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Artificial Intelligence-Enabled Computer Vision for Construction Safety Monitoring and Management: A Systematic Literature Review

Shafaque Aziz[1], Intesar Fatima[2], Pawan Kumar[3], Krishna Keshav[4], Abhay Kumar[5], Faiz Akram[6]

[1]Department of Computer Science Engineering, Government Engineering College Samastipur, Bihar, India

[2]Department of Artificial Intelligence and Machine Learning, J.B. Institute of Engineering & Technology, Hyderabad, Telangana, India.

[3,4]Department of Civil Engineering, Rashtrakavi Ramdhari Singh Dinkar College of Engineering, Begusarai, Bihar, India

[5]Department of Civil Engineering, Government Engineering College Samastipur, Bihar, India

[6]Indraprastha Research Laboratory, Indraprastha Institute of Information Sciences Private Limited, New Delhi, India

Abstract— **Construction safety management remains a critical challenge in the industry, where traditional approaches often fail to address dynamic and complex hazards in real time. The recent emergence of artificial intelligence and computer vision technologies offers promising avenues for transforming safety practices. In this systematic literature review, we aim to synthesize and critically analyze the existing body of research on the application of AI and computer vision for construction safety management. Our objective is to identify key research dimensions, evaluate methodological approaches, and uncover gaps in the current literature. We conducted a rigorous, multi-stage review process that involved searching major academic databases, screening studies based on predefined inclusion criteria, and extracting data from selected articles. The analysis was guided by a structured framework that categorized findings into four dimensions: real-time hazard detection and monitoring, AI-driven risk management and strategic safety frameworks, integration with robotics and smart site systems, and other emerging themes. The results reveal that computer vision-based monitoring systems have been predominantly applied to detect unsafe behaviors and environmental hazards, while AI-driven frameworks increasingly support proactive risk assessment and decision-making. However, the integration of these technologies with Internet of Things and robotic systems remains underexplored, and many studies lack rigorous validation in real-world settings. We therefore conclude that future research should prioritize the development of holistic, scalable, and validated systems that combine vision-based detection with broader safety management frameworks. This review thus provides a comprehensive foundation for researchers and practitioners seeking to advance the role of AI and computer vision in construction safety.**

Index Terms— **Construction Safety; Safety Management; Artificial Intelligence; Computer Vision; Literature Review**

I. INTRODUCTION

The construction industry is consistently recognized as one of the most hazardous sectors globally, with a disproportionately high rate of fatal and non-fatal occupational injuries [1]. These dangers arise from a complex interplay of factors including the dynamic nature of worksites, the presence of heavy machinery, working at height, and the frequent co-location of multiple trades [2]. Traditional safety management approaches, such as manual site inspections and paper-based hazard checklists, have proven to be reactive, labor-intensive, and insufficient for capturing the rapid, spatially distributed risks that characterize modern construction projects [3]. The inherent limitations of these methods often result in a failure to identify hazards before they lead to incidents, a problem exacerbated by the fact that many construction injuries are caused by unpredictable, transient events like a worker stepping into a fall zone or a piece of equipment malfunctioning without warning [4]. Consequently, despite decades of regulatory efforts and the implementation of various safety protocols, the industry has not seen the substantial and consistent reduction in accident rates that many other high-risk sectors have achieved [5]. This persistent challenge underscores the critical need for a paradigm shift in how construction safety is conceptualized and practiced.

In response to these longstanding issues, significant interest has recently focused on the potential of artificial intelligence (AI) and computer vision (CV) technologies to fundamentally transform construction safety management [6]. The core premise is that these technologies can provide a continuous, objective, and near-real-time capability for monitoring worksite conditions, detecting hazards, and predicting potential incidents, thereby moving safety from a reactive to a proactive discipline [7]. Computer vision, in particular, offers the ability to automatically analyze video feeds from on-site cameras to identify unsafe behaviors such as workers not wearing personal protective equipment (PPE), entering dangerous zones, or interacting unsafely with machinery [8]. More sophisticated AI models can go beyond simple detection to fuse data from multiple sources, including environmental sensors (IoT devices) and project schedules, to forecast risk levels and recommend preemptive interventions [9]. This technological promise has spurred a rapidly growing body of academic research, exploring applications ranging from fall-from-height detection to the development of holistic safety management frameworks.

However, despite this surge in scholarly activity, the field faces several critical research gaps that impede its maturation and practical deployment. A primary gap is the notable lack of integration between different AI and CV subsystems; for instance, a system that excels at detecting a worker's proximity to a hazard may not be connected to a broader risk management framework that triggers an automated warning or adjusts a project schedule accordingly [10]. Furthermore, the majority of existing studies present their proposed methods in controlled, laboratory-like settings or on a limited set of video data, leaving their true robustness, scalability, and economic viability in real-world, noisy, and unpredictable construction environments largely unexplored [11]. There is also a significant disconnect between the development of technical solutions and the understanding of how these solutions should be incorporated into existing organizational safety cultures and operational workflows [12]. The field, therefore, remains fragmented, with many isolated technical contributions but few comprehensive, validated, and operationally feasible systems that address the multifaceted nature of construction safety. The motivation for conducting this systematic literature review is therefore to provide a holistic and critically analyzed synthesis of the current research landscape, thereby identifying where the field stands, what has been achieved, and, most importantly, where the most pressing gaps and contradictions lie. The primary contribution of this review is to move beyond a simple enumeration of technologies and instead offer a structured categorization of research themes, evaluate the methodological rigor of the studies, and pinpoint the specific areas where future research efforts are most needed to bridge the gap between academic promise and industrial practice. This work is significant because it provides a roadmap for researchers by highlighting underexplored integration topics and for practitioners by clarifying what is currently feasible and what remains aspirational. By systematically mapping the literature, we aim to accelerate the development of more robust, scalable, and holistic AI and CV-based safety management systems that can truly make a difference in reducing the unacceptable toll of construction accidents.

