



Article

IMPLEMENTING ADVANCED TECHNOLOGIES FOR ENHANCED CONSTRUCTION SITE SAFETY

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Citation:

Hossain, M. I., Hosen, M. M., Sunny, M. A. U., & Tarapder, S. A. (2025). Implementing advanced technologies for enhanced construction site safety. *American Journal of Advanced Technology and Engineering Solutions*, 1(2), 1–31.

<https://doi.org/10.63125/3v8rpr04>

Received:

February 19, 2025

Revised:

March 21, 2025

Accepted:

April 16, 2025

Published:

May 02, 2025



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ABSTRACT

The construction industry remains one of the most hazardous sectors worldwide, consistently reporting high rates of workplace accidents, injuries, and fatalities. Traditional safety management approaches, while essential, are often reactive and limited in their ability to predict and prevent incidents. As the industry evolves, there is an urgent need for a paradigm shift toward more proactive and technology-driven safety strategies. This study investigates the implementation of advanced technologies—including the Internet of Things (IoT), Artificial Intelligence (AI), Virtual Reality (VR), Augmented Reality (AR), unmanned aerial vehicles (drones), and wearable safety devices—to significantly enhance safety outcomes on construction sites. IoT-enabled sensors can continuously monitor environmental conditions such as temperature, noise, air quality, and structural integrity, offering real-time data for early detection of potential hazards. AI algorithms further analyze this data to identify patterns, predict risks, and automate responses before accidents occur. VR and AR provide immersive training experiences and on-site hazard visualization, helping workers to recognize and respond to dangerous situations with higher accuracy and preparedness. Drones offer aerial surveillance capabilities, allowing for safe inspection of hard-to-reach or hazardous areas. Meanwhile, wearable technologies such as smart helmets, vests, and biometric monitors track workers' vital signs, movements, and proximity to danger zones, enabling real-time alerts and safety interventions. Collectively, these technologies represent a transformative approach to construction site safety by shifting from manual and fragmented safety processes to integrated, data-driven, and responsive systems. The integration of these tools not only reduces the probability of human error but also enhances compliance with safety regulations and improves overall situational awareness. The anticipated outcome of this project is a substantial reduction in injury and fatality rates, along with the development of more robust and proactive safety protocols tailored to the dynamic nature of construction environments. Through the adoption of smart technologies, the construction industry can advance toward a safer, more efficient, and future-ready operational model.

KEYWORDS

Construction Safety; Advanced Technologies; Wearable Devices; Artificial Intelligence (AI); Internet of Things (IoT)

INTRODUCTION

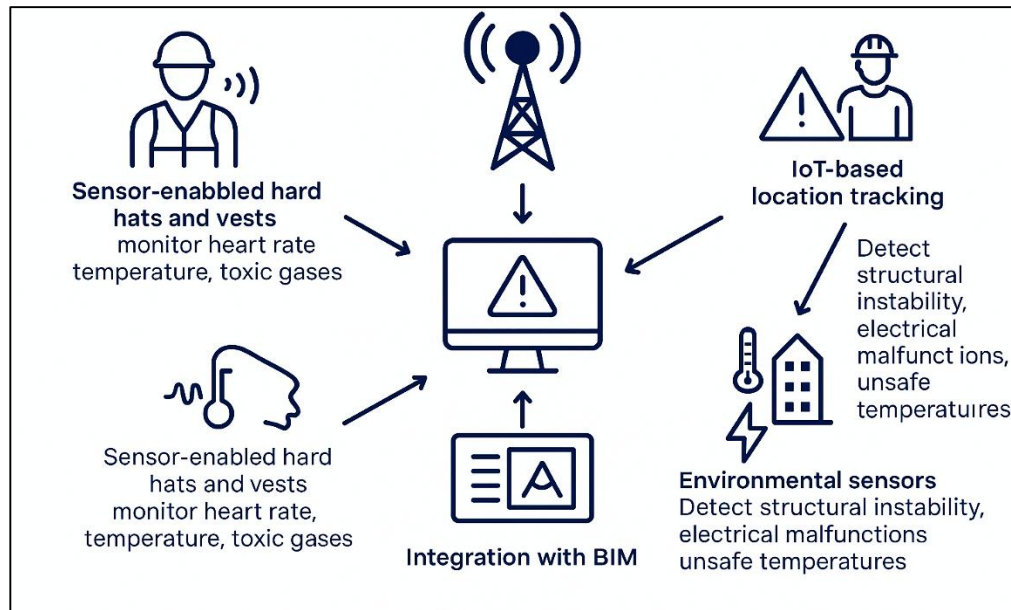
Construction site safety refers to the structured set of protocols, procedures, and preventive measures aimed at protecting workers, equipment, and the public from hazards inherent to construction environments (Soltanmohammadlou et al., 2019). These environments are characterized by ever-changing physical layouts, heavy machinery, working at heights, and hazardous materials, which contribute to their classification as high-risk workplaces (Azhar, 2017). According to the International Labour Organization (ILO), over 60,000 fatal accidents occur on construction sites globally each year, accounting for approximately one in every six workplace-related deaths (ILO, 2023). This staggering statistic underlines the urgent need for innovation in safety management. The World Health Organization (WHO) further reports that construction accidents lead to economic losses exceeding billions of dollars annually, primarily due to lost productivity, insurance claims, and compensation (WHO, 2020). In emerging economies such as India, China, and Brazil, rapid infrastructure development is often accompanied by minimal regulatory enforcement, amplifying the dangers faced by construction workers (Ayhan & Tokdemir, 2019). Similarly, in developed countries like the United States and the United Kingdom, the Occupational Safety and Health Administration (OSHA) and the Health and Safety Executive (HSE) report persistently high injury rates, indicating that current safety protocols are insufficient. As safety in construction transcends national boundaries and economic contexts, its improvement has become a pressing issue for international collaboration and technological advancement (Zhou & Ding, 2017).

Figure 1: Addressing Hazards On Construction Sites



Traditional construction safety management systems typically rely on manual observation, periodic inspections, safety training, and compliance checklists. While foundational, these approaches suffer from limited scalability, subjective assessments, and delayed hazard detection (Maliha et al., 2021). Human error remains a leading cause of construction accidents, as fatigue, distraction, and inadequate supervision contribute significantly to workplace mishaps (Sacks et al., 2015). Moreover, hierarchical communication structures and lack of real-time feedback further hinder the effectiveness of conventional methods (Carter & Smith, 2006). In many developing regions, safety training is insufficiently integrated into daily workflows, often due to limited financial resources and a focus on meeting project deadlines over workforce welfare (Raheem & Issa, 2016). Even in technologically advanced settings, data from post-incident investigations are often underutilized, stored in siloed formats that prevent meaningful analysis and predictive insights. Safety compliance audits, while essential, are typically retrospective and lack the capacity to forecast risk based on dynamic site conditions. These limitations necessitate the exploration of digital solutions capable of delivering real-time, proactive risk management. Studies have indicated that unless construction safety systems evolve to leverage data and automation, accident rates will likely remain static. Thus, there is a growing consensus in literature that traditional models must be augmented through intelligent systems to meet modern safety demands (Alkaissy et al., 2020; Raheem & Issa, 2016).

