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APPLICATION OF ARTIFICIAL INTELLIGENCE IN CONSTRUCTION HEALTH AND SAFETY MANAGEMENT: A SYSTEMATIC REVIEW AND PATH FORWARD

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***SUMMARY**: Effective worker health and safety (H&S) management remains a major concern in the construction industry. Traditional safety measurement methods, while valuable, fall short of achieving zero injuries in dynamic and complex work settings. In response to this limitation, researchers have turned to emerging techniques, such as artificial intelligence (AI), to enhance the efficiency of H&S management methods and develop predictive models for on-site mitigation of occupational hazards. Despite numerous studies showcasing potential benefits and limitations of AI in various construction H&S applications, a comprehensive synthesis tailored to construction workers' H&S management is needed. This study conducts a bibliometric and systematic literature review of various AI strategies (specifically machine learning and deep learning) for ensuring effective H&S management and identifies gaps in existing research. Leveraging a systematic review approach, 181 articles from relevant academic journals and conferences published up to July 2025 were analyzed. The findings suggest a rapid increase in AI-related H&S research, particularly in Asia and North America. Results revealed seven construction H&S management AI application themes: construction accidents, PPE detection, ergonomic risk, safety inspections, fatigue, safety behavior, and health and safety training. The study highlights the strengths and weaknesses of current applications and proposes areas for further investigation. This review offers foundational insights essential for developing robust prediction models and advancing the use of safe and ethical AI in construction H&S management.*

***KEYWORDS**: construction, artificial intelligence, health management, safety management.*

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1. INTRODUCTION

In the dynamic landscape of the construction industry, ensuring the safety of workers remains an imperative yet evolving challenge (Dong et al., 2018). Over the years, technological advancements, notably Artificial Intelligence (AI) integration, have emerged as a promising avenue to enhance construction efficiency and safety practices (Baduge et al., 2022). The benefits of AI, including real-time monitoring, predictive analytics, and adaptive safety protocols, have catalyzed a paradigm shift in the approach to construction site safety (Wu et al., 2023). The construction industry is large and complex and remains among the least digitized sectors globally, facing a substantial worker demand (Sakib, 2022). In addition, it stands out as one of the most hazardous job sectors, as the accident rate continually increases over time (Fang et al., 2018). Safety concerns in the construction industry are a worldwide issue, not exclusive to any specific country. Accidents in construction result in fatalities, injuries, and various significant direct and indirect consequences for construction workers (Fang et al., 2015, Khan et al., 2024). The construction sector in the United States witnessed 1,056 fatalities in 2022, representing 20% of all workplace fatalities in the US (OSHA, 2022). According to the US Bureau of Labor Statistics, approximately 1 in 5 workplace deaths took place in the construction industry in 2022 (BLS, 2023). Despite the implementation of construction safety laws, regulations, and management systems by various countries over the past decades in response to the high incident rate (Chang et al., 2022), safety performance in the construction industry remains unsatisfactory (Fang et al., 2020). Previous studies affirmed that humans are at the center of construction safety concerns (Rivera & Oñate 2021). Hence, there is a need to reassess existing safety management theories, methods, and technologies and explore innovative ideas for the future of construction safety (Liang et al., 2020; Okonkwo et al., 2023). Currently, the construction industry heavily depends on traditional safety management methods that rely on human oversight, periodic inspections, and non-automated processes (Baduge et al., 2022; Musarat et al., 2024). However, this approach has inherent drawbacks, including subjective evaluation and limited cognitive evaluation capability (Baduge et al., 2022). Traditional safety management approaches heavily depend on managers' experiential knowledge and onsite observations, which could be biased, tedious, and time-consuming processes that can adversely impact construction workflows (Guo et al., 2023).

As construction sites grow in complexity and the demand for efficiency rises, conventional safety measures need to be revised to adapt to the intricacies of the modern work environment (Forcael et al., 2020). Recognizing this gap, researchers have turned to AI as a transformative tool capable of not only mitigating risks but also proactively predicting and preventing potential hazards (Liu et al., 2021). This surge in interest has led to a proliferation of research works and publications on AI in construction workers' Health and Safety Management (AI-in-H&S). Mostafa and Hegazy (2021) argued that AI technologies, such as computer vision, offered a promising solution for safety management in construction due to their non-intrusive nature. The driving forces behind these developments are machine learning (ML) and deep learning (DL), a subfield of AI, focusing on making predictions and recognitions based on past experiences (Baduge et al., 2022). Artificial Intelligence (AI) refers to computational systems capable of performing tasks that traditionally require human intelligence, including learning from experience, recognizing patterns, making decisions, and adapting to new inputs (Jordan & Mitchell 2015). AI encompasses multiple subdisciplines, including expert systems, fuzzy logic, genetic algorithms, natural language processing, machine learning (ML), and deep learning (DL). This study focuses on ML and DL, as they are the most prominent and interconnected AI domains, frequently applied and foundational to diverse construction H&S applications (Nath et al., 2020). ML generally includes a broader range of algorithms such as regression, classification, clustering, and decision trees, while DL involves the stacking of multiple layers of neural networks to create deeper architecture capable of effectively being trained on complex data (Lung et al., 2025). This methodology has shown significant breakthroughs in complex data-processing tasks (Amirgaliyev et al., 2025), such as image and video analysis for safety monitoring. However, the rapid expansion of literature in this domain poses a considerable challenge to comprehensively understanding the current state of knowledge. This, in turn, heightens the risk of overlooking essential areas and questions crucial for research and practice improvement. To address this scientific challenge, a rigorous review and analysis of the domain are deemed necessary.

While past literature reviews in this domain (Guo et al., 2021; Jiaming et al., 2021; Liu et al., 2021; Zhou et al., 2021) have made commendable contributions, they exhibit certain limitations. Earlier review papers have predominantly explored the intersection of AI and construction management, addressing worker safety at a broad level (Darko et al., 2020). Most of the previous review papers focused on computer vision technology or AI algorithms that addressed specific safety concerns, such as falls or hazard recognition alone. For instance, Wang et al. (2021) comprehensively reviewed human interaction in construction hazard recognition research from 2000 to 2021, mainly focusing on the use of AI for hazard recognition. Liu et al. (2022) also conducted a thorough review of the various DL-based data generation techniques in construction H&S. This review was extended by Rabbi and Jeelani (2024) to cover other AI-based data generation techniques such as textual, visual, and audio, though neither study focused on the practical application on a construction site. Similarly, (Seo et al., 2015; Fang et al., 2020; Guo et al., 2021; Wang et al., 2021) conducted comprehensive reviews of construction safety management that were constrained to computer vision only, or DL only (Liu et al., 2022). Furthermore, existing review studies showcase a tendency toward narrowed perspectives, often concentrating on specific applications of AI (Jin et al., 2019, Fang et al., 2020, Sarkar & Maiti, 2020; Mostafa & Hegazy, 2021, Donisi et al., 2022, Wang et al., 2020). A Pertinent example is Wang et al. (2020), which meticulously examines the integration of AI in fall detection processes, shedding light on its efficacy. Donisi et al. (2022) focused on wearable devices integrated with AI to detect musculoskeletal disorders. Wang et al. (2020) delved into the review of human fall detection. However, these studies are constrained by (1) their exclusive focus on a singular aspect of AI application (e.g., fall prevention), neglecting the broader spectrum of AI applications in construction H&S management, (2) focusing on a specific class of AI (e.g., computer vision), and (3) their lack of consideration for learning curves. Learning curves are essential for determining whether a model effectively learns from the data rather than merely memorizing it, and they also provide critical insights into overfitting or underfitting. Including such analysis would enhance the transparency and robustness of research, particularly in the construction domain. Since the construction industry is dynamic and prone to several hazards and accidents, the broader spectrum of this paper includes fall prediction, PPE detection, safety inspections, fatigue prediction, ergonomic risk assessment, general construction accidents, safety behavior, and safety training. Considering these observations, it becomes evident that existing review studies, collectively, fall short of providing a comprehensive depiction of the state-of-the-art research on AI in H&S.

The aim of this study is two-fold: firstly, to undertake a critical assessment of AI (specifically machine and deep learning) applications in construction H&S management to ensure effective H&S management, and secondly, to identify gaps in existing research and opportunities for future research. To achieve these goals, a thorough literature review was conducted to develop keywords, facilitating the identification of relevant literature from scientific databases like Web of Science and Scopus. This research will systematically identify key publication trends at the nexus of construction H&S management, and AI. Notably, it delved into the extensive utilization of AI techniques, examining their applications within the construction safety context. Furthermore, the study assessed the accuracy and effectiveness of each AI technique in proactive safety and health management, delineating their respective strengths and weaknesses. This holistic approach aims to provide a nuanced understanding of the current state of AI integration in construction H&S management, contributing valuable insights to both academic research and practical applications in the industry. This study will answer the following Research Questions (RQ):

- **RQ1:** What are the research publication trends in health and safety management utilizing AI?
- **RQ2:** In which construction health and safety domains are AI applied, and what degrees of accuracy are reported?
- **RQ3:** What are the future research directions and applications of AI in the construction H&S management domain?

The comprehensive analysis will help identify areas where AI has demonstrated notable success in construction safety. By highlighting the accuracy levels of specific AI algorithms in various safety applications, researchers and industry professionals will be able to make informed decisions when implementing technology-driven safety measures. The study will also serve as a practical guide for integrating AI solutions tailored to specific safety challenges, ultimately contributing to the enhancement of overall safety protocols on construction sites. The insights garnered from this research will empower industry stakeholders to adopt effective AI applications, fostering a safer and more efficient working environment for construction workers. Finally, by critically synthesizing the limitations, challenges, and future research recommendations identified across the reviewed literature, this study derives and presents key future research directions to guide scholars and practitioners advancing AI applications in construction health and safety.

2. METHODOLOGY

This research applied a bibliometric and systematic literature review. The bibliometric analysis provided quantitative insights into publication trends, influential authors, and collaboration networks, offering a broad overview of the research landscape (Zupic & Čater 2015). It enabled the identification of research gaps and emerging themes, thus highlighting areas for future investigation. The systematic review methodology distinguishes itself from narrative reviews through its reproducibility, scientific rigor, and transparency (Siddaway et al., 2019). This systematic review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Liberati et al., 2009). Aligned with the study's research questions, Boolean strings were crafted around the domains of AI techniques (ML and DL), Construction, Worker, and Safety and Health Management by referencing keywords commonly used in previous reviews (Fang et al., 2020; Sarkar & Maiti 2020; Wang et al., 2020; Guo et al., 2021; Jiaming et al., 2021; Mostafa & Hegazy 2021; Zhou et al., 2021). The study employed a two-stage search strategy: a broad bibliometric search to map the entire AI in construction H&S landscape, followed by a focused systematic review search narrowing specifically to ML and DL applications. This design ensures that the prominence of ML and DL identified in the bibliometric analysis reflects a genuine finding from the broader AI literature rather than a predetermined outcome of the search strategy. By conducting both bibliometric and systematic literature reviews, the authors aimed to capture a comprehensive and in-depth perspective on the topic.

2.1 Data Collection

2.1.1 Data Collection Process for Bibliometric Analysis

This study aims to examine the characteristics of publications and identify research trends in DL and ML applications within construction health and safety using bibliometric analysis. Due to the significant increase in scientific research, it has become challenging for researchers to keep up with the relevant literature. This challenge necessitates the use of quantitative bibliometric methods to manage extensive data, highlight impactful studies, and uncover the fundamental structure of a field (Zupic & Čater 2015). Bibliometrics involves the statistical and quantitative analysis of publication characteristics, such as authors, subjects, cited authors, publication details, and cited sources.

For the data collection process in bibliometric analysis, the keywords “deep learning,” “machine learning,” ‘health and safety,” or “safety and health” and “construction” were selected to find relevant studies in the construction safety domain. An online search was performed on July 20, 2025, in both Web of Science and Scopus using Advanced Search. The search included keywords: The exact search strings used were Web of Science (Bibliometric): TS= (("Deep Learning" OR "Machine Learning") AND ("Construction") AND ("Health and Safety" OR "Safety and Health")). Scopus (Bibliometric): TITLE-ABS-KEY (("Deep Learning" OR "Machine Learning") AND ("Construction") AND ("Health and Safety" OR "Safety and Health")). The keyword selection was intentionally broad to ensure comprehensive coverage of literature in the domain of AI applications in construction H&S management. Given the interdisciplinary nature and evolving terminology in this field, a broader approach helped capture all relevant studies and mitigated the risk of omitting critical works due to narrow phrasing. Both term orderings, “health and safety” AND “safety and health”, were incorporated to ensure publications were not excluded based on author terminology preference. This strategy also aligned with bibliometric best practices, aiming to retrieve a diverse and inclusive dataset for robust trend and thematic analysis. The time span for the search was from All time to 2025 July 20, resulting in a unique dataset of 696 unique publications.