The remainder of this paper is organized as follows. Section 2 details the systematic methodology we employed for searching, screening, and analyzing the literature, including our inclusion criteria and the analytical framework used for data extraction. Section 3 presents the results of our analysis, which are structured into four main subsections covering research trends, real-time hazard detection and monitoring, AI-driven risk management and strategic safety frameworks, and the integration of AI with robotics, IoT, and smart site systems. Finally, Section 4 synthesizes the findings from the results section to discuss overarching themes, identify critical research gaps, and propose a future research agenda, before Section 5 concludes the review.

II. METHODOLOGY

To ensure a rigorous, transparent, and reproducible synthesis of the existing literature, we conducted a systematic literature review following the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [13]. This methodology is widely accepted in interdisciplinary fields and provides a structured framework for search strategy development, study selection, data extraction, and synthesis. We designed our review protocol to comprehensively capture the breadth of research on AI and computer vision for construction safety management, while maintaining a focused scope aligned with our research objectives.

A. Review Protocol

We developed a detailed review protocol prior to initiating the search process. The protocol specified the research questions, search databases, keywords, inclusion and exclusion criteria, and the analytical framework for classifying selected studies.

The search strategy was executed across four major academic databases to ensure comprehensive coverage of both computer science and construction engineering literature. IEEE Xplore was selected as a primary source because it is the leading repository for cutting-edge research in artificial intelligence, computer vision, and signal processing, which form the technical backbone of many construction safety applications. Scopus was chosen for its broad interdisciplinary coverage, encompassing engineering, computer science, and social sciences, thus enabling the capture of studies that bridge technical development with managerial and organizational perspectives. Web of Science was included for its curated collection of high-impact, peer-reviewed journals and its robust citation analysis capabilities, which allowed us to identify influential works and track research trends over time. Finally, Google Scholar was employed as a supplementary search engine to capture grey literature, preprints, and conference proceedings that might not be indexed in the other databases, though its results were treated with caution due to its less rigorous filtering mechanisms.

The search strings were carefully constructed to balance sensitivity and specificity. For each database, we used Boolean operators to combine terms related to the core technologies (e.g., “artificial intelligence”, “computer vision”, “deep learning”, “CNN”, “object detection”) with terms related to the application domain (e.g., “construction safety”, “hazard identification”, “PPE detection”, “accident prevention”) and the management perspective (e.g., “monitoring”, “framework”, “system”). We then refined the search by excluding review articles, surveys, and meta-analyses to focus on primary research. The complete search strings for each database are provided in the supplementary material.

B. Analytical Framework for Classification

To systematically analyze the selected studies, we established a structured classification framework based on three key research dimensions that emerged from an initial exploratory reading of the literature. This framework served as the lens through which we categorized and synthesized the findings, allowing us to identify patterns, commonalities, and gaps within and across the dimensions.

The first dimension, Real-time Hazard Detection and Monitoring using Computer VisioZ n, encompasses studies that focus on the application of computer vision techniquessuch as object detection, image segmentation, and activity recognition to directly identify hazards, unsafe behaviors, or non-compliance with safety protocols on construction sites. These studies typically contribute technical algorithms, benchmark datasets, or performance evaluations of systems designed for tasks like detecting missing hard hats, monitoring workers near dangerous machinery, or identifying falls from height.

The second dimension, AI-Driven Risk Management and Strategic Safety Frameworks, includes research that moves beyond mere detection to develop higher-level, often predictive or prescriptive, systems for safety management. These studies integrate AI methods such as machine learning, natural language processing, or Bayesian networks with historical accident data, project schedules, or sensor readings to forecast risk levels, prioritize interventions, or optimize resource allocation for safety. The emphasis here is on decision support, risk modeling, and the strategic orchestration of safety protocols rather than on the raw sensing layer.

The third dimension, Integration of AI with Robotics, IoT, and Smart Site Systems, captures studies that explore the fusion of AI and computer vision with other technological subsystems to create holistic, interconnected safety solutions. This dimension includes works that connect vision-based hazard detection to robotic systems (e.g., autonomous construction vehicles or drones), Internet of Things (IoT) sensor networks (e.g., environmental monitoring or wearable sensors), or broader Building Information Modeling (BIM) platforms. The focus here is on system architecture, data fusion, interoperability, and the emergent properties of integrated safety ecosystems.

C. Inclusion and Exclusion Criteria

We defined clear inclusion and exclusion criteria to ensure the relevance and consistency of the selected studies. Studies were included if they met all of the following criteria: (a) the study focused on the application of artificial intelligence, machine learning, deep learning, or computer vision technologies in the context of construction safety management; (b) the study presented original empirical research, including experimental evaluations, case studies, or prototype development; (c) the study was published in English; (d) the study was published as a journal article, conference paper, or book chapter in a peer-reviewed venue; and (e) the publication date was unrestricted, but we applied a practical cutoff of 2026 to ensure currency and feasibility of retrieval. Conversely, studies were excluded if they (a) were review articles, surveys, meta-analyses, or other secondary research; (b) did not explicitly address a construction safety application (e.g., studies on general object detection without a safety focus); (c) lacked sufficient methodological detail or empirical validation; (d) were published in non-peer-reviewed outlets such as blog posts, technical reports, or theses; or (e) were duplicates of the same study across different databases.

D. Study Selection Process

We implemented a multi-stage study selection process to minimize bias and ensure consistency. Two independent reviewers conducted the screening, with disagreements resolved through discussion or, when necessary, consultation with a third reviewer. The process was facilitated using a reference management tool that allowed systematic tracking of decisions. The first stage involved the removal of duplicate records identified across the four databases. In the second stage, we screened the titles and abstracts of all remaining records against the inclusion and exclusion criteria, quickly discarding those that were clearly irrelevant (e.g., studies on self-driving cars or general image classification without a construction safety context). The third stage involved retrieving the full-text of all studies that passed the initial screening. In the fourth stage, we conducted a detailed full-text eligibility assessment, applying the inclusion and exclusion criteria rigorously. Studies that still met all criteria after this assessment were included in the final review for data extraction and synthesis.