Figure 2: IoT in construction safety



The Internet of Things (IoT) encompasses a network of interconnected devices embedded with sensors, software, and communication tools that collect and exchange data in real time. In construction, IoT applications are revolutionizing safety monitoring by enabling continuous surveillance of site conditions and equipment performance (Yu & Hunt, 2002). For instance, sensor-enabled hard hats and vests can monitor workers' heart rate, temperature, and exposure to toxic gases, automatically alerting supervisors to health threats (Mosly, 2015). IoT-based location tracking enhances worker visibility, preventing incidents in restricted or hazardous zones. Furthermore, environmental sensors deployed across the site can detect structural instability, electrical malfunctions, or unsafe temperature fluctuations, triggering automated safety protocols. The integration of IoT with Building Information Modeling (BIM) further enhances predictive safety analytics by simulating construction workflows and identifying potential hazards before they materialize (Ayhan & Tokdemir, 2019; Mosly, 2015). Azhar (2017) shows that IoT systems significantly reduce response time to safety breaches, increase accountability, and support better resource allocation. Nonetheless, implementing IoT requires robust data security measures, as the collection of personal health and location data introduces privacy concerns. When effectively managed, IoT networks create an interconnected safety ecosystem that reduces reliance on manual oversight and elevates proactive hazard detection (Ayhan & Tokdemir, 2019).

Artificial Intelligence (AI) is defined as the simulation of human cognitive processes by machines, including learning, reasoning, and self-correction (Abioye et al., 2021). In construction, AI applications include image recognition for real-time hazard detection, natural language processing for incident report analysis, and machine learning for risk prediction based on historical data. One of the most impactful uses of AI is in computer vision, where cameras integrated with deep learning models detect unsafe behaviors such as not wearing protective gear or entering danger zones. AI systems can also process vast datasets from IoT devices and historical logs to identify patterns associated with near-miss events, enabling predictive maintenance and risk forecasting (Abioye et al., 2021). For example, AI models have successfully predicted crane failure risks, scaffolding instability, and material storage hazards, allowing preemptive mitigation (Goh & Chua, 2010). By analyzing text from safety logs, emails, and inspection reports, natural language processing tools extract key insights and categorize emerging safety concerns. According to Márquez-Sánchez et al. (2021), AI adoption has been linked to improved safety decision-making, reduction in lost-time injuries, and enhanced training personalization. However, the effectiveness of AI hinges on data quality, algorithm transparency, and workforce acceptance, issues that require ongoing attention. Nonetheless, AI represents a fundamental shift in transforming construction safety from reactive to preventative management.

Virtual Reality (VR) and Augmented Reality (AR) are immersive technologies that enhance human interaction with simulated or augmented digital environments. VR creates fully artificial experiences, while AR overlays digital elements onto real-world views (Zhou et al., 2013). In construction safety, VR is widely used for scenario-based training, allowing workers to experience dangerous situations without real-world consequences (Getuli et al., 2020). This approach improves cognitive retention, hazard recognition, and situational awareness, leading to safer on-site behaviors. AR, on the other hand, provides real-time safety alerts and visual guidance directly through smart glasses or mobile devices during site operations. For instance, workers can view 3D models of buried cables or load-bearing structures, reducing the risk of unintentional damage or collapse. Li et al. (2018) emphasize that AR improves communication, especially in multilingual workforces, by replacing verbal instructions with visual cues. Moreover, VR simulations assist in pre-construction risk assessments, allowing safety managers to walk through digital site replicas and identify risk hotspots. As training-related accidents remain a significant concern, immersive learning technologies offer scalable, repeatable, and engaging alternatives to conventional classroom instruction. Research shows that VR-trained workers demonstrate a 30–40% increase in hazard recall compared to those trained through traditional means (Le et al., 2015). These technologies serve as vital tools in cultivating a robust safety culture grounded in experiential learning.

Drones, or unmanned aerial vehicles (UAVs), are increasingly employed in construction for site surveillance, structural inspection, and progress tracking. Equipped with high-resolution cameras and thermal imaging sensors, drones offer a safe alternative to manual inspection of high-risk or inaccessible areas, such as tall scaffolding, rooftops, and confined spaces (Seo et al., 2018). Their ability to rapidly capture site data enables early identification of structural weaknesses, environmental hazards, and violations of safety protocols (Karakhan et al., 2018). Aerial imagery processed with photogrammetry and 3D modeling software enhances spatial awareness and supports real-time decision-making. Drones also play a critical role in emergency response by locating trapped workers, assessing fire damage, or delivering supplies to isolated zones. According to Bogue (2018), drone usage in construction reduces inspection time by 50% and improves safety audit coverage, ensuring compliance with regulatory standards. Their data can be integrated into BIM platforms or AI systems for comprehensive risk analysis. Although legal regulations concerning airspace and data privacy pose challenges to drone deployment, their safety benefits are well-documented and increasingly accepted in construction practice (Seo et al., 2018). Compared to manual inspections, drones significantly reduce the exposure of safety personnel to hazardous conditions, thus supporting injury prevention and efficient site supervision.

Wearable technologies refer to electronic devices embedded in clothing or accessories that monitor physiological and environmental parameters. In the context of construction, wearables such as smart helmets, wristbands, and vests collect data on heart rate, temperature, fatigue, posture, and location, providing real-time insights into worker health and behavior (Guo et al., 2017). These devices alert users and supervisors to potential dangers, such as overexertion, proximity to moving equipment, or exposure to toxic substances (Barata & da Cunha, 2019). Wearables also promote accountability by tracking adherence to safety practices, including PPE usage and restricted area compliance (Abbasianjahromi & Ghazvini, 2021). Lingard et al. (2019) demonstrated that fatigue-monitoring wearables reduced musculoskeletal injury risks among laborers by 34%. Additionally, GPS-enabled wearables facilitate contact tracing and evacuation management during emergencies. When integrated with AI, wearable data contributes to predictive analytics, highlighting systemic risk factors and guiding policy improvements. Wearables are particularly beneficial in remote or large-scale projects where continuous supervision is impractical. However, issues such as device discomfort, data reliability, and worker privacy must be managed to ensure sustained adoption (Márquez-Sánchez et al., 2021). As part of a comprehensive safety system, wearable technology empowers proactive risk identification and real-time intervention, reinforcing a culture of safety and accountability in construction environments.

