ASME Journal of Engineering for Sustainable Buildings and Cities
Online journal at:
https://asmedigitalcollection.asme.org/sustainablebuildings

Enhancing Sustainability and Construction Safety Research in the Era of Artificial Intelligence

Abhijeet Gupta[1]
Department of Computer Science,
University of Dayton,
Dayton, OH 45469
e-mail: guptaa19@udayton.edu

Shruti Singh
Department of Computer Science,
University of Dayton,
Dayton, OH 45409
e-mail: singhs30@udayton.edu

Vijayan Asari
Department of Electrical and
Computer Engineering,
University of Dayton,
Dayton, OH 45469
e-mail: vasari1@udayton.edu

Tam V. Nguyen
Department of Computer Science,
University of Dayton,
Dayton, OH 45469
e-mail: tnguyen1@udayton.edu

Construction remains one of the most hazardous global industries, with worker fatalities occurring approximately every 99 min. However, safety is intrinsically linked to broader project performance; a truly safe construction site is hazard free, organized, and efficient, thereby minimizing waste and resource depletion. In response, a growing body of research has explored the use of advanced technologies, such as machine learning, robotics, wearable, and immersive visualization, to synergize safety improvements with sustainable building practices. In this article, we systematically review 165 peer-reviewed articles in the era of artificial intelligence (AI) that capture how technologies have evolved to address the dual imperatives of safety and sustainability in response to technology-driven transformation. To analyze this inflection, the article develops a four-domain taxonomy spanning AI, visualization, surveillance, navigation and collaboration, and wearable technology each mapped against both earlier and recent research studies. Crucially, we highlight emerging dual-utility applications, such as the use of "green digital twins" for real-time lighting optimization and UAVs for building envelope energy auditing. By mapping this transition, this article provides a grounded perspective on current capabilities, identifies research practice gaps, and supports informed decision-making for the implementation of future-integrated safety and sustainability technologies. The insights derived are aimed at supporting researchers, technology developers, and industry professionals to guide future integration of advanced, sustainable construction safety practices. Our review identifies recurring themes in the recent studies, including the integration of real-time sensing, multimodal data fusion, and user-centered system design. It also highlights unresolved challenges related to cross-project generalizability and long-term field adoption. By offering this structured analysis, the review aims to contribute a domain-wise benchmark of progress, capturing the recent technological inflection in construction safety and sustainability, and outlining future opportunities to support researchers, technology developers, and industry professionals. [DOI: 10.1115/1.4071434]

Keywords: construction safety, artificial intelligence, sustainable construction, wearables, robotics, augmented reality, virtual reality, digital twins, human–AI collaboration, real-time monitoring, cognitive sensing, big data, building, carbon-neutral, clean energy, conservation, efficiency, hybrid systems, integrated design, interactive buildings, interactive systems, renewable, resilient buildings, resilient systems, smart buildings, smart cities, sustainability

1 Introduction

Construction has long been recognized as a physically demanding and inherently hazardous industry. Despite decades of regulatory enforcement [1], worker training programs [2,3], and improvements in safety management practices [4], the sector continues to face persistently high rates of injury and death. In 2023 alone, a worker died every 99 min in the United States from a construction-related incident, a statistic that has improved only marginally in recent years [5,6]. A closer look reveals the four main causes as falls, electrocutions, object struck incidents, and caught-in/between hazards, accounting for nearly 60% of these deaths [7,8].

Termed the "fatal four", the aforementioned hazards have remained consistent over time. As a result, the construction industry has seen the rapid evolution of the technologies surrounding hazard identification [9]. These persistent "fatal four" hazards underscore the need for innovative approaches potentially driven by technology [10] to break the plateau in safety improvements. However, the fatal four hazards extend beyond just physical harm to the workers, and they also challenge the industry's broader commitment to sustainability [11,12]. In the context of modern "sustainable buildings and cities," the definition of sustainability has evolved beyond carbon footprints and energy efficiency to encompass social sustainability, the "S" in the environmental,

---

[1] Corresponding author.

Manuscript received December 11, 2025; final manuscript received March 16, 2026; published online April 7, 2026. Assoc. Editor: Hamidreza Najafi.

social, and governance (ESG) framework, as protecting the workforce is a critical component of preserving human capital [13]. Furthermore, unsafe sites directly contribute to project delays, rework, and material damage, all of which increase a project's embodied carbon and energy waste. A project cannot be considered truly sustainable if it achieves energy efficiency at the cost of the health and safety of its builders. Therefore, reducing worksite fatalities is not just a regulatory obligation, but a prerequisite for sustainable urban development. During the past decade, and especially since 2020, researchers have increasingly adopted emerging technologies [14–19], leading to a surge in innovation aimed at proactive hazard mitigation. We refer to this accelerated shift as a technological inflection point—one that closely aligns with the larger disruption caused by the COVID-19 pandemic [20]. As construction sites experienced shutdowns, labor shortages and supply chain delays, and traditional safety strategies, relying on manual supervision, in-person audits, and reactive reporting proved insufficient [21–25]. In response, the industry accelerated the exploration and adoption of digital tools that could support remote monitoring, enhance situational awareness, and enable adaptive safety practices [26–29].

The recent technological inflection point (post-2020) facilitated more than just remote monitoring; it enabled the broader adoption of "lean construction" principles [18]. With the increased use of digital tools, the industry began shifting toward addressing two problems simultaneously: physical waste and site clutter [30]. This shift demonstrated that efficient sites are inherently safer and more sustainable.

On the other hand, the industry also witnessed the rapid rise in large language models: GPT-4 [31], Gemini [32], Llama 3 [33], a factor that also catalyzed a wave of technological experimentation and adoption. This catalyst followed the expansion in capabilities of artificial intelligence (AI) systems: to understand, generate, and interpret natural language, and these models opened new opportunities for integrating diverse approaches into safety workflows. This advancement did not occur in isolation: it complemented and accelerated parallel developments across other domains. Applications such as machine learning models for the prediction of safety risks [34–36], immersive augmented reality (AR)/virtual reality (VR) platforms for training and visualization [37,38], drones and autonomous robotics for site monitoring in real time [39–41], and wearable biosensors for physiological and behavioral monitoring [42–44] became increasingly prominent. Many of these solutions were initially designed for fields such as healthcare or manufacturing, but were rapidly adapted and repurposed for construction use cases [19].

This convergence of urgent operational needs and emerging technologies created a unique opportunity that is still reshaping the direction of construction safety research. Rather than incremental improvements, the recent period marked a substantial broadening in both the number of studies and the diversity of technological solutions being investigated. To better understand this shift, we quantify the surge in safety-focused publications and explore their implications in the methodology (Sec. 2).

The proposed taxonomy, presented in Fig. 1, organizes this literature into four core domains: AI, visualization, surveillance, navigation, and collaboration (SNC), and wearable technology. Each domain reflects a distinct dimension of safety technology development, ranging from real-time multimodal fusion to user-based behavior tracking while illustrating broader trends in deployment context and user interaction. The classification emerges from an inductive analysis of the construction safety technology literature and reflects the clustering of research efforts across distinct technological domains. While reviewing 165 peer-reviewed studies, clear patterns emerged in terms of the underlying technological foundations and safety outcomes. Based on these recurring patterns, the following taxonomy (Fig. 1) was developed, where each of the four categories represents a fundamentally different mode of sensing, interpreting, or responding to hazards. Since many recent systems are inherently hybrid, it is important to note that the proposed taxonomy is function oriented. For example, a UAV equipped with computer vision (CV) and linked to a digital twin (DT) spans the AI, SNC, and Visualization domains simultaneously. In such cases, we classify the study based on its primary functional contribution to construction safety (e.g., aerial monitoring under SNC versus data-driven hazard prediction under AI versus immersive visualization under Visualization). This approach captures the dominant research intent of each study while acknowledging cross-domain convergence, which we discuss as a key emerging trend throughout the review.

(1) *AI:* Studies in this domain share a common focus on computational interpretation of safety-related data, particularly computer vision and machine learning. These technologies

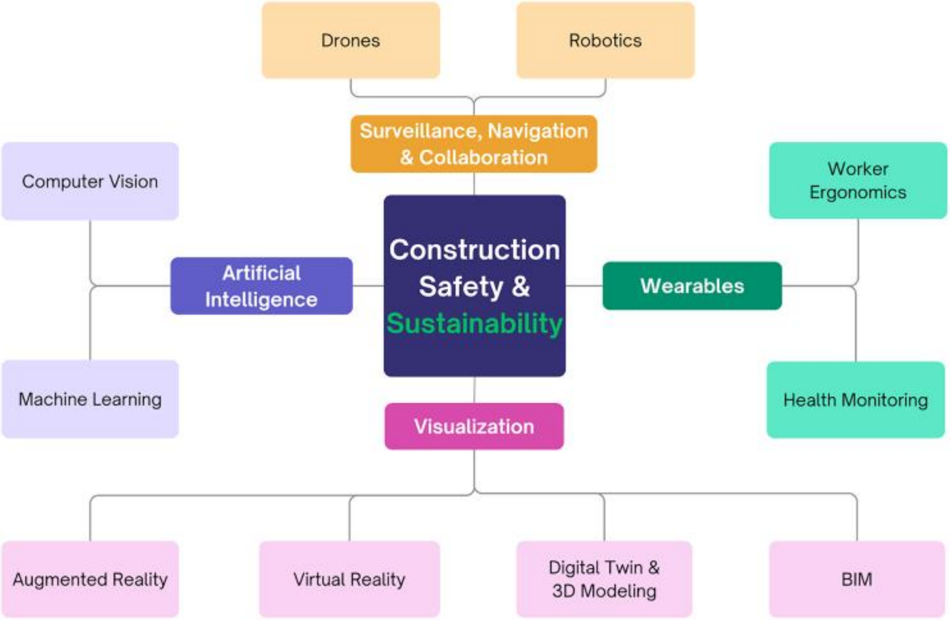

Fig. 1 Taxonomy of our construction safety technologies: four core domains and thematic subfields

form a unified cluster because they use algorithmic inference often from images, videos, or historical data to detect hazardous conditions, predict risks, and optimize resource allocation. The methodological foundations across these studies (data-driven modeling, pattern recognition, supervised learning) make AI a distinct category that is capable of addressing both physical safety hazards and operational inefficiencies.

(2) *Visualization Technologies*: A second cluster revolves around technologies whose primary purpose is to enhance human understanding of the construction environment. Augmented reality, virtual reality, digital twins, and building information modeling (BIM) all support situational awareness through visual representation. Despite varied hardware and software implementations, they share the functional goal of transforming raw information into immersive or interpretable visual forms that support training, risk anticipation, and lifecycle management. These tools visualize complex data and enable decision-making that enhances both worker safety and the long-term sustainability of building operations.

(3) *SNC:* Drones, robotics, and autonomous navigation tools form a third domain characterized by physical mobility and spatial awareness. These systems perform real-time site monitoring, environmental scanning, structural inspection, and physical interaction with the environment. This is different from the AI and Visualization domain, as the theme here is spatial intelligence: the ability to perceive, map, and act efficiently within dynamic site conditions to mitigate human exposure to dangerous situations.

(4) *Wearable Technologies:* The final category, wearables, emerged from the literature focusing on *worker-centric* sensing. These studies share an emphasis on physiological data, ergonomics, biometrics, and behavioral monitoring. Wearable sensors operate at the level of the individual worker rather than the environment, focusing on the social aspect of sustainability by preserving human capital. This makes this domain fundamentally different in purpose, shifting the focus to long-term health and retention of the workforce.

Although our initial interest centered on investigating the increase in publication volume, our review findings suggest a deeper transformation. The increase in research was not only quantitative; it marked a qualitative change in how safety technologies are designed, evaluated, and implemented. Notably, our analysis revealed that recent advancements across all four domains reflect a shared trajectory—technologies have increasingly shifted from static, fragmented solutions toward real-time responsiveness, user-centered design, and intelligent integration as we describe in the following sections.

Across the four domains, recent studies show an increasing emphasis on real-time integration, field validation, and cross-functional applications. Recent review articles have provided valuable information on the role of emerging technologies in construction safety, but exhibit distinct limitations in scope, methodology, and focus. For example, Elenany et al. [30] conducted a systematic review of automation technologies for construction safety that focused primarily on tools such as robotics, VR, BIM, and AI, but without a detailed analysis of how these technologies have evolved in the recent period. Seo and Yoon [18] used topic modeling to identify emerging research clusters in smart construction safety, including AI-driven monitoring and Internet-of-thing (IoT) integration in order to improve construction safety, efficiency, and sustainability. Conversely, sustainability research often isolates environmental performance from site safety. For instance, Oraz and Sözer [45] provided a comprehensive assessment of energy efficiency in campus buildings. They developed a color-grading scale to support decision-making for energy retrofits. While such studies are vital for the environmental aspect of ESG focusing on Heating, Ventilation, and Air Conditioning (HVAC) optimization and renewable integration, they typically exclude the social aspect of worker safety during the retrofitting process. Newaz et al. [46] offered a critical review of safety behavior technologies, focusing primarily on the feasibility and limitations of tools such as VR, eye tracking, and real-time positioning, which characterize construction safety behavior. Su et al. [13] conducted a bibliometric study on occupational safety and health risk assessment technologies, identifying research trends and gaps.

Several prior syntheses have provided important, technology-specific reviews that have shaped the industry. For example, Li et al. [47] critically reviewed VR/AR applications for construction safety and highlighted design and usability barriers for immersive training; Seo et al. [48] surveyed computer vision techniques for safety and health monitoring, emphasizing core vision algorithms and practical challenges such as occlusion and lighting; and Ahn et al. [49] summarized wearable sensing applications, drawing attention to sensor ergonomics, data quality, and deployment hurdles. These domain-focused reviews provide deep and useful accounts of specific technologies, but they predate the recent wave of multimodal integration and AI-driven, real-time systems that increasingly combine sensing, analytics, and sustainable approaches into unified solutions. Our review builds on this prior work by synthesizing findings across these technology areas by explicitly mapping how recent advances (through November 2025) converge into four functional domains such as AI, Visualization, Surveillance/Navigation/Collaboration, and Wearables. We adopt a cross domain, function-oriented taxonomy (Fig. 1), and link domain-specific weaknesses to targeted, evidence-based research. Our article is an attempt to benchmark the technological inflection point (post-2020) of safety and sustainable systems and their emergence. This review is also an attempt to expand on the earlier, single-domain reviews and point out their remaining critical gaps. Before diving into the review, we summarize the current categories in our taxonomy and discuss their weaknesses.

1.1 Artificial Intelligence for Safety Monitoring.

Existing AI-based safety systems continue to show strong potential for automated hazard recognition, behavior classification, and predictive analytics especially leveraging large volumes of unstructured data (video, images, sensor feeds) that would overwhelm manual oversight. For example, Alateeq et al. [50] demonstrated how deep learning models can reliably detect a variety of site hazards using only vision data. Multitask frameworks such as “Multi Task Intelligent Monitoring of Construction Safety Based on Computer Vision” employ advanced object detection, segmentation, pose estimation, and tracking (e.g., via YOLOv8) to provide real-time, multifaceted safety monitoring from personal protective equipment (PPE) detection to unsafe behavior tracking [51]. Crucially, this computational power enables a dual-benefit approach as the same computer vision algorithms used to identify safety hazards (e.g., debris blocking a path) can now simultaneously identify operational inefficiencies (e.g., material waste or idling equipment). By optimizing site logistics to prevent accidents, these AI systems inadvertently support “lean construction” principles, reducing the project’s environmental footprint through minimized rework and resource wastage. A recent review of AI in construction safety notes a growing shift beyond pure vision to include text, audio, and multimodal data sources expanding the feasibility for predictive risk detection across more diverse contexts [52]. Nevertheless, significant weaknesses persist. Many AI-based studies remain heavily reliant on visual data (camera/image), which remains problematic in low visibility, occluded, or highly cluttered construction environments [53]. The same review finds that nonvision modalities (e.g., audio, environmental sensors) remain underutilized [52]. This limitation is particularly critical for sustainability, as AI systems cannot effectively monitor nonvisual hazards such as noise pollution, air quality, or energy waste. Moreover, few systems have been validated in long-term, large-scale, real-world deployments raising questions about generalizability across different sites, contractors, and environmental conditions [54]. These constraints limit the scalability, robustness, and trustworthiness of AI-based systems when applied to the holistic monitoring of safe and sustainable construction environments.

1.2 Visualization, Simulation, and Immersive Training Technologies. Immersive and extended reality (XR) technologies including VR and AR introduce simulated training platforms. The immersive trend is attracting growing interest for safety training, hazard awareness, and preconstruction visualization in the construction industry. For instance, Seo et al. demonstrated that incorporating interactive learning elements into immersive VR safety training significantly enhances personal learning performance and intrinsic motivation compared to passive training methods [55]. This domain also serves as the strongest bridge between safety and sustainability. Such immersive training allows workers to rehearse hazardous scenarios in a controlled environment, potentially improving hazard recognition and compliance before workers step into real-world hazardous conditions.

However, limitations remain, where VR/AR training studies are conducted under controlled, simplified conditions, with limited fidelity to the complex, dynamic nature of real construction sites [54]. The gap between simulation and real-world site variability (layout changes, lighting, unpredictable hazards) reduces the validity of these training outcomes. There is still limited empirical evidence demonstrating long-term retention of safety behaviors, transfer of training to actual onsite safety improvement, and reduction in real accidents following immersive training [54]. Additionally, integrating live site data (e.g., from IoT sensors, drones, real-time structural changes) into XR environments remains rare, limiting the potential for real-time site aware simulation [54,56].

1.3 Surveillance, Sensing, and Site-Monitoring Technologies. The use of drones, camera networks, LiDAR, and other environmental sensors remains a key strategy for improving situational awareness on dynamic construction sites. A recent review of UAV (drone) usage in construction safety monitoring highlights how drones can rapidly capture site-wide spatial data and detect hazards from aerial perspectives that are difficult to monitor manually [57]. These surveillance tools are also increasingly becoming a part of proactively identifying structural irregularities and thermal leaks, hence supporting the goal of “lean construction” in reducing material waste and rework. An interesting take here is the frameworks integrating all sorts of AI technologies—IoT sensors, environmental monitoring, and computer vision to detect hazards, unauthorized access, or unsafe site conditions and resource optimization proactively [56].

Despite these advantages, deployment limitations still remain. Real-world site conditions such as occlusion, dynamic obstacles, changing layouts, and weather often degrade sensor performance [54]. Integration of heterogeneous sensing modalities (visual, environmental, positional) remains technically challenging, complicating fusion of data streams and robust hazard detection. Furthermore, issues such as privacy, data governance, worker acceptance, and cost hinder large-scale adoption in practice [54].

1.4 Wearable Technologies for Worker-Centered Safety. Wearable sensing devices (WSDs) (e.g., smart helmets, vests with sensors, inertial measurement units (IMUs), physiological monitors) are increasingly studied as tools to monitor worker health, posture, fatigue, stress, ergonomic risk, and other individual-level safety metrics. A recent review systematically explains how wearables have been used to track physiological responses (heart rate, stress, attention), ergonomic posture, and fatigue offering personalized, real-time data streams complementary to environment-level monitoring [58]. Furthermore, Awolusi et al. reviewed the integration of the IoTs with wearable devices, identifying key application areas such as physiological tracking and environmental sensing to enhance construction safety monitoring and preempt accidents [59]. Therefore, we observe that by transitioning from reactive injury management to proactive health preservation, this example highlights the importance of the social pillar of ESG criteria.

