies are also important for future development of the field. Hybrid approaches were found in seven studies, large language models in four, wearable-sensor analytics in four and explainable AI in two. Generative AI, AutoML, IoT-based analytics and multimodal AI appeared as individual or low-frequency categories. These emerging categories reflect the movement from isolated model applications towards systems that integrate structured information, text, vision, sensor data and human judgement. Table 3 summarises the main categories of techniques, their common safety applications and representative papers. Selected examples are provided in the table to maintain the readability of the main article, while Appendix A gives author-year traceability for the complete group of 79 included studies.

Table 3.

AI/ML technique categories and their construction safety applications.

Technique category	Count	Construction safety application	Representative examples
Computer vision	45	PPE detection, worker tracking, hazard-zone intrusion, floor openings, struck-by hazards and visual compliance monitoring.	Q. Fang et al. (2018); Park et al. (2024).
Deep learning	42	Object detection, pose estimation, CNN-based recognition, graph and attention models, automated safety reporting.	Nath et al. (2020); Wen et al. (2024).
Traditional machine learning	20	Accident prediction, injury type, severity, disability, safety leading indicators and risk prioritisation from structured data.	Choi et al. (2020); K. Koc et al. (2023a).
NLP/text mining	15	Accident-report classification, case retrieval, causal factor extraction and accident-activity association.	Goh and Ubeynarayana (2017); Khan et al. (2024).
Hybrid model	7	Combination of ML, text mining, resampling, LLMs or graph structures for accident classification and safety prediction.	Cheng et al. (2020); J. Wang et al. (2026).
Large language model	4	Construction accident prediction and report classification using LLM-based or lightweight LLM approaches.	Park (2026); Wang et al. (2025).
Wearable-sensor analytics	4	Work-at-height prediction, posture recognition, material-handling risk events and physiological/sensor-based risk.	Karatas (2025); Duan et al. (2023).
Explainable AI	2	Interpretable fatal accident prediction and SHAP-based severity analysis.	K. Koc et al. (2023a); Son et al. (2026).
Generative AI/AutoML	2	Construction accident prediction using generative AI/AutoML and automated predictor selection.	Toğan and Mostofi (2022); Seo et al. (2026).
IoT or multimodal AI	2	Sensor/site-monitoring integration and vision-	Sahraoui et al. (2026); Pujari et

Technique category	Count	Construction safety application	Representative examples
		language hazard detection.	al. (2024).

Table 3 shows that visual and predictive analytics remain at the centre of the research field, although the area is developing towards language-based, sensor-based and hybrid systems. The table further limits excessive citation clustering in the narrative by presenting representative author-year evidence within a structured form. This type of presentation is suitable for the systematic review since it creates a direct link between the methodological category and its safety application instead of providing a long list of studies within one sentence.

3.3. RQ2: Data sources, modalities and prediction/detection targets

RQ2 investigates the alignment of model type with data source, modality and safety target, where the most visible pattern is the frequent use of image datasets, mixed data and video, CCTV or drone footage. Image datasets and mixed data were each coded 41 times, while video, CCTV or drone footage occurred 34 times. These sources support PPE detection, monitoring of safety compliance, hazard identification, struck-by hazard recognition, tracking of workers, floor-opening risk and work-zone monitoring. The major safety domains are shown in Figure 4, and Figure 5 presents the principal types of data sources. Since the categories can overlap, the reported values represent coding frequency and should not be interpreted as 79 mutually exclusive single-label studies.

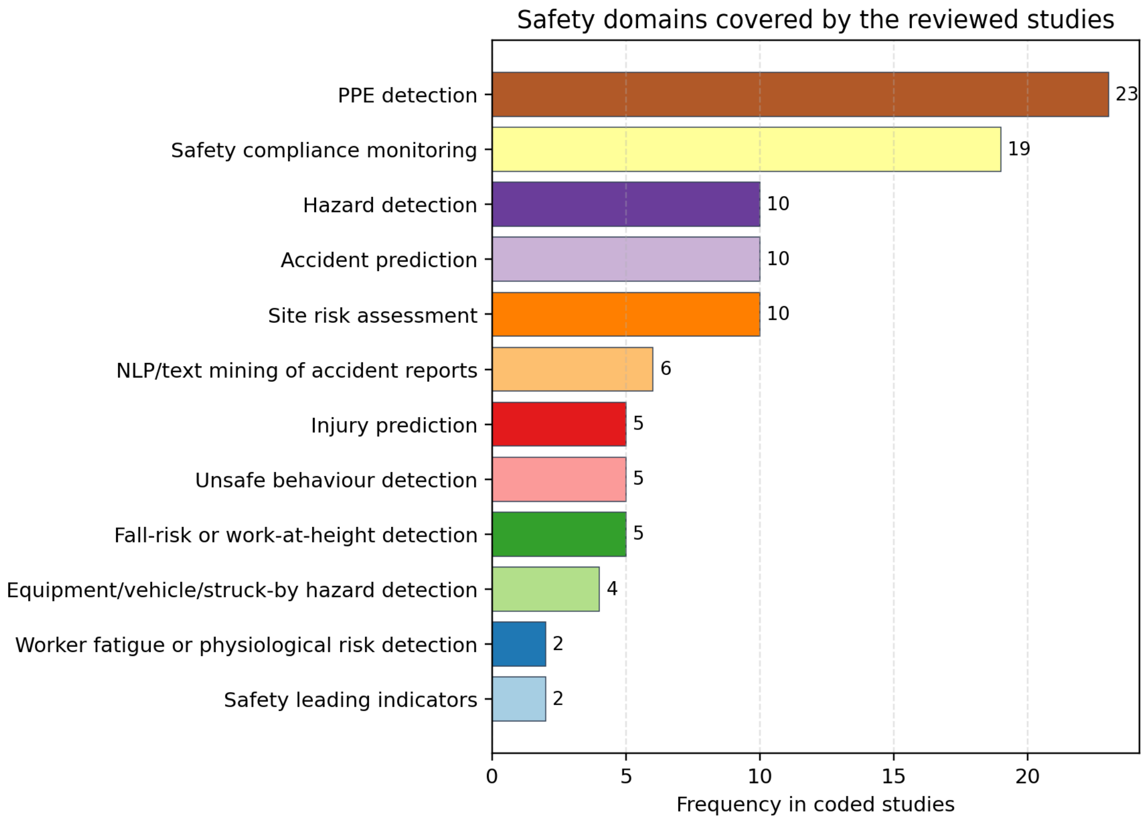

Figure 4. Safety domains covered by the reviewed studies.