The primary objective of this study is to critically examine the role and effectiveness of advanced technologies—namely, the Internet of Things (IoT), Artificial Intelligence (AI), Virtual Reality (VR), Augmented Reality (AR), drones, and wearable technologies—in mitigating safety risks on construction sites. The goal is to establish a comprehensive framework through which these technologies can be systematically integrated into daily safety management practices to reduce accident frequency and severity. Given the persistent global concern surrounding construction site

injuries and fatalities, this study aims to move beyond theoretical discussions by exploring real-world applications and outcomes. By reviewing current implementations, pilot programs, and case studies across diverse construction environments, this research seeks to identify the specific mechanisms through which each technology contributes to hazard detection, accident prevention, and emergency responsiveness. Another core objective is to evaluate the interoperability and combined impact of these technologies when applied as part of an integrated safety system. For example, the study will assess how IoT sensor data, when combined with AI-driven analytics and wearable alerts, enhances decision-making and real-time risk mitigation. In addition, the study aims to assess user acceptance and operational challenges associated with these technologies, particularly in developing regions where digital literacy, cost constraints, and infrastructure gaps may limit adoption. The study also explores how immersive training via VR/AR contributes to safety culture and compliance. Furthermore, this investigation will assess the scalability of these technologies for small- and medium-scale projects, ensuring practical relevance beyond large corporate settings. Ultimately, the objective is to deliver evidence-based insights that support construction firms, safety managers, and policymakers in making informed decisions regarding the adoption and optimization of technology-enhanced safety systems in construction.

LITERATURE REVIEW

The construction industry is fraught with complex operational challenges, and safety remains one of its most pressing concerns. Traditional safety management systems, while foundational, have proven insufficient in mitigating the dynamic and often unpredictable risks that emerge on construction sites. As a result, academic and industry researchers have increasingly turned their focus toward integrating advanced technologies to transform safety outcomes through real-time monitoring, predictive analytics, and immersive training. This literature review aims to critically examine the current body of knowledge surrounding the use of Internet of Things (IoT), Artificial Intelligence (AI), Virtual Reality (VR), Augmented Reality (AR), unmanned aerial vehicles (drones), and wearable safety technologies within the construction sector. Each technological category is explored in terms of its conceptual basis, application context, effectiveness, limitations, and implementation challenges. This section synthesizes empirical findings from scholarly journal articles, industry white papers, case studies, and technical reports to offer a multi-dimensional perspective on how technology is reshaping construction safety. Particular attention is given to comparative evaluations of technology adoption in high-risk versus low-risk environments, cross-cultural implementation outcomes, integration challenges in small and medium enterprises (SMEs), and regulatory or ethical considerations. The literature is further analyzed to identify gaps in current research, such as underreported case studies, lack of longitudinal data, or insufficient exploration of inter-technology synergy. This review lays the foundational basis for identifying best practices, proposing integrated safety frameworks, and informing the methodological approach of the current study. The structure follows a logical progression—from foundational safety challenges to technology-specific applications—offering both depth and clarity in understanding the evolving role of innovation in construction site safety.

Occupational Safety Standards in the Construction Sector

The development of occupational safety standards in the construction sector has evolved significantly over the past century, transitioning from rudimentary guidelines to comprehensive regulatory systems enforced by international bodies. Historically, construction safety was guided by reactive measures, focusing on post-accident responses rather than prevention. The establishment of the International Labour Organization (ILO) in 1919 marked a pivotal moment, initiating efforts to harmonize labor standards globally (ILO, 2023). The ILO's Convention No. 167 and Recommendation No. 175, which specifically address construction safety, laid the foundation for many national regulatory frameworks. These standards emphasize hazard identification, the use of protective equipment, worker training, and employer accountability (Xia et al., 2021). In parallel, the World Health Organization (WHO) has highlighted construction safety as a public health priority, reinforcing the need for occupational risk management in low- and middle-income countries (WHO, 2020). Many developed nations have implemented robust frameworks based on these international guidelines. For example, the United States' Occupational Safety and Health Administration (OSHA) enforces the OSHA 1926 Construction Safety Regulations, covering fall protection, scaffolding, and electrical safety. Similarly, the United Kingdom's Health and Safety Executive (HSE) introduced the Construction (Design and Management) Regulations to address risks at the design stage. These

international and national efforts are often underpinned by the hierarchy of controls model, which prioritizes hazard elimination over administrative controls (Wang et al., 2015). However, despite these advancements, implementation inconsistencies persist globally due to economic disparities, political will, and industry enforcement challenges (Chen et al., 2018). Research indicates that harmonizing global standards and adapting them to local contexts remain essential for effective occupational safety governance (Rashidi et al., 2024).

Occupational safety regulations in the construction sector vary considerably across jurisdictions, influencing their overall effectiveness in reducing workplace injuries and fatalities. In countries like the United States, OSHA regulations have resulted in measurable improvements in worker safety, with data showing significant reductions in fatal injury rates since their inception. In the United Kingdom, the HSE reports have similarly credited regulatory changes with marked declines in construction-related deaths. However, the same cannot be said for many developing countries, where enforcement of safety laws remains sporadic due to limited resources and weak institutional frameworks. In Nigeria, for example, although safety legislation exists, it is often poorly implemented, leading to high accident frequencies and underreporting of injuries (Oyedele & Tham, 2007). Comparative studies further reveal that even within developed nations, compliance varies significantly based on project size, contractor reputation, and geographic location (Oyedele et al., 2015). Oluwatayo et al. (2014) highlights that smaller firms frequently lack the capacity to meet all safety requirements, while larger firms tend to embed safety in their organizational culture. Cultural factors also play a critical role; in Japan, for instance, collective responsibility and safety rituals contribute to higher compliance levels (Yamamura et al., 2017). Conversely, in Latin American contexts, a lack of safety training and low safety awareness are persistent issues (Marshall & Stutz, 2018). These disparities illustrate the limitations of a "one-size-fits-all" approach to safety regulation. While national regulations are essential, their success hinges on local enforcement capabilities, cultural adaptability, and integration into the construction project lifecycle.

