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ARTIFICIAL INTELLIGENCE DRIVEN SYSTEMS FOR ENHANCING WORKER SAFETY MONITORING IN CONSTRUCTION ENVIRONMENTS: A COMPREHENSIVE REVIEW

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ABSTRACT

The construction industry remains one of the most hazardous sectors globally, largely due to inefficiencies, high operational costs, and delayed risk detection associated with traditional safety procedures. This comprehensive review synthesizes findings from 88 peer-reviewed studies published between 2017 and 2025 to evaluate the potential of Artificial Intelligence (AI)-driven systems in enhancing worker safety. The review addresses three primary objectives: (1) evaluating the effectiveness of AI technologies in improving safety monitoring, (2) examining regional variations in AI adoption and their influence on safety outcomes, and (3) identifying key challenges related to implementation, scalability, and ethical considerations. The analysis reveals that AI technologies significantly contribute to improved safety outcomes. For instance, drone-based inspections reduce assessment times from several days to approximately 1.5 hours with high accuracy; computer vision systems detect personal protective equipment (PPE) violations with over 91% precision; and predictive analytics forecast accident risks among migrant workers with 89% accuracy. Regional case studies highlight disparities, such as a 60% reduction in fall incidents in the United Arab Emirates through convolutional neural network (CNN) based surveillance, contrasted with barriers in Ghana, including high implementation costs and cultural resistance. Despite these advancements, challenges persist, including privacy concerns, technological limitations, and inadequate infrastructure in low-resource settings. The review underscores the need for explainable AI models, adaptable frameworks for diverse environments, and harmonized international regulations to ensure equitable and effective deployment of AI-driven safety systems.

Keywords: *Artificial Intelligence; Construction Safety; Ethical Governance; Predictive Analytics; Real-time Monitoring.*

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1. INTRODUCTION

Occupational fatalities in the construction industry represent approximately 20% of global work-related deaths, primarily resulting from electrocution, falls, and equipment misuse. These incidents are often exacerbated by dynamic work environments and human error (Jaafar et al., 2018; Saleh & Othman, 2022). Traditional safety practices, including manual inspections and reactive hazard assessments, have proven inefficient, with reported accuracy rates between 50% and 60% and delays of up to three days in risk identification (Jaafar et al., 2018; Tamoor et al., 2023). The economic impact of workplace injuries, exceeding $170 billion annually, underscores the urgent need for more effective safety interventions (Vitharana et al., 2015). Recent advances in Artificial Intelligence (AI) offer promising alternatives to conventional safety protocols. AI-driven systems enable automation in compliance monitoring, structural analysis, and real-time data integration from wearables, drones, and Internet of Things (IoT) devices. For example, IoT-based structural health monitoring can identify material degradation earlier than manual methods (Plevris & Papazafeiropoulos, 2024), while AI-powered simulations can model structural resilience under environmental stress (Sargiotis, 2024).

This study aims to evaluate the potential of AI-based technologies in enhancing worker safety within construction environments. Specifically, it examines the efficacy of systems such as wearables, drones, and computer vision in reducing risks related to falls, environmental exposure, and equipment hazards. Notable findings include a 40% reduction in heatstroke incidence with wearable use (Tamoor et al., 2023) and the ability of drones to perform structural inspections in under two hours with high precision (Häikiö et al., 2020). Additionally, the study investigates regional disparities in AI adoption, (Shanti et al., 2021) as well as barriers in countries like Ghana, where adoption is hindered by financial constraints and cultural resistance (Acheampong et al., 2025; Mustapha et al., 2024). By addressing issues of scalability, ethical concerns, and regulatory fragmentation, this review contributes to a more comprehensive understanding of the transformative role AI can play in construction safety management.

2. METHODOLOGY

This study employs a structured Systematic Literature Review (SLR) guided by established frameworks such as PRISMA and Kitchenham (Kitchenham et al., 2009; Ogunmakinde et al., 2024). The process is organized into four phases: planning, selection, execution, and analysis. Each tailored to the study's objectives and summarized in Figure 1 to ensure rigor, transparency, and reproducibility.