However, persistent challenges hinder the system’s widespread adoption. Awolusi et al. identified several technical limitations: short battery life, discomfort when worn with standard PPE, limited durability in harsh construction environments, and lack of ruggedized design (for dust, water, or extreme temperature exposure), which reduces practicality for real-world, long-term use [59]. Moreover, many of the studies remain small scale, using prototypes rather than large, diverse worker populations [58]. Adoption barriers also include cost, concerns about data privacy and surveillance, and low worker acceptance, indicating that wearables are still perceived as intrusive and burdensome rather than protective [49].

To summarize the article’s original contribution, this review focuses on *recent* advancements in safety technologies capturing the rapid acceleration in AI, sensing, and automation research up to November 2025. The review utilizes a function-oriented taxonomy that synthesizes more than 100 peer-reviewed studies into four technological domains: (1) AI and predictive analytics, (2) visualization and immersive systems, (3) SNC, and (4) wearable and physiological sensing. This cross-domain taxonomy enables the identification of converging technological patterns, which we note as follows: multimodal data fusion, real-time hazard interpretation, and user-centered system design. These patterns have not been noted in prior domain-specific reviews of VR/AR, computer vision, or wearables. By analyzing both the strengths and unresolved weaknesses across these domains, the review attempts to benchmark the transformative perspective on how construction safety technologies are evolving.

1.5 Our Contributions. Our article makes the following key contributions to construction safety research. First, it synthesizes previously fragmented work across the four domains: AI, visualization, SNC, and wearable technology. Earlier reviews (prior to 2020) (e.g., studies by Li et al. [47]; Seo et al. [48]; Ahn et al. [49]) examined these technologies in isolation, limiting cross-domain insight. In contrast, this review discusses recent examples of how these domains interact and converge, while summarizing the patterns noted in the example studies. Second, the article introduces a comparative benchmarking approach that evaluates recent research studies against review studies discussing limitations. We examine the constraints such as weak field validation, limited generalizability, fragmented data, and inadequate real-time performance as the common theme over the four categories. The comparative approach reveals cumulative patterns in technological evolution and also helps identify meaningful advancements and persisting challenges. Third, the review offers domain-specific assessments for each technology category. We demonstrate advancements through example studies and gaps noted in prior reviews. We note how these advancements have addressed the gaps and structural areas for improvement and for further research.

This article finally proposes targeted research directions (summarized in discussions) grounded in the limitations identified throughout the comparative review process. Through its integrated synthesis, historical benchmarking, updated trend analysis, and evidence-based recommendations, the review attempts to provide practical guidance for researchers and practitioners in the construction industry. The technological trends across the four domains, AI, visualization, SNC, and wearable technology, are assessed on five criteria: application scope, integration and convergence, field deployment readiness, outcomes, and limitations. The recommendations include improving model generalizability, addressing privacy and governance, and bridging the gap between safety monitoring and sustainable building practices. Next, Secs. 2 and 3–6

Table 1 Distribution of selected papers by journal (final screened distribution, $n = 165$)

No. of papers	Journal title
57	*Automation in Construction*
20	*Journal of Computing in Civil Engineering*
11	*Buildings*
7	*Frontiers in Built Environment*
5	*Journal of Information Technology in Construction*
5	*Practice Periodical on Structural Design and Construction*
3	*Construction Innovation (England)*
3	*Journal of Building Engineering*
2	*Canadian Journal of Civil Engineering*
2	*CivilEng*
2	*IEEE Transactions on Visualization & Computer Graphics*
2	*Information Sciences*
2	*International Journal of Civil Engineering*
3	*Sustainability*
41	Others with 1 paper each
165	*Total*

present the detailed methodology and summarize the review, respectively. Finally, Secs. 7 and 8 discuss and summarize potential future research directions in construction safety and sustainability, respectively.

2 Review Methodology

To explore our central hypothesis that the technological inflection not only increased research volume but also catalyzed a qualitative shift in construction safety technologies, we adopted a hybrid review methodology. This approach integrates quantitative bibliometric analysis, thematic clustering, and domain-specific benchmarking across 165 peer-reviewed recent studies (as shown in Table 1).

2.1 Data Collection and Inclusion Criteria. We conducted a comprehensive bibliometric search in four major academic databases: Web of Science Core Collection, Scopus, IEEE Xplore, and the ASCE Library. These platforms were selected to ensure disciplinary coverage that spans civil engineering, computing, safety innovation, and sustainable construction. To avoid premature filtering of the results, we used the general topic term "construction safety." Our article focuses on studies published between 2020 and 2025, to capture the recent period identified in Sec. 1 as a technological inflection point. The initial query returned 23,787 records from four major academic databases: WOS (15,640), Scopus (660), IEEE Xplore (4642), and ASCE Library (2845). We then applied a multistage screening protocol (Fig. 2), following the Preferred Reporting Items for Systematic Reviews and Meta Analysis (PRISMA) [60] guidelines and adapted best practices from the systematic review. The initial filter restricted records by geographic scope (worldwide), language (English), and subject categories relevant to construction safety, resulting in 678 articles. The first round of screening excluded 294 articles based on duplicate entries, inaccessible full text, or lack of relevance. To explicitly address the convergence of safety and environmental goals, we conducted a concurrent supplementary search combining "construction safety" with keywords such as "sustainability," "energy efficiency," and "ESG." This yielded a distinct set of 100 sustainability-focused articles, which were merged with the 284 general safety articles retained from the initial screening, producing a combined intermediate pool of 384 articles ($n = 284 + 100$). These 384 articles were used for the bibliometric trend analysis in Fig. 3, with Figs. 3(*a*) and 3(*b*), illustrating the sustainability-focused and general safety subsets, respectively. Subsequently, the second round removed 219 articles based on a relative, field-aware screening approach informed by established bibliometric methodology.

Albarrán et al. [61] demonstrated that a single fixed citation threshold can inadequately capture research impact due to the skewed and time-dependent nature of citation distributions. To calibrate a threshold, we consulted the Google Scholar Top Publications ranking for civil engineering [62], which reports h5-index values (i.e., the h-index over a rolling 5-year window) for the leading venues in the field. Even the lowest-ranked journal in the top 20 holds an h5-index of 52, which corresponds to roughly 10 citations per year. Accordingly, we adopted a year-adjusted baseline of approximately ten citations for earlier papers (2020–2022), which was relaxed for more recent publications (2023–2025) to account for shorter citation accrual windows. We also considered the impact factor and standing of the publishing venue as a secondary quality indicator. This final filtration removed lower-impact studies, yielding the final set of 165 articles (149 general safety + 16 sustainability) for the qualitative review.

To manage the large volume of results, we applied a region filter, focusing on studies conducted in the United States. We acknowledge that this geographical focus may introduce bias; construction safety regulations, workforce demographics, labor practices, and technology adoption rates vary significantly across jurisdictions. Similarly, in the second screening round, we excluded papers with very low citation counts as a pragmatic measure to prioritize the influential work. We recognize that this criterion might inadvertently omit very recent (2025) high-quality papers that have not yet accrued citations. To mitigate this, we retained any conceptually novel papers. While these inclusion criteria inherently bias the review toward more established or mainstream topics, we justify them as necessary trade-offs to manage scope while still capturing high-impact research in the field. To reflect the interdisciplinary nature of the recent research, we mapped each study to one or more subject categories ranging from civil engineering and construction technology to artificial intelligence, remote sensing, and cybernetics (Table 2). This broad mapping supports our hypothesis that safety innovation increasingly draws from cross-functional and computational disciplines. Finally, to explicitly address the convergence of safety and environmental goals, we performed a supplementary targeted search; Table 3 summarizes the 16 additional studies selected through this process, categorizing them by their technological domain and their specific contribution to sustainability.

2.2 Quantitative Analysis: Recent Trends. To assess the trajectory of recent research, we examined the volume of published articles and citation performance by year. Figure 3 presents a dual perspective on this evolution. Figure 3(*b*) illustrates the sustained growth in general construction safety research, confirming the broad technological adoption in the field. Figure 3(*a*) highlights the emergence of the "safety-sustainability," revealing a distinct upward trend in studies that integrate safety with environmental goals post-2020. The citation count demonstrates significant momentum, with numerous studies (since 2023) already gaining early attention, signaling the academic and industrial demand for integrated, technology-driven solutions.

2.3 Qualitative Analysis: Domain Identification and Taxonomy Formation. So far we saw the bibliometric trends, and we then performed a structured manual review during screening phase 2 to categorize the final 165 studies into four key technological domains. This classification was not based on predefined categories, but instead emerged through a conceptual grouping of studies based on their technological characteristics, safety functions, and application contexts. We examined paper titles, abstracts, and keyword fields (Fig. 4) to identify common patterns in focus areas, safety enhancement mechanisms, and integration methods. Rather than imposing predefined categories, we relied on themes that are derived organically based on conceptual and

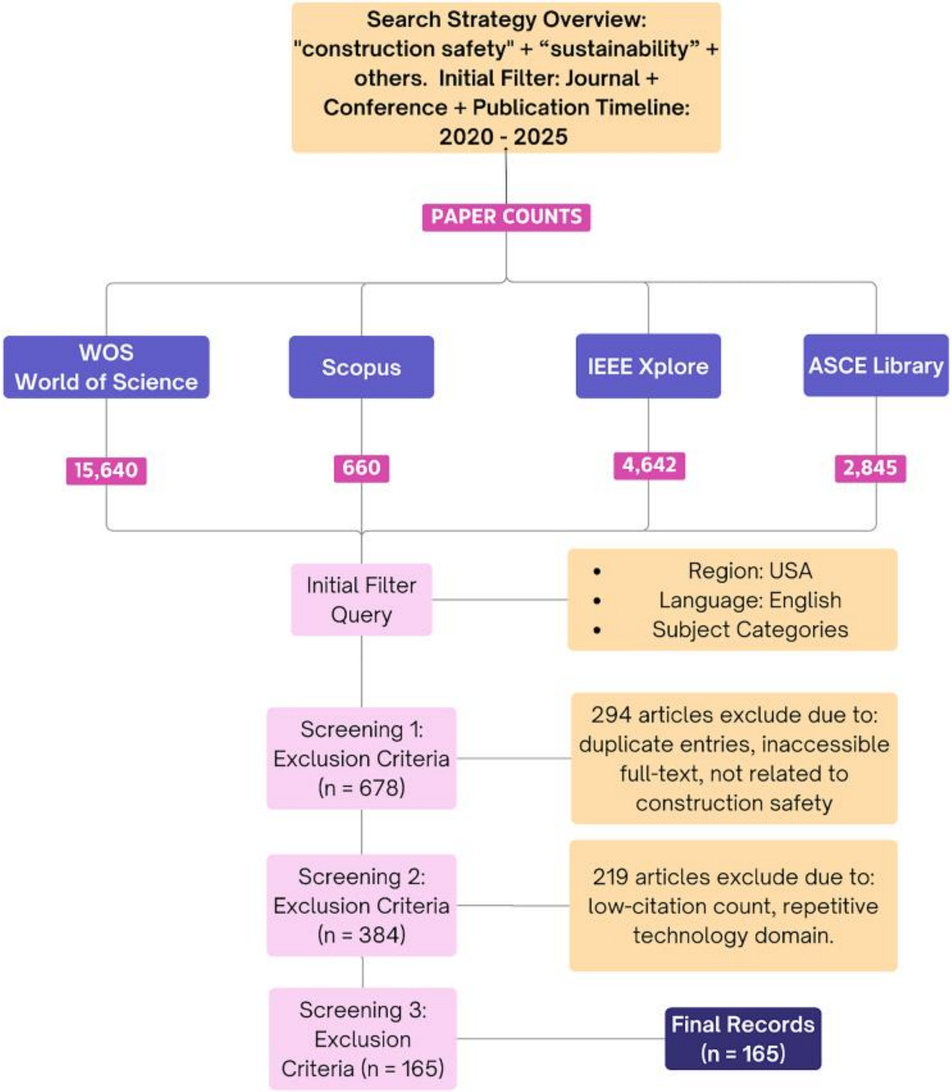

Fig. 2 PRISMA flowchart used to refine and curate the final collection of 165 peer-reviewed recent construction safety studies (2020–2025). The intermediate screening pool ($n = 384$) consists of 284 general safety articles retained from the initial search and 100 sustainability-focused articles added from the supplementary search. From this combined pool, 219 articles were excluded to yield the final 165 records.

linguistic similarity. This approach mirrors previous domain-level review strategies in the construction safety literature [47]. This classification revealed four dominant domains in recent construction safety research: AI, visualization technologies (including AR/VR and digital twins), SNC, and wearables and human-centric systems. Table 2 summarizes the generalized subject categories used in our screening. As noted in Sec. 1, each study was classified based on its primary functional contribution to safety. Studies involving multiple technology types (e.g., drone-based computer vision integrated with BIM) were assigned to the domain reflecting their dominant safety function, while their cross-domain characteristics are discussed as part of the convergence trends identified in this review.

2.4 Comparative Benchmarking With Timeline Literature. To assess how recent studies have seen advancement in the field, we utilized "2020–2025" as our review timeline. We state this period as our technological inflection point. For each domain, we identify limitations noted in earlier work (e.g., lack of field validation, poor scalability) and evaluate the extent to which recent innovations address the safe and sustainable vision. This benchmarking approach follows a gap-oriented framework, to emphasize cumulative improvements between technologies.

It enables us to track whether recent research has advanced toward more adaptive, validated, and integrated safety systems and also if they are more resource efficient and environmentally responsible. The results of this analysis are presented in Secs. 3–6, where each domain is discussed using the following structure.

- A summary of the early development of the domain and applications in construction safety.
- Identification of previous limitations based on the prior review literature.
- A synthesis of how recent studies addressed these limitations through technological innovation, empirical validation, and real-world implementation.

3 Artificial Intelligence

The recent period has witnessed an unprecedented expansion of AI applications in construction safety. This is driven by advances in machine learning, computer vision, natural language processing, and multimodal integration. AI is no longer confined to

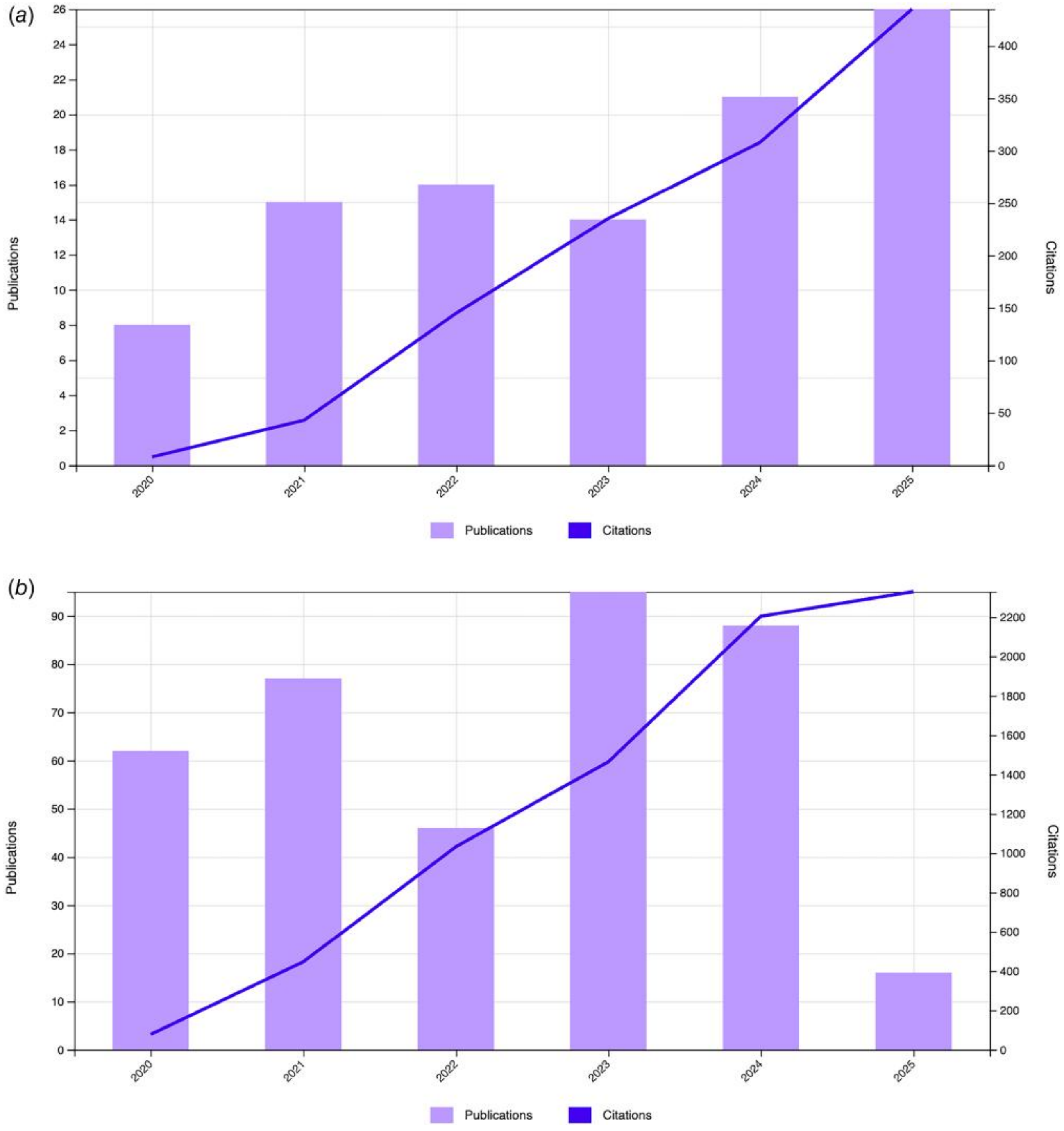

Fig. 3 (*a*) Bibliometric analysis of research trends (2020–2025). Safety-sustainability focus: annual distribution of the primary supplementary search illustrating the surge in sustainability and safety interest (100). (*b*) General construction safety: annual publication volume of construction safety ($n = 384$) prior to final exclusion, capturing the broad technological inflection point in the field.

isolated, lab-scale prototypes; instead, it is increasingly embedded in real-time safety (Fig. 5) and sustainability workflows. Recent literature defines this convergence as “automated sustainable construction engineering management”, where AI enables dynamic risk prediction and proactive hazard detection while simultaneously optimizing resource usage and carbon footprints [65]. This section maps the key technological trends that have emerged in safety AI research, highlighting how machine learning, computer vision, and cognitive modeling are transforming safety management into a data-driven and anticipatory and resource-efficient process.

3.1 Machine Learning. The construction industry’s application of AI in safety dates back to expert systems such as How Safe in the 1980s. In the early 2010s, machine learning in construction safety was limited by isolated datasets, lack of real-time feedback, and minimal field application. Abioye et al. [66] identified key limitations in AI and machine learning (ML) safety systems, including breach of security, talent shortage, high costs, and lack of proper connectivity onsite. We analyze studies and observe if these challenges have been addressed and how they emerged, one that took advantage of large datasets, multimodal fusion, and real-time deployment to bring AI to active construction sites.