Figure 3: Occupational Safety Standards In Global Construction

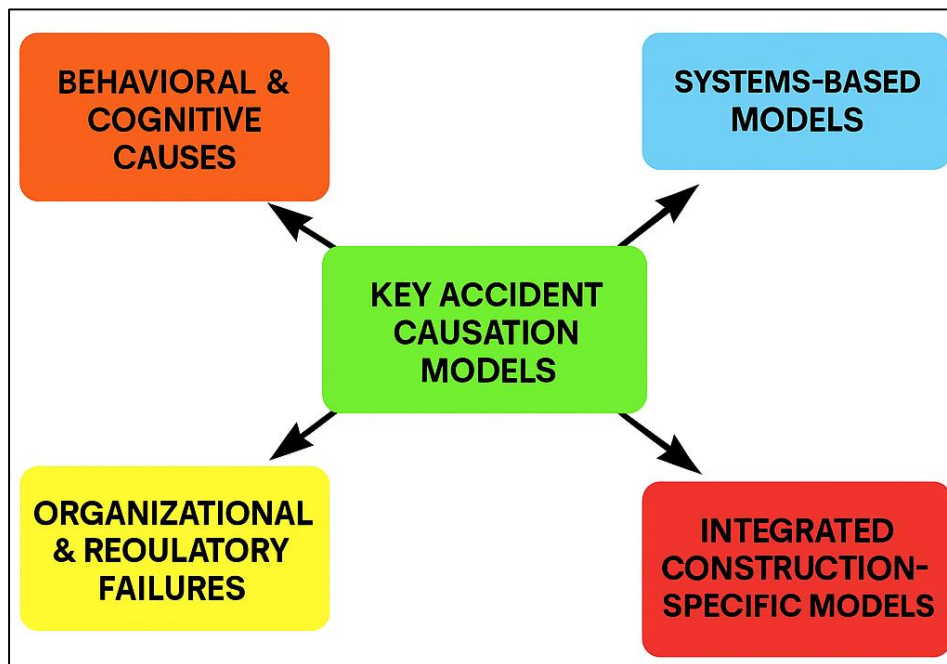


The effectiveness of occupational safety standards depends heavily on enforcement mechanisms, which include inspections, penalties, certifications, and mandatory reporting requirements. Regulatory bodies such as OSHA in the U.S. and HSE in the U.K. utilize structured inspection programs and maintain databases of violations to identify high-risk firms and allocate oversight resources accordingly (Winfield & Jirotko, 2018). Penalties for non-compliance serve as deterrents and are often complemented by incentive programs aimed at fostering voluntary compliance. However, the frequency and thoroughness of inspections remain inadequate in many countries due to insufficient staffing and funding (Park & Kim, 2013). A global review by Park et al. (2013) revealed that reactive inspection systems—those initiated after incidents—are less effective than proactive ones designed to prevent accidents. In many low-income settings, corruption and regulatory capture further diminish enforcement credibility (Fang et al., 2016). Additionally, subcontracting practices complicate accountability chains, with principal contractors often failing to enforce safety obligations across smaller subcontractors (Mohammadi et al., 2018). Another enforcement challenge arises from the use of temporary or migrant labor, who may lack awareness of local safety laws and fear retaliation for reporting unsafe conditions (Park et al., 2013). Despite regulatory frameworks, studies indicate that actual compliance is often symbolic, with safety plans existing only on paper and not reflected in daily practices (Le et al., 2015). These challenges underscore the need for multifaceted enforcement strategies that combine legal mandates with education, training, and cultural shifts to promote genuine safety commitment across the sector (Park et al., 2017).

Key Accident Causation Models in Construction Safety Research

Accident causation models have long served as theoretical frameworks to understand, analyze, and prevent accidents in the construction industry. Among the earliest and most widely recognized is Heinrich's Domino Theory, which proposed a linear sequence of five factors: ancestry, fault of person, unsafe act or mechanical hazard, accident, and injury. Heinrich emphasized that unsafe acts caused the majority of accidents, a view that shaped early safety interventions in construction by prioritizing worker behavior modification (Lean, 2001). However, later critiques highlighted the model's individual-centric focus and its failure to account for organizational or environmental influences. Bird's Loss Causation Model expanded on Heinrich's work by incorporating management system failures into the causal chain, introducing concepts such as "basic causes" and "lack of control," which placed greater responsibility on organizational structures (Winfield & Jirotko, 2018). While these traditional models laid the foundation for safety thinking, they were limited by their linearity and lack of adaptability to dynamic construction environments. Nonetheless, their influence persists, especially in compliance-driven safety programs that prioritize incident investigation over proactive risk analysis. These models remain instructive for basic root cause analysis but often fail to capture the complexity of modern construction projects characterized by multi-employer worksites, subcontracting, and time-sensitive deliverables (Zhu et al., 2021).

The limitations of linear accident models in capturing complex causality led to the emergence of systems-based approaches, with Reason's Swiss Cheese Model gaining widespread acceptance in safety-critical industries, including construction. This model conceptualizes accidents as the result of multiple latent failures within different layers of defense, with hazards passing through "holes" in each barrier until a failure event occurs (Mondragon et al., 2018). The model underscores the role of organizational weaknesses—such as poor communication, inadequate training, and flawed decision-making—in shaping frontline behaviors. Studies applying this model in construction have identified systemic failures such as inadequate safety leadership, ineffective hazard communication, and flawed work planning as precursors to accidents (Jung et al., 2006). Similarly, Rasmussen's Risk Management Framework emphasized that decision-making at all levels of an organization—from policy-makers to site operatives—can influence accident causation through dynamic interactions. This multi-layered model has been applied in construction to trace how budget constraints or subcontractor pressures may lead to shortcuts in safety procedures. System-Theoretic Accident Model and Processes (STAMP) further advanced this perspective by framing safety as a control problem and emphasizing the role of system constraints rather than component failures. STAMP-based studies have shown efficacy in uncovering software-related and organizational interaction failures in complex construction projects (Mohammadi et al., 2018). Collectively, these systems models have pushed the construction safety discourse toward a more holistic and proactive risk management paradigm, recognizing that safety outcomes are emergent properties of socio-technical systems rather than isolated events (Park & Kim, 2013).