2.1.2 Data Collection Process for Systematic Literature Review

In the second stage of the research, after identifying studies in the field through bibliometric analysis, a systematic literature review was conducted to obtain more comprehensive and detailed findings. This approach was used to extract key information and construct articles in AI and DL in construction safety. Systematic literature reviews analyze studies in a particular field in a collective and systematic manner, providing guidance for future research (Zupic & Čater 2015). For the systematic literature review, the search was narrowed to focus specifically on ML and DL applications in construction health and safety. The exact search strings used were: Web of Science (Systematic Review): TS= (("Deep Learning" OR "Machine Learning" OR "Deep Learn*" OR "Machine Learn*") AND ("Construction*" OR "Build*") AND (("Health and Safety") OR ("Safety and Health") OR ("Health* and

Safety*") OR ("Safety* and Health*"))). Scopus (Systematic Review): TITLE-ABS-KEY (("Deep Learning" OR "Machine Learning" OR "Deep Learn*" OR "Machine Learn*") AND ("Construction*" OR "Build*") AND (("Health and Safety") OR ("Safety and Health") OR ("Health* and Safety*") OR ("Safety* and Health*"))). The initial search, conducted without filters, yielded 448 unique articles. To ensure comprehensive coverage, the search strategy incorporated both term orderings: "health and safety" OR "safety and health." Additionally, the study employed Boolean wildcards, including the asterisk (*) to capture grammatical variations. The asterisk wildcard was applied to key search terms to capture morphological variants as follows: Deep Learn* retrieved "deep learning" and "deep learned"; Machine Learn* retrieved "machine learning" and "machine learned"; Construct* retrieved "construction," "constructing," and "constructed"; Build* retrieved "building" and "buildings"; Health* retrieved "health" and "healthy"; and Safety* retrieved "safety" and "safe." This approach ensured we did not inadvertently exclude relevant publications due to minor linguistic variations.

The search results were then refined to include studies published between 2014 and 2025, written in English, and categorized under deep learning and machine learning in the construction health and safety domain. This filtering process resulted in 294 articles. The systematic literature review, however, focused on AI studies in the construction safety domain published between 2014 and July 2025. The main reason for this time frame was to ensure that the studies were current and the number of studies was manageable for a thorough examination. Similarly, the analysis was limited to studies written in English because the researchers are proficient in English.

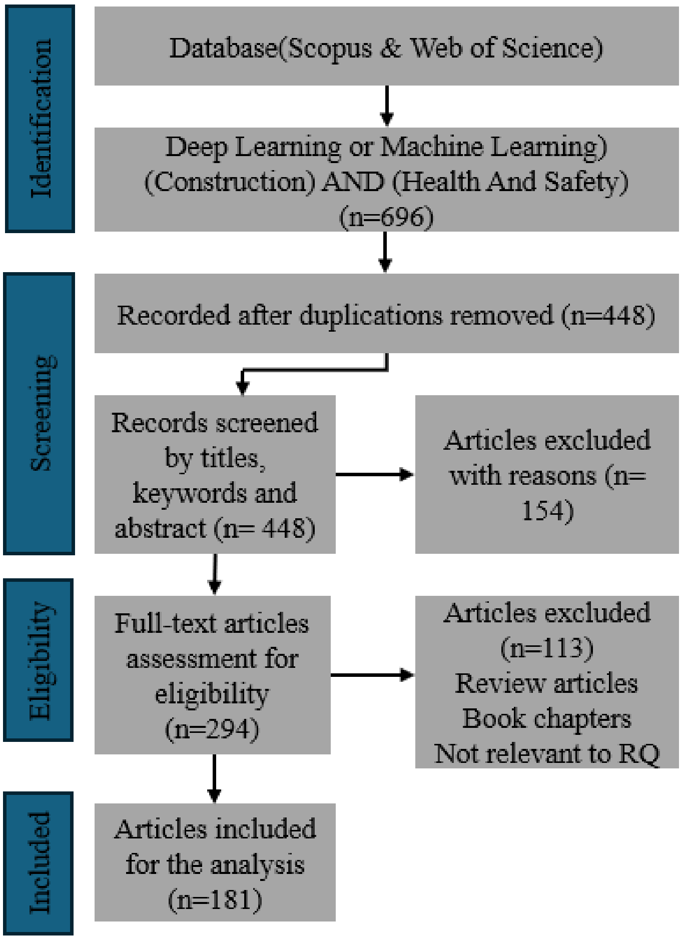

Figure 1: The process of the systematic review (based on the PRISMA method).

To ensure systematic and replicable article selection, the study established explicit inclusion and exclusion criteria applied by three independent reviewers during the screening process. Studies were included if they: (1) were written in English; (2) employed machine learning or deep learning techniques; (3) specifically addressed construction health and safety management applications such as accident prediction, fall detection, PPE detection, ergonomic risk assessment, fatigue monitoring, safety behavior, or safety training; and (4) reported clear methodology with full-text availability through institutional or open access. Studies were excluded if they: (1) focused on other industries such as manufacturing, mining, or agriculture; (2) addressed non-safety construction applications such as project scheduling or cost estimation; (3) were opinion pieces, editorials, conference abstracts without full papers, or book chapters lacking empirical data; or (4) were available only as abstracts or inaccessible due to paywall restrictions.

These criteria were applied sequentially during the screening process. Articles failing to meet any single criterion were excluded from further analysis. To ensure reliability, three researchers independently reviewed all 294 articles identified after initial database filtering. Inter-rater reliability for inclusion decisions was strong, indicating substantial agreement among reviewers. In cases of disagreement, consensus was reached through discussion among all three reviewers. This rigorous screening process resulted in 181 articles meeting all inclusion criteria for in-depth systematic review and data extraction. Figure 1 illustrates the flow diagram of the steps followed for identifying and selecting documents in the systematic literature review data collection process. The diagram is based on the PRISMA flow diagram for new systematic reviews (Page et al., 2021).

2.2 Data Visualization and Analysis

The Sankey diagrams (Figures 6 and 7) were produced using SankeyMatic (sankeymatic.com), an open-source flow diagram tool. From each of the 181 reviewed articles, we systematically extracted the specific AI algorithm(s) employed, the H&S application domain (e.g., fall prediction, PPE detection, fatigue assessment), and the reported accuracy metrics. We then created a flow matrix documenting the frequency of each algorithm-application pairing. For example, if 12 studies used CNN for PPE detection with accuracies ranging from 85-97%, this was recorded as a single flow with weighted thickness.

The visualization structure includes source nodes on the left representing ML algorithms (e.g., SVM, Random Forest, Decision Tree) and DL algorithms (e.g., CNN, YOLO variants, ResNet), while target nodes on the right represent H&S application domains (Construction Accidents, PPE Detection, Ergonomic Risk, Safety Inspection, Fatigue, Safety Behavior, Safety Training). Flow thickness is proportional to the number of studies employing that specific algorithm-application combination, with color coding grouping algorithms by family (e.g., all YOLO variants in similar hues).

Average accuracy ranges are displayed for each flow, calculated from all studies employing that specific algorithm-application pair. For instance, if 8 studies used YOLOv3 for PPE detection reporting accuracies of 89%, 92%, 87%, 93%, 91%, 90%, 88%, and 94%, the flow displays '89-94%' as the accuracy range. Three independent researchers cross-checked the flow assignments to ensure accuracy and inter-rater reliability. This visualization approach allows readers to immediately identify which algorithms are most applied to specific H&S domains, the performance ranges achieved, and research gaps where certain algorithm-application combinations remain unexplored.

3. RESULTS AND DISCUSSION

3.1 Publication Trend Analysis

Analyzing the publication patterns of articles focusing on AI-in-construction-for-H&S is essential for discerning the annual volume of published work, the primary geographical regions of study, and the specific environments (laboratory or construction site) where the research was conducted. Additionally, this examination aims to identify the prominent journals and conferences contributing to this field. The insights derived from this study are crucial for understanding the current trajectories in AI-based prevention research and pinpointing potential avenues for future investigations.

3.1.1 Number of publications per year

In the AI-in-H&S research domain, there has been a notable uptrend in the number of publications per year as shown in Figure 2. The compilation of articles shows a definitive upward trajectory in the volume of publications from 2014 through 2025, however, the timing of data extraction ended in July of 2025. This suggests an increasing interest and focus on the development and deployment of AI models to enhance safety at construction sites over the years. Key themes such as AI-based prevention strategies, innovative safety technologies, and human-centric approaches have prominently featured in these publications. The upward trend not only underscores the field's vitality but also suggests a collective commitment to addressing contemporary challenges and fostering advancements in construction safety.

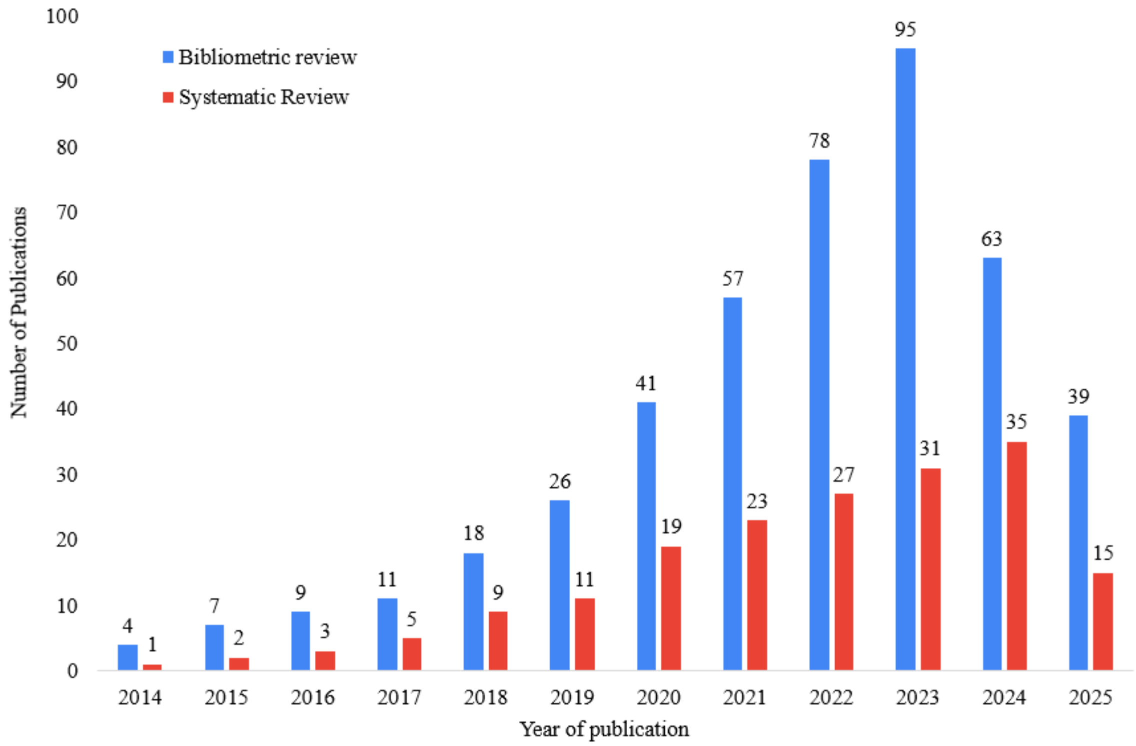

Figure 2: Number of publications per year (2014- July 2025).

3.1.2 Publication based on country

The data shows the distribution of publications in AI framework development and construction safety deployment, broken down by country based on the origin of the first author, as shown in Table 1. China leads with 103 and 47 publications in the bibliometric, and systematic review respectively, followed by the USA with 85 and 34, then Hong Kong with 65 and 20 publications respectively. There is a significant drop in numbers as we move down the list, with South Africa at 5 and 3, and several countries contributing between 1 and 2 publications. This indicates that research in this area is concentrated in certain regions, with China and the USA being the most prolific contributors. This geographical distribution may reflect these countries' focus and investment in AI-in-H&S and their capacity for research and development in this domain. This distribution underscores the concentrated research output from key players in AI-in-H&S, emphasizing the global collaboration needed to address industry challenges comprehensively.

Table 1: Number of publications by country.

Country	Publications	
	Bibliometric review (n=448)	Systematic Review (n=181)
China	103	47
USA	85	34
Hong Kong	65	20
South Korea	37	18
India	22	5
Canada	19	7
France	13	6
Taiwan	11	4
UK	10	3
Germany	9	4
Japan	8	3
Italy	7	2
Singapore	6	2
South Africa	5	3
Others	48	23

3.1.3 Publication based on Journal/Conference

Table 2 presents publication venues for both the bibliometric analysis and systematic review to demonstrate the representativeness of our systematic sample. The proportional distribution across key journals (e.g., Automation in Construction: 12.9% bibliometric vs. 23.2% systematic; Safety Science: 5.1% vs. 7.2%; Advanced Engineering Informatics: 6.2% vs. 9.4%) confirms that our focused systematic review (n=181) captures the disciplinary breadth of the larger bibliometric sample (n=448), thereby validating the generalizability of our in-depth findings. The higher percentages in the systematic review reflect our quality filtering process, which emphasized peer-reviewed journal articles with complete methodological reporting. Notably, the "Others" category, which includes conference proceedings, showed the largest proportional reduction (142 to 22, representing an 84.5% reduction), illustrating that journal publications more consistently met our rigorous inclusion criteria for the systematic review.

Table 2: Number of publications per Journal/Conference.

Journals/Conferences	Publications	
	Bibliometric Review (n=448)	Systematic Review (n=181)
Automation in Construction	58	42
Journal of Construction Engineering and Management	35	25
Advanced Engineering Informatics	28	17
Safety Science	23	13
Journal of Information Technology in Construction	26	12
Buildings	13	5
Journal of Computing in Civil Engineering	11	5
Sustainability	13	4
Journal of Building Engineering	6	3
IEEE Access	10	4
Smart and Sustainable Built Environment	6	4

Journals/Conferences	Publications	
	Bibliometric Review (n=448)	Systematic Review (n=181)
Sensors	15	3
Applied Sciences	22	7
Frontiers in Built Environment	8	2
International Journal of Construction Management	4	2
Engineering, Construction and Architectural Management	4	2
Journal of Safety Research	6	2
Construction Research Congress	18	7
Others	142	22

3.1.4 Authors' Keywords Analysis (Bibliometric)

Figure 3 illustrates a visualization of the co-occurrence analysis of these keywords in the publications. The findings reveal the most frequently used keywords and the links between them. Keywords with a minimum of two occurrences were included in the dataset. For all keywords, the occurrences and the cumulative link strength with other keywords were computed. Machine learning (ML) and deep learning (DL) emerged as the most frequently used. A significant portion of the articles from the bibliometric review covers the ML and DL applications in the construction H&S domain. Therefore, the authors focused on these clusters to identify future research gaps, which, when addressed, could help mitigate construction hazards and accidents proactively.