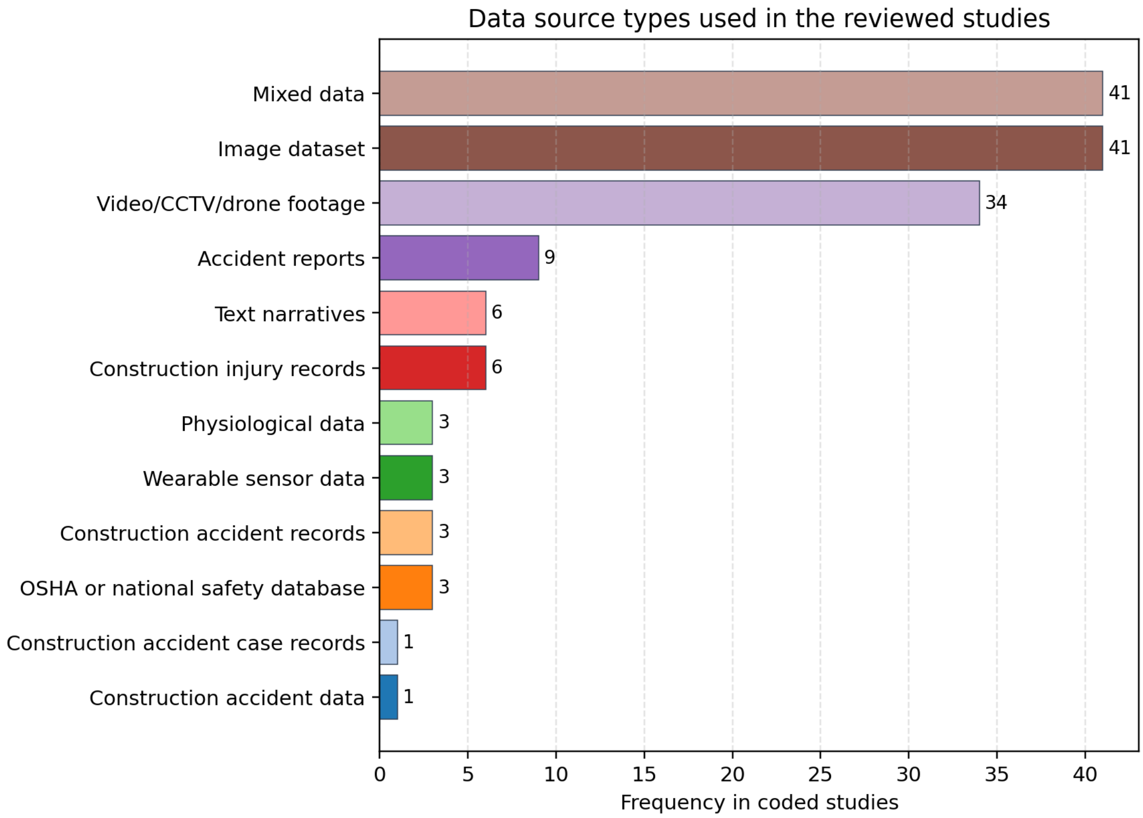

Figure 5. Data source types used in the reviewed studies.

The distribution of safety domains indicates that PPE detection was the largest area, followed by safety-compliance monitoring, accident prediction, hazard detection and assessment of site risk. PPE and compliance applications are attractive for visual AI because their target classes are concrete and can be labelled within an image or video frame. Q. Fang et al. (2018) and Delhi et al. (2020) demonstrate this direction through visual studies of harness use and PPE compliance. In contrast, accident and injury prediction depends more strongly upon structured records, narratives, safety indicators and national-level datasets. K. Koc et al. (2023b) and Erkal et al. (2024) show how such models investigate less visible outcomes, including severity, disability and categories of accident risk. Therefore, two connected but different research streams can be identified: real-time visual monitoring of observable safety states and predictive analysis of recorded accident or injury outcomes.

Textual and narrative information continues to be important because many safety events are recorded in accident reports, OSHA or national databases, investigation notes and case descriptions. Within the coded dataset, accident reports appeared nine times, construction injury records six times and textual narratives six times. Tixier et al. (2016b) and Li and Wu (2023) demonstrate how NLP can classify records and extract important safety information from accident narratives. Wearable-sensor and physiological information appeared less frequently; however, such data can address worker risks that cameras may not identify directly, including posture, material-handling strain, work-at-height activity, fatigue and perceived risk. Karatas (2025) provides an example of predicting work-at-height activity from sensor data, whereas Antwi-Afari et al. (2022) show the usefulness of wearable insole data for posture-related safety analysis. Thus, the limited number of studies represents an important research gap rather than limited practical value.

Table 4 establishes the relationship among model families, data sources, prediction or detection targets and common safety applications. The alignment suggests that one algorithm cannot be universally identified as preferable. According to the reviewed studies, model selection should be influenced by the data modality, the safety action required and the accepted tolerance for error within the relevant task. However, exact comparison of performance across the studies was restricted because most metric values, validation procedures and paper-specific limitations still require manual extraction from the full text.

Table 4.

Model-data-task alignment in worker-safety prediction studies.

AI/ML approach	Common data source	Main prediction/detection target	Typical safety use	Interpretation based on reviewed studies
Traditional ML	Structured accident, injury, exposure or safety-indicator data	Accident occurrence, severity, fatality, disability or safety-risk category	Risk prioritisation, accident prevention planning and safety-resource targeting	Useful where tabular data exist and interpretability is required, but reporting of validation details varies.
NLP/text mining	Accident reports, injury narratives, OSHA/national records and regulatory text	Accident classes, causes, precursors, outcomes and activity associations	Report analysis, learning from incidents and regulatory/safety knowledge extraction	Strong for unstructured text; quality depends on coding schemes, language coverage and narrative completeness.
Computer vision/deep learning	Images, CCTV, drone footage, site videos and visual datasets	PPE, helmet, harness, unsafe acts, workers, equipment, floor openings and hazard zones	Real-time monitoring, automated inspection and visual alerting	The most developed stream; performance may shift with site layout, lighting, camera angle, occlusion and PPE variation.
Graph, hybrid and attention models	Accident networks, pose/skeleton sequences, image-text or structured-text combinations	Human-object interaction, compliance, accident networks and contextual safety states	Context-aware monitoring and richer safety reasoning	Promising for relational tasks but often experimental and dependent on task-specific modelling assumptions.
Wearable and IoT analytics	Smartphones, physiological sensors, insoles, accelerometers, gyroscopes and site-monitoring streams	Posture, work-at-height activity, material-handling risk, fatigue or physiological risk	Worker-centred alerts and ergonomic or physiological intervention	Important for non-visual risk, but adoption raises comfort, maintenance, privacy and data-governance issues.
LLM and vision-language approaches	Accident text, prompts, images, visual descriptions and mixed safety data	Report classification, safety reasoning, hazard labelling and compliance interpretation	Safety-report assistance, training, inspection support and multimodal decision support	Early-stage category; requires construction-specific validation, prompt control and human review before deployment.