Table 2 Generalized subject categories used for screening (Construction safety)

Subject category	Record count	%
Civil engineering	540	79.646
Construction building technology	311	45.870
Computer science—interdisciplinary applications	51	7.522
Computer science—information systems	29	4.277
Computer science—artificial intelligence	35	5.162
Remote sensing	9	1.327
Statistics and probability	5	0.737
Computer science—software engineering	15	2.212
Automation and control systems	37	5.457
Computer science—theory and methods	6	0.884
Robotics	11	1.622
Computer science—hardware and architecture	7	1.032
Computer science—cybernetics	2	0.294

Note: The total record count exceeds the number of screened papers ($n = 678$) because individual papers are frequently classified under multiple subject categories in the Web of Science database.

This section traces the progression of research across key themes: real-time detection, predictive modeling, human-centered safety, robotics, infrastructure monitoring, and multimodal integration.

3.1.1 Real-Time Hazard Detection and Compliance Monitoring. To address the lack of real-time integration noted in recent studies, we observe applications of ML for active monitoring of PPE compliance and site safety conditions. An example of a YOLOv3-based system demonstrates the automated detection of the use of a hardhat and vest [64]. Other frameworks classify audio and video data for recognition of activity and equipment [67–69]. Other sets of studies show that enhanced distance tracking and sensor fusion frameworks further strengthen site-wide compliance and proximity monitoring [70,71]. We note automated image captioning and safety documentation as an approach to reduce reporting delays and human bias [72,73], while robust detection models improve visual performance in complex lighting [74].

3.1.2 Predictive Risk Modeling. Earlier risk analysis lacked adaptability and often relied on static checklists [66]. Recently, ML systems have shifted the field from reactive assessment to proactive prediction by leveraging large-scale text, audio, and project datasets. The extraction of leading indicators from structured and unstructured reports [75], prediction of project-level risk attributes [76], and hazard classification using graph databases and Natural Language Processing (NLP) techniques [77,78] provided a scalable and consistent pipeline for prediction. Crucially, these predictive capabilities are now being integrated with BIM to create “smart construction” schedules. For example, Pan and Zhang [79] demonstrated a BIM data mining integrated digital twin framework that uses IoT data and process mining to forecast bottlenecks and optimize resource allocation in real time. By anticipating potential delays and risks, such integrated AI-BIM systems not only prevent accidents but also reduce cost overruns and material waste, directly contributing to lean construction goals. These methods not only automate risk identification but also reveal latent trends and contextual patterns that conventional rule-based systems could not capture. Cognitive modeling approaches now use event sequence inference [80], new mathematical operators for decision-making under uncertainty [81], and biometric predictors derived from wearables [82], thus expanding the predictive risk analytics beyond surface-level site conditions. ML approaches now capture underlying behavioral and physiological precursors to accidents. Studies have also shown emerging interpretable models, such as local linear forests [83], semantic hazard descriptors using Text convolutional neural network (CNN) [84], and automated computer vision pipelines [85], which improve model transparency. This enables safety managers to understand *why* the system predicts specific risks. Together, these advances transition predictive modeling tasks from a checklist-driven process into a dynamic, data-driven process that is capable of anticipating hazards, personalizing warnings, and supporting real-time decision-making.

3.1.3 Ergonomic Safety and Human-Centered Systems. A study by Guo et al. [86] noted a lack of motion-based safety information. Recent systems address this gap by integrating ML with wearable and nonintrusive sensing to monitor real-time human behavior and ergonomic risk factors. Models using long short-term memory (LSTM) and CNN architectures are used to classify complex motion patterns with high temporal fidelity [87–89]. This enables automated identification of posture anomalies and unsafe movements [90] that previously required manual observation.

The shift is also seen in wearable devices that can predict free fall detection using Wi-Fi signal distortion [91], addressing persistent limitations in sensor fatigue, cost, and user compliance. Similarly, models in physiological state prediction use respiratory sensors [92] and multimodal electromyography (EMG)/IMU fusion for activity recognition [93], extending safety systems toward holistic human state estimation. These examples help demonstrate the move of ergonomic safety from periodic assessment to continuous monitoring that adapts to individual workers and dynamic site conditions.

3.1.4 Robotics and Autonomous Systems. Early reviews in this subcategory highlighted limited robotic integration and narrow focus on equipment such as tower cranes [94]. Recent developments expand the role of ML in robotics for safety-aware autonomy and human–robot collaboration. Developments in modeling trust now support a safer deployment of co-robots working alongside human crews [95], while predictive modeling of human movement enables robots to plan safe, collision-free paths [80]. These advances represent a shift from isolated robotic systems to shared workspaces where perception, prediction, and communication enable collaborative safety management.

3.1.5 Infrastructure and Equipment Monitoring. Traditional safety systems often overlook broader infrastructure performance [96]. Therefore, recent research integrates ML into lifecycle monitoring systems, enhancing the reliability of safety operations. ML techniques validate the structural health in real time [97,98], while vision image labeling via BIM [99] improves detection in visually degraded environments. Beyond safety, these monitoring systems are increasingly used for “Green AI” applications. For example, AI-driven structural health monitoring can now track carbon

Table 3 Distribution of supplementary sustainability-focused studies added to the review ($n = 16$) inclusive of the 165 final count

Domain	No. of papers	Key sustainability themes addressed
AI	3	Waste reduction, rework prediction, smart schedule optimization
Visualization	5	LCA integration, energy efficiency, proactive governance, human–robot collaboration
SNC	5	Thermal envelope inspection, automated waste management, smart vision for safety and energy
Wearables	3	Social sustainability, occupational health management, personalized environmental monitoring
Total	16	

Fig. 4 Word cloud visualizations derived from the titles of the screened 165 construction safety papers. (Left) Title-level word cloud from construction safety papers. (Right) Title-level word cloud from sustainable papers.

footprints and energy efficiency in real time, ensuring that buildings remain not only safe for occupants but also environmentally optimized throughout their lifecycle [65]. There is the example of bridge deck degradation where the prediction model is trained on historical data [96] to support long-term risk management and maintenance planning. This is a perfect example of linking safety monitoring with asset integrity for the first time.

3.1.6 Multimodal Integration and Cognitive Modeling. Early reviews noted fragmented applications and weak contextual inference [100] in this category. Recent ML systems integrate vision, BIM, sensor streams, and text into cohesive multimodal frameworks that are capable of reasoning across heterogeneous data sources. Vision-to-NLP systems map hazards to regulatory requirements [101], while leading indicators are predicted using project statistics [102]. An example of cognitive risk perception modeling using a functional near-infrared spectroscopy brain activity [103] introduces a new dimension in understanding how workers interpret site hazards. While another example of using sensor biomechanical hybrid models enhances back injury prevention through personalized risk assessment [104]. These multimodal approaches mark a major step toward context-aware, safety systems that are capable of learning site norms, and providing adaptive warnings.

3.1.7 Artificial Intelligence for Sustainable Resource Optimization and Waste Reduction. An emerging domain is the application of AI to predict and prevent rework, a major source of both safety hazards and environmental waste. Rework in green building projects is often caused by design variability and complex material specifications. Recent research demonstrates that machine learning models, specifically gradient boosting and random forest algorithms, can predict rework occurrences with up to 97% accuracy [105]. Crucially, rework is caused by safety accidents, and quality failure is a primary driver of carbon increases, as it necessitates the amount of material production, transport, and installation. By identifying high-risk activities early, these models allow managers to intervene before errors occur. This “prevention through prediction” approach serves a dual purpose: it reduces the physical hazards associated with re-doing work and minimizes the material waste and embodied carbon associated with rework, thereby supporting the economic and environmental pillars of green building initiatives.

3.2 Computer Vision. Early CV applications in construction safety were often constrained by their limited ability to process dynamic environments, manage large-scale visual data, and deliver robust real-time detection [86,100]. Xu et al. [100] emphasized these limitations, noting challenges in scene complexity, contextual awareness, and reliable visual tracking. Recent developments have significantly addressed these gaps, as seen in the following themes: real-time hazard detection, synthetic data and simulation, ergonomic analysis, and compliance monitoring.

3.2.1 Real-Time Hazard Detection and Localization. Earlier work before 2020 struggled with reliability in identifying hazards in real time [48]. Since then, several recent studies have taken different approaches to work around this limitation. One example connects a semantic model and CV outputs with ontology to improve fall-from-height hazard detection [106]. Another research uses real-time simultaneous localization and mapping-based frameworks, which helped the systems handle both static and moving site conditions more effectively [107]. Even though we notice varying levels of success in the aforementioned studies, they still introduce context-aware vision-based systems that can dynamically detect threats to safety.

3.2.2 Synthetic Data and Simulation for Safety Training and Recognition. A frequent issue in limitations under this category is the lack of annotated data and the time required to label it [100]. Recent studies approached this differently by using synthetic data, which turned out to be a practical workaround for model training. Research shows using synthetic pipelines to convert 3D virtual assets into 2D pose sequences, allowing models to learn fall-related hazards even when only a few real examples are available [108,109]. Although these synthetic setups vary in quality, they still offer scalable training without depending entirely on real-world annotations.

3.2.3 Ergonomic Analysis and Posture Detection. The inability to monitor ergonomic hazards in earlier systems [49] has been addressed by visual assessment of posture. A monocular vision system allows for nonintrusive biomechanical analysis in modular construction [110], and models of human-object interaction enable automatic violation inference [111]. These approaches advance the monitoring of physical behavior and safety-critical actions in real time.

3.2.4 Automated Safety Compliance and Spatial Monitoring. Earlier challenges with contextual accuracy and limited automation [86] have been addressed in several different ways. Some systems rely on direct visual compliance checks, for example, an application of hand-signal recognition for crane operations shows a remarkable accuracy above 93% even when lighting or backgrounds vary [112]. Another work links the IDC4D approach with 4D BIM information and CV models to flag situations when workers enter restricted or hazardous zones [113]. Several teams have also explored variations of real-time monitoring: pose-anchored PPE checks [114], gesture-based compliance cues [115], and video systems that help improve safety assessments based on compliance checks and the specific site environment [116]. The aforementioned research shows examples of recent CV developments that address the limitations outlined by Guo et al. [86]. At the same time, Xu et al. [100] also provide supporting evidence that CV models benefit from improved validation strategies, especially when scenes or tasks change between projects. Work in real-time detection [106,107,117], simulation and

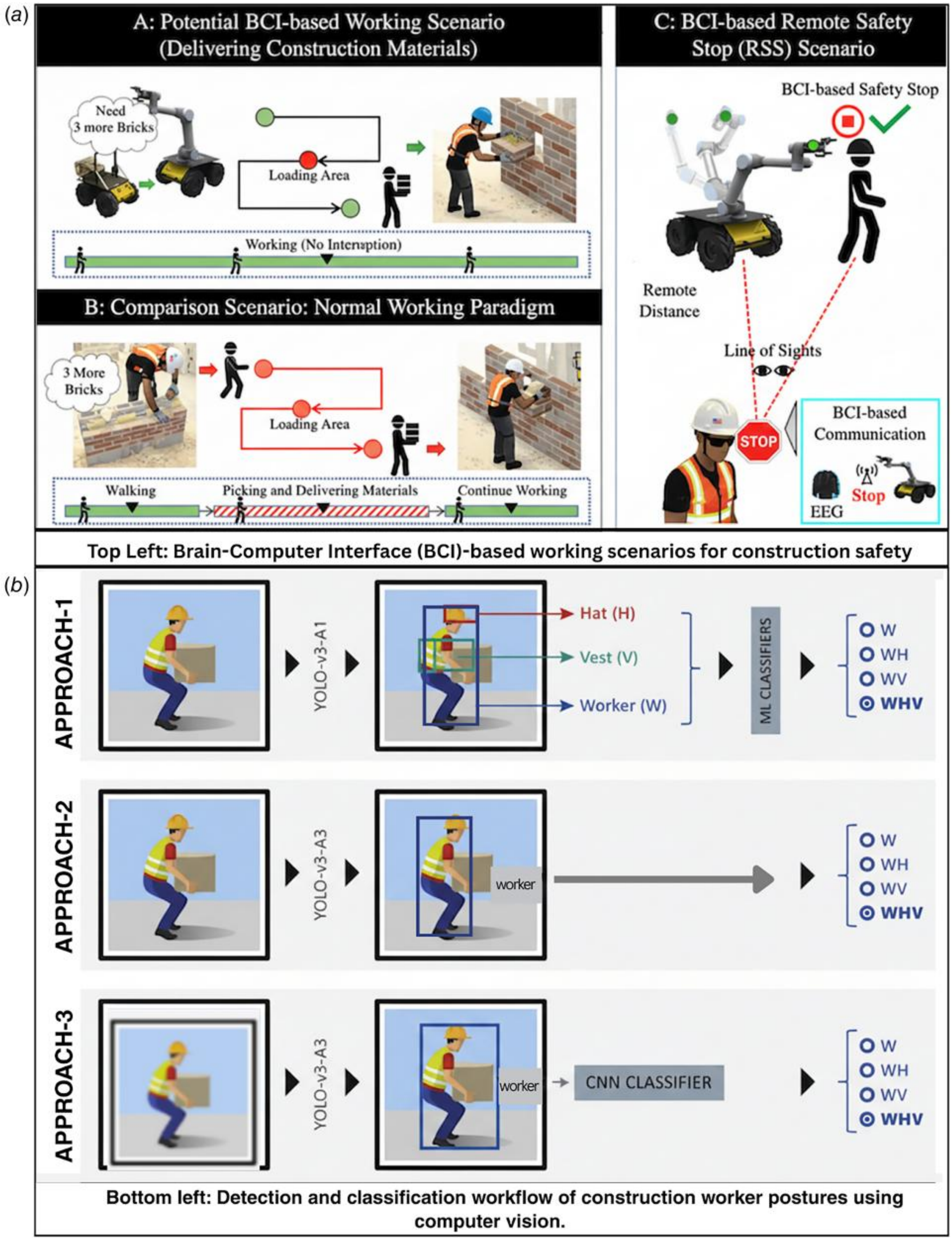

Fig. 5 Summary of emerging AI-based approaches in construction safety: (*a*) BCIs for remote safety interventions (adapted from the study by Liu et al. [63]) and (*b*) computer vision posture recognition methods (adapted from the study by Nath et al. [64]).

synthetic data pipelines [108,109], ergonomic and posture-oriented analysis [110,111], and a wide set of compliance-monitoring tools [112–116] point toward a maturing and increasingly scalable direction for CV-based safety management.

3.2.5 Vision for Waste and Energy Monitoring. While early computer vision applications in construction were predominantly designed for hazard detection [50], recent scholarship indicates a functional expansion toward sustainable site management.

Modern vision-based frameworks are increasingly capable of multitasking; they can simultaneously monitor safety compliance and identify operational inefficiencies, such as material waste or idling machinery, thereby directly supporting the principles of lean construction [51].

A critical area of advancement is the automation of construction and demolition (C&D) waste management. Visual recognition algorithms are now being integrated with robotic systems to automate the segregation of site debris. For instance, recent research developed a robotic system capable of visually distinguishing between hazardous materials and recyclables [118]. This approach not only enhances the purity of recycled material streams but also mitigates the health risks associated with manual sorting. Furthermore, vision-enabled AR systems have been deployed to facilitate human–robot collaboration in waste processing, allowing operators to remotely identify and label complex waste types—such as distinguishing treated wood from plastics—without physical exposure to the sorting line [119].

Beyond waste, computer vision is becoming a vital tool for energy auditing and envelope inspection. The fusion of visual data with UAV infrared thermography (UAV-IRT) allows for the rapid, noninvasive detection of thermal anomalies, insulation failures, and moisture entrapment in high-rise structures [120]. This capability supports targeted retrofitting efforts to reduce operational energy waste while eliminating the need for workers to access dangerous heights for inspection. In indoor environments, vision systems have been integrated with digital twins to track occupant movement in real time; studies demonstrated that this method could optimize lighting controls to reduce energy consumption by 79% while ensuring adequate illumination for safety [121]. These applications suggest that visual data are evolving from a tool for strict safety surveillance into a dual-purpose mechanism for lifecycle sustainability and carbon footprint reduction.

4 Visualization

The use of VR in construction sites began in the early 2000s, when Messner and Horman [122] explored the use of VR models to enhance design visualization. AR followed shortly after, with Webster et al. [123] examining AR's potential to overlay virtual images on real-world construction contexts. A 2018 review by Li et al. [47] emphasized the emerging role of AR and VR in the identification and planning of hazards and safety, but also noted significant limitations in the design of user interfaces and integration with project management systems. Similarly, DT applications remained mostly static before 2020, with limited real-time integration and use in dynamic field environments [124,125]. Recent advancements, however, have expanded the scope of visualization technologies beyond safety alone, increasingly leveraging them to visualize energy performance, embodied carbon, and lifecycle sustainability metrics.

4.1 Augmented Reality. Construction safety studies under AR published before 2020 were often limited by finite integration with existing tools and usability challenges [47]. We found examples of recent research focusing on overcoming these limitations through improved BIM integration, mobile deployment, and real-time visualization.

An example worth mentioning is a BIM and AR-integrated system that enables mobile inspections and real-time updates using risk data captured on smartphones [126]. This suggests an advanced integration system that improves safety planning. Termed as a mobile projective augmented reality system, the method eliminates the need for wearable hardware by employing a camera projector unit that delivers centimeter-level projection [127].

Crucially, AR is emerging as a key enabler for "human–robot collaboration" (HRC) in sustainable waste management. Chen et al. [119] developed an AR-enabled sorting system where workers can remotely identify construction waste types (e.g., plastics versus wood) for robotic arms to sort. This system improves sorting accuracy by 15% directly enhancing material recycling rates, while keeping human workers physically distant from hazardous conveyor belts. This dual-benefit application demonstrates AR's potential to bridge the gap between circular economy goals and occupational health.

Recent work has also advanced the efficiency of the XR pipeline. For example, the GenXR model [128] reduces the BIM to XR data transfer time by up to 66.7%, supporting streamlined workflows across VR, AR, and mixed reality (MR) platforms. Additional AR applications include the integration of HoloLens into the production strategy process, allowing users to visualize 3D BIM data to enhance collaboration and planning during construction. This approach has shown measurable improvements in usability and decision-making within healthcare construction projects. AR has also demonstrated accuracy improvements in precision-sensitive tasks such as wood fastening, where it helps visualize construction details to meet industry standards [129]. These advancements are visually summarized in Fig. 6, which illustrates the AR-based visualization of mechanical, electrical, and plumbing (MEP) systems, safety-enhancing VR environments, and immersive digital twin sets. Collectively, these studies demonstrate that AR has evolved from an experimental visualization aid to a field-ready technology integrated with BIM and construction management processes. These advances address pre-2020 limitations in system integration, field usability, and real-time visualization [47], marking a notable shift in how AR supports decision-making and site safety planning in modern construction environments.

4.2 Virtual Reality. VR applications before 2020 were often limited by low immersive experience, generic training content, and a lack of integration of behavioral or physiological feedback [47]. While reviewing the set of VR studies, we noted four core themes: personalized training, physiological sensing, VR BIM integration, and behavior modeling.

Personalized Training: Newer approaches dynamically adapt VR training content to individual user needs [132]. An example demonstrates how adjustments in the scenario's complexity in real time produce higher posttraining scores compared to static platforms [133]. Together, these studies exhibit improvement in immersion and retention, a limitation noted by Li et al. [47].

Physiological Feedback Integration: A number of newer VR studies have begun incorporating biometric inputs such as electroencephalography (EEG), EMG, and IMU data to track stress, cognitive load, and posture during simulated tasks [134,135]. This extra layer of feedback helps the system adjust to the user in real time, something earlier VR setups struggled to do.