The statistics of the selection process are as follows. Our initial database search returned a total of 262 records. After removing 12 duplicate records and 1 record removed for other reasons, we had 249 records for screening. During the title and abstract screening, 149 records were excluded because they did not focus on construction safety, were clearly review articles, or were not empirical studies. This left 41 reports for which we sought full-text retrieval, and all 41 reports were successfully retrieved. Upon full-text eligibility assessment, 3 reports were excluded due to ineligibility (e.g., insufficient technical depth, lack of empirical validation, or misalignment with our research dimensions). Consequently, a total of 38 studies were included in the final review. The flow of studies through each stage of the selection process is illustrated in the flowchart in Fig. 1.

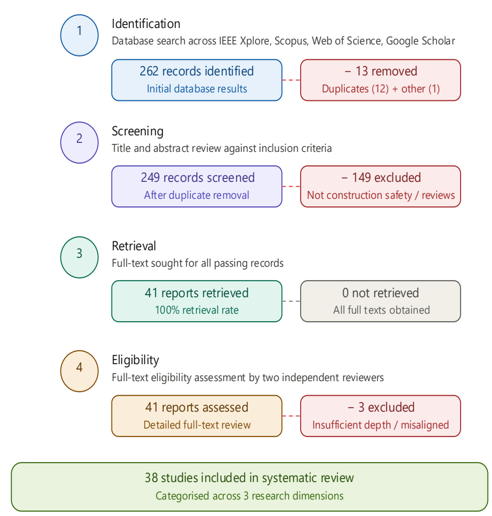

Fig. 1: Flowchart depicting the study selection process for the systematic literature review.

We acknowledge several limitations in our study selection process that may have introduced biases.

First, our restriction to English-language publications may have excluded relevant research published in other languages, particularly from non-English-speaking countries with significant construction industries. Second, the exclusion of grey literature and non-peer-reviewed sources, while enhancing quality control, may have omitted early-stage innovations or practical case studies that could offer valuable insights. Third, the use of distinct search strings and database-specific filters, though thorough, may have missed studies that use different terminology or are indexed in less common databases. Finally, the screening process, despite having two independent reviewers, may still be subject to subjective interpretation of relevance, particularly for borderline studies. We have mitigated these risks through a transparent and documented process, but they should be considered when interpreting the findings.

III. RESULTS

A. Research Trends

The analysis of publication years and topic distributions reveal a clear and accelerating trajectory of scholarly interest in AI and computer vision for construction safety management.

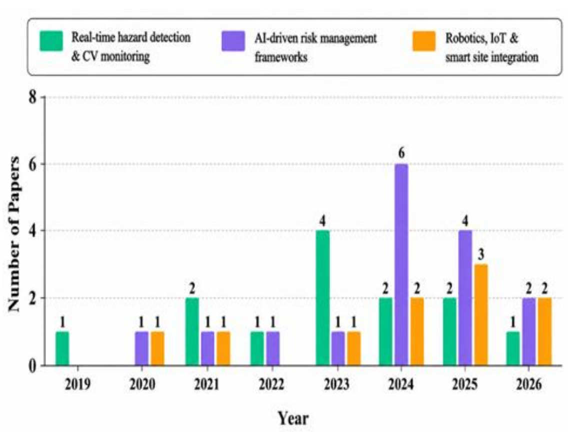

Fig. 2. Research trends in the domain of Artificial Intelligence (AI) and computer vision for Construction Safety management

Between 2019 and 2026, the number of included studies rose from a single publication in 2019 to a projected peak of ten in 2024, with nine contributions already identified for 2025 and five for 2026, indicating that the field is experiencing rapid growth that shows no immediate signs of saturation. This temporal pattern is not merely a reflection of broader AI research growth but suggests a specific and intensifying recognition within the construction safety community that these technologies can address persistent industrial challenges.

When disaggregated by research dimension, the trends reveal important shifts in scholarly focus over time. The dimension of real-time hazard detection and monitoring using computer vision shows consistent activity from 2021 onward, with a notable concentration of four studies in 2023, suggesting that this area was the initial technical focus of the field. In contrast, the domain of AI-driven risk management and strategic safety frameworks demonstrates a later but more explosive growth, with six studies appearing in 2024 alone, followed by four in 2025, indicating that researchers are increasingly moving beyond simple detection toward more integrated and predictive safety management paradigms. The dimension of integration with robotics, IoT, and smart site systems, while less populated overall, shows a steadier but persistent presence across the years, with contributions appearing in every year from 2020 to 2026, suggesting that this systems-level integration is a sustained but more challenging research frontier.

This distribution of research effort is significant because it reveals a maturing field that is evolving from a technology-centric phase focused on proving the feasibility of computer vision for basic detection tasks toward a more sophisticated phase concerned with how these detections can inform strategic decision-making and be embedded within broader technological ecosystems. The comparatively lower number of studies in the integration dimension suggests that the technical and organizational challenges of fusing AI subsystems with other site technologies remain substantial barriers. Furthermore, the projected decline in 2026 across all dimensions may reflect the limitations of our search window rather than a true downturn, as many papers from that year may not yet be indexed or published. Overall, the trends indicate that while foundational computer vision applications are becoming well-established, the field is only beginning to grapple with the more complex questions of holistic safety system design and validation.