From Table 4, it can be observed that the modality of data strongly determines the type of safety question that can be answered. Visual methods are suitable for observable conditions, NLP obtains meaning from textual records, traditional machine learning supports structured risk prediction and wearable systems examine embodied conditions of workers. Therefore, a practical safety-management system may need several models operating together rather than one algorithm considered as the best model for every purpose.

A further implication of this alignment concerns the changing unit of prediction across the reviewed field: in visual safety monitoring, the unit is commonly a person, object, frame, bounding box or short video sequence. In structured accident modelling, it may be an accident record, worker characteristic, project attribute or severity category, while an NLP study generally considers a sentence, narrative, report or extracted entity. These units cannot be directly interchanged, and due to this reason differences in accuracy or F1 score do not provide simple evidence that one model family is superior. The coded papers should therefore be understood as task-specific demonstrations whose practical value depends upon whether a model output is connected to a realistic safety decision, for example an inspection priority, warning, change in work sequence or targeted training activity.

3.4. RQ3: Key challenges of ML-based worker-safety prediction in construction

RQ3 addresses the barriers that restrict the deployment of ML-based worker-safety prediction within actual construction safety management. The verification notes and coding fields of the workbook indicate that manual full-text checking is still required for many exact performance measures, limitations and recommendations for further study. This produces an immediate evidence-quality problem because results cannot be compared consistently without standard extraction of datasets, train-test divisions, external-validation conditions and definitions of metrics. Beyond the reporting issue, the reviewed papers repeatedly identify small or customised datasets, imbalanced accident categories, restricted access to accurately annotated images, incomplete accident narratives and weak cross-site validation. Such problems influence structured-data prediction and real-time visual monitoring, although the form of the problem varies according to the data source.

Generalisation represents another major challenge because a model developed from one construction site, country, camera position, PPE category or reporting procedure may not provide reliable results in another project environment. Visual monitoring is influenced by occlusion, weather, illumination, camera distance, worker posture and equipment differences. Similarly, textual and structured-data models are affected by national reporting practices, missing fields, terminology and uneven accident documentation. Wearable systems further introduce problems of sensor positioning, battery duration, continuity of data and acceptance by workers. Wang et al. (2021) and H. Kim et al. (2023) show the operational possibilities of visual monitoring and struck-by hazard detection; however, these studies also reflect the requirement for validation beyond controlled or limited datasets. The main challenges and their implications for construction safety management are presented in Table 5.

Table 5.

Key challenges and implications for construction safety management.

Challenge	Meaning in reviewed studies	Implication for construction safety management
Data quality and class imbalance	Accident, injury and near-miss data can be incomplete, sparse or dominated by non-event classes.	Use data-quality audits, imbalance-aware sampling, transparent preprocessing and conservative interpretation of rare-event predictions.
Small or custom datasets	Many CV and sensor studies depend on project-specific images or limited field samples.	Develop shared benchmarks and report dataset composition, labelling rules and site context.
Limited cross-site generalisability	Models may not transfer across countries, contractors, PPE styles, camera layouts or reporting systems.	Require external validation and local calibration before operational use.
Lack of standardised benchmarks	Different studies use different targets, metrics and validation schemes.	Adopt common evaluation protocols for PPE, hazard, injury and accident-report tasks.
Manual annotation burden	Visual and text models often require labour-intensive labelling by trained reviewers.	Use active learning, weak supervision and quality-controlled annotation workflows.

Challenge	Meaning in reviewed studies	Implication for construction safety management
Real-time processing constraints	Video and sensor systems must handle latency, edge devices and unreliable site connectivity.	Match model complexity to field hardware and define alert thresholds carefully.
Limited interpretability and trust	Black-box outputs may be difficult for safety managers to accept or audit.	Use explainability, evidence display and human validation for high-risk decisions.
Privacy and surveillance concerns	Cameras, wearables and worker tracking can create ethical and labour-relations risks.	Implement consent, minimisation, access control, anonymisation and clear governance.
Workflow integration	Alerts may not fit inspection routines, permit systems, toolbox talks or stop-work authority.	Embed AI outputs into existing safety-management processes rather than separate dashboards.
Pilot-stage maturity	Many systems remain prototypes with limited real-world deployment evidence.	Evaluate field impact, false alarms, user behaviour and control effectiveness before scaling.

Table 5 indicates that technical improvement by itself will not make worker-safety prediction operational. Construction organisations must also consider data governance, consent of workers, model maintenance, training of safety professionals, response to alerts and integration with established control processes. Without these organisational arrangements, a technically promising model may remain a laboratory prototype or an isolated pilot application.

The identified challenges further explain why field implementation should be considered as a socio-technical change process rather than a simple installation of software. Data-governance systems, participation of workers, supervisory procedures, alert thresholds and accountability rules influence whether a prediction will be trusted and followed by action. Although a model can identify an unsafe condition, decisions concerning work stoppage, behavioural correction, access modification, isolation of equipment or redesign of a task remain a professional and managerial responsibility. Therefore, explainability and human validation are considered as conditions of deployment in this review, rather than optional features of a technical system. This position is supported by the coded findings because studies reporting promising algorithms generally provide limited evidence about long-term implementation, worker acceptance and measurable reduction of incidents after deployment.

3.5. RQ4: Risk-control framework and future directions

RQ4 converts the reviewed evidence into a practical framework for risk control, developing a pathway from acquisition of data towards continuous learning because a prediction has value when it produces a timely and accountable control activity. Figure 6 presents the proposed framework for machine-learning-based worker-safety prediction and risk control. The pathway begins by collecting images, video, accident reports, inspection findings, sensor streams, wearable signals and site-monitoring information. After this stage, the data pass through preprocessing, cleaning, labelling, feature engineering and model development, after which model outputs are interpreted through explainability and human validation, while the final stages connect the prediction with a safety decision, intervention, feedback and updating of the model.