Figure 4: Accident Causation Models in Construction Safety

Behavioral theories and cognitive models have significantly influenced the understanding of accident causation in construction by focusing on human error, decision-making processes, and risk perception. The Human Error Theory distinguishes between slips, lapses, and mistakes, each representing different cognitive failures that may lead to unsafe acts (Park et al., 2013). This distinction has been applied in construction to design interventions tailored to specific error types, such as visual

reminders for lapses and retraining for knowledge-based mistakes (Fang et al., 2016; Park & Kim, 2013). The Theory of Planned Behavior (TPB), developed by Ajzen (1991), has also been adapted for construction safety research to explore how attitudes, subjective norms, and perceived behavioral control influence workers' intentions to follow safety protocols (Kanchana et al., 2015). Findings from these studies suggest that workers who perceive strong safety norms and feel empowered to act safely are more likely to engage in risk-averse behavior. Safety climate research, which measures workers' perceptions of management commitment to safety, has emerged as another behavioral framework with strong predictive power for incident frequency and severity (Shafiq et al., 2013). Studies have found that when workers perceive their supervisors as supportive and safety-oriented, the likelihood of accidents declines significantly (Altuwaim et al., 2023). Cognitive failure studies further highlight the impact of stress, fatigue, and cognitive overload on worker performance, particularly in high-tempo construction environments (Chu et al., 2010). Together, these models underscore the importance of human-centered interventions in construction safety programs, revealing that behavioral factors are as critical as structural or procedural safeguards (Eadie et al., 2015).

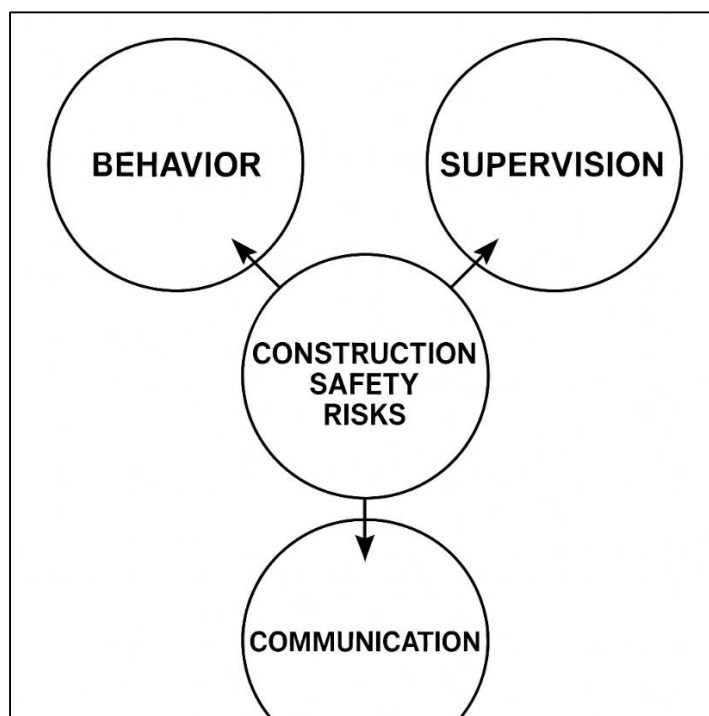
Integrated models of accident causation attempt to unify various theoretical strands—behavioral, systems-based, and organizational—into a single analytical framework. Schuld et al. (2021) proposed the Accident Causation Model for the Construction Industry, which categorizes contributing factors into three domains: project, organizational, and individual. This model has been validated in multiple case studies, revealing how the interplay of poor scheduling, inadequate training, and management lapses contributes to unsafe conditions (Alaka et al., 2018). Similarly, Alaloul et al. (2021) developed a dynamic model that maps safety behavior to upstream organizational decisions, illustrating how early-stage planning affects frontline execution. Empirical applications of these models often rely on mixed methods, combining incident data analysis, site observations, and worker interviews to capture a comprehensive view of accident causation (Babalola et al., 2023). In a large-scale study, Zulu and Khosrowshahi (2021) used a multi-criteria decision-making approach to rank 16 critical success factors for safety programs, validating that leadership support, clear procedures, and worker participation are primary barriers against accidents. Other researchers have employed grounded theory and systems thinking to derive contextualized causation models that reflect the nuances of local construction practices in countries such as China, Brazil, and India (Nnaji & Karakhan, 2020). These studies highlight that no single model can comprehensively explain all accident scenarios; rather, customized, data-driven approaches that consider contextual variables tend to yield the most actionable insights. The increasing use of

digital tools, such as BIM and AI, has also enriched empirical modeling by enabling predictive analytics and simulation-based safety planning (Karakhan et al., 2018). Integrated models thus provide a versatile platform for both diagnostic and preventative safety strategies in construction.

Factors: Behavior, Supervision, and Communication Gaps

Worker behavior is a dominant factor in construction site safety, influencing the likelihood of both minor incidents and severe accidents. Unsafe behaviors often stem from risk-taking tendencies, lack of hazard awareness, and poor safety attitudes (Kotsiantis, 2007). The Theory of Planned Behavior (Ajzen, 1991) has been widely used to explain why workers choose to ignore safety rules, with key determinants including perceived control, social norms, and individual attitude (Altuwaim et al., 2023; Kanchana et al., 2015). Studies show that even when safety training is provided, its effectiveness depends largely on whether workers internalize safety values and believe in the personal benefits of compliance (Altuwaim et al., 2023; Eadie et al., 2015). In many cases, workers under pressure to meet tight deadlines may prioritize speed over safety, leading to shortcut behavior and negligence. Moreover, cultural attitudes toward authority and individual responsibility can shape risk perceptions and compliance levels, particularly in multinational or migrant workforces (Eadie et al., 2015). Schuldt et al. (2021) identified stress, fatigue, and cognitive overload as major predictors of lapses in safety behavior, especially during prolonged shifts or peak workloads. Furthermore, enforcement inconsistency and the absence of real-time feedback mechanisms often contribute to the normalization of deviance in worker behavior (Alaka et al., 2018). Thus, while rules and training are foundational, behavioral adherence to safety practices ultimately hinges on psychological readiness, motivation, and perceived organizational support.

Figure 5: Interconnected Factors Influencing Construction Site Safety



Supervision is a key intermediary between safety policy and field implementation, yet its impact is frequently under-acknowledged. Effective supervision can reinforce safety behaviors, ensure procedural compliance, and bridge communication between management and workers. Supervisors are responsible for monitoring hazards, conducting toolbox talks, verifying the use of personal protective equipment (PPE), and guiding workers through safe practices. Research by Chu et al. (2010) found that safety-conscious supervisory behavior—such as positive reinforcement and corrective feedback—was strongly correlated with lower accident rates. However, in many construction settings, supervisors often lack formal safety training or are burdened with excessive administrative responsibilities, which limits their ability to perform proactive safety oversight. Studies also indicate that inconsistent supervisory enforcement can create ambiguity around safety expectations, leading to risk-tolerant behaviors among workers (Eadie

et al., 2015). In some cases, supervisors may implicitly encourage unsafe behavior to meet productivity targets, especially when project timelines are constrained. The dual accountability of supervisors—to both project delivery and safety—can result in conflicting priorities that undermine safety commitment. Moreover, supervisory relationships heavily influence safety culture; workers are more likely to engage in safe practices when they feel respected, heard, and fairly treated by their supervisors. The supervisory role, therefore, is not merely procedural but relational, requiring skills in communication, leadership, and ethical judgment to effectively manage site safety.