VR BIM Integration: VR platforms are also being linked with BIM models to improve realism and reliability in safety planning scenarios [136]. This approach allows spatial layouts to be reproduced accurately, and it keeps training modules aligned with any digital design changes. Studies report that this combination improves both immersion and interoperability [137], two areas where older systems often fell short.

Behavior Modeling and Evaluation: Recent studies have also evaluated how training impacts real-world behavior, using behavioral tracking (eye, body, gestures) and biometric data (heart rate, facial expressions). This is done in an effort to track changes in hazard recognition and safety response [135,138]. The insights generated from this tracking help refine training and design a response to the earlier recommendations [47]. Together, VR-based safety training after 2020 shows itself to be a more responsive, personalized, and cognitively grounded tool. With advances in immersion, feedback, and behavioral alignment, modern VR systems directly address the limitations prior to 2020 outlined by Li et al. [47] and now occupy a central role in construction safety education.

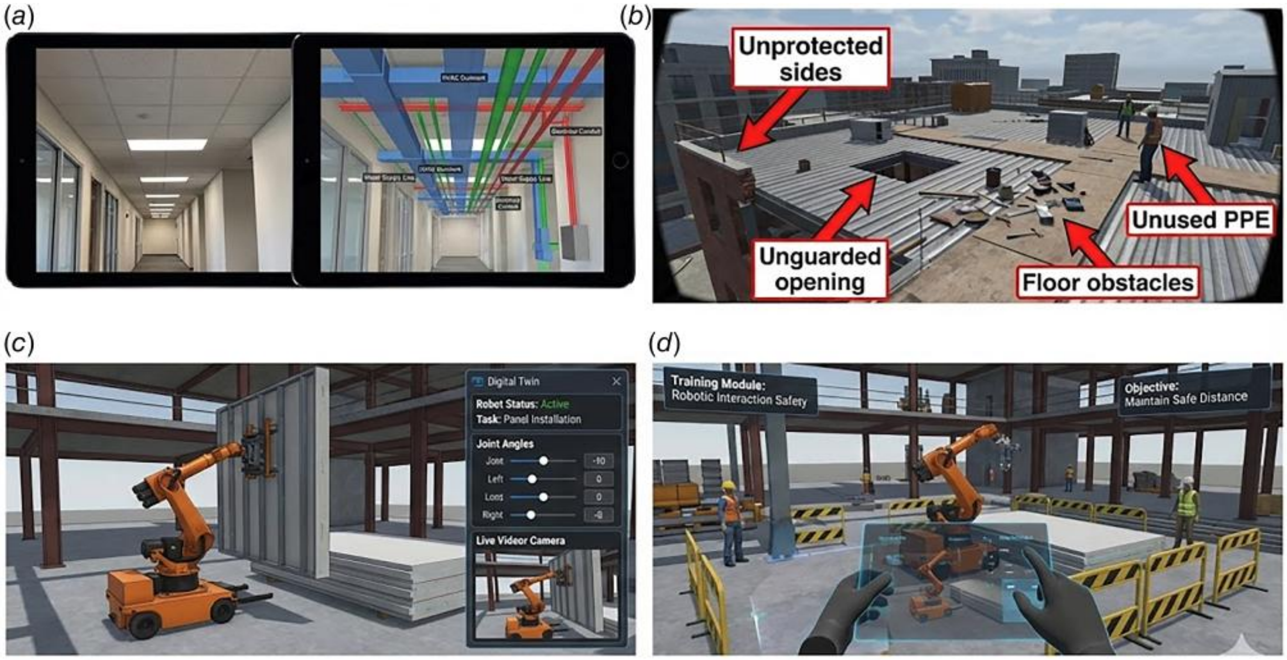

Fig. 6 (*a*) Augmented reality (AR) application allowing users to visualize MEP systems hidden above ceilings through an iPad (Adapted from the study by Liao et al. [130]). (*b*) Virtual reality (VR) training scenarios showing an environment with hazard scenarios overlaid. (*c*) Digital twin setups illustrating a robotic operation environment. (*d*) A corresponding immersive VR training environment (both adapted from the study by Wang et al. [131]).

4.3 Digital Twins and 3D Modeling. The applications of DTs and 3D modeling in construction safety prior to 2020 were largely static. In practice, limited real-time integration and operational relevance [124,125] were common issues. DT implementations often lacked dynamic data feedback, and 3D models remained isolated from active job site processes. We see how recent studies have advanced in both the technologies through real-time monitoring, predictive risk modeling, and immersive learning.

Digital Twins: Recent research has strengthened DT integration with cyber physical systems (CPS), IoT, and machine learning. This has helped enhance safety through real-time monitoring and provided data-driven control.

An example of CPS DT-integrated framework for building operation provides support through continuous tracking and automated risk detection [139]. Furthermore, digital twins are evolving into “green digital twins.” Tan et al. [121] proposed a digital twin-driven lighting system that combines computer vision with dynamic BIM. By tracking occupant movement in real time, the system optimizes lighting energy consumption by 79% (sustainability) while ensuring adequate illumination for visual comfort and safety. While reviewing, we noticed synergies between BIM, AI, IoT, and CPS, and this was also seen in a review paper that calls for underexplored safety in domains such as transportation and operation [140]. On the other hand, DTs have been applied on heat-prone construction sites, demonstrating how live weather data can be fused with digital site models [141]. We noted this as a proactive heat risk mitigation.

3D Modeling: Recent work addresses the static nature of traditional 3D models by improving their dynamism, computational efficiency, and utility in real-time settings. Methods focusing on point cloud reconstruction show significant gains in density and loop closure robustness, improving hazard detection and spatial monitoring accuracy [142]. Monocular camera-based 3D reconstruction techniques also enhance the separation of dynamic and static elements, reducing computation costs while improving frame rates [143]. In educational contexts, immersive 3D and 360 deg videos have been used to increase engagement and retention in safety-related construction training [144].

Together, these advances demonstrate a notable evolution in DT and 3D modeling technologies. By improving real-time responsiveness, integrating sensor-driven data, and supporting immersive safety learning, these tools have progressed from static representations to dynamic systems that directly support proactive construction safety management.

4.4 Building Information Modeling. Before 2020, BIM was recognized for its potential to improve planning and coordination in the Architecture, Engineering, and Construction (AEC) industry, but its integration into safety workflows remained limited. The key challenges identified in previous reviews include interoperability issues, regulatory uncertainty, and insufficient training [145,146]. Recent research has aimed to address these limitations by embedding BIM in real-time site monitoring, training, and safety decision-making.

Real-time Hazard Monitoring and Site Coordination: BIM has been increasingly used for proactive safety monitoring through 4D visualization and dynamic task coordination. An example of one framework combines BIM with real-time collision detection and animation of crane safety to visualize operational risks [147]. This trend is also seen in another study where integration of indoor positioning systems and IMUs with BIM is done to track worker movements and obtain location-based hazard notifications [148]. These kinds of advances support real-time safety assessments and address the earlier lack of live data integration.

Sustainability Integration (BIM-LCA): The integration of BIM with life cycle assessment (LCA) is a crucial development area [149]. Chen et al. [150] reviewed advancements in BIM-LCA integration, highlighting how automated data exchange (e.g., via Industry Foundation Classes (IFC) or plugins) allows for precise carbon footprint tracking. This capability makes BIM into a sustainability tool that enables safety managers to visualize not only physical hazards but also environmental “hotspots” in the construction process.

Immersive Simulation and Safety Training: Several BIM studies incorporate training environments to simulate real-world safety events. For instance, unity-based simulations use BIM models to recreate scaffolding failure and evacuation scenarios, improving hazard recognition and emergency response training [151]. Therefore, the need for intuitive scenario-driven training tools that have previously been missing in BIM-centered safety planning is addressed.

Regulatory Support and Risk Coordination: Risk coordination is seen across a lot of studies where advances in frameworks tackle the challenge of regulatory limitations by incorporating safety guidelines and incident data into BIM workflows. Chong et al. [152] propose a unified BIM-AI platform that shifts safety management from compliance to intelligence. By combining spatial data with AI probabilistic models, the system quantifies interdependencies among structural, environmental, and human risks, supporting the social sustainability goal of preserving human capital. A notable approach evaluates construction activities and assigns hazard scores using OSHA and NIOSH datasets [153]. This effort is one of the many examples that fill the gap in the management of overlapping work zones.

Organizational Adoption and Workforce-Specific Applications: Beyond technical innovations, recent studies explore the human and organizational dimensions of BIM adoption. Managerial frameworks factors like autonomy, career growth, and task clarity [154], combined with guided validated practices improve site layout and safety outcomes [155]. Another study highlights culturally specific safety research. Recurring fall risks among Hispanic workers are often due to noncompliance with PPE and improper ladder use [156]. A leadership research highlights how constructive traits, such as communication and reliability, enhance collaboration in BIM-centered teams [157].

In this section, we review recent BIM research and observe transitions from static modeling to dynamic, field-integrated safety planning. This transition in BIM improves real-time hazard detection, immersive safety training, and policy-based coordination addressing the barriers to interoperability, workforce training, and regulatory support [145,146]. We note the increasing continuous potential of BIM that shifts toward a support tool for proactive safety, lifecycle sustainability, and collaborative construction management.

5 Surveillance, Navigation, and Collaboration

5.1 Drones. The adoption of drones in construction began to gain traction around 2014, when Gheisari et al. [158,159] introduced early applications of unmanned aerial systems (UAS) for site inspections and safety documentation. Although promising, the then drone research faced several criticisms: limited autonomous navigation, lack of seamless real-time data integration, and weak interface design that hindered usability [160].

Surveillance: Recent drone developments are popularly used for intelligent aerial surveillance [161]. These AI-integrated systems detect safety violations such as mapping unsafe zones and triggering real-time alerts [162–165]. Attempts controlled experiments demonstrate the effectiveness of drones for debris detection, hazard zoning, and site-wide heat mapping [166]. These advances clearly help close the gap in continuous real-time risk detection.

Navigation: To overcome earlier limitations in autonomous control and navigation, emerging simulation-based frameworks now support safe flight planning and training. Rakha and Gorodetsky [167] highlight the shift toward fully automated building inspection procedures using UAS, which significantly reduces the time and risk associated with manual inspections. Furthermore, Liang et al. [168] identified advancements in UAV path planning that enable more precise monitoring of dynamic construction environments, ensuring reliable data capture even in cluttered sites. Through operator guidelines, drone control protocols, and simulation benchmarks, the system ensures reliability and usability [169–171]. These efforts make for a more confident and effective deployment especially in variable site conditions.

Collaboration: A newer approach of VR-based drone training environments supports safer drone–human interactions while maintaining operational awareness [172]. These systems use immersive interfaces to teach workers behaviors and safety rules. An excerpt in Fig. 7 demonstrates this through various training modes conceptual instruction, scenario-driven exercises, and site-wide monitoring simulations. A further study into operator behavior and simulations of drone response shows improved perception of hazards and operational proficiency [172,173].

Sustainability and Energy Efficiency: Beyond safety, drones are increasingly used for building performance evaluation. A recent review of UAV-IRT highlights their ability to perform rapid, efficient thermal inspections of building envelopes. By identifying thermal anomalies, moisture entrapment, and insulation failures, these UAV systems allow for targeted retrofitting, contributing to the sustainability goal of reducing operational energy waste [120]. This application exemplifies the safety sustainability used in UAV applications to inspect high-rise envelopes and eliminates the need for workers to work at heights while ensuring the building's thermal integrity.

In general, drone research has transitioned from mere experimental tools to autonomous, safety-oriented, and eco-efficient agents. By addressing earlier concerns about navigation, real-time data integration, and human drone interaction, drones are now seen to play a proactive role in surveillance, navigation, and collaboration across construction safety.

5.2. Robotics. An early example of construction robotics emerged in the 1980s, with the development of a robotic fireproofing sprayer by Shimizu Corporation that applied a coating to steel girders for extended hours [174]. Despite early success, robotics faced the most challenges: unstructured work environments, high costs, limited autonomy, safety risks, and a lack of human–robot interaction (HRI) design [94]. Recent advancements show remarkable progress in key topics relevant to SNC.

Collaboration: Addressing the limited capability of HRI and associated trust concerns, we focus on recent studies on brain–computer interfaces (BCIs), cognitive adaptation, and shared task coordination. Robots have incorporated EEG signals from human workers to adapt actions in real time [63,175]. Learning from demonstration techniques enables robots to generalize quasi-repetitive tasks in unstructured environments [176], while conceptual HRI taxonomies improve trust and ergonomic alignment [177]. Digital twin systems also bridge the gap with human strategy and robotic execution through immersive VR interfaces [178]. There are also several reinforcement learning examples that optimize co-robotic ergonomic support [179], and Generative Adversarial Network (GAN) based cognitive load tracking. This approach allows robots to adapt according to worker stress [180]. These collective developments are some examples that overcome previous issues related to robotic unpredictability, manual controls, and low human acceptance.

Robotics for Sustainability (Waste Sorting): A critical emerging application is the use of robotics for onsite waste management. Chen et al. [118] developed a robot specifically for automatic waste sorting on construction sites. By automating the segregation of hazardous and recyclable materials, this system addresses two critical goals: it removes workers from the dangerous task of manual sorting and ensures higher recycling rates by reducing contamination in waste streams.

Surveillance and Smart Infrastructure: Some novel robotics platforms actively detect transient hazards like falls in indoor environments [181]. While collision risks are also proactively predicted using deep learning and UAV-integrated frameworks [182].

Navigation and Training: We have seen the use of VR-based training above, and it is also seen here to enhance familiarity and trust in robotic systems. Interactive simulations improve operator confidence, situational awareness, and real-world task transfer [183]. In addition, VR-based collaborative tasks also support real-time trust modeling in HRC by psychophysiological feedback [184]. Recent advances in robotics have seen development from single-purpose automation tasks to intelligent collaborative

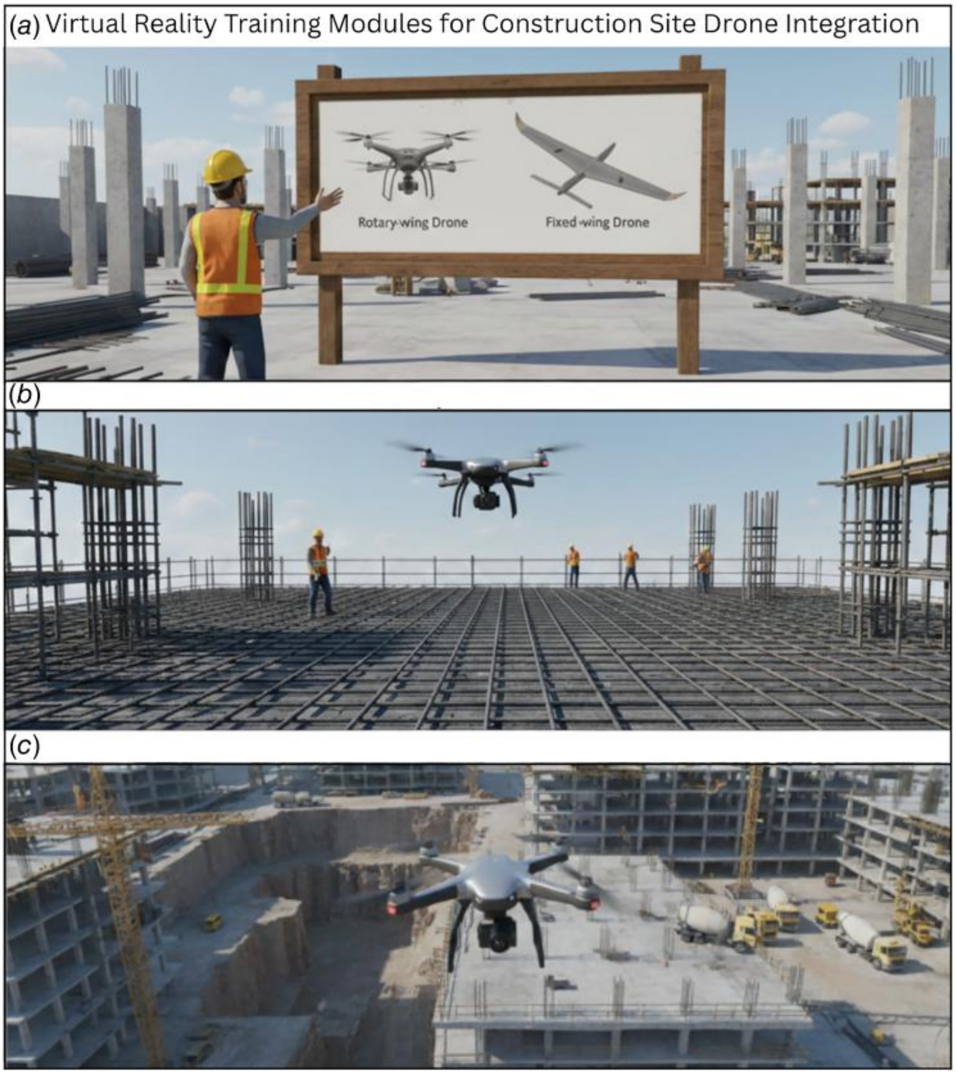

Fig. 7 **Training modes include (*a*) conceptual instruction, (*b*) scenario-driven exercises, and (*c*) site-wide monitoring simulations (adapted from the study by Cheng et al. [172]).**

agents. These systems thus overcome previous challenges in adaptability, ergonomics, and cognitive integration [94], and are now supporting predictive hazard detection, responsive task execution, and dynamic interaction with human colleagues.

6 Wearable Technology

The concept of wearable safety technologies in construction has been investigated since the early 2000s, with research such as Thorpe et al. [185] facilitating the link between point-of-production workers and corporate Information and Communications Technology (ICT) systems. These early efforts established the groundwork for modern wearable sensors that monitor worker behavior and physiological metrics in real time. Reviews such as those by Awolusi et al. [186] highlight the potential of wearables to improve safety through real-time monitoring and physiological monitoring. However, limitations with wearable technology were often faced with low-field validation, accuracy concerns in dynamic settings, worker adoption, and limited integration with safety frameworks. Recent studies have shifted the narrative from simple injury prevention to social sustainability. By continuously monitoring worker health and well-being, wearables are now seen as essential tools for preserving human capital, the industry's sustainable resource. We see how recent studies have since made major strides in addressing these gaps, particularly in the domains of worker behavior, ergonomics, and real-time cognitive sensing.

6.1 Worker Behavior and Ergonomics. A notable example of the use of bluetooth low energy–based positioning systems has been seen to deliver high-precision alerts to prevent struck-by incidents. They combine the angle-of-arrival tracking with wearable wristbands [187]. Hybrid systems also enhance tracking accuracy by fusing computer vision with Radio-Frequency Identification (RFID), enabling precise 3D localization of workers in high-risk zones [188]. These examples are a part of the collective studies that help resolve earlier issues with the cumbersome cable and inaccurate field positioning. Construction sites have seen unsafe behaviors and their detection has improved significantly with AI-enhanced video analytics. Attention-based neural networks such as OP-Net enable high accuracy identification of unsafe acts in real-world environments [189], while LSTM-based prediction models help anticipate environment-aware mobility paths and potential collisions [190]. These advances directly address previous concerns about missing behavioral cues in complex site environments [4,191].