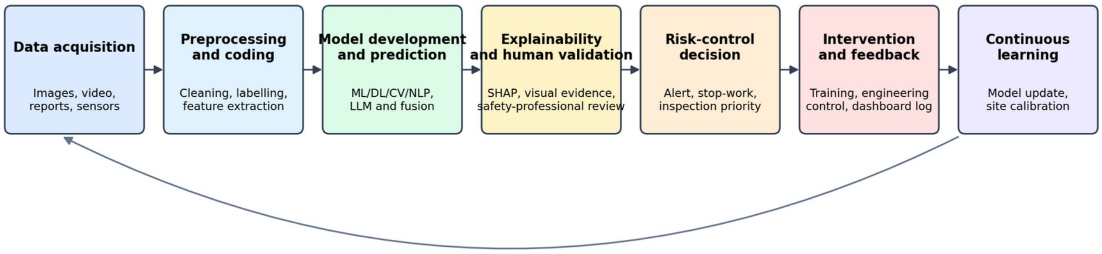

Figure 6. Proposed machine-learning-based worker-safety prediction and risk-control framework.

The proposed framework contains a managerial dimension together with its technical dimension because a PPE detector, accident-severity classifier or work-at-height prediction model should not automatically replace professional safety judgement. Instead, the model should generate evidence that safety professionals can examine, prioritise and transform into appropriate action. In practice, this may include a dashboard identifying repeated PPE non-compliance, a text-mining application showing repeated causal factors in accident narratives, a wearable device alerting supervisors about high-risk material handling or a computer-vision system identifying hazardous proximity between workers and equipment. Table 6 explains the stages of the framework with their corresponding AI functions, safety outputs and managerial actions.

Table 6.

Risk-control framework stages, AI functions, safety outputs, and managerial actions.

Framework stage	AI function	Safety output	Managerial action
Data acquisition	Collect visual, text, sensor, wearable and site-monitoring data.	Images, videos, accident reports, inspection logs, sensor streams and worker signals.	Define data purpose, obtain consent, document source quality and assign data responsibility.
Preprocessing and coding	Clean data, label hazards, extract features and structure narratives.	Model-ready datasets, classes, features, labels and metadata.	Audit labels, address imbalance, preserve uncertainty and document preprocessing choices.
Model development and prediction/detection	Train ML, DL, CV, NLP, LLM, sensor or hybrid models.	Risk scores, accident classes, PPE status, hazard detections, posture or proximity alerts.	Select model by task, validate locally and set alert thresholds according to risk tolerance.
Explainability and human validation	Generate interpretable evidence and require professional review.	Feature importance, saliency, image evidence, rule match or text rationale.	Review false positives/negatives, confirm critical alerts and maintain human accountability.
Risk-control decision	Convert outputs into safety-control priorities.	Inspection priority, stop-work recommendation, retraining need or engineering-control trigger.	Allocate resources, issue instructions and link decisions to permit, inspection or supervision systems.
Intervention and feedback	Implement controls and record outcomes.	Corrected PPE use, changed work method, retraining, exclusion zone or design modification.	Track response time, worker feedback, near misses and residual risk.

Framework stage	AI function	Safety output	Managerial action
Continuous learning	Update models and rules using new site evidence.	Recalibrated models, improved labels, benchmark results and governance records.	Schedule periodic review, monitor drift, revise controls and share validated lessons.

The principal directions for future research develop directly from the limitations of the evidence base. Standardised multimodal datasets, cross-site and cross-country validation, stronger reporting of training and testing divisions, explainable AI, privacy-aware visual and wearable monitoring, human-in-the-loop systems, BIM and digital-twin integration, real-time dashboards and evaluation under industry conditions are required. LLM and NLP methods may support safety reports, regulatory compliance, training and learning from incidents; however, construction-specific validation and careful human examination are necessary for these applications. Moreover, multimodal systems combining vision, text, sensors and contextual project information have significant promise because actual construction risk is seldom contained in one source of data. Their practical contribution will nevertheless depend on reliability, interpretability and acceptance by workers and safety managers.

4. Discussion

4.1. Interpretation of major findings

The major pattern found from the review is the dominance of computer vision and deep learning, while traditional machine learning continues to have an important relationship with structured accident and injury information. Visual monitoring has developed further because many construction safety conditions, including helmet use, presence of a harness, PPE compliance, worker location, proximity to equipment and entry into a hazardous zone, can be observed directly and represented through image objects, bounding boxes, poses and spatiotemporal relationships. Therefore, these applications are suitable for CNNs, YOLO-based detectors, pose-estimation techniques and graph models, and the studies of Q. Fang et al. (2018) and Nath et al. (2020) demonstrate why rapid development has occurred in this particular direction. However, maturity in visual detection does not confirm complete maturity in risk control because detection of an unsafe condition represents the first stage only, since construction managers still require validated thresholds, dependable alert procedures, worker participation and evidence that the intervention reduces harm.

PPE detection and visual compliance monitoring are common because they provide visible practical value and relatively clear technical boundaries. Compared with complex causal dimensions such as production pressure, quality of supervision, risk perception and coordination among subcontractors, the relevant classes are easier to determine. As a result, image-based systems can be developed and tested by using local construction photographs, web-sourced images or customised datasets. This increases the feasibility of research, but it also explains the narrow nature of many systems. A helmet-detection model may show strong performance in one visual environment without considering broader risk pathways related to fall planning, unsafe sequencing, movement of equipment or fatigue. Therefore, the findings show a gap between monitoring visible compliance and developing deeper predictive risk control, while Chen et al. (2024) and Wen et al. (2024) indicate progress towards integrated reporting and more advanced safety reasoning through visual question answering; unfortunately, this direction remains less developed than single-task PPE detection.

Traditional machine learning remains relevant because construction firms, regulatory authorities and insurers maintain structured or semi-structured information that cannot be converted into visual data. Accident severity, exposure to fatality, post-accident disability, injury categories and leading safety indicators are generally recorded in administrative datasets, incident reports and inspection systems. Models developed from such data can assist strategic prevention, distribution of safety resources and early identification of high-risk conditions. K. Koc et al. (2023a, 2023b) demonstrate how interpretable modelling and structured prediction can support managerial decisions by using national or coded accident information. This research stream may be less visible than computer vision; however, it has significant relevance to safety governance because the predictions can be connected with organisational controls, policy development and project planning.