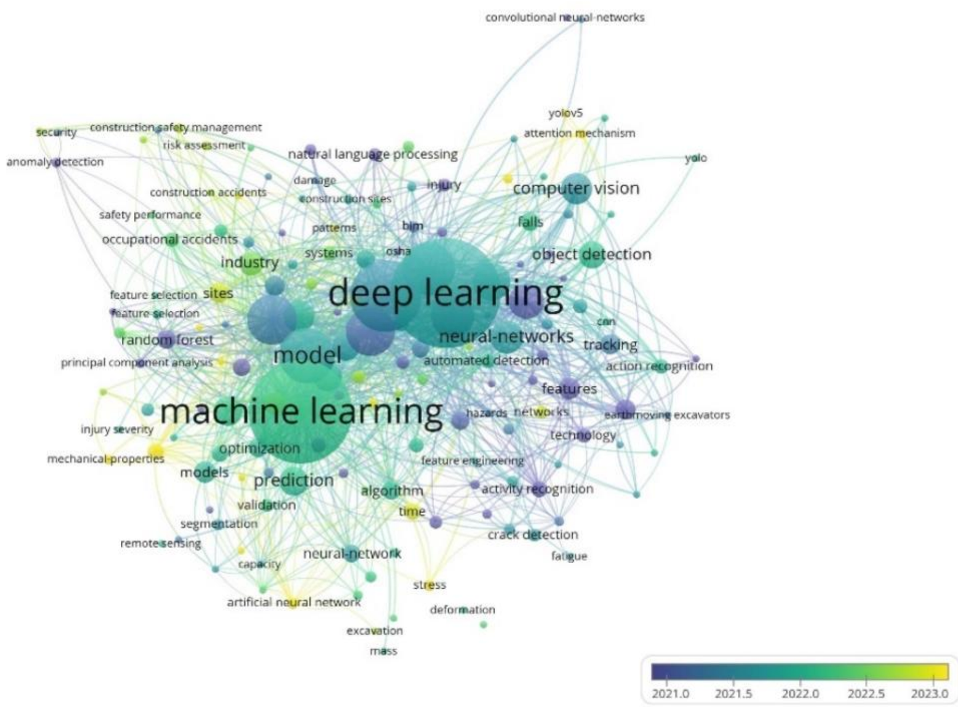

Figure 3: The co-occurrence analysis.

3.1.5 Publication based on research environment

Figure 4 shows the distribution of research publications on AI-in-construction-for-H&S based on the research environment and the type of dataset used, as reviewed during the systematic analysis. Most of the research (53%) was conducted in a laboratory (Lab) setting, emphasizing the primary use of controlled environments for developing AI applications. On-site (Site) research comprises 34%, indicating practical, real-world application testing. Combined settings (Site/Lab) account for 4% of the publications, reflecting studies that bridge both controlled and real-world conditions. Lastly, research utilizing archival datasets makes up 7%, pointing to analyses done on pre-existing datasets, while site or web imageries constitute 2%. This breakdown showcases a diverse approach to exploring AI-in-H&S with a predominant focus on lab-based research in this domain.

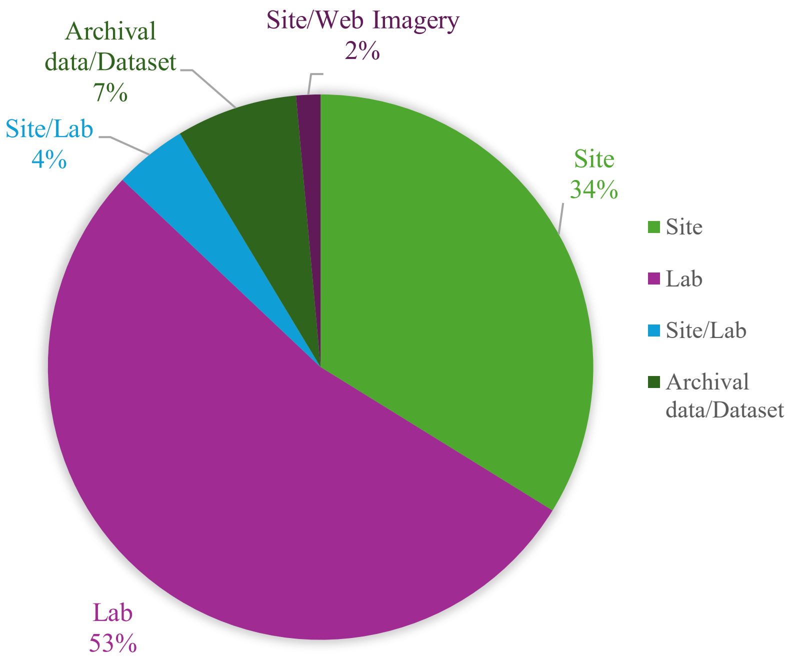

Figure 4: Publication based on the research environment.

3.1.6 Publication based on AI Applications in Construction H&S

The integration of AI within the construction sector is spotlighted in recent data, showcasing a diversified application landscape with a significant emphasis on enhancing safety measures on construction sites. According to the findings illustrated in Figure 5, construction accident detection emerges as the most predominant focus of research with 49 articles. Construction accidents include falls, struck-by, caught in-between, slip/strip, electrocution, etc. This focused attention highlights the ongoing efforts to mitigate one of the most common sources of accidents in construction and the need for targeted interventions to prevent such occurrences. Personal Protective Equipment (PPE) detection was the second focus of research in the domain with 36 articles exploring AI's efficacy in ensuring that workers are adequately equipped to minimize injury risks. The use of AI for ergonomic or posture-related research was covered in 28 articles. This indicates the pivotal role of preventing postures that reduce Work-related musculoskeletal disorders (WMSDs). Safety inspection research was also covered in 24 articles, which underscores the need to eliminate potential hazards and reinforce safety protocols in construction environments. The assessment of worker fatigue is also well-documented, with 20 articles. These studies reflect the industry's commitment to leveraging AI for real-time surveillance and the early detection of fatigue among workers, both crucial in averting accidents and safeguarding worker health. The areas of safety behavior, and safety training, though less represented with 13 and 11 publications each, are acknowledged for their critical contributions to proactive safety management in construction. These studies underscore the rising importance of predictive analytics and behavior analysis in preempting potential hazards, shedding light on the need to enhance safety education among construction personnel. This trend signals potential research gaps or burgeoning areas that could shape future research directions in construction safety. The robust application of AI across various facets of construction safety not only highlights its multifaceted contributions but also accentuates the transformative impact AI harbors in advancing safer construction practices and minimizing occupational hazards. The breadth of research underscores an evolving landscape where AI-driven innovations are at the forefront of redefining safety standards in the construction industry.

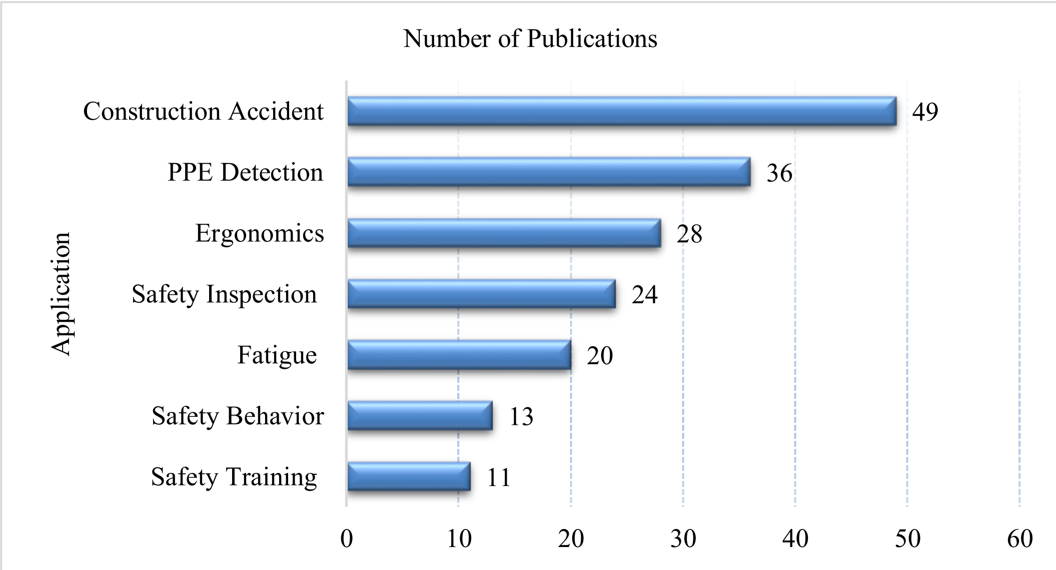

Figure 5: The number of publications based on the AI application in the construction of H&S.

According to the findings illustrated in Figure 5, construction accident detection emerges as the most predominant focus of research with 49 articles. The seven H&S application categories were established through a five-phase categorization process. First, three independent researchers conducted open coding of all 181 articles, identifying 27 preliminary themes. Second, these themes were cross-referenced against established safety taxonomies, including OSHA's Fatal Four categories and NIOSH Construction Safety Research Program focus areas. Third, the 27 themes were clustered based on shared accident causation mechanisms, similar AI detection approaches, and common intervention strategies. Fourth, the research team refined and validated the final categories through three iterative rounds of discussion and reconciliation, achieving strong inter-rater agreement. Finally, operational definitions were established for each category to ensure consistent article classification: Construction Accidents (predicting/detecting fall-related incidents, struck-by, caught-in/between, electrocution, slips/trips, and collisions); PPE Detection (identifying compliance with hard hats, vests, harnesses, boots, gloves, and goggles); Ergonomics Risk (assessing posture, movement patterns, musculoskeletal load, and overexertion); Safety Inspections (detecting hazards, unsafe conditions, or safety protocol violations); Fatigue (monitoring physiological indicators of worker fatigue, stress, or impaired cognitive function); Safety Behavior (analyzing worker actions, compliance patterns, or behavioral risk factors); and Safety Training (developing or evaluating AI-enhanced safety education methods).

3.2 ML and DL Techniques

The review paper categorized the existing studies into ML and DL, which are the most prominent and rapidly advancing areas in AI application for construction H&S. ML and DL are distinct fields of AI with unique characteristics and applications (Jordan & Mitchell 2015). The focus on ML and DL for this in-depth review is empirically justified by our bibliometric analysis. As illustrated in Figure 3, the keyword co-occurrence network analysis of 696 publications shows ‘machine learning” and “deep learning’ as two of the largest and most centrally positioned nodes, indicating their high frequency of occurrence and their role as foundational methodologies connecting diverse construction H&S applications. This visual pattern is further supported by the quantitative analysis in Section 3.1.4, where "machine learning" and "deep learning" emerged as the most frequently occurring AI-related keywords, substantially exceeding other AI techniques such as expert systems, fuzzy logic, and genetic algorithms in recent literature (2014-2025). Additionally, temporal analysis revealed an accelerating trend toward ML/DL adoption, with these approaches becoming increasingly dominant during 2019-2025, reflecting both technological advances and expanding application possibilities in construction safety. Both the bibliometric analysis and the systematic literature review revealed that majority of recent studies in AI applications for construction H&S management have employed ML and DL techniques. This trend highlights the importance and relevance of these methods in current research. While this study acknowledges the contributions of other AI techniques such as expert systems, fuzzy logic, and genetic algorithms to construction safety management, their representation in recent literature was substantially lower. This review strategically focuses on ML and DL to provide an in-depth analysis of the dominant and most rapidly evolving AI approaches in construction H&S, rather than a broad but shallow coverage of all AI techniques. This focused approach enables detailed accuracy benchmarking, algorithm-specific performance analysis, and implementation insights that would not be feasible with a broader review. This section, therefore, depicts the most commonly used ML and DL algorithms and their area of application in H&S.

3.2.1 ML Algorithms

This section explores the ML algorithms that academic researchers and industry practitioners are using to enhance construction H&S, particularly in the domain of research. The driving forces behind these developments are ML and DL, as discussed in the introduction, subfields of AI, focusing on making predictions and recognitions based on past experiences (Baduge et al., 2022). ML is a discipline that enables computers to learn without being explicitly programmed, offering them the capability to acquire knowledge autonomously (Samuel, 2000). Xu and Saleh (2021) defined ML as a set of methods designed for learning from data and revealing patterns within it. This acquired knowledge can then be utilized for inference, prediction, or decision-making under uncertainty.