The primary objective was to assess how AI-driven systems contribute to improving safety monitoring in construction environments. To guide the review, a structured protocol was developed that included the definition of inclusion and exclusion criteria, database selection, Boolean search strategy, and a multi-stage screening process.

Studies were included in this review if they met the following criteria: (1) publication in peer-reviewed journals between 2017 and 2025; (2) a primary focus on the real-world application of AI technologies in construction worker safety; (3) publication in the English language; and (4) provision of empirical results, either quantitative or qualitative.

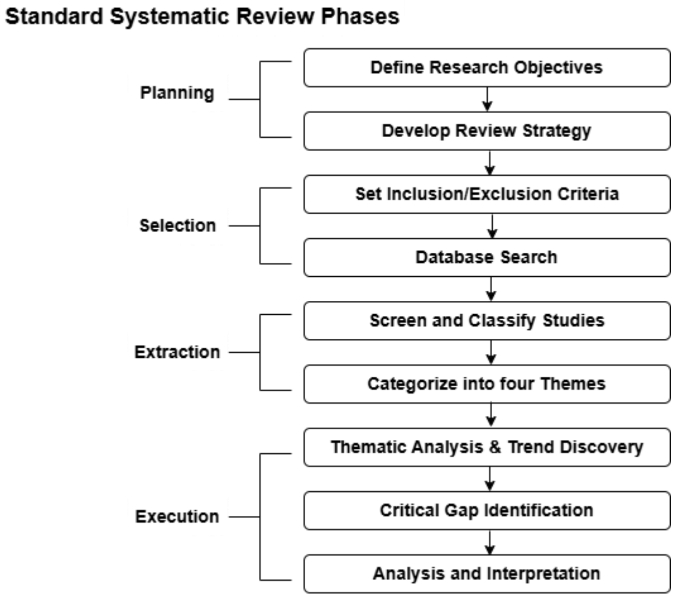

Figure 1: Method and steps of systematic literature review (SLR)

Conversely, studies were excluded if they were conceptual or theoretical without practical validation, if they addressed general industrial safety outside the construction context, if they were published in languages other than English, or if they focused on unrelated safety domains such as environmental protection. To identify relevant literature, a comprehensive search strategy was employed using Google Scholar as a supplementary tool to broaden access across disciplines. Boolean queries were applied, and although Google Scholar does not support database filtering, each article's publication venue and indexing status were manually verified via DOI metadata and publisher records. The final dataset comprised 88 peer-reviewed studies published between 2017 and 2025, sourced from the following databases: Scopus (n = 46), Google Scholer (n = 40), Research Gate (n = 36), ScienceDirect (n = 17), and other reputable academic sources (n = 25). This hybrid approach ensured both methodological rigor and broad disciplinary coverage, in alignment with systematic review standards.

The Boolean queries used included:

- ("artificial intelligence" OR "AI") AND ("worker safety monitoring" OR "worker safety") AND ("construction environment" OR "construction sites")
- ("AI-driven systems" OR "AI-powered systems") AND ("worker safety" OR "worker safety monitoring") AND ("construction industry" OR "construction environments")
- ("artificial intelligence") AND ("safety monitoring systems") AND ("construction worker safety")
- ("AI applications" OR "AI technologies") AND ("worker safety monitoring") AND ("construction sites" OR "construction environments")
- ("real-time safety monitoring" OR "real-time hazard detection") AND ("AI-driven") AND ("construction worker safety")

These initial records were subjected to a multi-stage screening process as described below.

1. Duplicate Removal.
   - 17 duplicate records were identified and removed across databases.
2. Title and Abstract Screening.
   - Of the remaining 147 articles, 12 were excluded for irrelevance to AI-driven worker safety monitoring in construction (e.g., studies focused on non-construction sectors or unrelated AI applications).
3. Full-Text Review.
   - 135 articles underwent full-text assessment against predefined inclusion and exclusion criteria.
   - Exclusions at this stage were as follows.
     - 14 studies excluded for lacking empirical data or real-world validation.
     - 11 studies excluded due to being conceptual or theoretical without actionable insights.
     - 8 studies excluded for language other than English.
     - 14 studies excluded for focusing on unrelated safety topics outside worker monitoring (e.g., environmental safety).
4. Final Inclusion.
   - A total of 88 peer-reviewed studies met all criteria, providing empirical evidence on AI applications for worker safety monitoring in construction environments.