NLP, LLMs, wearable analytics and multimodal AI can be considered as the emerging directions of the field. NLP has particular importance because accident reports include detailed descriptions of tasks, causal factors, agents, injuries and outcomes. LLMs may improve classification, summarisation and safety education, although their results require verification because prompt sensitivity, specialised vocabulary and hallucination risk can influence reliability. Wearable and physiological monitoring can identify posture, material-handling strain and work-at-height activities that may remain invisible to a camera. However, these systems create further questions regarding comfort, worker consent, ownership of data and monitoring ethics. Park (2026) illustrates the emerging application of LLMs for construction accident prediction, while Karatas (2025) extends monitoring beyond visible compliance through sensor-based prediction of work-at-height activity. From the above evidence, these areas remain substantially experimental and large-scale validation in the field is still limited.

From the risk-control perspective, prediction should have a direct relationship with the hierarchy of controls and a documented managerial response. When a visual detector identifies missing PPE, an immediate correction can be made. However, a more permanent response may involve procurement, supervision, coordination of subcontractors or redesign of the working method. Similarly, a model of accident severity can determine high-risk profiles, but its contribution depends upon whether managers change their planning, allocate inspection resources or revise the training system. This difference has importance because several reviewed papers end with detection or classification, whereas fewer papers demonstrate how the alert changes behaviour in the field or reduces residual risk. Future deployment should therefore examine the full control pathway, including quality of data, output of the model, human interpretation, intervention, response of workers and recurrence of the condition. Such an evaluation can move the field from algorithm-centred reporting towards evidence of effective safety management by determining whether alerts influence decisions, reduce the duration of exposure and improve supervisory consistency across changing work fronts and teams.

The above findings also change the way model effectiveness should be evaluated because laboratory studies generally communicate effectiveness through accuracy, precision, recall, F1 score and mean average precision. In the practical context of construction safety management, it should further include timeliness, actionability, false-alert burden, transparency and the ability to reduce exposure before an injury occurs. A comparatively simple model producing an auditable, understandable and timely warning may offer greater usefulness to a safety manager than a slightly more accurate black-box model that cannot be explained or integrated within site procedures. Therefore, the reviewed findings support a balanced evaluation of AI performance. Algorithmic measures are necessary, but they remain insufficient without a relationship to site-level controls, managerial authority and the feedback of workers who are influenced by the monitoring system.

4.2. Implications for researchers

The research implications are methodological as well as technical, and future papers should report the source and size of the dataset, definitions of classes, annotation procedures, training and testing divisions, cross-validation, external validation and analysis of errors in a more consistent way. Shared benchmarks are also required for PPE detection, hazard identification, accident-narrative classification, prediction of injury severity and sensor-based recognition of worker risk. Moreover, models should be compared with practical baselines instead of limiting the comparison to alternative algorithms. A model showing a small improvement in accuracy may provide limited managerial value if it cannot be interpreted or deployed. Explainability should therefore be incorporated within model development, particularly for high-consequence outcomes including fatality exposure and stop-work alerts. A stronger link between construction-safety theory and machine-learning design is also necessary so that the developed models represent hazard causation, worker exposure, the hierarchy of controls and site operations rather than the availability of data alone.

Sharing of datasets and reproducibility remain major requirements for future research because many computer-vision papers apply local images or customised visual datasets, whereas accident-prediction studies frequently use national or organisational records that are not publicly available. Consequently, comparison becomes difficult and the cumulative development of knowledge is slowed. Therefore, researchers should provide metadata, coding dictionaries, annotation protocols and de-identified benchmark subsets whenever possible. For multimodal research, the procedure for synchronising different data streams, treating missing observations and reaching decisions when the sources provide conflicting information should be clearly reported. Such reporting will enable future systematic reviews to evaluate the effectiveness of models more accurately instead of depending on incomplete summaries from accessible sources.

4.3. Implications for construction safety managers

For construction safety managers, the review supports AI as a form of decision support while professional judgement remains necessary. AI systems can assist in prioritising inspections, detecting repeated problems of compliance, identifying hazardous proximity, organising accident narratives and providing early warnings. However, these results should be examined with consideration of site conditions, task planning, experience of workers and feasibility of the required control. A dashboard that identifies PPE non-compliance needs a relationship with supervision, training, procurement and disciplinary fairness. Similarly, an accident-severity model can support planning and allocation of resources, but it cannot remove the requirement for engineering controls, supervision and worker participation. Human validation is therefore established as a central part of the proposed framework.

Before visual or wearable monitoring is introduced, managers must further consider privacy, consent and integration with existing workflows. Continuous monitoring through cameras and sensors may be understood as surveillance when workers do not receive clear information about the purpose, storage, access and use of their data. Effective implementation therefore needs transparent governance, data minimisation, consultation with workers, role-based access, audit trails and a procedure for reviewing or challenging an automated alert. AI systems should be connected with existing practices, including permits, inspections, pre-task planning, toolbox meetings, incident learning and stop-work authority. Without this connection, the alerts may become additional noise rather than useful evidence for risk control.

Operational implementation should therefore follow a staged process in which a construction organisation may begin with a specific and auditable application, for example PPE monitoring or classification of accident reports, and expand the system after local validation, consultation with workers and development of response procedures. Pilot studies should record model outputs together with the person receiving the alert, the time required for review, the intervention that followed and whether the unsafe condition occurred again. This evidence is important because an AI safety system may otherwise develop a false impression of control. A dashboard can show the existence of risk, but it cannot ensure that responsibility, authority and adequate resources are available for corrective action. For this reason, the proposed framework treats AI as one part of a broader safety-management cycle that connects prediction, accountability, intervention and organisational learning.

4.4. Limitations of the review

This review contains limitations due to the nature of the verified coded workbook, which was prepared from accessible publisher, DOI, index and official metadata sources. Scopus, Web of Science and Google Scholar were not accessed directly, and since the search is not claimed as an equivalent of direct database exports, some relevant papers may remain outside the evidence base. The review is also dependent upon the coded fields available in the workbook, while many exact performance metrics, paper limitations and recommendations for future research need manual full-text checking. According to the README, 73 included records require manual extraction of full-text metrics, and all 79 studies contain at least one coding issue that depends on the full text. Due to this reason, the paper provides systematic mapping, thematic synthesis and framework development instead of statistical meta-analysis. Before final submission, incomplete authorship details, exact metrics, validation environments and paper-level limitations should be checked against full texts wherever access is available.