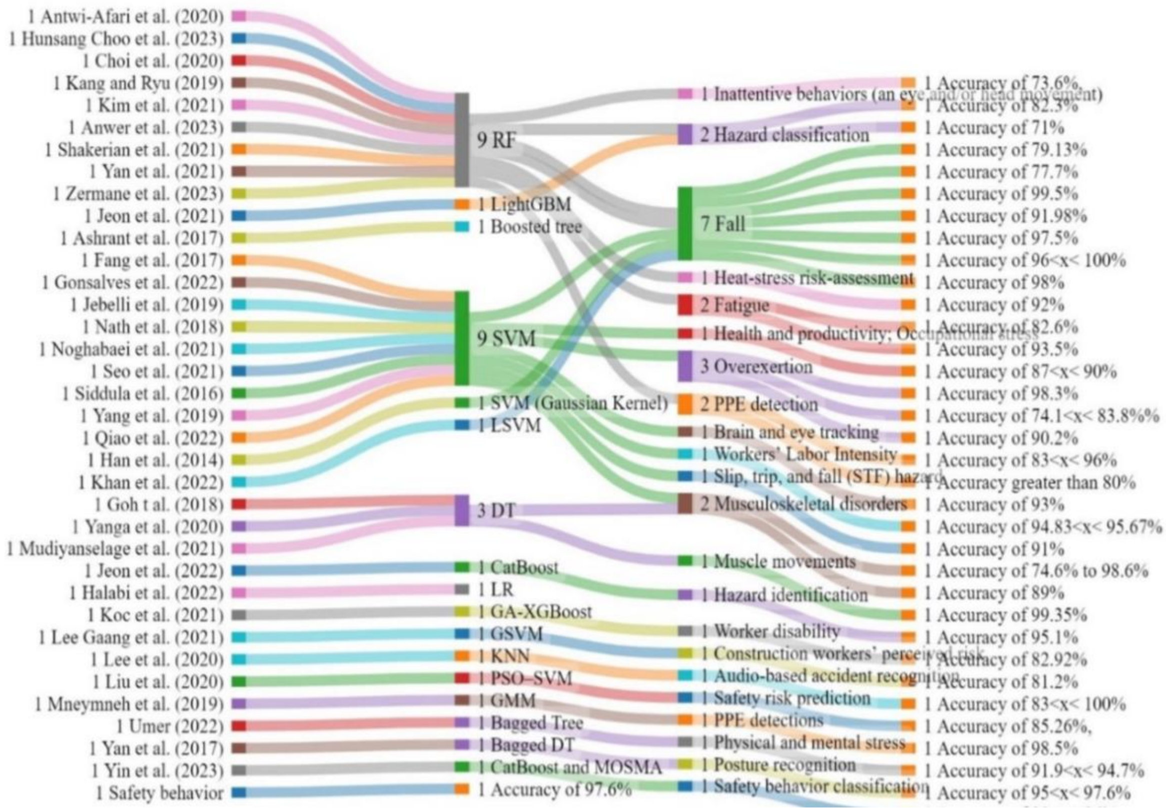

Figure 6: ML-based model deployment at the construction H&S.

A range of ML algorithms have been predominantly utilized for predicting falls and fall-related activities, including random forest (RF) (Zermane et al., 2023), support vector machine (SVM) (Siddula et al., 2016; Fang and Dzeng, 2017), Gaussian kernel (Han et al., 2014), logistic regression (LR) (Halabi et al., 2022), linear support vector machine (LSVM) (Khan et al., 2022) were predominantly used to predict fall and fall-related activities as shown in Figure 6. The accuracy of these algorithms ranges from 77.7% to 100%. Logistic regression recorded the lowest accuracy rate of 77.7% as reported by (Halabi et al., 2022) meanwhile SVM (Gaussian Kernel), and random forest (RF) (Zermane et al., 2023) achieved the highest accuracy rate of 100%. The ML algorithms that were used to detect PPEs were mostly the Gaussian Mixture Model (GMM) (Mneymneh et al., 2019) and random forest (Yan et al., 2021, Zermane et al., 2023). These algorithms achieved accuracy ranging from 80% to 98.5%. Meanwhile, safety behavior was predicted with the aid of a decision tree (DT) (Goh et al., 2018), RF (Kim et al., 2021), and CatBoost (Yin et al., 2023) that generated an accuracy rate of 73.6% to 97.6%. Physical and mental stress involving fatigue, overexertion, musculoskeletal disorders, muscle movements, and labor intensity were predicted using RF (Antwi-Afari et al., 2020), boosted tree (Aryal et al., 2017), SVM (Nath et al., 2018; Seo & Lee 2021; Gonsalves et al., 2022), DT (Yang et al., 2020, Mudiyanselage et al., 2021), and Bagged tree (Umer, 2022). The accuracy rate of these algorithms varied between 74.1% and 99.35%. These algorithms present distinct methodologies for predicting falls, hazards, and the use of PPEs, by analyzing images, movements, databases, or a combination of all. The impressive high level of accuracy of ML underscores the effectiveness of these models in ensuring safety management and compliance in the settings of construction sites if deployed effectively. The SankeyMatic diagram below depicts the use of ML algorithms in construction H&S management.

3.2.2 DL Algorithms

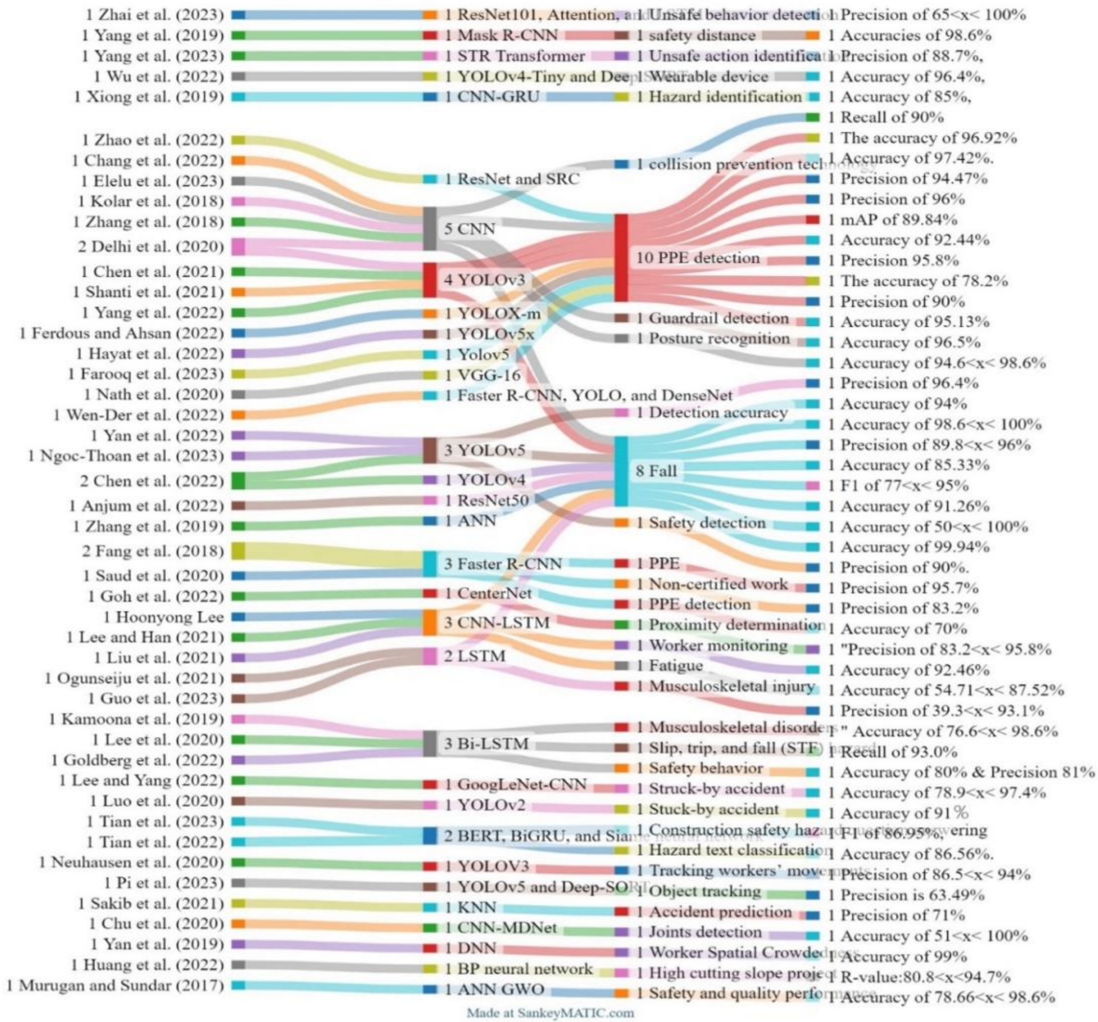

Figure 7: Deep learning-based model deployment at the construction safety and health.

DL is a subfield of ML that utilizes artificial neural networks with multiple layers (typically more than three) to learn hierarchical representations of data. The deep architecture allows the model to automatically learn features from raw data, enabling it to handle complex tasks such as images and speech recognition (Lecun et al., 2015, Bengio et al., 2016). Numerous researchers have adopted the use of DL algorithms to predict, classify, and detect construction safety databases, case studies, and reports as shown in Figure 7. The utilization of various DL algorithms for fall prediction is evident in recent research. These include Convolutional Neural Networks (CNN) as explored by Chang et al. (2022), ResNet50 as investigated by (Anjum et al., 2022), a combination of CNN and Long Short-Term Memory Networks (CNN-LSTM) (Lee & Han 2021; Goldberg, 2022), and YOLOv3 as applied by (Shanti et al., 2021). Each of these algorithms exemplifies the progressive utilization of DL methods in the realm of fall detection and prevention, yielding accuracy rates that span from 77% to 95%. Cutting-edge DL algorithms have been employed for the prediction of PPEs in the construction industry. These include the likes of CNN (Delhi et al, 2020), ResNet (Zhao, 2022), YOLOv3 (Yan et al., 2021), YOLOX-m (Ferdous & Ahsan 2022), YOLOv5x (Hayat & Morgado-Dias 2022), Yolov5 (Kisaezehra et al., 2023), Faster R-CNN (Fang et al., 2018; Saudi et al., 2020), Faster R-CNN, YOLO, and DenseNet (Yu et al., 2022), VGG-16 (Nath et al., 2020) were used to predict PPEs in the construction industry. Most of these algorithms generated an accuracy that ranges from 80 to 100%. These algorithms, employed for predicting PPE usage in the construction industry, achieved accuracy rates ranging from 70% to 97.42%. there was an outlier involving YOLOv5 and Deep-SORT that achieved an accuracy rate of 63.49%. For hazard detection and identification, common deep learning (DL) algorithms such as ResNet101, Attention, and LSTM (Zhai et al., 2023), STR transformer (Yang et al., 2023), CNN-GRU (Xiong et al., 2019), YOLOv4 (Chen et al., 2022), and a combination of BERT, BiGRU, and Siamese neural network (Tian et al., 2022, 2023) have been employed. These algorithms have shown significant effectiveness, generating an accuracy rate ranging from 65% to 100%. Meanwhile, construction safety risk assessment has been effectively predicted using algorithms like the hourglass structure (Yu et al., 2019), and YOLOv5 (Chen et al., 2022). These methods have demonstrated substantial accuracy, achieving rates that range from 70% to 96%. Similarly, (Yan et al., 2019) adopted deep neural network (DNN) algorithms to predict workers' spatial crowdedness, resulting in an accuracy rate of 99%.

3.3 AI Application in Construction H&S

3.3.1 Construction accidents

Forty-nine out of the 181 articles focused on construction accident predictions representing 27.07% of the reviewed articles, making this the most extensively researched application domain in both bibliometric (n=127) and systematic (n=49) analyses. This research concentration reflects both the societal importance of accident prevention, with OSHA's Fatal Four accounting for 63.7% of construction fatalities, identified through bibliometric trends, and the technical feasibility demonstrated by systematic accuracy analysis (75–100% across algorithms). The convergence of bibliometric volume and systematic performance data underscores both the urgency of accident prevention and the demonstrated capability of AI-based solutions. The dynamic and complex nature of the construction site leads to the frequent occurrence of various types of accidents (Amiri et al., 2016). For this review, construction accidents include falls, struck-by, caught-in-between, collisions, slip/trip, etc. It is worth noting that some researchers used databases that included two or more types of construction accidents.

Analyzing learning curves, it becomes necessary to assess how well the model is generalizing to unseen data, which is crucial for making reliable predictions in real-world scenarios. The detailed insights gained from learning curves can help identify overfitting or underfitting issues, ensuring that the model is not only accurate but also trustworthy and transparent in its predictions. This level of scrutiny is essential in construction injury prediction, where the stakes for accurate forecasting are high.

3.3.1.1 Fall and fall-related accidents prediction

Falls are the primary cause of fatalities in the construction industry. In 2020, out of 1,008 deaths in construction, 351 were due to fatal falls to lower levels (OSHA). Globally, falls from height (FFH) are a major public health concern in construction, causing 54% of occupational fatalities (Khan et al., 2022; Kim et al., 2022). Fall is often due to loss of balance or fatigue (Fang & Dzeng, 2017), and varies by project type, worker attributes, and safety measures (Halabi et al., 2022; Lee & Han 2021). Fall may result from ladders, scaffolds, openings, and other such hazards (Khan et al., 2022). Halabi et al. (2022) resorted to using archival data recorded by OSHA from 2000 to 2020 to assess fall accidents in the construction industry. According to Fang et al. (2017), different approaches such as DL, ML, or both can be used to predict fall accidents at complex construction sites. Numerous papers deployed AI to predict FFH accidents which include falls from ladders, scaffolds, and roof (Fang and Dzeng 2017, Shanti et al., 2021; Khan et al., 2022; Zermane et al., 2023). A significant number of these AI models achieved high accuracy, ranging from 75% to approximately 100%. These models efficiently detected and classified fall-related actions associated with ladders, scaffolds, roofs, flat surfaces, or heights. These findings demonstrated the efficacy of AI in prediction patterns and risk factors associated with fall accidents.

It was observed that scaffold-associated falls were mostly detected using ANN, DNN, SVM, and CNN-LSTM algorithms, with ANN recording the highest accuracy of 99.94%. For example, Zhang (2022) integrated a smartphone with ANN to explore the potential of near-miss falls while working on a scaffold with a model training accuracy of 99.94%. However, Khan et al. (2022) integrated computer vision with IoT and closed-circuit TV (CCTV) by training the SVM algorithm for real-time monitoring and classification of falls from scaffolds with an accuracy of 98%. Lee et al. (2021) developed a CNN-LSTM model with an F1 detection and classification of 72 to 78% and 93 to 97% to minimize the incorrect classification of fall-related movement of the worker using scaffolds by installing the sensors on the scaffold. The detection of fall potential associated with tiling and other dangerous motions of construction workers, such as sudden swaying, unsteady footsteps, and loss of balance, was achieved by Fang et al. (2017) utilizing electroencephalography (EEG) sensors and SVM algorithm that resulted in an accuracy of 79.13% and a detection of 76.86%. The experiment was monitored by CCTV.