6.2 Managing Risk for Social Sustainability. The integration of occupational health and safety management systems (OHSMS) is now recognized as a critical driver for sustainable industry growth. Kineber et al. [12] conducted a systematic review demonstrating that the benefits of OHSMS extend beyond accident reduction; they include improved safety culture, reduced absenteeism, and enhanced project efficiency. By systematically identifying and controlling risks, construction firms can comply with regulatory requirements while simultaneously fostering a "safety climate" that values human capital. Bourahla et al. [11] further emphasize that managing Occupational Health and Safety (OHS) risks is a pathway to social sustainability. Their review identifies that nontechnical risks such as human behavior, lack of training, and poor communication are dominant factors in construction accidents. Wearable technologies address these "soft" risks by providing data-driven insights into worker behavior and fatigue levels. For instance, wearables can detect when a worker is entering a high-risk zone or exhibiting signs of heat stress, allowing for immediate administrative interventions that protect the worker's long-term health and livelihood. This proactive management ensures that the infrastructure we build promotes social well-being for those who build it. As one would expect, wearables are also used to study the cognitive and ergonomic effects of stimuli on workers. VR-based simulations test whether ambient sound filtering improves operator focus [192], while other studies examine how proximity to drones influences worker stress and attentiveness [193]. Empowerment-focused research evaluates the relation of wearable and digital tools to participation and communication in safety [194,195]. There have also been advances in simulation models that predict responsibility in fall incidents based on behavioral data [196]. An inertial sensor-based system identifies loss-of-balance events to detect slippery zones with high recall precision results [197]. On the practical side, onsite assessment tools have also emerged for evaluating worker safety under time and skill constraints [198].

We acknowledge that one of the most essential challenges of wearable—user acceptance still remains a critical focus. Studies that have built conceptual models from field surveys point toward the importance of ergonomics, trust, and data privacy on mobile devices [199]. Beyond acceptance, continuous physiological and behavioral monitoring raises broader ethical concerns. Technologies such as EEG-based cognitive sensing, wearable biosensors, and real-time location tracking collect highly personal data, yet frameworks governing data ownership, storage duration, third-party access, and worker consent remain largely undefined in the construction domain. Without transparent data governance policies, workers may perceive monitoring systems as employer surveillance rather than safety tools, potentially undermining the social sustainability goals that these technologies are designed to support. A study introduces tracking of EEG-based cognitive functions to demonstrate the adaptability of field-ready neurosensing equipment [200]. Another study introduces tactile vests and belts that offer haptic feedback to warn of nearby equipment in visually or acoustically constrained environments [201].

These developments are visually represented in Figs. 8 and 9, which illustrate biosensor-driven risk classification and tactile feedback systems designed to enhance hazard awareness. In a concluding article, Panahi [202] explores the concept of personalized sustainability, where traditional systems that monitor the site as a whole, personalized sustainability focuses on the individual's interaction with their immediate environment. In short, recent wearable technology research has seen expansion that is far beyond basic activity tracking. Through the integration of real-time behavioral monitoring, ergonomic modeling, hazard anticipation, and cognitive assessment, wearable systems now serve as essential tools for proactive and personalized construction safety management. The aforementioned advances help address the earlier noted gaps in data accuracy, behavior integration, environmental adaptability, and user trust.

6.3 Health Monitoring and Human Capital Sustainability. Construction health-related research focused primarily on general wellness topics such as occupational stress and nutrition. However, as Nwaogu et al. [203] observed, construction health monitoring systems often lacked integration with real-time physiological tracking, mental health metrics, and field-ready implementation strategies. Their review identified key challenges: (1) physiological monitoring, (2) the mental health effects of shift work were underexplored, and (3) health technologies lacked adoption due to cost, usability, and training barriers.

Recent studies have made important strides in addressing these issues. For example, Ghafoori et al. [204] developed a deep learning system that predicts heart rate using wearable sensor data and CNN-LSTM algorithms, helping detect early signs of overexertion. This addresses the challenge associated with real-time physiological tracking. Similarly, Zhou et al. [205] applied topic modeling to a large corpus of construction safety literature, showing how new methods can move beyond citation network bias to surface actual health-related trends over time. Recent reviews also emphasize the importance of physiological monitoring in long-term sustainability of the workforce. Nnaji and Karakhan [206] argue that WSDs are pivotal for mitigating work-related musculoskeletal disorders, a leading cause of early retirement and workforce depletion. By proactively monitoring physical strain and fatigue, WSDs help extend the working life of skilled laborers, thereby supporting the economic sustainability of the construction industry. Mental health monitoring has also improved as seen in the study by Kumar Singh et al. [207], where they conducted a field study with 1400 workers. The study showed that misaligned sleep cycles due to irregular work schedules significantly affected mental and physical well-being. Their results therefore reinforce the need for organizational interventions, a gap noted in the earlier review.

From an implementation perspective, barriers to adopting this technology have also been examined. Nnaji and Karakhan [206] surveyed 102 construction professionals and highlighted why the adoption of health technologies lags: cost, lack of training, and perceived value. A broader review of wearable technologies [208] points to solutions such as centralized data management and ergonomically designed devices to improve usability and lower costs. Building on this, Yadav et al. [209] identified five practical design principles for worker-friendly wearables: weather resistance, battery life, traceability, comfort, and social acceptability.

As a result, we note emerging systems are now tracking a wide range of vitals, heart rate, temperature, breathing rate, and muscular load, using off-the-shelf wearables. For example, Pillsbury et al. [210] found that fitter workers had lower physiological stress on different tasks, underscoring the value of personalized data in work allocation and injury prevention. To date, we see recent research in health monitoring has moved from static wellness metrics to dynamic, real-time physiological monitoring and mental health management. These examples in advance respond directly to the gaps described by Nwaogu et al. [203] and align with the broader goals of social sustainability by treating worker health as a renewable resource that must be protected. Together, they demonstrate a growing focus on proactive, data-driven worker health systems, bringing the industry closer to a holistic model of construction safety and sustainability.

7 Discussion

The review critically examined technological advances in four domains AI, visualization, SNC, and wearable technology, highlighting the "technological inflection" point. The analysis demonstrated a transition from isolated tools in the prototype stage to integrated, adaptive, and context-aware safety systems that address safety hazards and sustainability goals.

7.1 Safety Sustainability. AI technologies, which were historically constrained by limited real-time capabilities, like inconsistent data, and poor interpretability, have seen several studies with substantial developments serving a dual purpose. Recent AI approaches now enable proactive hazard detection, while the same predictive analytics are being leveraged for resource

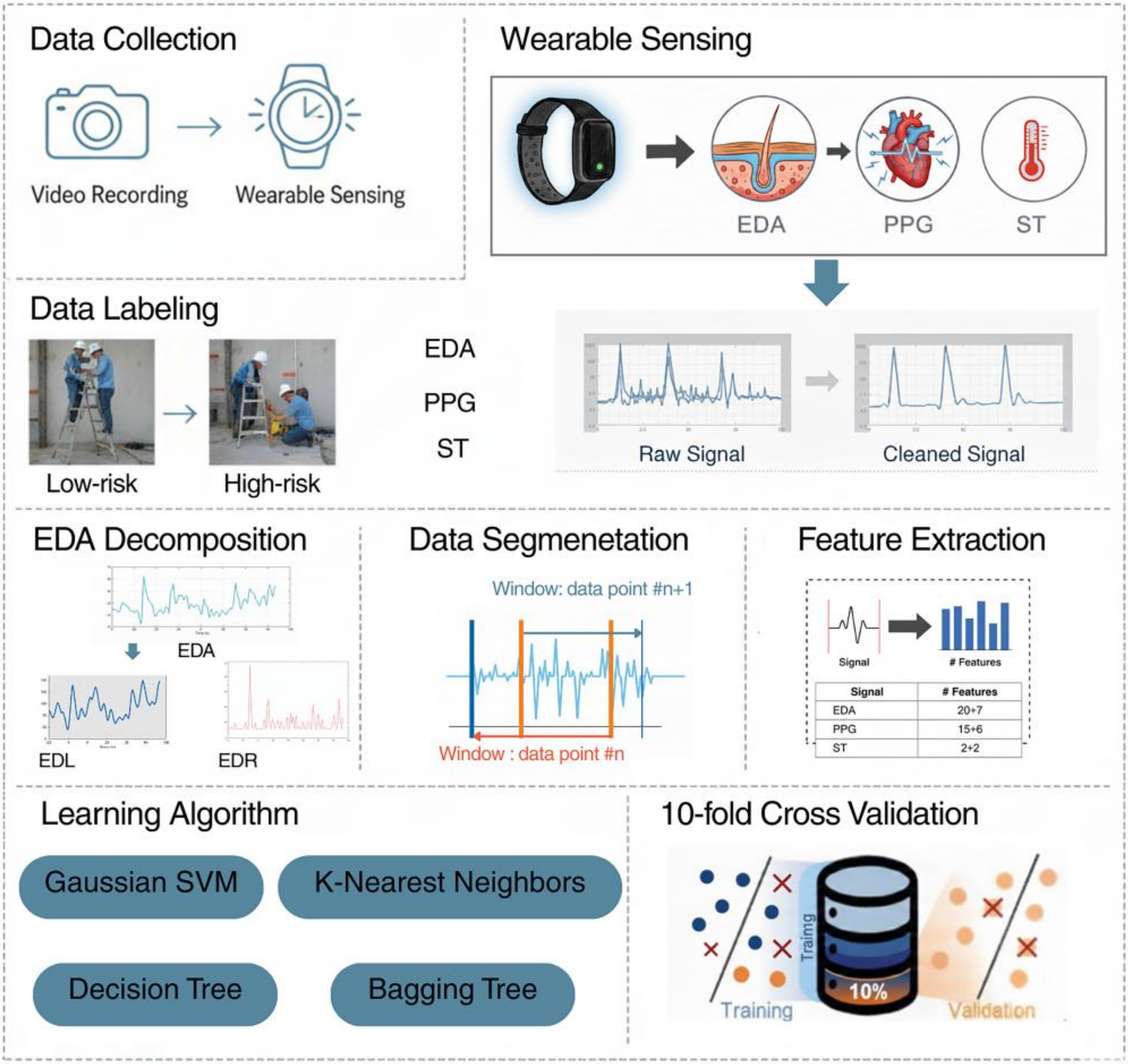

Fig. 8 Overview of a wearable biosensor system for assessing construction workers' perceived risks. Physiological signals including electrodermal activity (EDA), photoplethysmography, and skin temperature are collected via wristband sensors. Note: EDL refers to electrodermal level (the tonic component of EDA) and EDR refers to electrodermal response (the phasic component of EDA). (Adapted from the study by Lee et al. [82].)

optimization. For example, BIM-integrated digital twin frameworks that use data mining to predict process bottlenecks not only prevent safety risks associated with scheduling failures but also significantly reduce material waste and embodied carbon [79].

Visualization Technologies: Visualization technologies, which include AR, VR, DT, and BIM, evolved from static, isolated models to immersive, real-time, and integrated platforms such as "green digital twins." Recent advances have significantly improved user experience and practicality. The integration included studies using AR and VR systems, with BIM, physiological feedback as approaches to improve hazard recognition and energy performance. The integration of BIM with LCA tools is another notable example that visualizes both physical risks (e.g., clashes) and environmental "hotspots" (e.g., carbon-intensive activities) in real time [121,150]. Technologies using digital twins advanced predictive monitoring by improving continuous data integration. BIM has increasingly become an active safety management tool supporting real-time hazard identification.

SNC Technologies: Drones and robotic technologies under the SNC domain have overcome earlier challenges of autonomy, real-time data integration, and human–machine interaction. Drone systems now support continuous AI-enhanced site monitoring, which is an autonomous navigation to predict hazards that includes thermal envelope inspection and energy auditing. Similarly, robotics has seen much improvement in integrating brain–computer interfaces, immersive training, as well as adopting the "green robotics" application, such as onsite waste sorting.

Wearable Technologies: Advances in this category have addressed prior limitations in field validation, user adoption, and behavioral integration by shifting the focus to social sustainability. The recent innovations now provide workers with accurate real-time tracking, ergonomic monitoring, cognitive sensing, and health assessments essentially preserving the human capital. We noted studies that align wearables with ESG goals, ensuring the management of workforce health as a renewable resource.

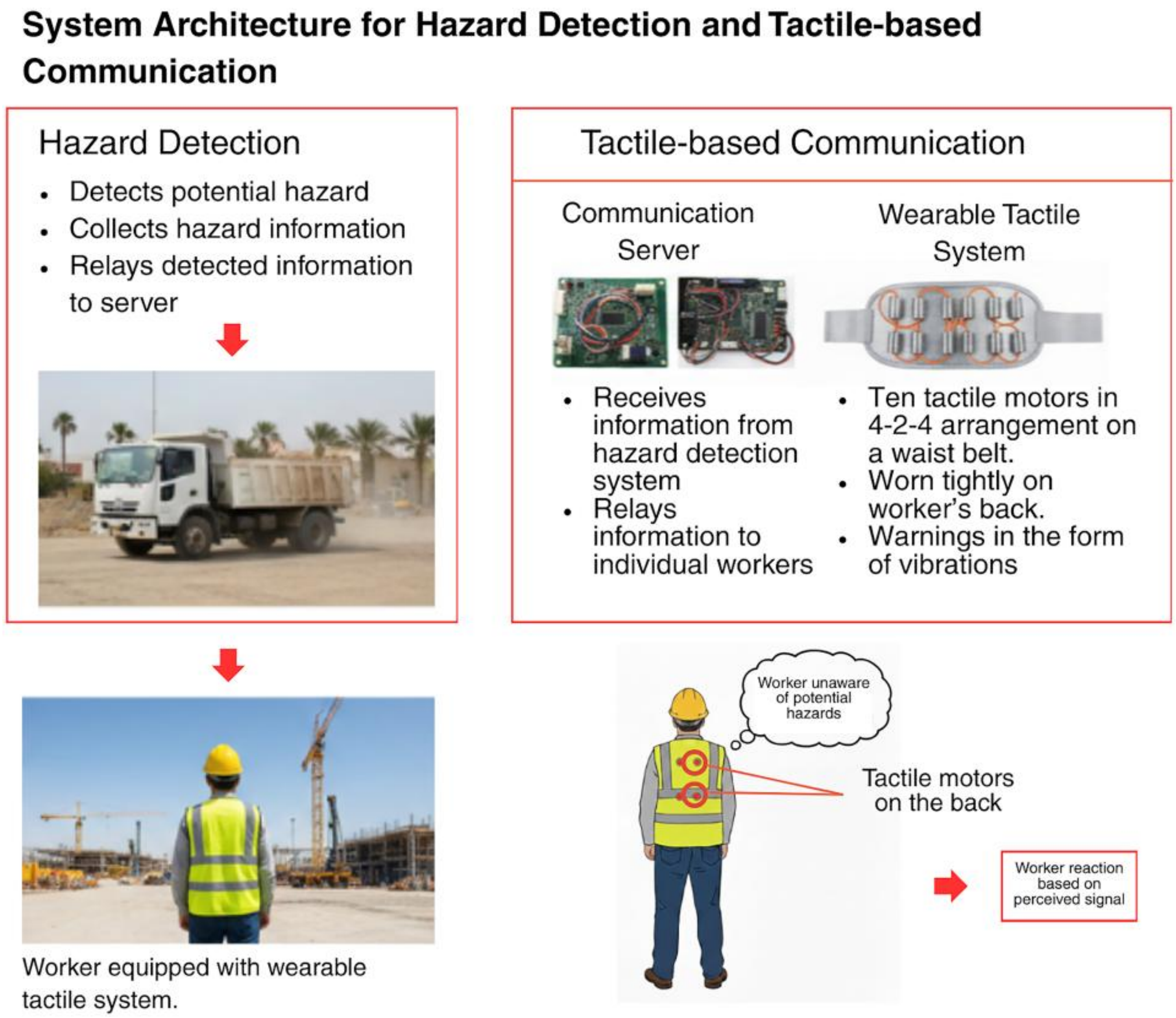

Fig. 9 A wearable tactile feedback system designed to enhance hazard perception for construction workers. The device uses vibration motors integrated into a vest or belt to provide immediate physical alerts, effectively warning workers of nearby equipment or collision hazards even in noisy or visually restricted environments. (Adapted from the study by Sakhakarmi et al. [201].)

7.2 Future Research Directions. Future work in construction safety technologies should directly address the main gaps identified across the four domains. Most AI models still rely on limited datasets and thus fail to generalize across common tasks. A potential research direction would involve shared benchmarks and testing systems under construction site conditions with dynamic conditions, such as multiple sites and varying weather conditions. In addition, as AI models become more complex, their own computational energy consumption rises. We encourage more studies to explore "green AI" architectures that minimize the carbon footprint of training large safety models.

AR, VR, and digital twins face significant challenges regarding long-term usability. Factors such as high costs and limited fit with daily site routines are barriers. Studies analyzing long-term field evaluations and cost–benefit analyses could provide more insights into improving them. In the SNC domain, drones and robots still struggle in cluttered or unpredictable environments. Therefore, research and experiments on combining multiple sensor types and clearer communication standards are some directions to address it. Wearable technologies have progressed in monitoring movement, stress, and behavior, but workers still face issues related to discomfort and accuracy loss over time. Research on more data on ergonomics, varied approaches to improve personalized sustainability monitoring, and privacy will help enable worker trust, adaptability, and career longevity. More broadly, ethical considerations around data privacy and surveillance apply across all four domains, not only wearables. AI-driven video analytics and computer vision systems continuously capture worker behavior; drone-based monitoring records site-wide activity from aerial perspectives; and VR/AR training platforms may collect biometric responses such as eye tracking and heart rate. As these technologies become more pervasive, the absence of standardized data governance frameworks that address data minimization, and informed consent, represents a significant barrier to responsible adoption. Future research should adopt privacy-by-design principles and ensure that monitoring systems empower workers rather than subject them to unchecked surveillance. Furthermore, we identify a critical link that extends these findings from the construction site to the city scale. As data from AI, visualization, SNC, and wearables becomes more granular, it presents an untapped opportunity for Urban Governance and Policy. Future implementations should investigate how site-level safety data, such as noise pollution, air quality, and waste metrics, can inform municipal "Smart City" frameworks and adaptive building codes. This integration effectively bridges the gap between microlevel occupational safety and macrolevel sustainable infrastructure planning. While the technological trends identified in this review reflect developments observed primarily within the US construction industry, practices in other regions and economic contexts remains

Table 4 Rationale for classification of recent literature into four reviewed domains

Domain	Representative keywords	Key safety contributions	Sustainability implications
AI	Detection, prediction, classification, deep learning, algorithm, waste reduction	ML-based hazard detection, PPE recognition, risk prediction models	Resource optimization: reduces material waste and rework through predictive accuracy; supports lean construction principles
Visualization	BIM, VR, AR, simulation, 3D, digital twin, LCA	Safety training via VR/AR, risk overlays, design-time hazard simulation, energy performance	Lifecycle management: tracking of carbon and energy performance; facilitates "green digital twins" for environmental auditing
SNC	Robot, drone, camera, monitoring, interaction, navigation, thermal inspection	UAV inspections, robotic site mapping, human–robot collaboration	Environmental supervision: automates hazardous tasks (e.g., waste sorting) to improve recycling purity; detects thermal leaks and energy loss
Wearables and human-centric systems	Sensor, fatigue, biosignal, wearable, health, ergonomics, social sustainability	Smart PPE, stress detection, physiological signal processing, long-term workforce health	Social sustainability: preserves human capital by monitoring long-term health; supports ESG goals by ensuring safe, equitable, and sustainable working conditions

an open question. Regions with different safety enforcement capacities, labor structures, or digital infrastructure may experience different adoption trajectories. Future reviews should incorporate comparisons of multiple regions to assess the generalizability of these findings.