5. Conclusions

This paper reviewed machine-learning-based worker-safety prediction within construction project environments by treating the verified coded workbook as the authoritative evidence base. The final synthesis covered 79 primary empirical or technical studies published from 2016 to 2026, while 10 background reviews and seven excluded or reclassified records were maintained outside the primary group. The review was developed around four research questions by applying PRISMA-informed study selection, descriptive mapping, thematic synthesis and framework development. Since several exact metrics and limitations still need extraction from full texts, this study was deliberately presented as systematic mapping and thematic synthesis rather than a statistical meta-analysis.

In response to RQ1, we found computer vision and deep learning as the dominant techniques, particularly for PPE detection, safety compliance, hazard detection, tracking of workers, fall-related risk and equipment-related hazards. Traditional machine learning also remains important for structured information on accidents, injuries, severity, disability and safety indicators. NLP and text mining support the classification of accident reports, retrieval of cases, extraction of causal factors and learning from incidents. However, LLM, wearable, IoT and multimodal approaches are emerging at a lower level of maturity. For RQ2, the findings show a clear model-data relationship nexus. Visual models are used for observable safety conditions, traditional ML is applied to structured records, NLP examines textual narratives and wearable analytics identifies embodied worker conditions.

From the findings of RQ3, the major barriers include poor data quality, class imbalance, small or customised datasets, limited generalisability across sites, weak standardisation of benchmarks, insufficient external validation, manual annotation requirements, real-time processing constraints, interpretability, privacy and integration with the organisational workflow. These limitations explain why a considerable number of studies remain experimental or pilot-based despite reporting promising results. In response to RQ4, the proposed framework converts the evidence into a risk-control pathway beginning with data acquisition and continuing through preprocessing, model development, explainability, human validation, managerial decision, intervention, feedback and continuous learning. Therefore, the framework confirms that AI output should be followed by accountable safety action.

The contribution of this review has two major dimensions. First, it presents a traceable thematic map covering methods, data sources, modalities, prediction targets and challenges within ML-based construction worker-safety prediction. Second, it develops a practical framework through which researchers and construction managers can link prediction with risk-control activities. Future AI systems for construction safety should therefore be explainable, externally validated, privacy-aware, human-centred and operationally integrated. Systems developed with these characteristics are more likely to support practical improvements in worker safety than isolated algorithms that show high performance only within a controlled dataset.

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Appendix A. Final included primary empirical/technical studies

This appendix provides author-year traceability for all 79 primary empirical or technical studies included in the review. Where the workbook contained incomplete metadata, details were verified against accessible publisher or DOI metadata where possible; study-level performance entries remain limited to the coded workbook and should still be checked against full texts before journal submission.

ID	Study citation	Title	Technique category	Data source type	Safety domain
R001	A. Tixier et al. (2016a)	Application of machine learning to construction injury prediction	Traditional machine learning	Construction injury records	Injury prediction
R002	A. Tixier et al. (2016b)	Automated content analysis for construction safety: A natural language processing system to extract precursors and outcomes from unstructured injury reports	NLP/text mining	Construction injury records	Injury prediction; NLP/text mining of accident reports
R003	Goh and Ubeynarayana (2017)	Construction accident narrative classification: An evaluation of text mining techniques	NLP/text mining	Accident reports; Text narratives; Mixed data	NLP/text mining of accident reports
R004	Poh et al. (2018)	Safety leading indicators for construction sites: A machine learning approach	Traditional machine learning; NLP/text mining	Accident reports; Text narratives; Mixed data	Accident prediction; NLP/text mining of accident reports
R005	Zhang et al. (2019)	Construction site accident analysis using text mining and natural language processing techniques	NLP/text mining	Accident reports	Construction accident analysis
R006	T. Kim and Chi (2019)	Accident Case Retrieval and Analyses: Using Natural Language Processing in the Construction Industry	NLP/text mining	Construction accident case records	Construction accident case retrieval
R007	Cheng et al. (2020)	Text mining-based construction site accident classification using hybrid supervised machine learning	Traditional machine learning; NLP/text mining; Hybrid model	Accident reports	Accident prediction
R008	Choi et al. (2020)	Machine learning predictive model based on national data for fatal accidents of construction workers	Traditional machine learning	Construction injury records	Accident prediction
R009	Zhu et al. (2021)	Application of machine learning techniques for predicting the consequences of construction accidents in China	Traditional machine learning	Construction accident data	Accident consequence prediction
R010	Lee et al. (2020)	A study on data pre-processing and accident prediction modelling for occupational accident analysis in the construction industry	Traditional machine learning	Occupational accident data in construction	Accident prediction
R011	Xu et al. (2021)	An improved text mining approach to extract safety risk factors from construction accident reports	NLP/text mining	Accident reports	Site risk assessment
R012	Koc et al. (2021)	Integrating Feature Engineering, Genetic Algorithm and Tree-Based Machine Learning Methods to Predict the Post-Accident Disability Status of Construction Workers	Traditional machine learning	Construction injury records	Post-accident disability prediction
R013	K. Koc et al. (2022)	Accident prediction in construction using hybrid wavelet-machine learning	Traditional machine learning	Occupational accident time series	Construction accident forecasting
R014	K. Koc and Gurgun (2022)	Scenario-based automated data preprocessing to predict severity of construction accidents	Traditional machine learning	Construction accident records	Construction accident severity prediction
R015	K. Koc et al. (2023b)	Prediction of construction accident outcomes based on	Traditional machine learning	National construction accident	Construction accident outcome prediction