Meanwhile, several papers also predicted fall from the ladder using ResNet50, RF, and SVM (Gaussian Kernel). SVM (Gaussian Kernel) recorded the highest prediction rate of 99.5% in laboratory testing, and ResNet50 recorded 85.33%. According to Nadhim et al. (2016), fall from a ladder accounts for 17% of construction accidents. Anjum et al. (Anjum et al., 2022) employed Single Shot Multi ResNet50 with a reported accuracy of 85.33%, precision of 86.70%, recall of 85.6%, and F1 of 86.4% using CCTV. Choo et al. (2023) used several ML algorithms (AdaBoost, DT, SVM rbf kernel), but RF with leave-one-subject-out cross-validation generated the highest accuracy of 86.0%. The data were gathered from 20 construction sites, totaling 1,536 human trajectories, with each trajectory having a window size of 30 seconds. Han et al. (2014) employed SVM (Gaussian Kernel) algorithms with an accuracy of 99.5% in laboratory testing. The study involved four hours of climbing a ladder, with 25 samples taken from each action. This process generated four types of data: rotation angles, joint angles, position vectors, and movement directions.

A subset of articles-built datasets using images and videos from construction sites and web sources to predict and monitor falls in real time. Shanti et al. (2021), for example, adopted the YOLOv3 algorithm to predict FFH and reported an accuracy of 91.26% using 1,000 images obtained from local construction sites. Antwi-Afari (2018) utilized motion science systems such as wearable insoles with RF achieving the highest accuracy for classifying loss of balance events that lead to fall accidents, with more than 94% accuracy.

Despite the progress made in AI-in -construction-for H&S research and application, several critical challenges persist. Most of the models developed are limited to being applied to only one type of task on a construction site. Khan et al. (2022) developed a prediction model that was limited to only A-type ladder working at a height between 1.2m - 2.0m while workers standing behind the ladder were misidentified as standing on the ladder.

3.3.1.2 Struck-by accident prediction

Struck-by accidents are a major cause of fatal incidents, typically resulting from falling or suspended objects and collisions between workers and heavy machinery (Amiri et al., 2016). Potential struck-by hazards include falling objects, a swinging crane, moving trucks, and overhead equipment (Kim et al., 2022). Lee and Yang (2022) proposed a technology that integrates high-frequency sound with a CNN to recognize struck-by hazards. The system, which utilized a smartphone to emit high-frequency sound via a Bluetooth speaker, generated a total of 855 spectrogram images from indoor experiments and 1,524 spectrogram images from outdoor experiments. These spectrograms were used to train the CNN model, which achieved an accuracy of 84.4–97.4% for detecting movement direction and speed, and 78.9% for identifying near-miss situations. Kim et al. (2021) predicted workers' inattentiveness to struck-by hazards by monitoring biosignals during a construction task, integrating a virtual reality experiment that utilizes an SVM with a linear kernel to achieve a prediction accuracy of 72.2% by combining biosignals such as electrodermal activity, pupil dilation, and saccadic eye movements. A real-time surveillance system to prevent struck-by accidents was developed by Luo et al. (2020) utilizing YOLOv2 which achieved 91% accuracy. The study collected a total of 981 data instances during experiments involving 32 participants.

Dong et al. (2018) proposed a proactive struck-by risk detection method that combines movement pattern modeling and randomness modeling to predict workers' next locations on construction sites. This approach uses position probability grids to track and model worker movements, achieving an accuracy range of 81.4% to 98.3%. The technology relies on real-time location systems, including tags and anchors, and can be seamlessly integrated with existing proximity warning systems to provide early warnings and mitigate struck-by accidents. A total of 2986 trajectories were extracted from the location tracking records of the workers.

3.3.1.3 Dataset in construction accident

Several studies have employed both binary and multi-class classification techniques to categorize datasets into distinct classes. For example, binary classification was used to differentiate between two categories, while multi-class classification was applied to classify datasets into more than two categories (Yoo et al., 2023, Koc et al., 2023). This aims to predict the class samples by identifying patterns and features of the dataset (Jha et al., 2022). Although there are several ML algorithms used for multi-class classification, the most commonly used and effective algorithms are DT, RF, naïve bayes, and XGBoost. Yoo et al. (2023) gathered 152, 2867 accident reports from South Korean construction firms involving different accident types such as falls, struck-by, caught in between, fire and explosion, chemical, electrocution, collapse, machinery/vehicle, and others. The XGBoost showed the best performance with a multi-class area under the receiver operating characteristic curve (MAUC) score of 0.8603. According to Jeon and Cai (2022), a multi-class classification system for construction hazards using wearable electroencephalogram (EEG) devices was developed, achieving an accuracy of 82.3% in classifying various hazards, including struck-by incidents, falls, strip/trip, caught-in-between, and chemical/electrical (Lee et al., 2022). This system used an EEG classifier trained on data collected from workers in a virtual reality (VR) environment, employing an advanced two-step ensemble classification approach. A total of 30 participants were considered in control environment. Qiao et al. (2022) focused on construction accident narratives using SVM and CNN, achieving accuracies of 0.91 and 0.90, respectively. Data collection involved 4,770 construction accident reports from the OSHA.

Li et al. (2018) obtained 156 accident reports from the State Administration of Work Safety in China to facilitate better risk assessment and management processes. They employed a K-means clustering algorithm to classify safety risk factors identified from the accident reports, achieving clear categorization of the following accident risks: underground pipeline issues, hidden danger elimination, enclosure protection, safety consciousness, violation of regulations, hydrogeologic conditions, construction monitoring, advanced forecasting, dynamic control, and construction coordination. Other studies employed a hybrid deep neural network model combined with the Word2Vec skip-gram algorithm for classifying construction accident causes. The hybrid model included a CNN for feature extraction and a Bidirectional Long Short-Term Memory (BDLSTM) layer for sequence modeling, achieving a weighted average F1 score of 0.723, and a precision of 0.738 (Zhang, 2022). The hazards considered in the study included falls, struck-by incidents, electrocutions, and other typical construction-related accidents (Kang and Ryu 2019).

Many articles indicated the problem of sample size and the comprehensive dataset. The lack of datasets impacts the action recognition or prediction (Anjum & Nnaji 2025). The effectiveness and efficiency of an AI model is premised on the sufficiency of the data used for the training and testing of the model. Larger datasets are crucial for AI model performance. Shanti et al. (2021) highlighted the crucial role of training and testing models with significantly larger datasets, emphasizing this need after utilizing 1,000 images for their proposed model. Ding et al. (2018) asserted that insufficient training sample size and a restricted range of unsafe actions limit the recognition of certain worker actions. Larger datasets could enhance model accuracy, but the absence of a comprehensive public dataset, covering tasks like object detection, pose detection, and activity recognition across diverse construction sites, viewpoints, lighting, and occlusion conditions, remains a challenge. Shen et al. (2020) recognized constraints in data collection, highlighting the imperative for establishing a comprehensive database.

3.3.2 Safety inspections

Several researchers focused on safety and hazard detection with a total number of 24 publications representing 13.25%. The construction worker is typically unable to identify all hazards on a job site based on the training obtained (Jeelani et al., 2021). Despite providing training to construction workers, the likelihood of not identifying hazards is still on the rise (Jeelani et al., 2021, Elelu el., 2023, Kamoona et al., 2019, Lee et al., 2023, Chen et al., 2022) made use of NLP based syntactic structure analysis to predict hazards involving working from height and operating a grinder using YOLOv4 that achieved an accuracy range of 98.6% to 100% through on-site surveillance cameras.

Inspection of construction workers' safety behavior on-site improves workflow and aids the avoidance of hazards on-site (Neuhausen et al., 2020). Manual inspection of work on construction sites is time-consuming and labor intensive (Chi & Caldas 2012). A multitude of approaches exist including camera-based and tag-based techniques such as RFID, Ultra-Wideband or GNSS technology (Neuhausen et al., 2020), and proactive systems such as audio alert systems tagged to safety vests or equipment cabins (Tang et al., 2020). Monitoring systems warn workers from entering hazardous areas (Carbonari et al., 2011) and spell out whether the specific work sequence constitutes safe or unsafe action (Yang et al., 2021). Neuhausen et al. (2020) exemplified construction workers' safety monitoring by creating several 3D scenes of construction sites, the system detects workers in consecutive video frames using YOLOv3 in two environmental scenarios with a total of 3835 frames and 32 tracked subjects and tracks them by Kalman filtering (Yan et al., 2020). The authors however discovered that synthetic data offers a viable alternative for assessing tracking performance in hazardous situations without exposing the work to risks. Tang et al. (2020) adopted RCNN and LSTM to predict workers' and equipment motion trajectories. A total of Trajnet data of 11, 448 tracks from 58 scenes with each track having 20 steps to monitor construction workers' safety while Prediction heads for the Voyager dataset are configured to forecast future steps at intervals of 10, 20, and 40 (Tang et al., 2020). The result indicates that combining LSTM + Reg. model reduced the localization error by nearly 50% when compared with MLP + Reg. model. But with the ablation study which adopted RMSE at 40, the model achieved the best long-term prediction performance. The longer response times assist operators, managers and superintendents in reacting within a reasonable timeframe.

Yan et al. (2019) in their quest to monitor and improve safety performance, adopted computer vision to estimate worker-centric view invariant 3D spatial proximity for crowdedness. RGB Camera was selected purposely to detect worker-centric crowdedness. They utilized DNN, SVM, KNN, ensemble classifiers, Faster RCNN as regional proposal network and ResNet-50 as object detection network. ResNet-50 performed well in ImageNet detection, ImageNet localization, and common objects in Context (COCO) detection and COCO segmentation. Combining the Faster RCNN and ResNet-50-based person detection networks was observed to enhance the detecting range of 3D joint estimation, ensuring a larger coverage and reliable view-invariant feature extraction. The DNN achieved a test accuracy of 99%, decision tree (DT) 88%, SVM 92%, KNN 82% and EC 94%. The study involved 6 participants, and 6000 video frames were collected. Although Kolar et al. (2018) VGG-16 model, for safety guardrail detection in 2D images. The proposed model achieved a high accuracy rate of 96.5%. The study utilized 4,000 images gathered from real-world construction sites for training, equally split into 2,000 positive and 2,000 negative samples.

Saudi et al. (2020) for example, in detecting images based on safe and dangerous conditions facing workers on construction sites emphasized issues of low resolutions, momentum optimizers and thresholds. Chen et al. (2022) graph-based linguistic visual information model could only identify features SpaCY parser but failed in generating POS tags and dependency models. These constraints significantly limit the effective deployment and generalization of the models developed by various authors. This also suggests that industry practitioners and decision makers will have to take into consideration several models if they have the intention of deploying them on-site. Also employing a centralization data management system that will integrate data for each of the models presents another challenge. The ambiance of some models is limited to indoor environments and cannot be used outdoors. They also have a significant number of obstacles in the house or apartment due to fixed sensor positions, making implementation challenging.

Safety inspection research demonstrates 93% deep learning adoption with high reported accuracy (91–98% for YOLO variants), yet our systematic review found that only 12% of studies reported actual on-site deployment. This fundamental disconnect between laboratory performance and practical implementation, where algorithms excel under controlled conditions but face real-world barriers including lighting variability, occlusion, and computational constraints, emerges only from integrating bibliometric growth trends with systematic deployment evidence. Future research must prioritize field validation over incremental accuracy improvements.

3.3.3 Fatigue

The most critical accident precursors in the construction industry are the failure of workers to recognize hazards and the negligence of these hazards (Jamil et al., 2020). Safety monitoring must not only monitor workers' physiological status (e.g fatigue, illness, or inebriation), but also detect any dangerous motions caused by adverse physiological status before an actual accident occurs (Jamil et al., 2020). Several researchers have successfully employed motion monitoring, respiratory monitoring, and heart rate monitoring to assess the physiological status of construction workers (Khan et al., 2025; Antwi-Afari et al., 2017; Aryal & Becerik-Gerber 2017; Jebelli et al., 2019; Jingluan et al., 2021). Currently, there are several wearable sensors that can help measure personal physiological status which will help reduce WMSDs (Antwi-afari et al., 2023). For example, a heart-rate sensor evaluates a worker's fatigue level based on an electrocardiogram. However, the electrode attached to the skin is easily affected by perspiration (Fang & Dzeng 2017). Bespoke training systems on hazard recognition can be challenging due to differences in the number of safety managers and trainers compared to the number of construction workers (Bangaru et al., 2025).

Jebelli et al. (2019) focused on predicting the rate of energy expenditure of construction workers by evaluating physiological signals through the application of Gaussian Support Vector Machines (GSVM). The accuracy rate was 90% in recognition of low and high physical intensity levels and 87% for low, moderate, and high physical intensity levels. The study tested the KNN algorithm, Gaussian discriminant analysis (GDA), Linear SVM, cubic SVM, and quadratic SVM were reported as follows:76%, 71%, 81%, 83%, and 84% respectively. The dataset included diverse physiological signals from 10 workers performing various tasks at two different construction sites, resulting in a total of 9,216,000 data points. Jeelani et al. (2021) developed a model that includes a vision-based framework for worker localization and hazard detection, real-time localization based on Bag of Words (BoW) for locating workers and static hazards, and real-time detection of dynamic hazards using deep learning, achieved an accuracy of 93% during validation in two construction environments: static and dynamic environment. The success rate for identifying dynamic hazards was 85.7% in outdoor environments and 89.4% in indoor environments. Conversely, the failure to detect rate was 14.2% outdoors and 10.5% indoors. The study gathered 1000 images per class. Antwi-Afari (2023) classified physical fatigue levels of construction workers using wearable insole sensors that collected acceleration and plantar pressure data with random forest 86% accuracy for 10-fold cross-validation and 87.7% training accuracy. The study included 10 male participants in a controlled environment. Additionally, Umer et al. (2020) developed and evaluated a method for monitoring and modeling the physical exertion of construction workers through the combination of cardiorespiratory and thermoregulatory with bagged trees generating the highest accuracy of 95.3%. The research involved ten male individuals and 1,286 datasets of physiological data points with corresponding RPE labels for the participants.