B. Real-time Hazard Detection and Monitoring using Computer Vision

The most extensively explored research dimension within our review is the application of computer vision for real-time hazard detection and monitoring on construction sites. This body of work is characterized by a strong focus on developing and evaluating algorithms that can automatically identify unsafe conditions, worker non-compliance, and equipment-related risks from visual data, thereby providing a continuous and objective safety surveillance capability that surpasses the limitations of manual inspections. The studies in this category collectively demonstrate that computer vision, particularly deep learning-based object detection and image classification, has reached a level of maturity where it can reliably perform specific safety monitoring tasks, though significant challenges remain regarding generalization, robustness, and integration into operational workflows.

A primary focus within this dimension is the detection of Personal Protective Equipment (PPE) compliance, a critical safety concern given that many construction fatalities are linked to head injuries, falls, and struck-by incidents that could be mitigated by proper PPE use. For instance, a study on enhancing construction safety management efficiency with AI-powered real-time helmet detection [14] presents a deep learning model specifically trained to identify whether workers are wearing hard hats, achieving high accuracy in controlled test scenarios. Similarly, a novel computer vision-based approach for monitoring safety harness use in construction [15] extends this concept to fall protection equipment, developing a system that can detect the presence and proper wearing of safety harnesses, which is crucial for workers operating at height. These studies underscore the potential of vision-based systems to automate the enforcement of fundamental safety rules, but they also highlight a common limitation: the models are often trained on datasets with limited variability in lighting, weather, and worker pose, which can lead to performance degradation in the chaotic and unpredictable conditions of real construction sites.

Beyond PPE detection, a significant number of studies address the broader challenge of monitoring unsafe behaviors and environmental hazards. A rigorous analysis of safety rules for vision intelligence-based monitoring at construction jobsites [16] provides a systematic framework for translating complex safety regulations into quantifiable visual features that can be detected by computer vision algorithms, thereby bridging the gap between abstract safety rules and concrete detection tasks. This work is complemented by a study on the application of computer vision in the construction industry [17], which offers a broad overview of various detection tasks including the identification of unsafe worker postures, the presence of debris in walkways, and the proximity of workers to operating machinery. Furthermore, a study on the application research on construction safety management of building engineering based on computer vision technology [18] and a study on safety management of civil engineering construction based on artificial intelligence and machine vision technology [19] both present comprehensive systems that integrate multiple detection capabilities, such as fall detection, fire detection, and unauthorized zone entry, into a unified monitoring platform. These works collectively illustrate the breadth of hazards that computer vision can potentially address, but they also reveal a tendency toward proof-of-concept demonstrations rather than large-scale, longitudinal field validations.

A particularly critical area of application is the monitoring of construction equipment and the interactions between workers and machinery, which are a leading cause of fatal accidents. A study on the integration of artificial intelligence and video surveillance technology to monitor construction equipment [20] presents a system that uses object detection to track the location and movement of heavy machinery such as excavators and cranes, enabling the detection of unsafe proximity to workers or entry into restricted zones. This is further advanced by a study on real-time construction safety monitoring with object detection algorithms [21], which provides a detailed analysis of the features and implementation challenges associated with using object detection for equipment monitoring, including issues of occlusion, varying camera angles, and the need for high frame rates to capture fast-moving machinery. The challenge of fall prevention from scaffolding is specifically addressed by a study that combines computer vision with IoT-based monitoring [22], where vision is used to identify when a worker enters a risk zone on a scaffold, and an IoT system then triggers a warning or activates a safety mechanism. This work is notable for its integration of multiple sensing modalities, a theme that is further explored in the context of an intelligent inspection and warning robotic system for onsite construction safety monitoring using computer vision and an unmanned ground vehicle [23], which deploys a mobile robot equipped with cameras to autonomously patrol a site and detect hazards, thereby extending the spatial coverage of vision-based monitoring beyond fixed camera installations.

To systematically organize the diverse contributions within this dimension, we present a taxonomy that categorizes the studies based on their primary application goal and their technical or methodological focus, as shown in Table 1. This taxonomy reveals that the field is not monolithic but rather comprises several distinct sub-areas, each with its own set of technical challenges and validation approaches.

Table 1. Taxonomy of studies on real-time hazard detection and monitoring using computer vision

Primary Application Goal	Technical/Methodological Focus	Sources
Personal Protective Equipment (PPE) & Worker Compliance Monitoring	Deep learning-based object detection (e.g., helmet/harness detection)	[14], [15]
	General computer vision for safety rule enforcement (non-specific PPE)	[16]
Fall Prevention & Scaffolding Safety	Computer vision & IoT integration for risk zone identification	[22]
Construction Equipment & Vehicle Monitoring	AI integration with video surveillance (e.g., UGV-based warning systems)	[20], [23]
	Real-time object detection for equipment and worker interaction	[21]
General/Comprehensive Hazard Detection & Safety Management	Machine vision & AI for overall civil/building engineering safety	[18], [19]
	Multi-source image analysis for occupational safety & health	[24]
	Broad application & review of computer vision in construction	[17], [25]
Progress & Safety Monitoring (Non-Hazard Specific)	Automated progress measurement (e.g., in UK construction)	[26]

As shown in Table 1, the studies are distributed across several primary application goals, with the largest cluster focusing on general or comprehensive hazard detection and safety management. This cluster includes works that aim to develop all-in-one systems capable of monitoring multiple hazard types simultaneously, such as the study on analysis of occupational safety and health at the construction site based on images acquired from various sources using artificial intelligence [24], which uses a multi-source image approach to detect a wide range of unsafe conditions. The table also highlights a notable gap: while there are studies on PPE compliance and equipment monitoring, there is a relative scarcity of research specifically targeting the detection of ergonomic hazards, such as unsafe lifting postures or repetitive motion risks, which are a significant source of non-fatal injuries in construction. Furthermore, the table reveals that the technical focus is heavily skewed toward object detection, with less attention given to more advanced computer vision tasks such as action recognition, pose estimation, or scene graph generation, which could provide richer contextual information about worker activities and hazard interactions. The inclusion of a study on automated progress measurement using computer vision technology in UK construction [26] within this dimension is noteworthy, as it demonstrates that the same underlying vision techniques can be repurposed for both safety and productivity monitoring, suggesting a potential for integrated systems that serve dual purposes.