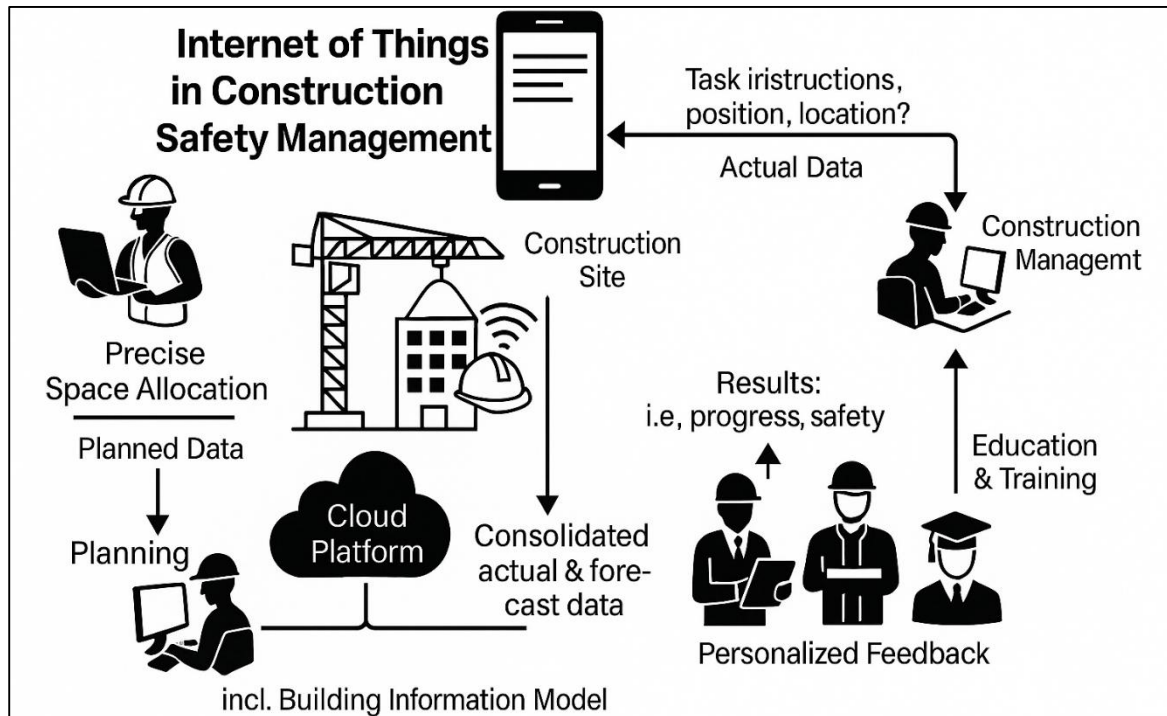
Communication plays a foundational role in maintaining safe construction environments, yet gaps in information flow are a persistent cause of accidents and near-misses. Ineffective communication

may stem from unclear instructions, language barriers, low literacy levels, or inadequate documentation of risks and safety procedures. Construction sites often host multicultural workforces, where variations in language and cultural norms can distort the intended meaning of safety messages. For example, a study by [Schuldt et al. \(2021\)](#) found that migrant workers in Ghana had lower comprehension of safety rules and were less likely to report unsafe conditions due to language limitations and fear of retaliation. Additionally, the absence of feedback loops—where workers can report concerns or clarify instructions—further compounds communication failures. On dynamic construction sites, safety updates may not be communicated consistently across shifts or subcontracting teams, resulting in confusion and procedural violations ([Alaka et al., 2018](#)). Toolbox meetings and safety briefings are standard mechanisms to ensure daily awareness, yet studies have shown these are often rushed, perfunctory, or poorly attended. Moreover, the reliance on printed materials or technical jargon in safety documentation can exclude less-educated workers from understanding essential guidelines ([Alaloul et al., 2021](#)). Communication is not only about dissemination but about dialogue—ensuring that safety information is received, understood, and actionable across all levels of the workforce.

Behavior, supervision, and communication are interrelated factors that collectively influence the safety performance of construction sites. Unsafe behavior often results from inadequate supervision, which in turn is exacerbated by poor communication systems ([Babalola et al., 2023](#)). For instance, workers who do not fully understand job risks due to communication breakdowns may rely on assumptions or past experience, increasing the likelihood of hazardous decisions ([Zulu & Khosrowshahi, 2021](#)). Supervisors serve as the linchpin in this triad, translating safety policies into daily practices and ensuring that communication flows smoothly between management and labor. When supervisory oversight is inconsistent, it sends ambiguous signals to workers about the importance of safety protocols, thereby fostering a culture of non-compliance ([Babalola et al., 2023](#)). Additionally, worker behaviors can influence supervisory strategies; proactive, safety-conscious teams often receive more participatory supervision, while risk-prone teams may be micromanaged or neglected. Effective communication can mitigate behavioral risks by clarifying expectations, enabling hazard reporting, and building trust in the supervisory process. Conversely, communication gaps can lead to delays in hazard mitigation, misinterpretation of safety standards, and underreporting of incidents. Thus, the triadic relationship between these factors must be viewed holistically; improvements in one area are often contingent on parallel improvements in the others. Safety outcomes are not determined by isolated variables but by the dynamic interplay of behavioral tendencies, supervisory engagement, and the quality of communication infrastructure on construction sites.