Fatigue resulting from crane operation was addressed by a hybrid neural architecture of CNN and LSTM algorithm that achieves an average accuracy rate of 78.28%, 29.96%, and 92.81% when applied to trained models respectively (Liu et al., 2021; Seo and Lee 2021). Although Liu et al. (2021) analyzed a dataset and adopted a hybrid of CNN and LSTM for fatigue detection among crane operators. The models achieved accuracy rates of 54.71% for UTA-RLDD, 72.76% for NTHU-DDD, and 87.52% for YawnDD. The research utilizes a scaled-down tower crane prototype to collect high-quality, real-time vibration data under cyclic loads, covering a lifespan of 0 to 70 years. Conducted in harsh environments, it addresses safety concerns by monitoring degraded lifting capacity due to structural fatigue and preventing crane failures. Fatigue among crane operators or heavy-duty equipment operators can lead to major construction accidents (Cheng & Teizer 2014). While Gonsalves et al. (2022) however reported a lower accuracy rate 83.8% with exoskeleton and 74.1% without exoskeleton using SVM, KNN, ensemble, NB, logistic regression, decision tree (DT) linear discriminant, and Kernel from the MATLAB toolbox to predict worker activities from spinae muscles measured with a wearable EMG. The incorporation of DNN model to predict high-stress and low-stress predictions resulted in 93.5% and 65.0% using the LOSOCV, while the field test was 78.5%. The Exo and NoExo conditions had 2,729,400 and 2,141,500 data samples, respectively. Wearable biosignals were used to gather EDA, PPG, and skin temperature data (Lee & Lee 2024). The utilizing of GSVM and DNN to predict construction workers' psychophysiological responses yielded 78% and 83% accuracy respectively using multimodal wristband-type biosignals. In the controlled environment, the dataset consisted of 5,218 low-stress data points and 6,442 high-stress data points. Meanwhile, the field data collection yielded 9,383 data points, comprising 4,906 low-stress and 4,477 high-stress case (Lee & Lee 2022).

Heat stress was assessed by Shakerian et al. (2021) using wearable sensors and analyzed with ANN, KNN, and RF. RF algorithm achieved the highest accuracy, with a prediction accuracy rate of 92%. Similarly, Yi et al. (2016) developed an early-warning system for construction workers against hot and humid climates, utilizing ANN to forecast the Rating of Perceived Exertion (RPE) based on a dataset containing 550 sets of synchronized work-related, environmental, and personal data. The ANN model demonstrated high accuracy, achieving R^2 values of 0.966, 0.907, and 0.918 for training, validation, and testing data sets respectively, with MAPE values of 0.814%, 1.795%, and 1.283%. The dataset consists of 550 sets of synchronized work-related, environmental, and personal data collected from 39 healthy and experienced construction rebar workers.

Aryal et al. (2017), in monitoring fatigue of construction workers, developed a model that was limited to only materials handling under room temperature. It was however clear from their studies that, once a real work world is mimicked, the application of the model could present significant biases. Seo and Lee (2021) introduced algorithms employing Support Vector Machines (SVM) for musculoskeletal disorder classification in single postures. The testing involved eight subjects simulating three representative postures (back-bending, arm-raising, knee-bending) recorded from three viewpoints, resulting in a total of 60,091 image frames extracted as testing images. Each subject contributed approximately 7,500 images. Moreover, some experiments did not account for influences from fatigue and other key variables. For instance, a prediction model developed by (Antwi-Afari et al., 2020) was limited to predicting only a wearable insole pressure system within the confinement of forces for lifting, lowering, carrying, and pushing or pulling which could not be extended to other construction activities. The study involved two healthy male participants in a controlled environment, with the following data samples in each activity category: grip force: 98,896 samples, lift/lower/carry: 487,274 samples, pull/push: 284,528 samples, and other non-risk activities: 187,852 samples.

Fatigue monitoring represents 20 articles (11%) in the systematic review, yet bibliometric trends show a disproportionately low research volume relative to its documented contribution to construction accidents. The systematic review reveals that while physiological signal-based approaches achieve strong accuracy (87–95% for GSVM and bagged tree algorithms), nearly all studies were conducted in controlled laboratory settings with small sample sizes (typically 10–15 participants). This combination of bibliometric underrepresentation and systematic evidence of limited field deployment reveals a critical gap: fatigue monitoring technology is technically mature enough for deployment yet remains largely confined to laboratory validation. Future research should prioritize real-world field studies with larger, more diverse participant samples.

3.3.4 PPE detection

For this review, PPE detection encompasses equipment and PPEs: hard hats, safety jackets/vests, dust masks, gloves, safety goggles, safety boots, and safety belts. The architectural, engineering, and construction (AEC) industry has remarkably leaned towards adopting DL in object detection (Chen & Demachi 2021; Kim et al., 2020). PPEs such as hard hats are an effective precautionary measure to reduce the likelihood of sustaining traumatic brain injury (Fang et al., 2018). The context of requiring PPE detection and its use compliance holds significant importance (Delhi et al., 2020). Thirty-six of the 181 articles' focal points were on object detection in SH management representing 19.89% of the review articles. Both machine learning and deep learning algorithms such as CNN, RCNN, YOLOv3, RCNN, Faster R-CNN, YOLOX, YOLOv5x, SSD, ResNet, spare representation-based classification and Darknet53 integrated with advanced computer vision techniques were commonly used for detecting PPEs, equipment, and machinery. Deep learning methods have exhibited outstanding performance in object detection across various visual tasks, although AI merged with computers is the most dominant technique in object detection (Mukhopadhyay & Biswas 2024). The YOLO series of detection methods has increasingly become the predominant approach for object detection (Li et al., 2024). These algorithms achieved the highest level of accuracy and F1 score. The review indicated that machine learning and deep learning algorithms have shown varying high accuracy rates, from 80% to 100%, in correctly predicting the use of safety equipment like hard hats, vests, hooks, safety boots, and machinery.

Although several studies have employed AI algorithms to develop and test models capable of recognizing multiple PPE types simultaneously, most studies primarily focus on advancing and refining hard hat and safety vests detection algorithms. Nath et al. (2019) created a model based on CNNs for detecting common objects related to construction, achieving 90% accuracy for single-label classification and 85% accuracy for multi-label classification. The single-label dataset consisted of 3,392 training images and 752 testing images, while the multi-label dataset comprised 1,589 training images and 398 testing images. Nath et al. (2020) developed and evaluated models using the YOLOv3 architecture for PPE (hard hat and vest) compliance among workers, achieving a 72% accuracy on real-world job sites. They also tested various classifiers like decision tree, VGG-16, ResNet-50, Xception, and Bayesian methods. The dataset contains approximately 1,500 annotated images and around 4,700 instances of workers wearing various combinations of PPE components. The images are categorized into different classes, such as workers with hats (WH), workers with vests (WV), and workers with hats and vests (WHV). The dataset includes both crowd-sourced and web-mined images, ensuring a diverse collection of data. The process of detecting PPEs operates as an independent platform alongside construction-related objects to facilitate the recognition of complex and elusive spatial relationships (Chen & Demachi 2021). Combining AI with advanced computer vision and UAV generated higher accuracy rates. When combined with sensor-based detection techniques and vision-based methods, AI utilizes standard cameras, pattern recognition, and sophisticated computer vision technologies to establish a solid foundation. The merging of these technologies has indeed sparked considerable interest. However, it seems that hybrid algorithms did not yield significantly higher accuracy or precision than a single developed algorithm (Yu et al., 2022). Commonly, Computer vision was mainly used with region-based CNN for detecting objects due to the availability of faster variants. For example, YOLOv5 excels in identifying larger objects and performs high-speed automatic feature learning while ensuring detection accuracy (Tan et al., 2021). The detecting model's high-level feature map has a broad responsive area focused on abstract semantic information, suitable for classification tasks but with low resolution and insufficient localization detail. In signal processing, deeper network layers often result in more significant information loss for small objects.

Within the context of object detection, several authors highlighted the detection of PPEs with fewer papers detecting workers, machinery, or equipment. Significantly, numerous hybrid AI algorithms have been implemented to enhance the recognition of safety helmets on construction sites, such as SSD, Faster R-CNN, improved YOLOv3 (Chan et al., 2022), Faster R-CNN, YOLO and DenseNet (Yu et al., 2022). The integration of AI with computer vision, Unmanned Aerial Vehicle (UAV,) and data analytics, particularly through deep learning algorithms, offers promising solutions for automatic, real-time detection of workers' non-compliance with PPE usage in construction. Several models predicting hardhats could give color coding (e.g., red, yellow, white, green etc.) and classification (Mneymneh et al., 2019). Delhi et al. (2020) explored CNN with YOLOv3 for real-time hard hat and jacket detection, achieving average precision, recall, and F1 of 96%. Zhao (2022) saw a recognition rate of safe and unsafe helmets at 96.83% and 98.33% respectively. The dataset used in the study consists of 2,509 images collected from video recordings taken at several construction sites. While Mneymneh et al. (2019) developed an integral automated hardhat detection by combining AI with computer vision generating a recall of 90% and precision of 98.5%. The training dataset for the cascade classifier includes 231 positive instances (images containing hardhats) and 375 negative instances (images without hardhats). The images were captured using a Canon EOS 1100D digital camera with a resolution of 1,280 × 720 pixels.

Wearing hard hats is crucial for safeguarding individuals on construction sites from accidents (Wu et al., 2019). Many authors working object detection within the context of construction safety have concentrated extensively on the domain of hard hats (Wu et al., 2019; Yu et al., 2022). Wu et al. (2019) utilized the Single Shot Multibox Detector (SSD) combined with a newly introduced reverse progressive attention for identifying non-hardhat use. They developed the GDUT-HWD benchmark dataset, compiled from images downloaded from the internet using search engines, to train their SSD-RPA model that achieved a mean average precision of 83.89%. Shen et al. (2021) introduced a method for NHU (Non-Hardhat Use) identification utilizing DenseNet-based face detection and bounding box regression. Typically, these methods output the worker's bounding box from the object detection model, proving effective in single hazard identification tasks like NHU, where the binary classification is either individual using PPE or individual not using PPE. The model achieved an accuracy rate of 94.47% accuracy, 96.2% recall, and 96.2% precision. Siddula et al. (2016) combined a Gaussian mixture model with CNNs for the purpose of detecting targets on construction site rooftops, achieving an accuracy rate of 97.5%. The images contain a total of 18,893 instances of hardhats. The dataset covers various on-site conditions, including different scenes, visual ranges, and illuminations.

Goh et al. (2022) for instance, used the SSD, RCNN, and YOLOv3 to detect hardhat among construction workers, algorithm's performance under varied construction site conditions, posing limitations to the generalizability of the proposed YOLOv3 improvements. Studies conducted in specific scenes, faces challenges in generalizing its findings to other construction sites that have a high degree of variability in background and pedestrian conditions. While Tang et al. (2020) held that objects outside the camera's field of view or obscured cannot be monitored, and in many cases, camera calibration is necessary to retrieve the 3D world coordinates of objects. Obstacles such as algorithms struggling to precisely detect PPEs that are small or appear cluttered in an image. These detection constraints are complicated by similar image regions or partial occlusions. However, misclassification occurred when workers were depicted holding large handheld tools or other objects. Several algorithms identified only workers with a specific pixel size Mneymneh et al. (2019) and Ngoc-Thoan (2023) indicated the poor performance of the model due to object size, complicated or unclear object background which affected optimization of the model.

The integration of bibliometric volume with systematic methodological analysis reveals a concerning pattern in PPE detection research. Despite high research concentration and strong DL performance (91.3% mean accuracy), the systematic analysis found that the majority of studies focus exclusively on hard hats and safety vests, the two most visible and easily detectable PPE items. Critical protective equipment including safety harnesses, respiratory protection, electrical gloves, and safety boots remain severely understudied. This disconnect between research popularity and comprehensive safety coverage is only visible by combining bibliometric volume with systematic accuracy analysis, the field has optimized detection of the most visible PPE items while neglecting those most critical to preventing fatal injuries.