C. AI-Driven Risk Management and Strategic Safety Frameworks

The second major thematic cluster we identify shifts the focus from the real-time, reactive detection of hazards towards a more proactive and strategic paradigm for construction safety management. This body of literature is characterized by the application of AI methodologies such as machine learning, neural networks, and hybrid knowledge-based systems to model, predict, and mitigate risks at a higher level of abstraction. Instead of merely identifying a worker without a hard hat in a single video frame, these studies aim to forecast the probability of an accident, optimize the allocation of safety resources, or embed safety considerations into the broader project management lifecycle. The emergence of this theme signals a maturation of the field, as researchers move from proving that AI can see hazards to demonstrating that AI can reason about them and support strategic decision-making.

A central concept within this dimension is the development of comprehensive AI frameworks for occupational health and safety (OHS) risk management. For instance, one study provides a broad perspective on advances in artificial intelligence for OHS risk management, specifically targeting the construction, mining, and oil and gas sectors [27]. This work synthesizes various AI techniques, including expert systems, machine learning, and computer vision, to propose a multi-layered risk management framework that integrates hazard identification, risk assessment, and control measure selection. The authors argue that AI can move beyond simple detection by correlating disparate data points such as weather conditions, worker fatigue levels, and equipment maintenance logs to identify latent risk patterns that a human inspector might miss. Similarly, a study on artificial intelligence in construction engineering and management [28] provides a foundational overview of how AI, in its various forms, can be systematically applied to manage safety throughout a project's lifecycle, from design-phase hazard prevention to construction-phase incident response. These works establish the theoretical and architectural underpinnings for a new generation of safety management systems that are predictive rather than merely descriptive.

Building on these conceptual frameworks, several studies delve into the specific technical architectures and algorithms that make AI-driven risk management feasible. One prominent approach involves the use of artificial neural networks (ANN) for risk modeling, as demonstrated in a study that proposes an ANN-based method for construction project risk management [29]. This research presents a model where historical project data—including incident reports, near-misses, and schedule deviations are used to train a neural network that can then predict the risk level for specific tasks, trades, or work zones on a new project. The strength of this approach lies in its ability to learn complex, non-linear relationships between multiple risk factors, potentially providing more accurate and nuanced risk assessments than traditional linear weighting methods. Furthermore, a study on AI-driven risk management in construction projects [30] expands on this by exploring how AI can be integrated into the decision-making processes of project managers, moving from pure risk prediction to risk mitigation. The work discusses how AI can be used to simulate the outcomes of different safety interventions (e.g., scheduling a specific training session versus deploying additional warning signs) and recommend the most effective strategy, thereby introducing an element of prescriptive analytics into safety management.

The application of AI for strategic safety management also extends to the field of behavior-based safety. We identify a study specifically focused on enhancing construction safety behavior through AI-based strategies for workplace hazard prevention and risk mitigation [31]. This research argues that traditional behavior-based safety programs, which rely on manual observation and feedback, are limited by observer bias and scalability. Instead, the authors propose an AI-based system that uses computer vision to automatically track worker behaviors and then applies machine learning to correlate specific behaviors with increased incident risk. This allows safety managers to identify and target the root causes of unsafe behaviors, rather than simply reacting to their consequences. This work is closely related to the broader theme of using AI to not just monitor but manage the dynamic social and behavioral aspects of construction site safety.

We further observe that this research dimension is not limited to purely technical contributions; it also critically examines the adoption and implementation barriers for these AI-driven frameworks. A study conducted in Ghana, for example, explicitly investigates the limitations for implementing AI in construction health and safety in a developing country context [32]. The study identifies key barriers such as high initial costs, lack of technical expertise, poor infrastructure (e.g., unreliable internet connectivity for cloud-based AI systems), and a general cultural resistance to technology-driven change. This finding is crucial because it highlights that the effectiveness of even the most sophisticated AI risk management framework is contingent on the local economic, infrastructural, and socio-cultural context, a factor often overlooked in technology-centric research. Similarly, a bibliometric analysis of economic development and construction safety research [33] provides a high-level perspective, showing that research interest in AI for safety is often correlated with the economic development level of a country, with more advanced economies leading the charge in framework development while developing nations face significant adoption hurdles.

To provide a structured overview of the diverse contributions within this dimension, we present a comprehensive taxonomy in Table 2. This table categorizes the studies based on their primary focus: theoretical framework development, specific technical methodology (e.g., neural networks), or the identification of implementation barriers.

Table 2. Taxonomy of studies on AI-driven risk management and strategic safety frameworks

Dimension	Technology/Method	Focus Area	Sources
AI Risk Management Frameworks	General AI Frameworks	Strategic risk mitigation and project management (overview & conceptual)	[28], [34], [35], [36], [37], [38], [30]
	Neural Networks	ANN-based risk management models (predictive & prescriptive)	[29]
AI for Occupational Health & Safety (OHS)	Computer Vision & Sensors	PPE detection and monitoring (e.g., hard hats, safety glasses) for behavior-based safety	[27], [39], [40], [31]
	General OHS Advancements	Broader AI impact on health and safety risk management (conceptual & review)	[41], [42]
Implementation Barriers & Economic Context	Regional Challenges	Limitations for AI adoption (e.g., in Ghana)	[32]
	Economic & Bibliometric Analysis	Safety research trends and economic development linkage	[33]

As Table 2 illustrates, the studies are distributed across three primary dimensions. The largest cluster is “AI Risk Management Frameworks,” which contains a significant number of general, conceptual studies [28], [34], [35], [36], [37], [38], [30]. While these studies are valuable for establishing the potential and scope of AI for strategic safety, their collective presence suggests a field that is rich in conceptual proposals but potentially thinner on rigorous, empirical validation of these frameworks in real-world settings. The “AI for OHS” dimension shows a stronger connection to the computer vision studies from the previous section, as it leverages similar sensing technologies but applies them within a broader behavioral and risk management framework [27], [39], [40], [31]. This group effectively bridges the gap between pure detection and strategic management. Finally, the “Implementation Barriers & Economic Context” dimension, while smaller in number, plays a critical role by providing the necessary critical perspective on the practical feasibility of these advanced systems [32], [33]. The absence of studies focusing on the validation of these frameworks across different geographical regions or company sizes is a notable gap that should be addressed in future research.