ID	Study citation	Title	Technique category	Data source type	Safety domain
		imbalanced dataset through integrated resampling techniques and machine learning methods		data	
R016	Mostofi and Toğan (2023)	Construction safety predictions with multi-head attention graph and sparse accident networks	Deep learning	Construction accident/safety network data	Construction safety prediction
R017	K. Koc et al. (2023a)	Developing a National Data-Driven Construction Safety Management Framework with Interpretable Fatal Accident Prediction	Traditional machine learning; Explainable AI	National occupational accident dataset	Accident prediction
R018	Toğan and Mostofi (2022)	Customized AutoML: An Automated Machine Learning Framework for Selecting Construction Accident Severity Predictors	Traditional machine learning	Construction accident records	Construction accident severity prediction
R019	Alkaissy et al. (2023)	Enhancing construction safety: Machine learning-based classification of injury types	Traditional machine learning; Hybrid model	Construction injury records	Injury prediction
R020	Erkal et al. (2024)	Predicting Serious Injury and Fatality Exposure Using Machine Learning in Construction Projects	Traditional machine learning	Construction project/safety exposure data	Injury prediction
R021	Khan et al. (2024)	Exploring associations between accident types and activities in construction using natural language processing	NLP/text mining	Accident reports	Construction accident-activity association
R022	Li and Wu (2023)	Deep Learning and Text Mining: Classifying and Extracting Key Information from Construction Accident Narratives	Deep learning; NLP/text mining	Accident reports; Text narratives; Mixed data	NLP/text mining of accident reports
R023	Cho et al. (2022)	Development of Machine Learning-Based Construction Accident Prediction Model Using Structured and Unstructured Data of Construction Sites	Traditional machine learning	Structured and unstructured construction-site data	Accident prediction
R024	Kim et al. (2022)	Analyzing Patterns of Multi-cause Accidents From KOSHA's Construction Injury Case Reports Utilizing Text Mining Methodology	NLP/text mining	OSHA or national safety database; Construction injury records; Mixed data	Injury prediction
R025	Son et al. (2026)	Data-Driven Approach to Analyzing Factors Influencing Construction Accident Severity Using SHAP Analysis	Traditional machine learning; Explainable AI	Construction accident records	Construction accident severity analysis
R026	Park (2026)	Comparative evaluation of machine learning and LLM-based approaches for construction accident prediction	Traditional machine learning; NLP/text mining; Large language model	Construction accident records/reports	Accident prediction
R027	Seo et al. (2026)	Construction Accident Prediction via Generative AI and AutoML Approaches	Generative AI; AutoML Generative AI and AutoML approaches	Construction accident/safety data	Accident prediction
R028	Q. Wang et al. (2026)	Construction Safety Risk Prediction Using SAE-SMOTE Data Augmentation and Adaptive Weighted Naive Bayes	Traditional machine learning; Deep learning; Hybrid model	Safety/risk indicator data	Safety leading indicators; Site risk assessment
R029	J. Wang et al. (2026)	Classifying construction accident reports with parameter-efficient fine-tuned LLMs and ensemble methods	NLP/text mining; Hybrid model; Large language model	Accident reports; OSHA or national safety database; Text narratives; Mixed data	Accident prediction; NLP/text mining of accident reports
R030	Wang et al. (2025)	Classifying OSHA construction accident reports: leveraging	NLP/text mining; Hybrid model;	Accident reports; OSHA or	Accident prediction; NLP/text mining of

ID	Study citation	Title	Technique category	Data source type	Safety domain
		ensemble learning and lightweight large language models (l-LLMs)	Large language model	national safety database; Text narratives; Mixed data	accident reports
R031	Q. Fang et al. (2018)	Detecting non-hardhat-use by a deep learning method from far-field surveillance videos	Deep learning; Computer vision	Video/CCTV/drone footage	PPE detection; Safety compliance monitoring
R032	W. Fang et al. (2018)	Falls from heights: A computer vision-based approach for safety harness detection	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection; Fall-risk or work-at-height detection
R033	Fang et al. (2019)	A deep learning-based approach for mitigating falls from height with computer vision: Convolutional neural network	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Fall-risk or work-at-height detection; Site risk assessment
R034	Nath et al. (2020)	Deep learning for site safety: Real-time detection of personal protective equipment	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection
R035	Delhi et al. (2020)	Detection of Personal Protective Equipment Compliance on Construction Site Using Computer Vision Based Deep Learning Techniques	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection; Safety compliance monitoring
R036	Tang et al. (2020)	Human-object interaction recognition for automatic construction site safety inspection	Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Automatic construction safety inspection
R037	Fang et al. (2020)	Knowledge graph for identifying hazards on construction sites: Integrating computer vision with ontology	Computer vision	Image dataset	Hazard detection
R038	Han and Zeng (2022)	Deep Learning-Based Workers Safety Helmet Wearing Detection on Construction Sites Using Multi-Scale Features	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection
R039	Wang et al. (2021)	Fast Personal Protective Equipment Detection for Real Construction Sites Using Deep Learning Approaches	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection
R040	Cheng et al. (2022)	Vision-based monitoring of site safety compliance based on worker re-identification and personal protective equipment classification	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection; Safety compliance monitoring
R041	Li et al. (2022)	Standardized use inspection of workers' personal protective equipment based on deep learning	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection
R042	Hayat and Morgado-Dias (2022)	Deep Learning-Based Automatic Safety Helmet Detection System for Construction Safety	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection
R043	Y.-R. Lee et al. (2023)	Real-time vision-based safety helmet detection using deep learning in construction sites	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection; Safety compliance monitoring

ID	Study citation	Title	Technique category	Data source type	Safety domain
R044	Lo et al. (2023)	Real-Time Personal Protective Equipment Compliance Detection Based on Deep Learning Algorithm	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection; Safety compliance monitoring
R045	Ferdous and Ahsan (2022)	PPE detector: A YOLO-based architecture to detect personal protective equipment for construction sites	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection
R046	J. Lee and Lee (2023)	Construction Site Safety Management: A Computer Vision and Deep Learning Approach	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Construction site safety management
R047	Alateeq et al. (2023)	Construction Site Hazards Identification Using Deep Learning and Computer Vision	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Hazard detection
R048	Wen et al. (2024)	Automated construction safety reporting system integrating deep learning-based real-time advanced detection and visual question answering	Deep learning; Computer vision	Safety inspection records; Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection
R049	Liu et al. (2024)	Multi-Task Intelligent Monitoring of Construction Safety Based on Computer Vision	Deep learning; Computer vision	Video/CCTV/drone footage	Unsafe behaviour detection
R050	Mohy et al. (2025)	Deep Learning Enabled Computer Vision Model for Automated Safety Compliance in Construction Environments	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Safety compliance monitoring
R051	López et al. (2025)	Automated PPE compliance monitoring in industrial environments using deep learning-based detection and pose estimation	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection; Safety compliance monitoring
R052	Park et al. (2024)	Preventing falls from floor openings using quadrilateral detection and construction worker pose-estimation	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Hazard detection; Fall-risk or work-at-height detection; Site risk assessment
R053	Xu and Huang (2023)	A novel computer vision-based approach for monitoring safety harness use in construction	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	PPE detection
R054	Karatas (2025)	Deep learning-based system for prediction of work at height in construction site	Deep learning; Wearable-sensor analytics	Wearable sensor data; Physiological data; Mixed data	Fall-risk or work-at-height detection; Site risk assessment
R055	Pan et al. (2025)	Enhancing Construction Safety: A Computer Vision Approach for Proactive Near-Miss Events Identification	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Hazard detection; Near-miss detection
R056	Shin and Kim (2022)	A Vision-Based Collision Monitoring System for Proximity of Construction Workers to Trucks Enhanced by Posture-Dependent Perception and Truck Bodies' Occupied Space	Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Equipment/vehicle/struck-by hazard detection
R057	H. Kim et al. (2023)	Real-Time Struck-By Hazards Detection System for Small- and Medium-Sized Construction Sites Based on Computer Vision Using Far-Field Surveillance Videos	Deep learning; Computer vision	Video/CCTV/drone footage	Hazard detection; Equipment/vehicle/struck-by hazard detection