7.3 Implications for Building Codes and Regulatory Evolution. The technologies reviewed across the four domains have significant implications for the evolution of building codes and construction safety regulations. Historically, codes such as the International Building Code (IBC) [211], OSHA [212] regulations have been reactive, but the influx of real-time data from AI, visualization, and wearables presents a new opportunity for proactive, evidence-based regulation [213].

In the AI domain, automated hazard detection and predictive risk models are now capable of performing continuous compliance verification, a function traditionally limited to periodic manual inspections. As these technologies mature, they promise to streamline code enforcement workflows, enabling safer and more consistent auditing frequencies [152].

Visualization technologies like BIM are already facilitating automated code checking against IBC provisions, utilizing large language models to semi-automate verification against complex regulations [214,215]. Furthermore, digital twins are evolving into living compliance records that document operational safety and energy performance throughout a building's entire lifecycle [216,217].

In the SNC domain, drone-based inspections are gaining recognition in revised protocols for high-rise and postdisaster assessments, offering a safer alternative to manual methods [218]. As UAV regulations align with evolving Federal Aviation Administration (FAA) guidelines [219], these autonomous systems are likely to become standard fixtures in code enforcement procedures. Wearable technologies are providing continuous physiological data, such as heat stress and fatigue metrics, which are essential for refining occupational safety standards [220]. This real-time evidence could directly inform future revisions to OSHA's [212] heat illness prevention guidelines and work-rest cycle regulations.

Collectively, these advancements suggest a paradigm shift toward dynamic, performance-based standards. Future research should investigate how this site-level data can feed into adaptive frameworks, allowing codes to evolve from static documents into responsive systems reflecting real-time conditions.

8 Conclusion

We systematically reviewed technologies in construction safety over the period (2020–2025) and summarized their transition. These transitions were based on the following perspectives: comparing the recent advances with the limitations of earlier studies and noting how these advancements addressed the earlier limitations. The technologies that were once isolated observed notable developments into more integrated, adaptive, and sustainability-aware safety systems. We examined 165 peer-reviewed studies and organized them into four core domains: AI, visualization (AR/VR, digital twins, BIM), SNC, and wearable technology. We discussed each domain's characteristics, integration, safety enhancement mechanisms, and its applicability in the field. Collectively, we summarized their contributions—in enhancing risk anticipation, site-wide situational awareness, and the enhancement of cognitive and environmental safety. We noted that these safety improvements also support broader sustainability goals by lowering lifecycle impacts, reducing inefficient practices, and enabling data-driven resource use.

The first domain contained AI technologies that observed more studies that improved the system's interpretability, predictive modeling, and workflow integration. This was seen as a huge contrast to earlier black-box–based studies. AI models now serve a dual purpose—predicting safety risks while simultaneously optimizing resource allocation to minimize material waste and rework.

Technologies under visualization were once identified as static and fragmented, but now can be seen with more efforts in studies focusing on better immersive experience, scenario-based training, and the integration of LCA tools. While BIM has also moved into a sustainability engine capable of visualizing embodied carbon and energy performance hotspots.

Third, the studies utilizing surveillance systems, such as drones and collaborative robots, shifted approaches toward interactive and safe agents. Recent applications include drones for predictive site intelligence and human–machine collaboration—thermal envelope inspection and robots for automated waste sorting.

Finally, wearable technologies shifted approaches from merely being used for posture and motion monitoring to supporting social sustainability. We saw more examples, and applications on stress detection, behavioral guidance, ergonomic-informed decisions, and workforce health preservation, aligning with broader ESG and safety objectives.

Therefore, these recent studies across four domains marked a massive progress toward proactive, integrated, and safe-sustainable systems. We summarize our findings in Table 4, for each domain. These findings came from several examples of studies that demonstrated how each domain addressed the common limitations in the pre-2020 literature. Collectively, each domain adopted developments that focused on real-time sensing, multimodal data fusion, and safety-efficiency design principles. Through this, we conclude that researchers, practitioners, and industry partners have rapidly moved beyond traditional technologies to practices that would have been difficult to anticipate in construction 5 years ago. This shift suggests that the field has entered a stage in which construction safety systems operate with a level of intelligence and integration that drive both human and environmental well-being.

Funding Data

- The National Science Foundation (NSF) (Grant No. 2302819).

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The authors attest that all data for this study are included in the paper.

References

[1] Occupational Safety and Health Administration (OSHA), 2023, "Construction Industry Regulations," https://www.osha.gov/construction, Accessed April 1, 2025.
[2] Ojha, J., Seagers, J., Shayesteh, S., Habibnezhad, M., and Jebelli, H., 2020, "Construction Safety Training Methods and Their Evaluation Approaches: A Systematic Literature Review," The International Conference on Construction Engineering and Project Management, Hong Kong SAR, Dec. 7–8, pp. 188–197.
[3] Lin, J., Cai, Y., and Li, Q., 2023, "Development of Safety Training in Construction: Literature Review, Scientometric Analysis, and Meta-Analysis," J. Manage. Eng., **39**(6), p. 03123002.
[4] Zhou, Z., Goh, Y. M., and Li, Q., 2015, "Overview and Analysis of Safety Management Studies in the Construction Industry," Saf. Sci., **72**, pp. 337–350.
[5] U.S. Bureau of Labor Statistics, 2022, "Injuries, Illnesses, and Fatalities," https://www.bls.gov/iif/, Accessed April 1, 2025.
[6] U.S. Bureau of Labor Statistics, 2024. "National Census of Fatal Occupational Injuries in 2023," https://www.bls.gov/news.release/pdf/cfoi.pdf, Accessed April 1, 2025.
[7] Occupational Safety and Health Administration (OSHA), 2024, "Commonly Used Statistics," https://www.osha.gov/data/commonstats, Accessed April 1, 2025.
[8] Occupational Safety and Health Administration (OSHA), 2020, "OSHA's Fall Prevention Campaign," https://www.osha.gov/stop-falls, Accessed April 1, 2025.
[9] Albert, A., Pandit, B., and Patil, Y., 2020, "Focus on the Fatal Four: Implications for Construction Hazard Recognition," Saf. Sci., **128**, p. 104774.
[10] Almaskati, D., Kermanshachi, S., Pamidimukkala, A., Loganathan, K., and Yin, Z., 2024, "A Review on Construction Safety: Hazards, Mitigation Strategies, and Impacted Sectors," Buildings, **14**(2), p. 526.
[11] Bourahla, A., Fernandes, G., and Ferreira, L. M. D. F., 2024, "Managing Occupational Health and Safety Risks in Construction Projects to Achieve Social Sustainability—A Review of Literature," Procedia Comput. Sci., **239**, pp. 1053–1061.
[12] Kineber, A. F., Antwi-Afari, M. F., Elghaish, F., Zamil, A. M., Alhusban, M., and Qaralleh, T. J. O., 2023, "Benefits of Implementing Occupational Health and Safety Management Systems for the Sustainable Construction Industry: A Systematic Literature Review," Sustainability, **15**(17), p. 12697.
[13] Su, X., Chau, K. Y., Ho, G., Yip, H. T., and Tang, Y. M., 2025, "A Bibliometric Study on Technology Usage for Occupational Safety and Health Risk Assessment in Construction Industry," J. Asian Archit. Build. Eng., pp. 1–16.
[14] Yang, Y., Chan, A. P., Shan, M., Gao, R., Bao, F., Lyu, S., Zhang, Q., and Guan, J., 2021, "Opportunities and Challenges for Construction Health and Safety Technologies Under the COVID-19 Pandemic in Chinese Construction Projects," Int. J. Environ. Res. Public Health, **18**(24), p. 13038.
[15] Zhang, Q., Liu, Z., and Yang, S., 2025, "Enhancing Construction Workers' Health and Safety: Mechanisms for Implementing Construction 4.0 Technologies in Construction Organizations," Eng. Constr. Archit. Manag., **32**(13), pp. 68–103.
[16] Xu, J., Li, J., and Chen, X., 2024, "Assessment of Technology Adoption in Construction Safety Management: Case Study in China," Sci. Prog., **107**(4). . 00368504241304198.
[17] Adekunle, S., Aigbavboa, C., Akinradewo, O., Adekunle, P., and Otasowie, O., 2023, "Beyond the Lockdowns: Investigating the Impact of COVID on Technology Adoption in the Construction Industry," Emerging Technol. Future Work, **117**, pp. 324–333.
[18] Seo, H. J., and Yoon, Y.-G., 2025, "Analyzing Research Trends in Smart Construction Safety: A Topic Modeling Approach," Buildings, **15**(4), p. 520.
[19] Maali, O., Ko, C.-H., and Nguyen, P. H., 2024, "Applications of Existing and Emerging Construction Safety Technologies," Autom. Constr., **158**, p. 105231.
[20] Ciotti, M., Ciccozzi, M., Terrinoni, A., Jiang, W.-C., Wang, C.-B., and Bernardini, S., 2020, "The COVID-19 Pandemic," Crit. Rev. Clin. Lab. Sci., **57**(6), pp. 365–388.
[21] Pamidimukkala, A., and Kermanshachi, S., 2021, "Impact of COVID-19 on Field and Office Workforce in Construction Industry," Project Leadersh. Soc., **2**, p. 100018.
[22] Alsharef, A., Banerjee, S., Jamil Uddin, S. M., Albert, A., and Jaselskis, E., 2021, "Early Impacts of the COVID-19 Pandemic on the United States Construction Industry," Int. J. Environ. Res. Public Health, **18**(4), p. 1559.
[23] Gamil, Y., and Alhagar, A., 2020, "The Impact of Pandemic Crisis on the Survival of Construction Industry: A Case of COVID-19," Mediterr. J. Soc. Sci., **11**(4), p. 122.
[24] Iqbal, M., Ahmad, N., Waqas, M., and Abrar, M., 2021, "COVID-19 Pandemic and Construction Industry: Impacts, Emerging Construction Safety Practices, and Proposed Crisis Management," Braz. J. Oper. Prod. Manag., **18**(2), pp. 1–17.
[25] Biswas, S., Ghosh, A., Kar, A., Mondal, T., Ghosh, B., and Bardhan, D. P. K., 2021, "The Impact of COVID-19 in the Construction Sector and Its Remedial Measures," J. Phys. Conf. Ser., **1797**(1), p. 012054.
[26] Ogunnusi, M., Hamma-adama, M., Salman, H., and Kouider, T., 2020, "COVID-19 Pandemic: The Effects and Prospects in the Construction Industry," Int. J. Real Estate Stud., **14**(S2), pp. 120–128.
[27] Ayat, M., and Kang, C. W., 2023, "Effects of the COVID-19 Pandemic on the Construction Sector: A Systemized Review," Eng. Constr. Archit. Manag., **30**(2), pp. 734–754.
[28] Chamola, V., Hassija, V., Gupta, V., and Guizani, M., 2020, "A Comprehensive Review of the COVID-19 Pandemic and the Role of IoT, Drones, AI, Blockchain, and 5G in Managing Its Impact," IEEE Access, **8**, pp. 90225–90265.
[29] Tavakoli, M., Carriere, J., and Torabi, A., 2020, "Robotics, Smart Wearable Technologies, and Autonomous Intelligent Systems for Healthcare During the COVID-19 Pandemic: An Analysis of the State of the Art and Future Vision," Adv. Intell. Syst., **2**(7), p. 2000071.
[30] Elenany, Y., Abbas, S., Wasef, M., Ali, I., and Beheiry, S., 2024, "A Systematic Review of Automation Technologies Used in Construction Safety Management," World J. Sci. Technol. Sustainable Dev., **19**(3/4), pp. 267–283.
[31] OpenAI, et al., 2023, "Gpt-4 Technical Report," arXiv Preprint.
[32] DeepMind, 2023, "Gemini: Google's Most Capable AI Models," https://deepmind.google/technologies/gemini, Accessed June 21, 2025.
[33] Meta AI, 2024, "Llama 3: Open Foundation and Instruction Models," https://ai.meta.com/blog/meta-llama-3, Accessed June 21, 2025.
[34] Syrowatka, N., Kuznetsova, M., Alsubai, A., Beckman, A. L., Bain, P. A., Craig, K. J. T., Hu, J., et al., 2021, "Leveraging Artificial Intelligence for Pandemic Preparedness and Response: A Scoping Review to Identify Key Use Cases," npj Digital Med., **4**(1), p. 96.
[35] Khan, J. I., Khan, J., Ali, F., Ullah, F., Bacha, J., and Lee, S., 2022, "Artificial Intelligence and Internet of Things (AI–IoT) Technologies in Response to the COVID-19 Pandemic: A Systematic Review," IEEE Access, **10**, pp. 62613–62660.
[36] Pham, Q.-V., Nguyen, D. C., Huynh-The, T., Hwang, W.-J., and Pathirana, P. N., 2020, "Artificial Intelligence (AI) and Big Data for Coronavirus (COVID-19) Pandemic: A Survey on the State of the Arts," IEEE Access, **8**, pp. 130820–130839.
[37] Khan, H. U., Ali, Y., Khan, F., and Al-Antari, M. A., 2024, "A Comprehensive Study on Unraveling the Advances of Immersive Technologies (VR/AR/MR/XR) in the Healthcare Sector During COVID-19: Challenges and Solutions," Heliyon, **10**(15), p. e35037.
[38] Chang, V., Abdel-Basset, M., Ramachandran, M., et al., 2022, "Augmented Reality, Virtual Reality and New Age Technologies Demand Escalates Amid COVID-19," *Novel AI and Data Science Advancements for Sustainability in the Era of COVID-19*, Elsevier, New York, pp. 89–111.
[39] Euchi, J., 2021, "Do Drones Have a Realistic Place in a Pandemic Fight for Delivering Medical Supplies in Healthcare Systems Problems?," Chin. J. Aeronaut., **34**(2), pp. 182–190.
[40] Kim, J. J., Kim, I., and Hwang, J., 2021, "A Change of Perceived Innovativeness for Contactless Food Delivery Services Using Drones After the Outbreak of COVID-19," Int. J. Hosp. Manag., **93**, p. 102758.
[41] Angurala, M., Bala, M., Bamber, S. S., Kaur, R., and Singh, P., 2020, "An Internet of Things Assisted Drone-Based Approach to Reduce Rapid Spread of COVID-19," J. Saf. Sci. Resilience, **1**(1), pp. 31–35.
[42] Channa, A., Popescu, N., Skibinska, J., and Burget, R., 2021, "The Rise of Wearable Devices During the COVID-19 Pandemic: A Systematic Review," Sensors, **21**(17), p. 5787.
[43] Sun, S., Folarin, A. A., Ranjan, Y., Rashid, Z., Conde, P., Stewart, C., Cummins, N., et al., 2020, "Using Smartphones and Wearable Devices to Monitor Behavioral Changes During COVID-19," J. Med. Internet Res., **22**(9), p. e19992.
[44] Natarajan, A., Su, H.-W., and Heneghan, C., 2020, "Assessment of Physiological Signs Associated With COVID-19 Measured Using Wearable Devices," npj Digital Med., **3**(1), p. 156.
[45] Oraz, E., and Sözer, H., 2025, "Critical Saving Exposed by Investigating Energy Efficiency Performance and Retrofitting Measures in University Campus Buildings: A Comprehensive Case Study," ASME J. Eng. Sustainable Build. Cities, **6**(2), p. 021005.
[46] Newaz, M. T., Ershadi, M., Jefferies, M., and Davis, P., 2024, "A Critical Review of the Feasibility of Emerging Technologies for Improving Safety Behavior on Construction Sites," J. Saf. Res., **89**(89), pp. 269–287.
[47] Li, X., Yi, W., Chi, H.-H., Wang, X., and Chan, A. P., 2018, "A Critical Review of Virtual and Augmented Reality (VR/AR) Applications in Construction Safety," Autom. Constr., **86**, pp. 150–162.
[48] Seo, J., Han, S., Lee, S., and Kim, H., 2015, "Computer Vision Techniques for Construction Safety and Health Monitoring," Adv. Eng. Inform., **29**(2), pp. 239–251.

[49] Ahn, C. R., Lee, S., Sun, C., Jebelli, H., Yang, K., and Choi, B., 2019, "Wearable Sensing Technology Applications in Construction Safety and Health," J. Constr. Eng. Manage., **145**(11), p. 03119007.

[50] Alateeq, M. M., Rajeena P.P., F., and Ali, M. A. S., 2023, "Construction Site Hazards Identification Using Deep Learning and Computer Vision," Sustainability, **15**(3), p. 2358.

[51] Liu, L., Guo, Z., Liu, Z., Zhang, Y., Cai, R., Hu, X., Yang, R., and Wang, G., 2024, "Multi-Task Intelligent Monitoring of Construction Safety Based on Computer Vision," Buildings, **14**(8), p. 2429.

[52] Rabbi, A. B. K., and Jeelani, I., 2024, "AI Integration in Construction Safety: Current State, Challenges, and Future Opportunities in Text, Vision, and Audio Based Applications," Autom. Constr., **164**, p. 105443.

[53] Chang, W.-C., Zhou, W., and Hasanzadeh, S., 2025, "AI-Driven Assistant for Worker Safety in Future Construction: Examining Opportunity and Challenges," Proceedings of the Human Factors and Ergonomics Society Annual Meeting, **69**(1), pp. 2104–2107.

[54] Yang, L., Allen, G., Zhang, Z., and Zhao, Y., 2024, "Achieving On-Site Trustworthy AI Implementation in the Construction Industry: A Framework Across the AI Lifecycle," Buildings, **15**(1), p. 21.

[55] Seo, S., Park, H., and Koo, C., 2024, "Impact of Interactive Learning Elements on Personal Learning Performance in Immersive Virtual Reality for Construction Safety Training," Expert Syst. Appl., **251**, p. 124099.

[56] Riaz, Z., Parn, E. A., Edwards, D. J., Arslan, M., Shen, C., and Pena-Mora, F., 2017, "BIM and Sensor-Based Data Management System for Construction Safety Monitoring," J. Eng. Des. Technol., **15**(6), pp. 738–753.

[57] Gupta, S., and Nair, S., 2023, "A Review of the Emerging Role of UAVs in Construction Site Safety Monitoring," Mater. Today: Proc.

[58] Kim, J., Lee, K., and Jeon, J., 2024, "Systematic Literature Review of Wearable Devices and Data Analytics for Construction Safety and Health," Expert Syst. Appl., **257**, p. 125038.

[59] Awolusi, I., Nnaji, C., Marks, E., and Hallowell, M., 2019, "Enhancing Construction Safety Monitoring Through the Application of Internet of Things and Wearable Sensing Devices: A Review," ASCE International Conference on Computing in Civil Engineering 2019, Reston, VA, June 17–19, pp. 530–538.

[60] Moher, D., Liberati, A., Tetzlaff, J., and Altman, D. G.; The PRISMA Group, 2010, "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement," Int. J. Surg., **8**(5), pp. 336–341.

[61] Albarrán, P., Ortuño, I., and Ruiz-Castillo, J., 2011, "The Measurement of Low- and High-Impact in Citation Distributions: Technical Results," J. Informetr., **5**(1), pp. 48–63.

[62] Google, 2025, "Top Publications—Civil Engineering," Google Scholar Metrics, https://scholar.google.com/citations?view_op=top_venues&hl=en&vq=eng_civilengineering, Accessed February 2026.

[63] Liu, Y., Habibnezhad, M., and Jebelli, H., 2021, "Brainwave-Driven Human-Robot Collaboration in Construction," Autom. Constr., **124**, p. 103556.