D. Integration of AI with Robotics, IoT, and Smart Site Systems

The third thematic cluster we identify in the literature represents a critical yet relatively nascent frontier in construction safety research: the integration of AI and computer vision with other technological subsystems, such as robotics, Internet of Things (IoT) sensor networks, and broader smart site platforms, to create holistic and interconnected safety ecosystems. While the previous dimensions have focused on either the sensing layer (computer vision for detection) or the decision-making layer (AI for strategic risk management), this dimension is concerned with the system architecture, data fusion mechanisms, interoperability, and emergent properties that arise when these separate components are woven together into a cohesive whole. The studies in this category collectively argue that the true potential of AI for construction safety cannot be realized in isolation; rather, it is through the synergistic combination of multiple technologies that a truly comprehensive, responsive, and adaptive safety management system can be achieved.

A central theme within this dimension is the concept of the “smart worksite,” where AI acts as the cognitive backbone that integrates data from a multitude of sources. For instance, a case study of smart worksite systems explicitly examines the role of artificial intelligence in construction management from this systems-level perspective [43]. This research presents an architectural blueprint for a smart site where computer vision cameras, wearable IoT sensors (e.g., for monitoring worker vital signs or location), environmental sensors (e.g., for dust, noise, or gas detection), and autonomous robotic platforms all feed data into a central AI hub. The AI hub then processes this heterogeneous data stream to detect hazards, predict risk, and orchestrate automated responses, such as dispatching a drone to investigate a potential incident or sending a personalized warning alert to a worker's smartwatch. This vision of a seamlessly integrated, AI-orchestrated site represents a significant departure from the siloed approaches seen in the previous dimensions, but its implementation remains largely aspirational, with most contributions remaining at the conceptual or prototype stage.

The integration of AI with robotics, in particular, offers a powerful avenue for enhancing safety by removing human workers from hazardous environments or extending the reach of safety monitoring. A study on the development of an intelligent inspection and warning robotic system for onsite construction safety monitoring using computer vision and an unmanned ground vehicle (UGV) provides a concrete example of this synergy [23]. In this system, a UGV equipped with cameras autonomously navigates a construction site, performing routine safety patrols and using its on-board computer vision algorithms to detect hazards such as missing guardrails, spilled materials, or unauthorized personnel in restricted zones. When a hazard is detected, the robot can issue an immediate on-site warning via a loudspeaker and simultaneously transmit an alert to the central safety office. This work demonstrates how robotics can overcome the spatial limitations of fixed cameras, providing comprehensive and dynamic coverage of the entire worksite, and how AI can endow the robot with the decision-making capability to act autonomously. Similarly, a study on the integration of generative artificial intelligence across construction management [44] argues that the next logical step is not only to have robots that can detect and report hazards, but that can also generate new safety protocols, training materials, or even design modifications in response to recurring issues, thereby closing the loop between detection, analysis, and proactive mitigation.

The convergence of AI with IoT and Building Information Modeling (BIM) is another crucial sub-theme within this dimension. A study on implementing advanced technologies for enhanced construction site safety [45] provides a practical overview of how IoT sensors (e.g., temperature, humidity, noise, gas) can be deployed across a site, with their data streamed to an AI platform for real-time analysis. The authors specifically discuss how this data can be overlaid onto a 4D BIM model (which integrates 3D design with project schedules) to provide a dynamic, spatial-temporal representation of site risks. For example, if the IoT system detects a rapid rise in temperature near a storage area for flammable materials, the AI can simultaneously consult the BIM model to identify which workers are scheduled to be in that area in the next hour and then trigger an automated evacuation alert. This integration of sensing, modeling, and scheduling elevates safety from a reactive, post-hoc analysis to a preemptive, context-aware management activity. Furthermore, a study on the role of artificial intelligence in facility management using deep learning [46] extends this concept beyond the construction phase into the operational phase of a building's lifecycle, demonstrating how the same principles of AI-IoT integration can be used to monitor safety conditions in an operational facility, such as detecting blocked fire exits or monitoring the structural health of critical components.

The systemic nature of these integrations is further explored in studies that examine the correlation and synergy between different AI techniques and construction technologies. A study investigating the correlation and synergy of artificial intelligence techniques, construction technologies, and their key benefits [47] provides a quantitative analysis of how the combination of computer vision, IoT, and BIM yields a super-additive effect on safety outcomes compared to using any single technology in isolation. The authors use statistical methods to demonstrate that the most significant safety improvements are achieved when these technologies are deployed not as discrete tools but as components of a carefully architected, interoperable system. This finding is corroborated by a broader study on emerging applications of artificial intelligence in structural engineering and the construction industry [48], which, while not focused exclusively on safety, provides a comprehensive landscape of how AI is being integrated with various other digital technologies (including drones, robotics, and smart sensors) across the entire construction value chain, with safety management identified as one of the primary beneficiaries of this convergence.