ID	Study citation	Title	Technique category	Data source type	Safety domain
R058	D. Kim et al. (2019)	Remote proximity monitoring between mobile construction resources using camera-mounted UAVs	Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Proximity monitoring/collision prevention
R059	Son and Kim (2021)	Integrated worker detection and tracking for the safe operation of construction machinery	Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Worker detection/tracking near machinery
R060	Lu et al. (2023)	Automated detection of dangerous work zone for crawler crane guided by UAV images via Swin Transformer	Deep learning; Computer vision	Image dataset	Dangerous work-zone detection; crane safety
R061	Mei et al. (2023)	Human Intrusion Detection in Static Hazardous Areas at Construction Sites: Deep Learning-Based Method	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Hazard detection; Safety compliance monitoring
R062	Hou et al. (2023)	Computer vision-based safety risk computing and visualization on construction sites	Computer vision; Hybrid model	Image dataset; Video/CCTV/drone footage; Mixed data	Safety compliance monitoring; Site risk assessment
R063	Wang and El-Gohary (2024)	Few-shot object detection and attribute recognition from construction site images for improved field compliance	Computer vision	Image dataset	Safety compliance monitoring
R065	Ma et al. (2026)	A Real-Time High-Accuracy Framework for Small-Scale PPE Detection in Complex Construction Environments	Deep learning; Computer vision	Image dataset	PPE detection; Safety compliance monitoring
R066	Khosiin et al. (2026)	Graph-Based Human-Object Interaction Detection for Automated Worker Accountability Monitoring on Construction Sites	Deep learning; Computer vision; Hybrid model	Image dataset; Video/CCTV/drone footage; Mixed data	Unsafe behaviour detection; Safety compliance monitoring
R067	Sahraoui et al. (2026)	Automated Hazard Detection in Construction Sites Using Vision-Language Models	Computer vision; NLP/text mining; Multimodal AI; Large language model	Image dataset; Text narratives; Mixed data	Hazard detection
R068	Malokar and S (2025)	Vision Based PPE Detection Using Deep Learning Algorithms	Deep learning; Computer vision	Image dataset	PPE detection; Safety compliance monitoring
R069	Azizi et al. (2024)	Comparison of machine learning approaches for robust and timely detection of PPE in construction sites	Deep learning; Computer vision	Image/video dataset	PPE detection; Safety compliance monitoring
R070	B. Lee et al. (2023)	Determination of workers' compliance to safety regulations using a spatio-temporal graph convolution network	Deep learning; Computer vision	Video/CCTV/drone footage	Unsafe behaviour detection; Safety compliance monitoring
R071	Li et al. (2020)	Deep Learning-Based Safety Helmet Detection in Engineering Management Based on Convolutional Neural Networks	Deep learning; Computer vision	Image dataset	PPE detection
R072	Huang et al. (2021)	Detection algorithm of safety helmet wearing based on deep learning	Deep learning; Computer vision	Image dataset	PPE detection; Safety compliance monitoring
R075	Ahmed et al. (2023)	Personal Protective Equipment Detection: A Deep-Learning-Based Sustainable Approach	Deep learning; Computer vision	Image dataset	PPE detection; Safety compliance monitoring
R077	Lee et al. (2021)	A deep learning-based approach for detecting safety harness in construction sites	Deep learning; Computer vision; Wearable-sensor analytics	Image dataset; Video/CCTV/drone footage;	PPE detection; Fall-risk or work-at-height detection; Site risk assessment

ID	Study citation	Title	Technique category	Data source type	Safety domain
				Mixed data	
R078	Duan et al. (2023)	Risk events recognition using smartphone and machine learning in construction workers' material handling tasks	Traditional machine learning; Wearable-sensor analytics	Wearable sensor data; Physiological data; Mixed data	Unsafe behaviour detection; Worker fatigue or physiological risk detection; Site risk assessment
R079	Kurniawan et al. (2026)	Optimizing Construction Site Safety with AI-Powered Detection in Indonesian Civil Engineering Projects	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Hazard detection; Safety compliance monitoring
R080	Pujari et al. (2024)	Integrating IoT and Machine Learning for Enhanced Construction Safety Management	Traditional machine learning; IoT-based safety analytics	BIM/digital twin/site monitoring data; Mixed data	Safety leading indicators; Site risk assessment
R081	Antwi-Afari et al. (2022)	Deep learning-based networks for automated recognition and classification of awkward working postures in construction using wearable insole sensor data	Deep learning; NLP/text mining; Wearable-sensor analytics	Wearable sensor data; Physiological data; Mixed data	Unsafe behaviour detection; Worker fatigue or physiological risk detection; Site risk assessment
R082	Duan et al. (2022)	SODA: A large-scale open site object detection dataset for deep learning in construction	Deep learning; Computer vision	Image dataset	Hazard detection; Equipment/vehicle/struck-by hazard detection
R083	S. Kim et al. (2023)	Small object detection system for comprehensive construction site safety monitoring	Deep learning; Computer vision	Image dataset; Video/CCTV/drone footage; Mixed data	Hazard detection; PPE detection; Safety compliance monitoring; Equipment/vehicle/struck-by hazard detection