[64] Nath, N. D., Behzadan, A. H., and Paal, S. G., 2020, "Deep Learning for Site Safety: Real-Time Detection of Personal Protective Equipment," Autom. Constr., **112**, p. 103085.

[65] Elmousalami, H., Maxy, M., Hui, F. K. P., and Aye, L., 2025, "AI in Automated Sustainable Construction Engineering Management," Autom. Constr., **175**, p. 106202.

[66] Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., Akinade, O. O., and Ahmed, A., 2021, "Artificial Intelligence in the Construction Industry: A Review of Present Status, Opportunities and Future Challenges," J. Build. Eng., **44**, p. 103299.

[67] Lee, Y.-C., Shariatfar, M., Rashidi, A., and Lee, H. W., 2020, "Evidence-Driven Sound Detection for Prenotification and Identification of Construction Safety Hazards and Accidents," Autom. Constr., **113**, p. 103127.

[68] Rashid, K. M., and Louis, J., 2020, "Activity Identification in Modular Construction Using Audio Signals and Machine Learning," Autom. Constr., **119**, p. 103361.

[69] Xie, L., Misra, S., Suresh, N., Soza-Soto, J., Furuhata, T., and Shimada, K., 2024, "Learning 3D Human–Object Interaction Graphs From Transferable Context Knowledge for Construction Monitoring," Comput. Ind., **164**, p. 104171.

[70] Liu, Y., Liu, L., Yang, L., Hao, L., and Bao, Y., 2021, "Measuring Distance Using Ultra-Wideband Radio Technology Enhanced by Extreme Gradient Boosting Decision Tree (XGBoost)," Autom. Constr., **126**, p. 103678.

[71] Naderi, H., Shojaei, A., and Ly, R., 2023, "Autonomous Construction Safety Incentive Mechanism Using Blockchain-Enabled Tokens and Vision-Based Techniques," Autom. Constr., **153**, p. 104959.

[72] Jung, Y., Cho, I., Hsu, S.-H., and Golparvar-Fard, M., 2024, "VisualSiteDiary: A Detector-Free Vision-Language Transformer Model for Captioning Photologs for Daily Construction Reporting and Image Retrievals," Autom. Constr., **165**, p. 105483.

[73] Tsai, W.-L., Le, P.-L., Ho, W.-F., Chi, N.-W., Lin, J.-J., Tang, S., and Hsieh, S.-H., 2024, "Construction Safety Inspection With Contrastive Language-Image Pre-Training (CLIP) Image Captioning and Attention," Autom. Constr., **169**, p. 105863.

[74] Nath, N. D., and Behzadan, A. H., 2020, "Deep Convolutional Networks for Construction Object Detection Under Different Visual Conditions," Front. Built Environ., **6**, p. 97.

[75] Baker, H., Hallowell, M. R., and Tixier, A. J.-P., 2020, "Automatically Learning Construction Injury Precursors From Text," Autom. Constr., **118**, p. 103145.

[76] Baker, H., Hallowell, M. R., and Tixier, A. J.-P., 2020, "AI-Based Prediction of Independent Construction Safety Outcomes From Universal Attributes," Autom. Constr., **118**, p. 103146.

[77] Wang, X., and El-Gohary, N., 2022, "Deep Learning-Based Relation Extraction and Knowledge Graph-Based Representation of Construction Safety Requirements," Autom. Constr., **147**, p. 104696.

[78] Zhang, L., Wang, J., Wang, Y., Sun, H., and Zhao, X., 2022, "Automatic Construction Site Hazard Identification Integrating Construction Scene Graphs With BERT Based Domain Knowledge," Autom. Constr., **142**, p. 104535.

[79] Pan, Y., and Zhang, L., 2021, "A BIM-Data Mining Integrated Digital Twin Framework for Advanced Project Management," Autom. Constr., **124**, p. 103564.

[80] Cai, J., Du, A., Liang, X., and Li, S., 2023, "Prediction-Based Path Planning for Safe and Efficient Human–Robot Collaboration in Construction via Deep Reinforcement Learning," J. Comput. Civil Eng., **37**(1), p. 04022046.

[81] Xiong, S.-H., Zhu, C.-Y., Chen, Z.-S., Deveci, M., Chiclana, F., and Skibniewski, M. J., 2023, "On Extended Power Geometric Operator for Proportional Hesitant Fuzzy Linguistic Large-Scale Group Decision-Making," Inf. Sci., **632**, pp. 637–663.

[82] Lee, G., Choi, B., Jebelli, H., and Lee, S., 2021, "Assessment of Construction Workers' Perceived Risk Using Physiological Data From Wearable Sensors: A Machine Learning Approach," J. Build. Eng., **42**, p. 102824.

[83] Friedberg, R., Tibshirani, J., Athey, S., and Wager, S., 2021, "Local Linear Forests," J. Comput. Graph. Stat., **30**(2), pp. 503–517.

[84] Shi, Y., Li, Z., Zurada, J., Manikas, A., Guan, J., and Weichbroth, P., 2024, "Ontology-Based Text Convolution Neural Network (TextCNN) for Prediction of Construction Accidents," Knowl. Inf. Syst., **66**(4), pp. 2651–2681.

[85] Tang, S., and Golparvar-Fard, M., 2021, "Machine Learning-Based Risk Analysis for Construction Worker Safety From Ubiquitous Site Photos and Videos," J. Comput. Civil Eng., **35**(6), p. 04021020.

[86] Guo, H., Yu, Y., and Skitmore, M., 2017, "Visualization Technology-Based Construction Safety Management: A Review," Autom. Constr., **73**, pp. 135–144.

[87] Kim, K., and Cho, Y. K., 2020, "Effective Inertial Sensor Quantity and Locations on a Body for Deep Learning-Based Worker's Motion Recognition," Autom. Constr., **113**, p. 103126.

[88] Lee, H., Yang, K., Kim, N., and Ahn, C. R., 2020, "Detecting Excessive Load-Carrying Tasks Using a Deep Learning Network with a Gramian Angular Field," Autom. Constr., **120**, p. 103390.

[89] Hong, S., Yoon, J., Ham, Y., Lee, B., and Kim, H., 2023, "Monitoring Safety Behaviors of Scaffolding Workers Using Gramian Angular Field Convolution Neural Network Based on IMU Sensing Data," Autom. Constr., **148**, p. 104748.

[90] Yong, G., Liu, M., and Lee, S., 2024, "Explainable Image Captioning to Identify Ergonomic Problems and Solutions for Construction Workers," J. Comput. Civil Eng., **38**(4), p. 04024022.

[91] Wang, C., Tang, L., Zhou, M., Ding, Y., Zhuang, X., and Wu, J., 2022, "Indoor Human Fall Detection Algorithm Based on Wireless Sensing," Tsinghua Sci. Technol., **27**(6), pp. 1002–1015.

[92] Sadat-Mohammadi, M., Shakerian, S., Liu, Y., Asadi, S., and Jebelli, H., 2021, "Non-Invasive Physical Demand Assessment Using Wearable Respiration Sensor and Random Forest Classifier," J. Build. Eng., **44**, p. 103279.

[93] Bangaru, S. S., Wang, C., Busam, S. A., and Aghazadeh, F., 2021, "ANN-Based Automated Scaffold Builder Activity Recognition Through Wearable EMG and IMU Sensors," Autom. Constr., **126**, p. 103653.

[94] Bogue, R., 2018, "What Are the Prospects for Robots in the Construction Industry?," Ind. Rob., **45**(1), pp. 1–6.

[95] Emaminejad, N., Kath, L., and Akhavian, R., 2024, "Assessing Trust in Construction AI-Powered Collaborative Robots Using Structural Equation Modeling," J. Comput. Civil Eng., **38**(3), p. 04024011.

[96] Assaad, R., and El-Adaway, I. H., 2020, "Bridge Infrastructure Asset Management System: Comparative Computational Machine Learning Approach for Evaluating and Predicting Deck Deterioration Conditions," J. Infrastruct. Syst., **26**(3), p. 04020032.

[97] Dzeng, R.-J., Cheng, C.-W., and Cheng, C.-Y., 2024, "A Scaffolding Assembly Deficiency Detection System With Deep Learning and Augmented Reality," Buildings, **14**(2), p. 385.

[98] Khan, N., Saleem, M. R., Lee, D., Park, M.-W., and Park, C., 2021, "Utilizing Safety Rule Correlation for Mobile Scaffolds Monitoring Leveraging Deep Convolution Neural Networks," Comput. Ind., **129**, p. 103448.

[99] Yang, L., and Cai, H., 2023, "Cost-Efficient Image Semantic Segmentation for Indoor Scene Understanding Using Weakly Supervised Learning and BIM," J. Comput. Civil Eng., **37**(2), p. 04022062.

[100] Xu, S., Wang, J., Shou, W., Ngo, T., Sadick, A.-M., and Wang, X., 2021, "Computer Vision Techniques in Construction: A Critical Review," Arch. Comput. Meth. Eng., **28**(5), pp. 3383–3397.

[101] Wang, Y., Xiao, B., Bouferguene, A., and Al-Hussein, M., 2024, "Proactive Safety Hazard Identification Using Visual–Text Semantic Similarity for Construction Safety Management," Autom. Constr., **166**, p. 105602.

[102] Awolusi, I., Marks, E., Hainen, A., and Alzarrad, A., 2022, "Incident Analysis and Prediction of Safety Performance on Construction Sites," Civileng, **3**(3), pp. 669–686.

[103] Lee, K., Pooladvand, S., Esmaeili, B., and Hasanzadeh, S., 2024, "Understanding Construction Workers' Risk Perception Using Neurophysiological Responses," J. Comput. Civil Eng., **38**(6), p. 04024039.

[104] Subedi, S., and Pradhananga, N., 2021, "Sensor-Based Computational Approach to Preventing Back Injuries in Construction Workers," Autom. Constr., **131**, p. 103920.

[105] Olanrewaju, A., 2025, "Machine Learning for the Prediction of Rework in Green Buildings," CIB Conferences, Purdue University, West Lafayette, IN, May 19–23.

[106] Fang, W., Ma, L., Love, P. E. D., Luo, H., Ding, L., and Zhou, A., 2020, "Knowledge Graph for Identifying Hazards on Construction Sites: Integrating Computer Vision With Ontology," Autom. Constr., **119**, p. 103310.

[107] Jeelani, I., Asadi, K., Ramshankar, H., Han, K., and Albert, A., 2020, "Real-Time Vision-Based Worker Localization & Hazard Detection for Construction," Autom. Constr., **121**, p. 103448.

[108] Torres Calderon, W., Roberts, D., and Golparvar-Fard, M., 2021, "Synthesizing Pose Sequences From 3D Assets for Vision-Based Activity Analysis," J. Comput. Civil Eng., **35**(1), p. 04020052.

[109] Wang, X., and El-Gohary, N., 2024, "Few-Shot Object Detection and Attribute Recognition From Construction Site Images for Improved Field Compliance," Autom. Constr., **167**, p. 105539.

[110] Chu, W., Han, S., Luo, X., and Zhu, Z., 2020, "Monocular Vision–Based Framework for Biomechanical Analysis or Ergonomic Posture Assessment in Modular Construction," J. Comput. Civil Eng., **34**(4), p. 04020018.

[111] Tang, S., Roberts, D., and Golparvar-Fard, M., 2020, "Human–Object Interaction Recognition for Automatic Construction Site Safety Inspection," Autom. Constr., **120**, p. 103356.

[112] Wang, X., and Zhu, Z., 2021, "Vision-Based Hand Signal Recognition in Construction: A Feasibility Study," Autom. Constr., **125**, p. 103625.

[113] Tran, S. V.-T., Lee, D., Bao, Q. L., Yoo, T., Khan, M., Jo, J., and Park, C., 2023, "A Human Detection Approach for Intrusion in Hazardous Areas Using 4D-BIM-Based Spatial–Temporal Analysis and Computer Vision," Buildings, **13**(9), p. 2313.

[114] Xiong, R., and Tang, P., 2021, "Pose-Guided Anchoring for Detecting Proper Use of Personal Protective Equipment," Autom. Constr., **130**, p. 103828.

[115] Wang, X., and Zhu, Z., 2021, "Vision-Based Framework for Automatic Interpretation of Construction Workers' Hand Gestures," Autom. Constr., **130**, p. 103872.

[116] Chern, W.-C., Hyeon, J., Nguyen, T. V., Asari, V. K., and Kim, H., 2023, "Context-Aware Safety Assessment System for Far-Field Monitoring," Autom. Constr., **149**, p. 104779.

[117] Xu, L., Feng, C., Kamat, V. R., and Menassa, C. C., 2020, "A Scene-Adaptive Descriptor for Visual SLAM-Based Locating Applications in Built Environments," Autom. Constr., **112**, p. 103067.

[118] Chen, X., Huang, H., Liu, Y., Li, J., and Liu, M., 2022, "Robot for Automatic Waste Sorting on Construction Sites," Autom. Constr., **141**, pp. 104387.

[119] Chen, J., Fu, Y., Lu, W., and Pan, Y., 2023, "Augmented Reality-Enabled Human-Robot Collaboration to Balance Construction Waste Sorting Efficiency and Occupational Safety and Health," J. Environ. Manage., **348**, pp. 119341.

[120] Zhang, D., Zhan, C., Chen, L., Wang, Y., and Li, G., 2025, "Review of Unmanned Aerial Vehicle Infrared Thermography (UAV-IRT) Applications in Building Thermal Performance: Towards the Thermal Performance Evaluation of Building Envelope," Quant. InfraRed Thermogr. J., **22**(3), pp. 266–296.

[121] Tan, Y., Chen, P., Shou, W., and Sadick, A.-M., 2022, "Digital Twin-Driven Approach to Improving Energy Efficiency of Indoor Lighting Based on Computer Vision and Dynamic BIM," Energy Build., **270**, p. 112271.

[122] Messner, J. I., and Horman, M., 2003, "Using Advanced Visualization Tools to Improve Construction Education," Proceedings of CONVR 2003 Conference, Blacksburg, VA (Virginia Tech), Sept. 24–26, pp. 145–155.

[123] Webster, A., Feiner, S., MacIntyre, B., Massie, W., and Krueger, T., 1996, "Augmented Reality in Architectural Construction, Inspection and Renovation," ASCE Third Congress on Computing in Civil Engineering, Anaheim, CA, June 17–19.

[124] Lu, Q., Parlikad, A. K., Woodall, P., Don Ranasinghe, G., Xie, X., Liang, Z., Konstantinou, E., Heaton, J., and Schooling, J., 2020, "Developing a Digital Twin at Building and City Levels: Case Study of West Cambridge Campus," J. Manage. Eng., **36**(3), p. 05020004.

[125] Boje, C., Guerriero, A., Kubicki, S., and Rezgui, Y., 2020, "Towards a Semantic Construction Digital Twin: Directions for Future Research," Autom. Constr., **114**, p. 103179.

[126] Alirezaei, S., Taghaddos, H., Ghorab, K., Tak, A. N., and Alirezaei, S., 2022, "BIM–Augmented Reality Integrated Approach to Risk Management," Autom. Constr., **141**, p. 104458.

[127] Xiang, S., Wang, R., and Feng, C., 2021, "Mobile Projective Augmented Reality for Collaborative Robots in Construction," Autom. Constr., **127**, p. 103704.

[128] Han, B., and Leite, F., 2022, "Generic Extended Reality and Integrated Development for Visualization Applications in Architecture, Engineering, and Construction," Autom. Constr., **140**, p. 104329.

[129] Fazel, A., and Adel, A., 2024, "Enhancing Construction Accuracy, Productivity, and Safety With Augmented Reality for Timber Fastening," Autom. Constr., **166**, p. 105596.

[130] Liao, X., Liu, Y., Huang, Y., Luo, Y., Zhou, Z., and Chong, H.-Y., 2025, "Integrating CAD, BIM, Immersive Technology, and 3D Gaussian Splatting for Construction Model Coordination With ISO 19650," Sci. Rep., **16**, p. 2410.

[131] Wang, X., Liang, C.-J., Menassa, C., and Kamat, V., 2020, "Real-Time Process-Level Digital Twin for Collaborative Human-Robot Construction Work," Proceedings of the International Symposium on Automation and Robotics in Construction (IAARC), Online, Oct. 27–28.

[132] Alzarrad, M., Miller, M., Durham, L., and Chowdhury, S., 2024, "Revolutionizing Construction Safety: Introducing a Cutting-Edge Virtual Reality Interactive System for Training US Construction Workers to Mitigate Fall Hazards," Front. Built Environ., **10**, p. 1320175.

[133] Hasanzadeh, S., Polys, N. F., and de la Garza, J. M., 2020, "Presence, Mixed Reality, and Risk-Taking Behavior: A Study in Safety Interventions," IEEE Trans. Visual Comput. Graphics, **26**(5), pp. 2115–2125.

[134] Li, W., Huang, H., Solomon, T., Esmaeili, B., and Yu, L.-F., 2022, "Synthesizing Personalized Construction Safety Training Scenarios for VR Training," IEEE Trans. Visual Comput. Graphics, **28**(5), pp. 1993–2002.

[135] Jeon, J., and Cai, H., 2021, "Classification of Construction Hazard-Related Perceptions Using Wearable Electroencephalogram and Virtual Reality," Autom. Constr., **132**, p. 103975.

[136] Habibnezhad, M., Shayesteh, S., Jebelli, H., Puckett, J., and Stentz, T., 2020, "Comparison of Ironworker's Fall Risk Assessment Systems Using an Immersive Biofeedback Simulator," Autom. Constr., **122**, p. 103471.

[137] Banfi, F., 2021, "The Evolution of Interactivity, Immersion and Interoperability in HBIM: Digital Model Uses, VR and AR for Built Cultural Heritage," ISPRS Int. J. Geo-Inf., **10**(10), p. 685.

[138] Ghanem, S. Y., 2022, "Implementing Virtual Reality-Building Information Modeling in the Construction Management Curriculum," J. Inf. Technol. Construct., **27**, pp. 48–69.

[139] Akanmu, A., Anumba, C. J., and Ogunseiju, O. O., 2021, "Towards Next Generation Cyber-Physical Systems and Digital Twins for Construction," J. Inf. Technol. Construct., **26**, pp. 505–525.

[140] Park, J., Lee, J.-K., Son, M.-J., Yu, C., Lee, J., and Kim, S., 2024, "Unlocking the Potential of Digital Twins in Construction: A Systematic and Quantitative Review Using Text Mining," Buildings, **14**(3), p. 702.

[141] Kim, Y., and Ham, Y., 2024, "Spatio-Temporal Heat Risk Analysis in Construction: Digital Twin-Enabled Monitoring," Autom. Constr., **168**(A), p. 105805.

[142] Liu, Z., Kim, D.-H., Lee, S., Zhou, L., An, X., and Liu, M., 2023, "Near Real-Time 3D Reconstruction and Quality 3D Point Cloud for Time-Critical Construction Monitoring," Buildings, **13**(2), p. 464.

[143] Ma, S., Fang, Q., Zhou, H., Yin, Y., and Ye, F., 2024, "Fast 3D Site Reconstruction Using Multichannel Dynamic and Static Object Separation," Autom. Constr., **168**(A), p. 105807.

[144] Shojaei, S., Rokooei, S., Mahdavian, A., Carson, L., and Ford, G., 2021, "Using Immersive Video Technology for Construction Management Content Delivery: A Pilot Study," J. Inf. Technol. Construct., **26**, pp. 886–901.