3.3.5 Worker's ergonomics risk assessment

The construction sector is one of the most ergonomically hazardous job sites with many employees still having to perform physically intensive and potentially dangerous tasks in their daily work leading to WMSD (Ogunseiju et al., 2021; Lins & Hein 2022). Construction workers are frequently exposed to elevated ergonomic risks due to prolonged static positions, uncomfortable bending and twisting, and heavy load handling during work activities. The assessment of WMSD, workers' posture and movement, and ability to carry load have been monitored using a combination of AI algorithms and wearable sensors (Zhang et al., 2018; Antwi-Afari et al., 2020; Yang et al., 2020; Mudiyanselage et al., 2021; Lins & Hein 2022). Overexertion is a major cause of WMSD leading to work-related illnesses affecting workers' backs and necks (Eaves et al., 2016). Lee et al. (2020) combined a hybrid CNN long short-term memory algorithms with single IMU to propose a technique for detecting excessive carrying load that achieved an accuracy rate of 92.46% and 96.33% for carrying modes and posture classification. A total of 360 sample data points were considered in the experiment, which was conducted in an indoor environment involving 14 male participants. Lins and Hein (2022) detected and classified harmful body postures of workers using NEAT algorithms and ANN with a total dataset of 111,275 posture shots for training the classifier postures involving legs, arms, and the back. The evolutionary-trained classifier demonstrates superior detection rates (with an average correct classification rate of 0.35 for back postures, 0.64 for arm postures, and 0.25 for leg postures) compared to a neural network trained using compared to neural network. Ogunseiju et al. (2021) adopted LSTM digital twin driven to provide real data on workers' actionable actual postures. Seo and Lee (2021) implemented a 2D image-based posture classification system, integrating SVM with computer vision, and achieved an accuracy of 89% in posture classification. A total of 60,091 image frames were extracted at 30 frames per second in a controlled laboratory environment. Yan et al. (2017) developed a posture classification method based on 2D skeleton motion for the back, arms, and legs. Using a Bagged decision tree, they optimized the classification accuracy for human arms, back, and legs to 96.5%, 95.0%, and 97.6% respectively, with overall accuracies of 89.2%, 88.3%, and 87.6%. The data collection involved 6 participants being recorded for approximately 60 minutes, excluding rest time, with video recordings made at a rate of 30 frames per second. The detection and classification of awkward posture by wearing insole pressure was investigated by Antwi-Afari et al. (2018) with SVM reaching a classification accuracy of 99.70%. Although, GRU model can generate precision values between 94.41% and 99.80% for different postures, and the best-recognized posture could reach an accuracy level of 99.30% (Antwi-Afari et al., 2022). Huang et al. (2022) used a Back Propagation (BP) neural network algorithm to develop a risk evaluation model. The training Mean Squared Error (MSE) value of the simulation training was 0.000176, which is below the target value of 0.0003, indicating high accuracy. The R-values for the training set and test set were 0.947 and 0.808, respectively and the maximum absolute value of the error in the test set data was 8.22%, confirming the satisfactory training effect of the model. The study utilized data from a total of 216 high-cutting slopes from various high-speed railways. Chen et al. (2022), however, adopted a YOLOV5 model of the deep learning family which integrated pose estimation with object detection to obtain motion data of human skeletons when climbing a ladder and a CNN to estimate 2D human pose information and skeleton data. The average precision of object detection was 96.0% and pose estimation was 89.8%.

Mudiyanselage et al. (2021) evaluated ergonomic risks in construction workers' manual material handling, specifically muscle movement, strain, and force, using electromyogram (EMG) and four AI algorithms: Random Forest, Decision Tree, Support Vector, and K-Nearest Neighbor for posture risk classifications. The Decision Tree classifier achieved the highest accuracy of 99.35%. Yang et al. (2020) utilized a bidirectional long short-term memory (Bi-LSTM) neural network under different load conditions to classify physical loads involving pushing, pulling, and carrying achieving an accuracy of 74.6% to 98.6% and an F score ranging from 0.59 to 0.99, demonstrating the Bi-LSTM's capability to classify with acceptable accuracy. Mehmood et al. (2023) focused on the safety management aspect of recognizing and mitigating the risks associated with awkward working postures in construction workers by employing Bi-LSTM that resulted in an accuracy of 99.94% when the data was gathered using insole sensor pressure. Antwi-Afari et al. (2020) for example, used 2 participants while Gonsalves et al. (2022) employed erector spinae muscle activity to discern workers' actions with or without exoskeletons, utilizing a sample size of only 10 participants. Mudiyanselage et al. (2021) proposed a machine modeling approach using sEMG-based to measure muscle activity with only 1 participant.

Ergonomic risk assessment accounts for 28 articles (15%) in the systematic review, with bibliometric trends showing steady growth particularly after 2019. The systematic review reveals that while ML and DL algorithms achieve consistently high accuracy in posture classification and musculoskeletal disorder risk assessment (74.6–99.94%), nearly all studies rely on single-participant or small-sample laboratory designs. Integrating bibliometric growth trends with systematic evidence of methodological constraints reveals a field expanding in volume but not yet in ecological validity. The increasing research interest identified bibliometrically has not yet translated into field-deployable solutions, representing a critical gap between demonstrated algorithmic capability and practical construction site application.

3.3.6 Safety behavior

Statistics reveal that over 80% of accidents on construction sites are due to workers' unsafe behavior, making it the primary cause of safety incidents (Zhang & Fang 2013). Duan and Zhou (2024) proposed behavioral pattern tags that encompass attitude, subjective norms, perceived behavioral control, behavioral intention, and actual behavior at the construction site (Goh et al., 2022; Fang et al., 2018). Goh et al. (2018) utilized a DT algorithm among six machine learning algorithms and logistic regression for predicting unsafe behavior in construction safety from 80 participants. It focused on cognitive factors from the Theory of Reasoned Action, finding social norms to have the greatest influence on safety behavior. The study combined TRA-based questionnaires and Behavior-Based Safety observation data to highlight the impact of social norms on workplace safety. Liu et al. (2021) discussed various machine learning and deep learning algorithms used to analyze the safety behavior of construction workers, specifically monitoring and identifying unsafe behaviors using computer vision and machine learning technologies to enhance construction site safety and prevent accidents. The machine learning algorithms included Faster R-CNN, SSD-MobileNet, YOLO v3, CNN-LSTM hybrid models, and ResNet-152, with detection accuracies reaching up to 99%. Tools used include 2D and 3D image data, RGB-D motion sensors, and wearable devices, significantly enhancing real-time detection and monitoring of worker safety and behavior.

Although other studies including (Yin et al., 2023; Kamoona et al., 2019) used different AI classifiers to uncover complex safety behavior patterns such as Logistic Regression (LR), SVM, RF, and Categorical Boosting (CatBoost). The CatBoost–MOSMA (Multi-Objective Slime Mould Algorithm) combinative method achieved the highest performance, with an accuracy ranging from 0.80 to 0.86 and an F1-score ranging from 0.79 to 0.86. Akhavian et al. (2016) monitored construction workforce safety behavior, state, and activity recognition using a neural network that achieved an accuracy of 87% to 97% for user-dependent cases, and 62% to 96% for use-independent cases based on data gathered using mobile phone accelerometer and gyroscope sensors in an outdoor workspace. The study used 120,755, 149,682, and 337,800 data points per sensor per axis for the first, second, and third categories, respectively. Earlier studies such as Joshua and Varghese (2011), predicted construction workforce safety behavior using multilayer perceptron that yielded an accuracy level of 80% in uninstructured environments by attaching accelerometers to both sides of the waist in an outdoor natural environment. The study used data segments of various lengths: 2 seconds, 4 seconds, and 4.23 seconds, with a sampling frequency of 60 Hz. Each data segment contained 120 (for 2 seconds), 240 (for 4 seconds), or 256 samples. In addition, Ryu et al. (2019) used embedded wristbands to predict the safety actions of the construction worker with SVM resulting in an 88.1% accuracy rate. Ten masons were involved in tasks such as spreading mortar, bringing and laying blocks, adjusting blocks, and removing remaining mortar. Each subject contributed to a dataset totaling 63,720 points. Other algorithms such as GSVM were used to assess the perceived risk levels of construction works using wearable sensors that generated an accuracy rate of 81.2%. Physiological data were collected from eight construction workers, including two carpenters, one-floor finisher, four electricians, and one foreman. The total amount of labeled data used to train and validate the classification model was 47,544 data points (Lee et al., 2021). KNN algorithm was adopted to provide prenotifications and identify safety hazards and accidents in real time on construction sites. The model achieved an accuracy rate of 93.4%. The study used 200 two-second time segments for each construction activity. Specifically, 100 segments comprised the training dataset, and the remaining 100 segments were used for testing (Lee et al., 2020). Noghabaei et al. (2021) conducted a feasibility study that combined EEG and eye-tracking in an immersive virtual environment to predict safety hazard behavioral patterns of construction workers, adopting Gaussian Kernel SVM that achieved an accuracy rate of 93%. Similarly, Wu et al. (2022) integrated Digital Twin (DT), DL, and Mixed Reality (MR) technologies into a real-time visual warning system for construction safety. This system tracks hazardous objects in real-time using a combination of the YOLOv4-Tiny algorithm and Deep SORT, presents hazard information via wearable MR devices, and achieved a hazard identification accuracy of over 96.1%, with an average hazardous area presentation accuracy of 11.47 cm, showcasing the system's efficacy in enhancing workers' safety behaviors and risk assessment accuracy.

Some algorithms had the potential for misclassification. For instance, Tian et al. (2023) in an attempt to quantify safety hazard text and obtain the text word vector, increased the number of GRU units which resulted in a poor performance of the model on text semantics analysis, and difficult to deeply extract features. Saudi et al. (2020) for example, in detecting safe and dangerous conditions facing workers on construction sites emphasized issues of low resolutions, momentum optimizers, and thresholds. Yang et al. (2023) employed a transformer and 3D CNN to detect unsafe behavior in construction. Their findings suggest the necessity of identifying, extracting, and integrating richer features when applying AI in construction safety management as well as a larger dataset (Liu et al., 2021).

Safety behavior research accounts for 13 articles (7%) in the systematic review, among the lowest representation across all seven themes, yet bibliometric trends indicate growing recognition of unsafe behavior as the primary driver of construction accidents, contributing to over 80% of incidents. The systematic review reveals that while algorithms such as CatBoost-MOSMA and SVM achieve accuracy rates of 80–97.6%, studies predominantly rely on controlled environments and self-reported behavioral data. The contrast between the bibliometrically documented importance of safety behavior and the systematically identified methodological limitations of current AI approaches reveals a field where research volume has not kept pace with the scale of the problem. Future research should focus on real-time, unobtrusive behavioral monitoring systems validated in authentic construction environments.

3.3.7 Safety training

Effective construction safety training (Feng & Chen 2021) is deemed essential in significantly lowering the occurrence of accidents (Duan et al., 2024). Unsafe construction behaviors frequently stem from inadequate safety training (Goh et al., 2018). Implementing safety training for construction workers is a crucial strategy to prevent these accidents, with effective training methods playing a key role in reducing the accident rate (Hussain et al., 2020). Although Haung et al. (2022) employed a deep EEG neural network (EEG-net) enhanced with batch normalization and ELU activation functions for real-time safety training assessment. The EEG-net achieved an accuracy of over 80%. VR was utilized to simulate potential construction site hazards, such as electrical injuries, object impacts, mechanical injuries, foundation collapses, confined spaces, and falls, to improve workers' safety awareness and health assessment.

Jeelani et al. (2018) used BiLSTM-CRF model for character classification, achieving high accuracy with mean values of accuracy and recall above 0.98. Tools such as VisualSFM for 3D reconstruction, SIFT for feature extraction, and eye-tracking glasses employing the Corneal Reflection Technique were utilized. The system records and analyzes workers' eye movements to provide personalized feedback, aiming to enhance hazard recognition and safety on construction sites. A total of 102 s and 2512 frames were extracted from category A, and 4562 image frames for category B. Although other studies including Guo et al. (2023) used different classifiers to carry out safety training using algorithms such as LR, SVM, RF, and CatBoost. CatBoost–MOSMA (Multi-Objective Slime Mould Algorithm) combinative method achieved the highest performance, with an accuracy ranging from 0.80 to 0.86 and an F1-score ranging from 0.79 to 0.86 (Yin et al., 2023). Jeon et al. (2021) employed Virtual reality (VR) and wearable EEG to enhance safety training, by CatBoost algorithm that achieved an accuracy rate of 95.1%. Twenty-eight graduate students participated in the experiment providing a total of 840 data points in the five categories of hazards (fall, slip and trip, struck-by, chemical and electrical, and other Hazards) that were stimulated.

Several studies lacked detailed information on the diversity of the dataset as experiments were limited to small sample sizes in a controlled laboratory setting. Therefore, the generalization and replicability of the models in solving real-world construction safety is a concern. Construction sites are dynamic, complex, and complicated. Therefore, additional training data is required from the multiple workers for algorithms to work efficiently and accurately. Operational challenges from singular sensor setup and maintenance, coupled with parameter optimization for a small participant sample are needed. Consequently, researchers face a challenging task in extracting patterns from varied data, especially unstructured free-text data.

Safety training represents the least researched theme with only 11 articles (6%) in the systematic review, despite bibliometric trends identifying safety training as an emerging priority particularly in the context of VR and EEG-based approaches. The systematic review reveals that while algorithms such as CatBoost and EEG-net achieve accuracy rates of 80–95.1%, studies are predominantly limited to small, controlled experimental designs involving graduate students rather than actual construction workers. Integrating bibliometric growth signals with systematic evidence of ecological limitations reveals a domain at an early stage of development, technically promising but far from field ready. Future research should prioritize training interventions validated with actual construction workers across diverse site conditions.

4. FUTURE RESEARCH DIRECTIONS

AI applications in construction H&S management represent a growing area of interest, but there is still much to be done to ensure their successful deployment. Below are potential future research directions that can improve the odds of successful AI implementation in construction H&S management (as shown in Table 3). The 11 future research directions presented in Section 4 were systematically derived from the reviewed literature through analysis of limitations, challenges, and future research recommendations explicitly stated by authors across the 181 reviewed articles. During the systematic review process, three independent researchers documented limitations and future work statements from each article, achieving inter-rater reliability for identifying and categorizing research gaps. Directions were included based on three criteria: (1) frequently and explicitly mentioned across multiple reviewed articles as a limitation or future need, (2) supported by accuracy rates and performance metrics reported across the reviewed studies, and (3) aligned with documented construction safety needs while remaining unaddressed in the literature.