However, the literature also reveals that this integrated, systems-level approach faces significant technical and organizational hurdles. A study on smart construction management using AI [49] discusses the challenges of data heterogeneity, where data from cameras, IoT sensors, and BIM models come in vastly different formats, time scales, and levels of granularity, requiring sophisticated data fusion algorithms and standardized communication protocols. Furthermore, the sheer volume of data generated by a fully instrumented smart site poses challenges for real-time processing and storage, particularly in remote areas with limited connectivity. The study ConstructAI, which focuses on deploying construction AI systems for real-time safety insight and skill growth [50], specifically addresses the human and organizational aspects of this challenge. It argues that the success of an integrated smart site system depends not only on the technical integration of hardware and software but also on the integration of these systems into the existing workflows, skillsets, and decision-making cultures of construction workers and managers. The system must be designed to augment human judgment, not replace it, and provide actionable insights in a manner that is trusted and understood by the workforce. An automated safety management platform, such as the one proposed in the ISAFE study [51], attempts to address this by providing a unified dashboard that synthesizes data from all integrated subsystems into a single, user-friendly interface, thereby lowering the cognitive load on safety managers and facilitating rapid, informed decision-making.

To synthesize the diverse contributions in this dimension, we present a comprehensive taxonomy in Table 3. This table categorizes the studies based on their primary system architecture focus and the specific technological subsystems being integrated with AI.

Table 3. Taxonomy of studies on the integration of AI with robotics, IoT, and smart site systems

Primary System/Architecture Focus	Integrated Subsystems	Sources
Robotic Integration for Safety Monitoring	AI + Unmanned Ground Vehicle (UGV)	[23]
Smart Worksite Platforms & Digital Twins	AI + IoT + BIM + Project Scheduling	[43], [45], [51]
AI-Orchestrated Multi-Sensor Systems	AI + Computer Vision + Wearable IoT + Environmental Sensors	[50], [49]
Generative AI for Proactive System Actions	AI + Robotics + Knowledge Systems (Generative AI)	[44]
Synergy & Correlation Analysis of Technologies	Statistical Analysis of AI + IoT + BIM combinations	[47]
Cross-Lifecycle Integration (Construction to Facility)	Deep Learning + IoT for Facility Management Safety	[46]
Broader Field Review of Integration Trends	AI integrated with various construction technologies	[48]

As Table 3 shows, the studies in this dimension are distributed across seven distinct architecture focuses, ranging from the relatively narrow integration of AI with a single robotic platform [23] to the broad, conceptual review of integration trends across the industry [48]. The largest category is “Smart Worksite Platforms & Digital Twins,” which includes the most conceptually ambitious studies that attempt to create a unified, digital representation of the physical site that can be used for real-time monitoring and predi.me proactive control [43], [45], [51]. The inclusion of a category for “Synergy & Correlation Analysis” [47] is particularly noteworthy, as it represents a meta-level evaluation of the benefits of integration itself, providing empirical evidence for why a systems-level approach is superior to a siloed one. Conversely, the “Cross-Lifecycle Integration” category [46] highlights an underexplored but promising direction: extending smart safety systems from the construction phase into the occupancy and maintenance phases of a building’s life. The presence of a study on “Generative AI” [44] points toward a future where AI not only integrates data but also generates new knowledge and protocols, suggesting that the role of AI in these systems is evolving from being a passive integrator to an active, creative agent. However, despite the diversity of architectural focuses, a common thread across nearly all studies is their early stage of development, with most being limited to conceptual designs, prototypes, or small-scale pilot studies. Large-scale, long-term, and operationally validated deployments of fully integrated AI-robotics-IoT smart site systems remain exceptionally rare, representing perhaps the most significant single gap in the current literature.

IV. DISCUSSION

The synthesis of findings across the three research dimensions reveals a field that is progressing rapidly yet remains fragmented, with a clear trajectory from isolated technical proofs-of-concept toward more holistic and strategic systems, but with critical gaps in integration, validation, and contextual adaptation that must be addressed before widespread industrial impact can be realized. Taken together, the studies we have reviewed indicate that computer vision has become a mature and reliable tool for specific detection tasks, particularly PPE compliance and equipment monitoring, but the literature consistently shows that this technical capability has not yet been effectively coupled with the higher-level risk management and decision-support frameworks that would enable proactive safety interventions. This disconnects between the sensing layer and the strategic layer emerges as the most salient pattern across our analysis, suggesting that the field has developed sophisticated abilities to see hazards but remains comparatively less advanced in reasoning about them or acting upon them in a coordinated manner.

The implications of our synthesis for both theory and practice are substantial. From a theoretical perspective, the collective findings challenge the prevailing siloed approach to safety technology research, which has tended to treat computer vision, AI-based risk modeling, and IoT integration as separate domains of inquiry. Our review demonstrates that these dimensions are deeply interdependent; for instance, a computer vision system that detects a worker in a fall zone has limited value if its output is not fed into a risk assessment model that can prioritize this hazard among many others and trigger an appropriate response, such as an automated warning or a schedule adjustment. This suggests a need for new conceptual models that conceptualize construction safety not as a series of discrete detection tasks but as a continuous, closed-loop process of sensing, reasoning, and acting, where AI serves as the cognitive infrastructure that binds these activities together. The theoretical contribution of this review, therefore, lies in providing a structured taxonomy that makes visible these interdependencies and offers a foundation for developing more integrated and systemic theories of AI-augmented safety management.

Practically, our findings carry significant implications for construction firms, technology developers, and policymakers. For practitioners, the clear message is that while commercially viable computer vision solutions for tasks like hard hat detection are now available, the investment in such systems should not be viewed as a standalone safety fix but rather as one component of a broader digital transformation strategy. A firm that deploys cameras for PPE monitoring without also establishing the data infrastructure, analytical capabilities, and organizational processes to act on that data is likely to realize only marginal safety improvements. For technology developers, the review highlights an urgent need to move beyond algorithm-centric development toward system-level design, where the focus is on creating open, interoperable platforms that can seamlessly fuse data from cameras, wearables, environmental sensors, and project management software. The studies that most convincingly demonstrate potential impact, such as the intelligent robotic inspection system [23] and the smart worksite platform integrating AI with BIM and IoT [43], are precisely those that have adopted this systems-thinking approach from the outset. For policymakers, the identification of significant implementation barriers in developing contexts [32] suggests that the deployment of AI for construction safety will not be uniform globally and that targeted interventions, such as funding for technology training, subsidies for hardware, or the development of open-source platforms, may be necessary to prevent the exacerbation of existing safety disparities between high-income and low-income countries.