[145] Azhar, S., 2011, "Building Information Modeling (BIM): Trends, Benefits, Risks, and Challenges for the AEC Industry," Leadersh. Manage. Eng., **11**(3), pp. 241–252.

[146] Zou, Y., Kiviniemi, A., and Jones, S. W., 2017, "A Review of Risk Management Through BIM and BIM-Related Technologies," Saf. Sci., **97**, pp. 88–98.

[147] Tak, N., Taghaddos, H., Mousaei, A., Bolourani, A., and Hermann, U., 2021, "BIM-Based 4D Mobile Crane Simulation and Onsite Operation Management," Autom. Constr., **128**, p. 103766.

[148] Liu, Z., Jin, Z., and Gambatese, J. A., 2020, "Scenarios for Integrating IPS-IMU System With BIM Technology in Construction Safety Control," Pract. Period. Struct. Des. Constr., **25**(1), p. 05019007.

[149] Santos, R., Costa, A. A., Silvestre, J. D., and Pyl, L., 2019, "Informetric Analysis and Review of Literature on the Role of BIM in Sustainable Construction," Autom. Constr., **103**, pp. 221–234.

[150] Chen, Z., Chen, L., Zhou, X., Huang, L., Sandanayake, M., and Yap, P.-S., 2024, "Recent Technological Advancements in BIM and LCA Integration for Sustainable Construction: A Review," Sustainability, **16**(3), pp. 1340.

[151] Zaman, A. U., Abdelaty, A., Sobuz, H. R., 2024, "Integration of BIM Data and Real-Time Game Engine Applications: Case Studies in Construction Safety Management," J. Inf. Technol. Construct., **29**, pp. 117–140.

[152] Chong, H.-Y., Ma, Q., Lai, J., and Liao, X., 2025, "Achieving Sustainable Construction Safety Management: The Shift From Compliance to Intelligence via BIM–AI Convergence," Sustainability, **17**(10), pp. 4454.

[153] Rashidi Nasab, S., Malekitabar, H., Elzarka, H., Nekouvaght Tak, A., and Ghorab, K., 2023, "Managing Safety Risks From Overlapping Construction Activities: A BIM Approach," Buildings, **13**(10), p. 2647.

[154] Zhang, L., Yuan, J.-W., Xia, N., Ning, Y., Ma, J., and Skibniewski, M. J., 2020, "Measuring Value-Added-Oriented BIM Climate in Construction Projects: Dimensions and Indicators," J. Civ. Eng. Manag., **26**(8), pp. 800–818.

[155] Whitman, J., Deshpande, A., Zech, W., and Perez, M., 2021, "Construction Site Utilization Planning: A Process Based upon Industry Best Practices," CivilEng, **2**(2), pp. 309–324.

[156] Kayastha, R., and Kisi, K., 2024, "Assessing Factors Affecting Fall Accidents among Hispanic Construction Workers: Integrating Safety Insights Into BIM for Enhanced Life Cycle Management," Buildings, **14**(9), p. 3017.

[157] Omer, M. M., Mohd-Ezazee, N. M. A., Lee, Y. S., Rajabi, M. S., and Rahman, R. A., 2022, "Constructive and Destructive Leadership Behaviors, Skills, Styles and Traits in BIM-Based Construction Projects," Buildings, **12**(12), p. 2068.

[158] Gheisari, M., Irizarry, J., and Walker, B. N., 2014, "UAS4Safety: The Potential of Unmanned Aerial Systems for Construction Safety Applications," Construction Research Congress 2014: Construction in a Global Network, Atlanta, GA, May 19–21, pp. 1801–1810.

[159] Gheisari, M., and Esmaeili, B., 2016, "Unmanned Aerial Systems (UAS) for Construction Safety Applications," Construction Research Congress 2016, San Juan, Puerto Rico, May 31–June 2, pp. 2642–2650.

[160] Li, Y., and Liu, C., 2019, “Applications of Multirotor Drone Technologies in Construction Management,” Int. J. Construct. Manage., **19**(5), pp. 401–412.

[161] Gheisari, M., and Esmaeili, B., 2019, “Applications and Requirements of Unmanned Aerial Systems (UASs) for Construction Safety,” Saf. Sci., **118**, pp. 230–240.

[162] Kim, K., Kim, S., and Shchur, D., 2021, “A UAS-Based Work Zone Safety Monitoring System by Integrating Internal Traffic Control Plan (ITCP) and Automated Object Detection in Game Engine Environment,” Autom. Constr., **128**, p. 103736.

[163] Zhu, Z., Jeelani, I., and Gheisari, M., 2023, “Physical Risk Assessment of Drone Integration in Construction Using 4D Simulation,” Autom. Constr., **156**, p. 105099.

[164] Martinez, J. G., Albeaino, G., Gheisari, M., Issa, R. R. A., and Alarcon, L. F., 2021, “iSafeUAS: An Unmanned Aerial System for Construction Safety Inspection,” Autom. Constr., **125**, p. 103595.

[165] Agyemang, O., Zhang, X., Adjei-Mensah, I., Acheampong, D., Fiasam, L. D., Sey, C., Yussif, S. B., and Effah, D., 2023, “Automated Vision-Based Structural Health Inspection and Assessment for Post-Construction Civil Infrastructure,” Autom. Constr., **156**, p. 105153.

[166] Albeaino, R., Gheisari, M., and Issa, R. R., 2022, “DroneSim: A VR-Based Flight Training Simulator for Drone-Mediated Building Inspections,” Constr. Innovation, **22**(4), pp. 831–848.

[167] Rakha, T., and Gorodetsky, A., 2018, “Review of Unmanned Aerial System (UAS) Applications in the Built Environment: Towards Automated Building Inspection Procedures Using Drones,” Autom. Constr., **93**, pp. 252–264.

[168] Liang, H., Lee, S.-C., Bae, W., Kim, J., and Seo, S., 2023, “Towards UAVs in Construction: Advancements, Challenges, and Future Directions for Monitoring and Inspection,” Drones, **7**(3), pp. 202.

[169] Kim, S., Irizarry, J., and Costa, D. B., 2020, “Field Test-Based UAS Operational Procedures and Considerations for Construction Safety Management: A Qualitative Exploratory Study,” Int. J. Civ. Eng., **18**(8A), pp. 919–933.

[170] Nwaogu, J. M., Yang, Y., Chan, A. P., and Wang, X., 2024, “Enhancing Drone Operator Competency Within the Construction Industry: Assessing Training Needs and Roadmap for Skill Development,” Buildings, **14**(4), p. 1153.

[171] Keyvanfar, A., Shafaghat, A., and Awanghamat, M. A., 2022, “Optimization and Trajectory Analysis of Drone’s Flying and Environmental Variables for 3D Modelling the Construction Progress Monitoring,” Int. J. Civ. Eng., **20**(4, SI), pp. 363–388.

[172] Cheng, J.-Y., Gheisari, M., and Jeelani, I., 2023, “Using 360-Degree Virtual Reality Technology for Training Construction Workers About Safety Challenges of Drones,” Int. J. Civ. Eng., **37**(4), p. 04023018.

[173] Sakib, M. N., Chaspari, T., and Behzadan, A. H., 2021, “Physiological Data Models to Understand the Effectiveness of Drone Operation Training in Immersive Virtual Reality,” Int. J. Civ. Eng., **35**(1), p. 04020053.

[174] Gharbia, M., Chang-Richards, A., and Zhong, R., 2019, “Robotic Technologies in Concrete Building Construction: A Systematic Review,” Proceedings of the International Symposium on Automation and Robotics in Construction, Banff, Alberta, Canada, May 21–24, pp. 10–19, IAARC Publications.

[175] Liu, Y., Habibnezhad, M., and Jebelli, H., 2020, “Brain-Computer Interface for Hands-Free Teleoperation of Construction Robots,” Autom. Constr., **123**, p. 103523.

[176] Liang, C.-J., Kamat, V. R., and Menassa, C. C., 2020, “Teaching Robots to Perform Quasi-Repetitive Construction Tasks Through Human Demonstration,” Autom. Constr., **120**, p. 103370.

[177] Rodrigues, P. B., Singh, R., Oytun, M., Adami, P., Woods, P. J., Becerik-Gerber, B., Soibelman, L., Copur-Gencturk, Y., and Lucas, G. M., 2023, “A Multidimensional Taxonomy for Human-Robot Interaction in Construction,” Autom. Constr., **150**, p. 104845.

[178] Wang, X., Liang, C.-J., Menassa, C. C., and Kamat, V. R., 2021, “Interactive and Immersive Process-Level Digital Twin for Collaborative Human–Robot Construction Work,” J. Comput. Civil Eng., **35**(6), p. 04021023.

[179] Amani, M., and Akhavian, R., 2024, “Intelligent Ergonomic Optimization in Bimanual Worker-Robot Interaction: A Reinforcement Learning Approach,” Autom. Constr., **168**(A), p. 105741.

[180] Liu, Y., Ojha, A., Shayesteh, S., Jebelli, H., and Lee, S., 2022, “Human-Centric Robotic Manipulation in Construction: Generative Adversarial Networks Based Physiological Computing Mechanism to Enable Robots to Perceive Workers’ Cognitive Load,” Can. J. Civ. Eng., **50**(3), pp. 224–238.

[181] Ojha, A., Liu, Y., Shayesteh, S., Jebelli, H., and Sitzabee, W. E., 2023, “Affordable Multiagent Robotic System for Same-Level Fall Hazard Detection in Indoor Construction Environments,” J. Comput. Civil Eng., **37**(1), p. 04022042.

[182] Kim, D., Lee, S., and Kamat, V. R., 2020, “Proximity Prediction of Mobile Objects to Prevent Contact-Driven Accidents in Co-Robotic Construction,” J. Comput. Civil Eng., **34**(4), p. 04020022.

[183] Adami, P., Rodrigues, P. B., Woods, P. J., Becerik-Gerber, B., Soibelman, L., Copur-Gencturk, Y., and Lucas, G., 2022, “Impact of VR-Based Training on Human-Robot Interaction for Remote Operating Construction Robots,” J. Comput. Civil Eng., **36**(3), p. 04022006.

[184] Chauhan, A., Pakbaz, A., Jang, Y., and Jeong, I., 2024, “Analyzing Trust Dynamics in Human-Robot Collaboration Through Psychophysiological Responses in an Immersive Virtual Construction Environment,” J. Comput. Civil Eng., **38**(4), p. 04024017.

[185] Thorpe, T., Ward, M. J., Bowden, S. L., and Price, A., 2005, “Facilitating the Link Between Point-of-Production Workers and Corporate ICT Systems in Construction,” 22nd CIB W78 International Conference on Information Technology in Construction., Dresden, Germany, July 19–21.

[186] Awolusi, E., Marks, M., and Hallowell, M., 2018, “Wearable Technology for Personalized Construction Safety Monitoring and Trending: Review of Applicable Devices,” Autom. Constr., **85**, pp. 96–106.

[187] Huang, Y., Hammad, A., and Zhu, Z., 2021, “Providing Proximity Alerts to Workers on Construction Sites Using Bluetooth Low Energy RTLS,” Autom. Constr., **132**, p. 103928.

[188] Cai, H., and Cai, H., 2020, “Robust Hybrid Approach of Vision-Based Tracking and Radio-Based Identification and Localization for 3D Tracking of Multiple Construction Workers,” J. Comput. Civil Eng., **34**(4), p. 04020021.

[189] Bonyani, M., Soleymani, M., and Wang, C., 2024, “Construction Workers’ Unsafe Behavior Detection Through Adaptive Spatiotemporal Sampling and Optimized Attention-Based Video Monitoring,” Autom. Constr., **165**, p. 105508.

[190] Yang, Q., Mei, Q., Fan, C., Ma, M., and Li, X., 2023, “Environment-Aware Worker Trajectory Prediction Using Surveillance Camera in Modular Construction Facilities,” Buildings, **13**(6), p. 1502.

[191] Li, X., and Long, H., 2019, “A Review of Worker Behavior-Based Safety Research: Current Trends and Future Prospects,” IOP Conf. Ser. Earth Environ. Sci., **371**(3), p. 03204.

[192] Rodrigues, P. B., Becerik-Gerber, B., Soibelman, L., Lucas, G. M., and Roll, S. C., 2024, “Impact of Selective Environmental Sound Attenuation on Operator Performance, Stress, Attention, and Task Engagement in Teleoperated Demolition,” Autom. Constr., **169**, p. 105876.

[193] Albeaino, G., Brophy, P., Jeelani, I., Gheisari, M., and Issa, R. R. A., 2023, “Psychophysiological Impacts of Working at Different Distances From Drones on Construction Sites,” J. Comput. Civil Eng., **37**(5), p. 04023026.

[194] Ramadan, B., Nassereddine, H., Taylor, T. R. B., and Goodrum, P., 2023, “Impact of Technology Use on Workforce Performance and Information Access in the Construction Industry,” Front. Built Environ., **9**, p. 1079203.

[195] Karakhan, A., Nnaji, C. A., Alsaffar, O., and Jin, Z., 2023, “Strategies for Employee Empowerment in Construction: US Industry Outlook,” Pract. Period. Struct. Des. Constr., **29**(4), p. 04024043.

[196] Akcay, E. C., and Arditi, D., 2022, “Predicting Employer and Worker Responsibilities in Accidents That Involve Falls in Building Construction Sites,” Buildings, **12**(4), p. 464.

[197] Lee, H., Lee, G., Park, S., Lee, S., Jacobs, J. V. V., and Ahn, C. R. R., 2023, “Collective Sensing of Workers’ Loss of Body Balance for Slip, Trip, and Fall Hazard Identification: Field Validation Study,” J. Comput. Civil Eng., **37**(1), p. 04022052.

[198] Lee, M., Kim, H., Yoo, W. S., Cho, H., and Choi, Y., 2023, “Developing a Field-Oriented Analytical Safety Assessment Model for Construction Workers,” KSCE J. Civ. Eng., **27**(10), pp. 4085–4100.

[199] Okpala, C., Nnaji, C., and Awolusi, I., 2022, “Wearable Sensing Devices Acceptance Behavior in Construction Safety and Health: Assessing Existing Models and Developing a Hybrid Conceptual Model,” Constr. Innovation, **22**(1), pp. 57–75.

[200] Ke, J., Du, X., and Luo, X., 2021, “The Effect of Noise Content and Level on Cognitive Performance Measured by Electroencephalography (EEG),” Autom. Constr., **130**, p. 103836.

[201] Sakhakarmi, S., Park, J., and Singh, A., 2021, “Tactile-Based Wearable System for Improved Hazard Perception of Worker and Equipment Collision,” Autom. Constr., **125**, p. 103613.

[202] Panahi, O., 2025, “Wearable Sensors and Personalized Sustainability: Monitoring Health and Environmental Exposures in Real-Time,” Eur. J. Innov. Stud. Sustain., **1**(2), pp. 11–19.

[203] Nwaogu, J. M., Chan, A. P., Hon, C. K., and Darko, A., 2020, “Review of Global Mental Health Research in the Construction Industry: A Science Mapping Approach,” Eng. Constr. Archit. Manag., **27**(2), pp. 385–410.

[204] Ghafoori, M., Clevenger, C., Abdallah, M., and Rens, K., 2023, “Heart Rate Modeling and Prediction of Construction Workers Based on Physical Activity Using Deep Learning,” Autom. Constr., **155**, p. 105077.

[205] Zhou, K., Wang, J., Ashuri, B., and Chen, J., 2023, “Discovering the Research Topics on Construction Safety and Health Using Semi-Supervised Topic Modeling,” Buildings, **13**(5), p. 1169.

[206] Nnaji, A., and Karakhan, A., 2020, “Technologies for Safety and Health Management in Construction: Current Use, Implementation Benefits and Limitations, and Adoption Barriers,” J. Build. Eng., **29**, p. 101212.

[207] Kumar Singh, A., Aljohani, A., Shakor, P., Awuzie, B. O., Uddin, S. M. J., and Shivendra, B. T., 2024, “Study on Safety Health of Construction Workers at Workplace: A Sustainable Perspective Approach,” Front. Built Environ., **10**, p. 1451727.

[208] Patel, V., Chesmore, A., Legner, C. M., and Pandey, S., 2021, “Trends in Workplace Wearable Technologies and Connected-Worker Solutions for Next-Generation Occupational Safety, Health, and Productivity,” Adv. Intell. Syst., **4**(1), p. 2100099.

[209] Yadav, N., Sadeghi, N., and Kang, J., 2024, “Five Factors Affecting the On-Body Placement of Wearable Tactile Safety Promotion Device for Construction Workers-on-Foot,” Constr. Innovation, **24**(2), pp. 537–557.

[210] Pillsbury, W., Clevenger, C. M., Abdallah, M., and Young, R., 2020, “Capabilities of an Assessment System for Construction Worker Physiology,” J. Perform. Constr. Facil., **34**(2), pp. 04019120.

[211] IBC: International Code Council (ICC), 2024, “2024 International Building Code (IBC),” Country Club Hills, IL, International Code Council, https://www.iccsafe.org/products-and-services/i-codes/2024-i-codes/ibc/, Accessed April 1, 2025.

[212] OSHA: Occupational Safety and Health Administration (OSHA), “Safety and Health Regulations for Construction,” 29 CFR 1926, US Department of

Labor, https://www.osha.gov/laws-regs/regulations/standardnumber/1926, Accessed July 2025.

[213] Badhan, S. J., and Samsami, R., 2025, "Artificial Intelligence (AI) in Construction Safety: A Systematic Literature Review," Buildings, **15**(22), pp. 4084.

[214] Alnuzha, M., and Bloch, T., 2025, "The Role of Machine Learning in Automated Code Checking—A Systematic Literature Review," J. Inf. Technol. Construct., **30**(2), pp. 22–44.

[215] Madireddy, S., Gao, L., Din, Z. U., Kim, K., Senouci, A., Han, Z., and Zhang, Y., 2025, "Large Language Model-Driven Code Compliance Checking in Building Information Modeling," Electronics, **14**(11), p. 2146.

[216] Beach, T., Yeung, J., Ghoroghi, A., and Rezgui, Y., 2025, "Moving Automated Compliance Checking to the Operational Phase of the Building Life-Cycle: Analysis and Feasibility Study in the UK," Int. J. Construct. Manage., **25**(7), pp. 840–849.

[217] Lemian, D., and Bode, F., 2025, "Digital Twins in the Building Sector: Implementation and key Features," EENVIRO 2024 (Sustainable Solutions for Energy and Environment), Bucharest, Romania, Oct. 28–Nov. 1.

[218] Zhong, W., Rasouli, S., Singh, A. K., Mohandes, S. R., Antwi-Afari, M. F., Cheung, C., Manu, P., and Agrawal, U., 2025, "The Adoption of UAVs for Enhancing Safety in the Construction Industry: A Systematic Literature Review," Intell. Infrastruct. Constr., **1**(1), p. 3.

[219] FAA: Federal Aviation Administration (FAA), "Small Unmanned Aircraft Systems," 14 CFR Part 107, U.S. Department of Transportation, https://www.ecfr.gov/current/title-14/chapter-I/subchapter-F/part-107, Accessed July 2025.

[220] Nazneen, S., Choi, S. D., and Ibarra-Mejia, G., 2025, "Extreme Heat Exposure in the Construction Industry: A Scoping Review on Risk Factors and Heat-Related Health Consequences," Int. J. Environ. Res. Public Health, **22**(11), p. 1651.