Internet of Things (IoT) in Construction Safety Management

The Internet of Things (IoT) refers to the interconnected network of physical devices embedded with sensors, software, and other technologies that collect, transmit, and exchange data over the internet. In the construction industry, IoT has emerged as a vital tool for safety management due to its capacity to provide real-time, continuous monitoring of site conditions and workforce activities ([Ahmed et al., 2022](#); [Schuldt et al., 2021](#)). Construction sites are inherently dynamic and hazardous, with ever-changing configurations, high-risk machinery, and vulnerable human elements. IoT-enabled systems help manage this complexity by embedding smart devices into safety equipment such as helmets, vests, boots, and tools ([Alaka et al., 2018](#); [Majharul et al., 2022](#)). These devices collect critical information on environmental parameters (e.g., temperature, gas levels), worker location, and physiological states (e.g., heart rate, body temperature), which can be transmitted to centralized dashboards for analysis ([Alaloul et al., 2021](#); [Masud, 2022](#)). The real-time nature of this data allows for proactive responses, including automated alerts when hazardous thresholds are surpassed ([Babalola et al., 2023](#); [Hossen & Atiqur, 2022](#)). Furthermore, the deployment of IoT in construction aligns with the larger framework of smart construction, promoting integration between safety management, productivity optimization, and digital site modeling ([Kumar et al., 2022](#)). Studies have shown that IoT adoption is positively correlated with reduced incident response times, increased situational awareness, and improved compliance with occupational safety standards ([Sohel et al., 2022](#); [Zulu & Khosrowshahi, 2021](#)). However, conceptual clarity remains essential, as the term "IoT" encompasses a broad range of applications, from basic wearable trackers to complex cyber-physical systems interfaced with AI and cloud computing ([Arafat Bin et al., 2023](#)). Hence, a comprehensive understanding of IoT's architectural, functional, and operational layers is critical to fully exploit its potential in safety management on construction sites.

Figure 6: Internet of Things (IoT) Integration for Real-Time Construction Safety Management

One of the most transformative applications of IoT in construction safety is its use in environmental hazard detection (Chowdhury et al., 2023). Construction sites often expose workers to volatile and dangerous conditions such as toxic gas emissions, high decibel noise levels, heat stress, and structural instability (Jahan, 2023). Traditional methods of detecting these hazards rely on manual observation or scheduled testing, which are often delayed or inconsistent (Maniruzzaman et al., 2023). IoT-enabled sensors embedded within the construction environment provide real-time data on air quality (e.g., CO₂, methane), humidity, vibration, noise, and temperature fluctuations. These data points are continuously transmitted to cloud-based platforms or on-site monitoring systems that enable immediate decision-making and hazard mitigation (Hossen et al., 2023). For example, vibration sensors placed on structural elements can detect early signs of stress, displacement, or impending collapse, thereby preventing severe accidents (Sarker et al., 2023). Similarly, acoustic sensors can measure noise exposure in compliance with occupational health guidelines, while gas detectors identify air quality breaches that could lead to respiratory distress (Shahan et al., 2023). Some systems even employ predictive analytics to detect patterns that precede hazardous environmental changes, enabling early intervention (Schuldt et al., 2021). In tunnel or underground construction, IoT sensors play a vital role in maintaining safe oxygen levels and detecting explosive gases (Siddiqui et al., 2023). The responsiveness of IoT technologies enhances the reliability of environmental monitoring and eliminates the delays associated with manual inspections (Alaloul et al., 2021). Moreover, integrating sensor data with Building Information Modeling (BIM) systems enables simulation of future risk scenarios, enhancing preemptive safety planning. These capabilities make IoT sensors indispensable for comprehensive environmental safety management on modern construction sites (Alam et al., 2024).

IoT-enabled wearable technologies are revolutionizing worker safety by offering continuous physiological and positional monitoring on active construction sites (Ammar et al., 2024). Wearables such as smart helmets, vests, wristbands, and boots are equipped with biometric sensors and GPS modules that track key indicators such as heart rate, fatigue, hydration levels, posture, and location (Bhowmick & Shipu, 2024). This data can detect early signs of heat exhaustion, overexertion, or fall risk, triggering immediate alerts for intervention (Schuldt et al., 2021). Positional tracking through RFID or GPS enhances geofencing capabilities, ensuring that workers do not inadvertently enter restricted or hazardous zones (Bhuiyan et al., 2024). In large-scale projects where continuous supervision is unfeasible, wearable technologies serve as digital supervisors that monitor behavior and

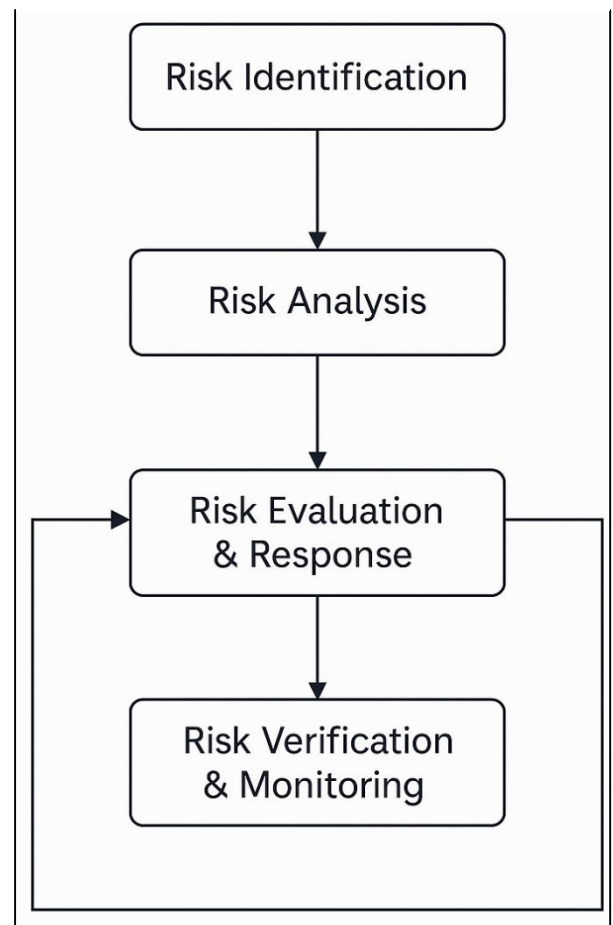
environmental exposure in real time (Dasgupta et al., 2024). For example, collision detection systems in wearable vests can alert machinery operators to nearby pedestrian workers, thereby preventing equipment-related injuries (Alaka et al., 2018). Furthermore, wearable data can be aggregated and analyzed to identify systemic safety risks, such as fatigue trends or high-risk areas on site, which informs both operational planning and policy formation (Dey et al., 2024). Although worker acceptance of wearables is generally positive, some studies point to challenges including discomfort, data privacy concerns, and technological literacy (Hasan et al., 2024). Despite these barriers, the consensus in literature affirms the effectiveness of wearable IoT technologies in enhancing individual safety, enabling early intervention, and promoting a proactive safety culture (Helal, 2024).