The selected 88 studies were then classified into four thematic areas to structure the analysis and synthesis effectively.

Table 1: Thematic categories of the literature review

No.	Category	Description
1	AI Technologies in Construction Safety	Identifying AI technologies that are increasingly applied to multiple facets of construction safety, primarily focusing on fall detection and prevention, unsafe act identification, behaviour monitoring, and predictive safety modelling.
2	Performance Evaluation of AI Safety Systems	Assessing the effectiveness of AI safety systems in construction requires comprehensive evaluation metrics, including accuracy, precision, recall, other performance indicators and model comparison
3	AI's Role in Labour Displacement	Explores ethical and workforce-related implications, including resistance, retraining needs, and job shifts.
4	Research Gaps and Future Directions	Identifies unresolved challenges including implementation barriers, privacy issues, and scalability.

3. LITERATURE REVIEW

The motivation for conducting this review stems from the urgent need to enhance safety standards in the construction industry, one of the most hazardous sectors globally, responsible for approximately 20% of occupational fatalities (Jaafar et al., 2018).

Traditional safety measures, including manual inspections and reactive hazard checklists, often suffer from inefficiency, high costs, and delayed risk detection, with accuracy levels ranging from 50% to 60% and inspection times extending over several days (Jaafar et al., 2018; Wu et al., 2020). Artificial Intelligence driven systems present promising alternatives by automating hazard detection, enabling real-time monitoring, and facilitating predictive risk management (Kim et al., 2025; Shanti et al., 2021; Tamoor et al., 2023). This review was undertaken to achieve three primary objectives. First, it aims to evaluate the effectiveness of various AI technologies such as drones, wearable devices, and computer vision systems in enhancing worker safety monitoring within construction environments. Second, it seeks to examine regional disparities in the adoption of AI-based safety systems and their corresponding impact on safety outcomes across different socioeconomic contexts. Third, the review identifies critical research gaps associated with global implementation, including challenges related to scalability and ethical concerns such as data privacy and algorithmic bias (Falco et al., 2021; Jaafar et al., 2018; Mustapha et al., 2024).

3.1 AI TECHNOLOGIES IN CONSTRUCTION SAFETY

Falls are a leading cause of injuries and fatalities on construction sites, with many studies using AI models like CNNs and deep learning to detect falls in real-time by analyzing video feeds and issuing alerts (Aslam & Badi, 2025; Kim et al., 2025; Shanti et al., 2021; Tunji-Olayeni et al., 2018). Wearable AI-enabled sensors monitor posture and movement to proactively predict fall risks (Tamoor et al., 2023), while behaviour recognition algorithms trained on annotated datasets accurately classify risky actions and notify site managers instantly (Abioye et al., 2021; Mohan & Varghese, 2019; Tang, 2024; Vitharana et al., 2015). Advanced systems employ multimodal data fusion combining video, audio, and sensor inputs for comprehensive behaviour tracking (Manuel et al., 2024). Predictive analytics using historical and real-time data forecast potential accidents based on site conditions and environmental factors, often integrated with BIM for spatial hazard mapping and dynamic risk assessments (Bajwa, 2025.; Gnoni et al., 2020; Okpala et al., 2020; Tamoor et al., 2023). IoT sensors enable continuous risk data collection to support preventive interventions (Abbas & Duijster, 2025; Barrera-Animas & Davila Delgado, 2023). Despite barriers in low-resource settings, AI's transformative potential in construction safety is clear, as seen with AI-powered drones reducing inspection times from days to hours with high accuracy in flaw detection (Tamoor et al., 2023). Table 2 compares AI adoption and impact between high- and low-income regions.