We must, however, acknowledge several limitations in our review that temper the strength of these conclusions. From a methodological standpoint, our search strategy, while comprehensive across four major databases, may have introduced a language bias by restricting inclusion to English-language publications, potentially overlooking significant bodies of research conducted in non-English speaking countries with vibrant construction industries, such as China, Japan, or Brazil. The exclusion of grey literature, including industry reports, white papers, and doctoral theses, may have further skewed our synthesis toward academic research, which tends to favor novel algorithms over practical deployment studies, thereby underestimating the amount of operational integration work that may be occurring outside academia. Our classification framework, while useful for organizing the literature, is inevitably a simplification of a complex and overlapping research landscape, and some studies could arguably be placed in multiple dimensions. Furthermore, the quality of the underlying studies is highly variable; while many present rigorous experimental evaluations on curated datasets, a non-trivial number offer only conceptual frameworks or small-scale proof-of-concept demonstrations that have not been validated in realistic, dynamic construction environments. This heterogeneity in methodological rigor limits our ability to draw firm, quantitative conclusions about the relative effectiveness of different approaches. Finally, our decision to include only studies published up to and including 2026, while necessary for feasibility, means that the very latest developments in this rapidly moving field may not be fully captured.

Based on the gaps and inconsistencies revealed by our synthesis, we propose several concrete directions for future research that are logically grounded in the limitations and findings of the current literature. First and foremost, there is a critical need for studies that explicitly design, implement, and rigorously evaluate integrated systems that combine real-time computer vision detection with AI-driven risk assessment and decision support, ideally within the context of an IoT-enabled smart site platform. While individual components have been demonstrated in isolation, very few studies have attempted to bridge the chasm between the sensing layer and the strategic layer in a way that allows for the automated, closed-loop safety interventions that are often theorized but rarely realized. Future research should explore how to architect such systems, what data fusion algorithms are most effective for combining heterogeneous streams (e.g., video, sensor telemetry, schedule data), and how to evaluate their holistic impact on safety outcomes compared to baseline practices. Secondly, the near absence of large-scale, longitudinal field validations is a profound limitation of the current literature. Future research should move beyond laboratory experiments and small-scale pilots to conduct rigorous, long-term case studies in active construction projects, measuring not just technical performance metrics like precision and recall but also practical outcomes such as incident reduction rates, return on investment, user acceptance, and changes in safety culture. Such studies are essential to build the evidence base that will convince risk-averse construction firms to invest in these technologies.

Third, the field would benefit greatly from research that examines the socio-technical and organizational dimensions of AI adoption for safety, particularly in diverse cultural and economic contexts. Our review found only one study explicitly investigating implementation barriers in a developing country [32], yet the successful deployment of any technology is as much a human and organizational challenge as a technical one. Future research should explore how factors such as organizational culture, workforce skills, trust in automation, and management support influence the adoption and effective use of AI safety systems. Comparative studies across different countries, company sizes, and project types would be particularly valuable for developing context-sensitive implementation guidelines. Fourth, understudied areas include the application of more advanced computer vision techniques, such as action recognition, pose estimation, and scene graph generation, for safety monitoring. Current research is heavily dominated by object detection for PPE and equipment, but the ability to understand complex worker activities, such as improper lifting techniques or unsafe interactions with machinery, could open new avenues for proactive ergonomic and behavioral safety interventions. Finally, the emerging area of generative AI for safety, as hinted at by one study [44], presents a fascinating frontier for future research. There is a need to explore how large language models and other generative architectures could be used to automatically generate safety protocols, training materials, hazard communication messages, or even design modifications based on patterns detected by vision and sensor systems, thereby creating a truly adaptive and self-improving safety management ecosystem.

V. CONCLUSION

This systematic literature review has synthesized the rapidly growing body of research on artificial intelligence and computer vision for construction safety management, revealing a field that has made substantial technical progress yet remains fragmented across three distinct but interdependent dimensions. Our analysis confirms that computer vision has matured into a reliable tool for real-time hazard detection, particularly for PPE compliance and equipment monitoring, while AI-driven frameworks increasingly offer sophisticated capabilities for predictive risk assessment and strategic decision-making. However, the most significant finding of this review is the persistent disconnect between these sensing and reasoning layers, with comparatively few studies addressing their integration into holistic, closed-loop safety systems that can autonomously detect, analyze, and respond to hazards in real-world settings.

The theoretical contribution of this work lies in its structured taxonomy that makes visible the interdependencies between detection, risk management, and system integration, thereby challenging the prevailing siloed approach to safety technology research and providing a foundation for more systemic conceptual models. Practically, our findings underscore that the deployment of isolated computer vision solutions without corresponding data infrastructure, analytical capabilities, and organizational processes will yield only marginal safety improvements, and that the most promising path forward lies in the development of open, interoperable platforms that fuse data from multiple sources. The identification of significant implementation barriers in developing contexts further suggests that policymakers must consider targeted interventions to prevent the exacerbation of global safety disparities.

Future research should prioritize the design and rigorous longitudinal evaluation of integrated systems that bridge the gap between real-time detection and strategic risk management, ideally within IoT-enabled smart site platforms deployed on active construction projects. The field would also benefit from deeper exploration of socio-technical adoption factors, advanced computer vision techniques such as action recognition and pose estimation, and the emerging potential of generative AI for creating adaptive, self-improving safety management ecosystems. By addressing these gaps, researchers and practitioners can move toward a future where AI and computer vision fulfill their promise of fundamentally transforming construction safety from a reactive discipline into a proactive, data-driven, and truly life-saving practice.

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