4.1 Need for large, diverse, and unbiased datasets

Dataset limitations emerged as one of the most consistently mentioned challenges across the reviewed literature. Multiple studies explicitly identified limited training data as constraining model generalizability and performance. Representative statements include: “Limited training dataset constrains generalizability” (Shanti et al., 2021), 'Insufficient sample size restricts action recognition' (Ding et al., 2018), “Larger datasets crucial for model performance” (Anjum et al., 2022), and '1000 images insufficient for robust model development' (Wu et al., 2019). This literature-identified gap is empirically supported by our systematic findings: studies using smaller training datasets generally reported lower accuracy and higher variance than those with access to larger, more diverse datasets. For example, studies with fewer than 1,000 training samples typically achieved accuracy in the 75-85% range, while those with larger datasets (>5,000 samples) consistently reported accuracy exceeding 90%.

Future studies should focus on developing comprehensive datasets by aggregating images and data, and environmental measurements (e.g., noise levels, temperature, and humidity) from a diverse range of construction sites. This will enhance the detection of PPEs, falls, and safety behaviors, allowing for practical implementation of CV integrated with ML or DL. Research should include diverse environmental conditions, such as varying weather conditions (e.g. rain, extreme heat, snow), and work tasks like heavy machinery operation, manual lifting, and high-altitude work, to generate robust classifications and predictions. For example, leveraging depth information to determine object distance from cameras can improve the accuracy of predicting worker safety behaviors.

4.2 Need to restructure H&S incident/accident reporting policies

Multiple studies relying on the OSHA accident database explicitly identified its limitations as constraining the depth and breadth of their findings. Authors across the construction accidents theme consistently recommended incorporating additional contextual data sources, including weather records, equipment logs, and subcontractor assessments, as a future research priority to improve AI model predictive capability. Incorporating additional data sources beyond the OSHA accident database is crucial for gaining deeper insights into construction health and safety (H&S). This includes detailed accident reports and comprehensive project information, such as weather records, equipment usage logs, worker training records, and subcontractor safety assessments. By gathering data on contextual factors like specific tasks being performed, equipment involved, exact locations, and prevailing weather conditions at the time of incidents, researchers can better understand the circumstances leading to construction accidents.

Detailed accident reports, enriched with information from interviews, site observations, and reports from other agencies (e.g., insurance and regulatory bodies), provide a valuable source of information for identifying patterns and developing effective prevention strategies. Natural Language Processing (NLP) techniques can be employed to extract and analyze textual data from these reports, while machine learning algorithms like Decision Trees (DT) and Random Forests (RF) can help identify patterns, correlations, and predictive insights. This comprehensive approach to data collection and analysis enhances AI models' predictive capabilities and contributes to the development of more effective safety measures in construction.

4.3 Need for ethical guidelines

The absence of privacy frameworks and worker consent protocols was a limitation frequently noted across studies deploying surveillance-based and wearable AI systems, particularly within the PPE detection and safety behavior themes where continuous monitoring of workers was involved. Ethical implications of AI in construction H&S management must therefore be fully explored, including how AI technologies affect workers' mental processes, behaviors, and overall safety culture. Guidelines should be developed to ensure fairness and ethical practice, protecting workers' privacy and providing them with the opportunity to opt-in or out of AI monitoring systems. Utilizing Explainable AI (XAI) techniques and privacy-preserving ML methods such as Federated Learning can help address these ethical concerns.

4.4 Need to optimize algorithms and reduce computational requirement

Optimization of AI algorithms, especially those with an accuracy below 60%, is necessary to reduce misidentification and improve the detection of smaller or clustered images. Researchers should focus on ensemble methods like Boosting and Bagging, fine-tuning hyperparameters through Grid Search and Random Search, and creating feedback loops without losing computational efficiency. Advanced transfer learning techniques, such as BERT and GPT, can manage variability and enhance the model's applicability in HS management.

4.5 Integration with biomechanics and wearable sensor technology

Across the fatigue and ergonomics themes, the integration of biomechanical analysis with wearable sensor technology emerged as a frequently recommended future research direction. Antwi-Afari et al. (2020) and Gonsalves et al. (2022), among others, noted that single-sensor approaches constrained the comprehensiveness of physiological data collection, limiting the ability of AI models to capture the full range of worker health indicators. AI integration with wearable computing, biomechanical analysis, and sensors (pressure, gravity accelerators) can significantly enhance data collection, leading to a better understanding of physiological data and safety behavior. This integration can address a broad spectrum of safety and injury prevention challenges, such as predicting falls, fatigue, or general safety behaviors on site. Utilizing SVM, LSTM, and RF can improve the accuracy of predictions based on sensor data.

4.6 Development of resources for selecting AI tools for specific applications

The absence of systematic guidance for selecting appropriate AI algorithms for specific H&S tasks was a recurring limitation identified across the reviewed literature. The lack of structured frameworks for evaluating algorithm suitability has contributed to inconsistent deployment decisions in practice. Current AI applications often focus on simple, repetitive actions, and future research should create guidelines and tools to categorize and evaluate AI algorithms based on their suitability for specific H&S management tasks. This will streamline AI algorithm selection, enhance effectiveness and efficiency, and ethically guide practitioners and researchers. Multi-criteria decision-making (MCDM) algorithms, Analytic Hierarchy Process (AHP), and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) can be utilized for this purpose.

4.7 Integration of AI algorithms for fall and fall-related action prediction

Exploring the integration of multiple AI algorithms, such as ANN, DNN, SVM, and CNN-LSTM hybrids, can substantially enhance the accuracy and robustness of fall prediction systems. Combining these algorithms can help identify intricate patterns associated with fall risks, reduce false positives and negatives, and provide a more reliable assessment of fall risks.

4.8 Wearable and non-wearable sensor fusion for real-time fall detection

Fall prediction and fatigue studies consistently identified reliance on either wearable or non-wearable sensors alone as a limitation constraining the comprehensiveness of detection. Khan et al. (2022) and Fang and Dzeng (2017) explicitly recommended sensor fusion as a priority future research direction for more reliable real-time monitoring. Investigating the combined use of wearable sensors (such as EEG and IMU) and non-wearable sensors (such as CCTV and IoT devices) for real-time fall detection and prevention can greatly improve construction site safety. Wearable sensors provide detailed data on a worker's physiological state and movements, while non-wearable sensors offer contextual data about the working environment. Fusing data from these sources using AI models like CNNs and RNNs can achieve a more holistic understanding of fall risks.

4.9 Context-aware fall prediction models

Developing context-aware AI models that consider environmental factors (weather conditions, site layout) and worker attributes (experience, physical condition, fatigue levels) can provide more accurate risk assessments. These models can use data from environmental sensors and wearable devices, processed through algorithms like RF and LSTMs, to offer personalized alerts and recommendations, leading to more effective interventions and reduced fall incidents.

Table 3: Future Research Directions.

Research Direction	Description	Expected Outcome	Algorithms to Address the Gap
Large, Diverse, and Unbiased Datasets	Aggregation of comprehensive datasets from diverse sites and conditions.	Improved accuracy in PPE detection, fall prediction, and safety behavior analysis.	CNN, RNN, GAN
Restructuring HS Incident Reporting	Incorporation of detailed reports from multiple sources for better insights.	Enhanced understanding of accident causes and more effective preventive measures.	NLP, DT, RF
Ethical Guidelines	Development of guidelines to ensure fair and ethical AI use.	Protection of worker privacy and ethical AI implementation.	XAI, Federated Learning, Bias detection
Algorithm Optimization	Focus on optimizing algorithms and reducing computational power.	Increased accuracy and efficiency in safety monitoring.	Boosting, Bagging, Grid Search, Random Search, Transfer Learning (BERT, GPT)
Integration with Wearable Sensors	Combining AI with biomechanical and wearable sensor technology.	Enhanced data collection and comprehensive safety behavior understanding.	SVM, LSTM, RF

Research Direction	Description	Expected Outcome	Algorithms to Address the Gap
AI Tool Selection Resources	Creating guidelines for categorizing and evaluating AI algorithms.	Streamlined selection and improved effectiveness of AI in H&S management.	MCDM, AHP, TOPSIS
Integration of AI Algorithms	Combining multiple AI algorithms for fall prediction.	Increased accuracy and robustness in fall risk assessments.	ANN, DNN, SVM, CNN-LSTM
Wearable and Non-Wearable Sensor Fusion	Using both wearable and non-wearable sensors for real-time monitoring.	Holistic understanding and timely detection of fall risks.	CNN, RNN
Context-Aware Fall Prediction Models	Developing models that consider environmental and worker-specific factors.	More accurate and personalized fall risk assessments.	RF, LSTM
Longitudinal Data Analysis	Conducting studies to understand long-term fall risk factors.	Improved predictive accuracy and proactive safety measures.	LSTM, RNN
Detailed Accident Reporting	Utilizing detailed accident and project information for AI models.	Enhanced pattern identification and prevention strategies.	NLP, DT, RF
Real-Time Safety Training Materials	Integrating detailed reports with AI for dynamic training content.	Improved safety education and compliance through real-time, tailored training.	NLP, Reinforcement Learning

4.10 Integration with real-time safety training materials

Current AI-enhanced training approaches have largely lacked the flexibility to adapt dynamically to specific site conditions or incorporate real-time safety data, a limitation consistently noted across the safety training theme. AI-generated, dynamically updated training content was recommended across multiple studies as a priority future research direction. Integrating detailed accident reports and project information with AI technologies can develop advanced safety training materials. Dynamic, real-time training content tailored to specific site conditions and tasks can enhance safety education and compliance. AI-generated training videos, created using speech or text-to-video algorithms, are particularly valuable because they allow for the rapid production of customized training content that can be easily updated as new safety data becomes available. This approach addresses current gaps in traditional safety tutorials, which often lack the flexibility to adapt to specific site conditions or the ability to incorporate the latest safety insights from real-world incidents. Furthermore, reinforcement learning can be applied to continuously improve the training content based on user feedback and performance data, making the training more engaging and effective over time.

4.11 Need to improve the trustworthiness of AI in construction H&S

Evaluation of AI models solely on training accuracy, without assessing generalizability to unseen data or diverse construction environments, was a consistently noted methodological limitation across the reviewed literature. The absence of learning curve analysis was particularly prominent as a gap undermining the trustworthiness and practical reliability of developed models. Future research should focus on enhancing the trustworthiness of AI models in construction H&S by addressing their generalizability. Current literature often lacks an emphasis on model generalizability, particularly through the use of learning curves. Integrating learning curves into model evaluations would enable a more rigorous assessment of how AI models perform across diverse construction environments, ensuring their reliability and effectiveness in real-world applications.

These directions outline a path forward for advancing the application of AI in construction health and safety management, ensuring a safer and more efficient work environment

5. CONCLUSION AND LIMITATIONS

This study thoroughly explores the integration of deep learning (DL) and machine learning (ML) technologies in construction health and safety management. It highlights the progressive increase in applications for predicting accidents and injuries, assessing ergonomic risks, recognizing personal protective equipment (PPE) usage, and monitoring safety protocols. The research underscores the effectiveness of AI algorithms in achieving high prediction accuracies, emphasizing their potential to significantly enhance safety management practices in the construction industry.

The study adopted a bibliometric and systematic literature review approach. The bibliometric analysis provided quantitative insights into publication trends, authors keywords, and collaboration networks, offering a broad overview of the research landscape. This was followed by a systematic review that adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, ensuring reproducibility, scientific rigor, and transparency. A total of 181 selected articles in the domain of construction health and safety were reviewed, providing a comprehensive and in-depth perspective on AI applications in human-centered construction health and safety management. The review revealed a significant increase in publications on the adoption of AI in H&S management over the past nine years.

Most research on AI applications in construction H&S management concentrates on PPE detection, hazard prediction, falls (e.g., falls from height, falls within restricted environments), accidents and injuries, workers' ergonomic risk assessment, and safety monitoring. The study generally revealed that most algorithms used for SH prediction or detection purposes fall within an accuracy range of 80 to 100%, with a few outliers below 60%.

The current adoption of AI in construction H&S management is predominantly focused on monitoring and predictions within this domain. This paper provided a comprehensive application of AI in construction H&S management, ranging from fall, fatigue, hazard, and object detection. It is intriguing that AI tools are being integrated with computer vision sensors and cameras, which are extensively used to monitor construction H&S management. The study delved into specific accuracies, precisions, and recalls of various models/frameworks developed to predict or detect health and safety management. Finally, it outlined some limitations and future publication trends of AI in construction H&S management. This study contributes to worker H&S and AI research, practice, and management in several dimensions. It pinpointed eight key areas where AI can be applied in construction H&S management: construction accidents (fall-related accidents, struck by, etc.); construction injuries, safety inspections, fatigue prediction, PPE detection, workers' ergonomics, safety behavior, and safety training. Additionally, through systematic analysis of limitations and future work recommendations across 181 reviewed articles, with strong inter-rater agreement ensuring consistent gap identification, integrated with performance gap analysis from our systematic review findings, we identified 11 critical research directions. These directions emerged from the collective assessment of the research community as documented in the reviewed literature, validated by empirical evidence from our systematic performance analysis. For example, dataset limitations were consistently and explicitly mentioned across numerous studies and empirically validated by the observed relationship between dataset size and model performance. Similarly, the deployment gap was both frequently mentioned by authors and confirmed by our finding that few studies progressed beyond laboratory validation to field implementation.

The study also revealed challenges and future research opportunities: limited application of developed models, technical restrictions, expanding dataset and sample size for model training and testing, diversity of datasets for testing and training of the models, and integrating AI with wearable computing and sensors. Despite the research team taking appropriate measures, there are certain limitations in this study. The notable limitation is that the review was confined to articles available only in Web of Science and Scopus, and only in English, potentially overlooking relevant studies published in other databases or languages.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data will be made available on request.

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