Table 2: Contrasting AI applications in high-income vs. low-income regions

AI Application	High-Income Regions (e.g., UAE, EU, USA, South Korea)		Low-Income Regions (e.g., Ghana, Nigeria, Malaysia)	
	Benefits	**Challenges**	**Benefits**	**Challenges**
AI-Powered Drones	100% accuracy in hazard detection Reduced inspection time from days to hours. (Tamoor et al., 2023) Real-time risk mapping	High setup costs Worker resistance Weather dependency	Potential for remote site monitoring Reduced manual labor	Limited infrastructure for data transmission Lack of skilled operators High import costs for advanced drones (Tamoor et al., 2023)
Computer Vision (PPE Detection)	91%+ accuracy in detecting safety gear. (Shanti et al., 2021) Real-time alerts for violations	Dataset diversity issues Integration with legacy systems	Basic surveillance for compliance	Lack of labeled training data. Poor lighting conditions on sites. Limited computational resources (Shanti et al., 2021)
Wearable IoT Sensors	Real-time health monitoring. Fatigue and hazard alerts.	Privacy concerns Battery life limitations (Häikiö et al., 2020), (Awolusi et al., 2019)	Low-cost solutions for migrant workers	Cultural resistance Lack of reliable power sources Minimal awareness of IoT benefits (Häikiö et al., 2020), (Awolusi et al., 2019)
Predictive Analytics	Reduced accident rates via risk prediction Customized safety training	Data integration complexity - Ethical concerns over worker surveillance (Kim et al., 2025), (Tamoor et al., 2023)	Potential to address high-risk scenarios (e.g., falls)	Scarce historical accident data - Limited AI expertise - Poor internet connectivity (Kim et al., 2025), (Tamoor et al., 2023)
AI-BIM Integration	Proactive hazard simulation Automated safety planning	High software costs Technical complexity (Mohan &	Long-term potential for compliance	Minimal BIM adoption Lack of standardized protocols

AI Application	High-Income Regions (e.g., UAE, EU, USA, South Korea)		Low-Income Regions (e.g., Ghana, Nigeria, Malaysia)	
	Benefits	Challenges	Benefits	Challenges
		Varghese, 2019)		Insufficient training (Mohan & Varghese, 2019)
Generative AI (e.g., ChatGPT)	Enhanced design and risk management Automated reporting	Ethical governance gaps Workforce scepticism (Rane, 2023)	Low-code tools for safety training	Language barriers Limited access to AI platforms Regulatory inertia (Rane, 2023)
AI for Regulatory Compliance	Automated audits (Falco et al., 2021) GDPR/OSHA alignment	Algorithmic bias risks Legal ambiguity	Potential to enforce safety laws	Weak enforcement institutions Corruption (e.g., bribery in Ghana, (Boadu et al., 2021)) Lack of localized AI frameworks
Key Regional Disparities	Advanced infrastructure Regulatory frameworks Funding for R&D	Workforce resistance Over-reliance on technology	Growing tech interest Low labor costs	Poor internet/electricity Fragmented policies Limited investment in AI

3.2 PERFORMANCE EVALUATION OF SAFETY SYSTEMS

Some specific studies report accuracy rates exceeding 90% for AI-based safety detection systems used in construction site monitoring. For example, Shanti et al. (2021) detail a CNN based model for PPE detection that achieved 91.26% accuracy and nearly 99% precision. Several studies employ confusion matrices to evaluate classification outcomes by comparing true positives, false positives, and false negatives. Notable works by Gao and Sultan (2023), Tamoor et al. (2023), and Kim et al. (2025) apply this technique to assess the performance of computer vision models used for onsite safety monitoring. In addition to classical metrics, advanced indicators such as the F1-score, Area Under the Curve (AUC), and Receiver Operating Characteristic (ROC) curves are increasingly adopted, particularly in cases involving imbalanced class distributions a common scenario in safety incident datasets (Manuel et al., 2024; Mohammed et al., 2024; Rane et al., 2023). As evidenced by, Gao & Sultan (2023), they have compared Faster R-CNN and YOLO models, concluding that YOLO is better suited for real-time applications due to its faster inference speed, albeit with slightly lower accuracy. Similarly, Abioye et al. (2021) advocated for ensemble learning approaches, which improve detection robustness by aggregating predictions from multiple models. A common theme across these studies is the trade-off between model accuracy and computational complexity. To address this, some researchers, such as Manuel et al. (2024), recommend lightweight models that can be deployed on edge devices in resource-constrained environments without significantly compromising detection performance. These metrics provide a more nuanced evaluation by balancing sensitivity and specificity, offering insights into the robustness of AI systems under varied site conditions.

3.3 AI'S ROLE IN LABOUR DISPLACEMENT

The integration of AI technologies into the construction industry is increasingly automating tasks traditionally performed by manual labourers, raising significant concerns regarding labour displacement particularly for low-skilled workers (Hajirasouli et al., 2025) . Innovations such as robotic exoskeletons, drones, and collaborative robots (cobots) are now capable of executing physically demanding or repetitive activities, including lifting heavy materials and performing routine safety inspections, thereby reducing the demand for human intervention in these roles (Licardo et al., 2024). Positions involving manual, routine labour are especially vulnerable, whereas roles requiring advanced technical competencies such as AI programming, robotics maintenance, and data analysis are experiencing growth (Alcover et al., 2021; Morandini et al., 2023). In the construction sector, upskilling initiatives will be critical in enabling workers to manage, operate, and collaborate effectively with AI-driven systems, thus supporting a more resilient and technologically adaptive workforce (Grant Nwaogbe et al., 2025).

3.4 RESEARCH GAPS AND FUTURE DIRECTIONS

According to Shanti et al. (2021), Gao and Sultan (2023), Okpala et al. (2020), and Gnoni et al. (2020), current AI safety frameworks in construction lack scalability, fail to integrate heterogeneous data sources effectively, and do not support advanced analytics or real-time decision-making. Existing systems tend to be narrowly focused, addressing discrete safety components such as PPE compliance or fall detection, without offering a comprehensive or integrative perspective. For example Bajwa, (2025) explicitly emphasizes the need for robust, end-to-end frameworks capable of managing diverse safety risks and operational variables across multiple construction phases. AI tools often function as standalone applications without interoperability with widely adopted systems such as Building Information Modelling (BIM) and project management software, resulting in fragmented safety monitoring solutions that limit efficiency and scalability, to overcome this, Okpala et al. (2020) and Manuel et al. (2024) emphasize the development of standardized interoperability protocols and middleware architectures to enable seamless data exchange and coordinated safety workflows across platforms.

Existing research on AI-driven construction safety predominantly focuses on a limited set of hazards and tends to be conducted under controlled or narrowly defined site conditions (Aslam & Badi, 2025; Kim et al., 2025; Vitharana et al., 2015). Recent studies have emphasized the importance of extending AI-based monitoring systems to diverse environmental contexts, such as underground construction, remote or inaccessible job sites, and developing regions, areas where data availability is often limited and infrastructure constraints pose significant implementation barriers (Barrera-Animas & Davila Delgado, 2023), (Abbas & Duijster, 2025).

4. DISCUSSION

This systematic review aimed to evaluate the effectiveness of AI technologies in enhancing worker safety monitoring, examine regional disparities in AI adoption, and identify key gaps in global implementation, scalability, and ethical considerations. In relation to Objective 1, the findings indicate that AI technologies significantly improve safety outcomes. For instance, AI-powered drones have reduced inspection times from 2–3 days to approximately 1.5 hours while maintaining near-perfect accuracy (Tamoor et al., 2023). Similarly, computer vision systems have achieved 91.26% precision in detecting PPE violations (Shanti et al., 2021), and predictive analytics models have forecasted migrant worker accidents with an accuracy rate of up to 89% (Kim et al., 2025).

Regarding Objective 2, the review reveals clear regional disparities in AI adoption and effectiveness. High-income countries, such as the United Arab Emirates and South Korea, have implemented AI technologies with measurable success—for example, a 60% reduction in fall-related incidents in the UAE through CNN-based surveillance (Shanti et al., 2021), and enhanced safety outcomes for migrant workers in South Korea using predictive models (Kim et al., 2025). Conversely, in low-income contexts such as Ghana, implementation is hindered by financial barriers (52%) and cultural resistance (30%) (Acheampong et al., 2025; Mustapha et al., 2024), limiting the scalability and utility of AI systems in such environments.

In addressing Objective 3, this review identifies several persistent challenges that hinder the global applicability and effectiveness of AI-driven safety monitoring systems. Chief among these are the opacity of black-box AI models, which limit explainability and hinder user trust (Gao & Sultan, 2023; Yang et al., 2024), and the risks of privacy violations stemming from surveillance-based tools such as computer vision and wearables (Aloisi & Gramano, 2019). Furthermore, algorithmic bias remains a critical concern, particularly when AI systems are trained on non-representative datasets, leading to unequal safety outcomes across worker groups (Falco et al., 2021). These technological and systemic issues are further compounded in low-resource settings by inadequate digital infrastructure and limited access to reliable connectivity (Acheampong et al., 2025; Boadu et al., 2021), restricting the scalability and adaptability of AI technologies.

Ethical considerations are central to AI's responsible deployment. Key issues include data privacy, algorithmic bias, and the lack of transparency in AI decision-making processes. These concerns are particularly acute in safety-critical sectors like construction. The literature highlights the necessity for transparent, explainable AI systems and the adoption of enforceable regulatory frameworks (Falco et al., 2021; Villegas-Ch et al., 2024). Mechanisms such as the AAA framework and international policy alignment (Cha, 2024) may help address these challenges by enhancing accountability and fostering public trust in AI systems.

A critical finding of this review is the lack of longitudinal research. Approximately 88% of the studies reviewed did not include long-term performance evaluations. This gap limits our understanding of how AI systems perform over time, particularly in relation to maintenance demands, risk adaptability, and performance degradation. For example, while AI-powered inspection drones offer short-term efficiency, there is limited evidence on their long-term effectiveness across varying construction phases and environmental conditions (Tamoor et al., 2023). Similarly, workforce adaptation and reskilling remain underexplored, especially concerning the impact of AI on productivity and safety behaviour (Li et al., 2022; Trivedi & Alqahtani, 2024). In order to create focused AI literacy programs for site workers and safety officials, industry leaders should collaborate with vocational schools. Legislators must provide tax breaks or subsidies to building companies that spend money on worker training connected to AI.

Another significant concern is the geographic imbalance in the literature, with a strong concentration of studies originating from high-income countries. Expanding AI field studies to low and middle-income countries (LMICs) is critical, given the unique contextual challenges they face, such as informal construction practices and exposure to extreme climatic conditions (Mustapha et al., 2024; Shanti et al., 2021; Tunji-Olayeni et al., 2018). Solutions such as IoT-enabled monitoring systems must be tailored for low-resource settings to overcome infrastructural and socio-cultural barriers (Awolusi et al., 2019; Hinze et al., 2022).

To fully leverage AI's transformative potential while mitigating its risks, policy and industry efforts must focus on two fronts: (1) developing ethical AI governance structures, and (2) investing in workforce reskilling initiatives. Regulatory mechanisms should target critical issues such as algorithmic fairness, data protection, and model transparency. Furthermore, policy initiatives must support tools like explainable AI, algorithm audits, and the standardization of safety metrics across jurisdictions (Cha, 2024; Falco et al., 2021).

Emerging AI paradigms also present promising directions for future research. Federated learning, which allows decentralized model training across multiple construction sites without sharing raw data, enhances both privacy and generalizability (Berkani et al., 2025; Li et al., 2022). Integrating federated learning into hazard prediction models (e.g., fall risks) may significantly improve scalability across diverse site conditions. Edge AI, which enables on-device processing in drones and wearables, can enhance real-time decision-making, especially in regions with limited cloud connectivity (Bajwa, 2025; Rane et al., 2023; Tunji-Olayeni et al., 2018). Finally, the integration of AI-driven digital twins, combining BIM, IoT, and AI for proactive risk forecasting, remains underexplored in construction safety and warrants further investigation (Gnoni et al., 2020; Pan & Zhang, 2023).

5. CONCLUSION

This review confirms that AI technologies such as drones, computer vision, and predictive analytics significantly enhance construction safety by automating hazard detection, improving monitoring precision, and enabling proactive risk management. However, their adoption remains uneven due to infrastructure limitations, high costs, and ethical concerns, particularly in low-resource settings. Key challenges include algorithmic bias, privacy risks, and the lack of long-term evaluations. Addressing these issues through explainable, scalable, and context-sensitive AI frameworks is essential for ensuring the responsible and equitable integration of AI into global construction practices.

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