Artificial Intelligence for Predictive Risk Management

Artificial Intelligence (AI), broadly defined as the ability of machines to simulate human intelligence through learning, reasoning, and self-correction, has emerged as a pivotal force in the transformation of safety engineering across multiple industries, including construction (Hossain et al., 2024). Machine learning (ML), a subdomain of AI, facilitates predictive modeling by allowing systems to autonomously detect patterns from large datasets and make informed decisions (Dobrev, 2012; Hossain et al., 2024). In construction safety, AI systems are increasingly deployed to address traditional limitations of manual hazard identification and reactive safety protocols (Mahabub, Jahan, Hasan, et al., 2024; Mahabub, Jahan, Islam, et al., 2024). By leveraging structured and unstructured data—including historical injury logs, environmental sensor inputs, and real-time worker activity—AI tools are capable of assessing risk conditions with a high degree of accuracy (Mohammad Shahadat Hossain et al., 2024). For example, AI models have been used to classify risk zones on construction sites and prioritize mitigation strategies based on real-time feedback (Roy et al., 2024). Safety engineering applications include predictive safety scoring, dynamic risk mapping, and adaptive training systems based on worker performance data (Luo et al., 2019; Sabid & Kamrul, 2024). The scalability of AI systems allows them to function across complex, multi-stakeholder construction environments, promoting proactive decision-making and data-driven interventions (Shipu et al., 2024). However, successful implementation requires a foundational understanding of how AI models function, their limitations, and how they integrate with other digital systems such as BIM and IoT. As the construction industry becomes increasingly digitized, AI is positioned as a core enabler of real-time risk management and system-level safety optimization (Bhuiyan et al., 2025; Winfield & Jirotko, 2018).

Computer vision, a subset of AI, involves training machines to interpret and analyze visual data from images and video, and it has become a critical tool in enhancing hazard recognition on active construction sites (Islam et al., 2025). This technology allows AI systems to detect unsafe acts, missing personal protective equipment (PPE), and hazardous proximity to machinery through continuous surveillance footage (Saiful et al., 2025; Márquez-Sánchez et al., 2021). In high-risk environments, computer vision systems can process live camera feeds and identify non-compliance behaviors such as workers entering danger zones or not wearing helmets, and immediately issue alerts to safety managers (Bigham et al., 2018; Khan, 2025). This real-time feedback loop significantly reduces the response time to hazardous events compared to traditional observational methods. AI-driven image

Figure 7: AI-Driven Risk Management Framework for Proactive Decision-Making



recognition models are trained on vast datasets to recognize different risk types and contextual site conditions, thereby improving detection accuracy over time. For instance, object detection algorithms such as YOLO (You Only Look Once) and SSD (Single Shot Detector) have been adapted to construction scenarios to classify machinery, materials, and workers within frame sequences (Hassabou, 2018; Sarker, 2025; Tsang et al., 2018). Computer vision is also used to track unsafe behavior frequency and spatial distribution across the worksite, contributing to risk heat maps and safety audits. Additionally, these systems support safety compliance documentation by automatically recording and archiving detected violations (Alaka et al., 2019; Soheli, 2025; Younus, 2025). While promising, these tools face technical challenges including poor lighting conditions, occlusions, and variability in worker appearance that can affect detection rates (Márquez-Sánchez et al., 2021). Nevertheless, computer vision enhances risk visibility and strengthens hazard mitigation strategies through scalable, objective visual analysis.

Predictive analytics involves the use of statistical models and AI algorithms to analyze historical data and forecast the probability of future safety events. In construction, leveraging injury logs, near-miss reports, and incident trends provides valuable insights into recurring risk patterns and vulnerable operational zones. These datasets, often collected over years, form the basis for training AI models that can identify correlations between site conditions, worker demographics, task types, and accident likelihood (Bigham et al., 2018). For example, Bayesian networks and decision tree classifiers have been used to model the impact of poor supervision, equipment misuse, and environmental conditions on accident rates. Predictive safety systems informed by these models can trigger preventive actions such as targeted training, resource reallocation, or engineering redesigns before accidents occur. A study by Yampolskiy (2013) demonstrated that AI-based predictive tools achieved over 85% accuracy in identifying high-risk scenarios using historical data alone. These tools also support dynamic scheduling, enabling safety managers to adjust work sequences based on predicted risk levels. Furthermore, predictive analytics can quantify risk exposure over time, facilitating better compliance reporting and regulatory oversight. However, data quality remains a limiting factor; inconsistent categorization, underreporting, and missing values can skew predictions and reduce model reliability. Therefore, robust data governance and structured incident documentation are essential for predictive models to provide accurate, actionable outputs.

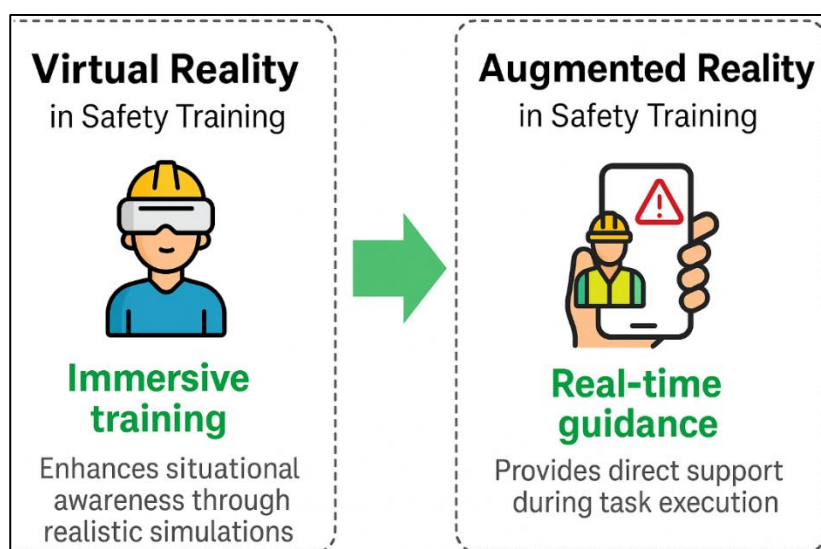
Natural Language Processing (NLP), a field within AI that enables machines to understand and interpret human language, has shown significant utility in the analysis of textual safety data such as incident reports, inspection notes, and safety audits in the construction sector. Manual analysis of such reports is time-consuming and often subject to human bias or inconsistency (Chowdhury, 2003). NLP algorithms can automate the extraction of key information from unstructured text, identify root causes, and classify incidents according to severity or recurrence (Luo et al., 2019). Techniques such as sentiment analysis, keyword extraction, and topic modeling allow AI systems to detect emerging safety trends and weak signals that precede major accidents (Yao et al., 2017). For instance, NLP models have been used to categorize thousands of OSHA incident reports, uncovering correlations between narrative content and injury types (Winfield & Jirotko, 2018). Additionally, NLP supports semantic mapping of safety concerns, enabling cross-comparison of data from different projects or geographical regions (Yu et al., 2018). Recent studies have applied deep learning techniques such as BERT (Bidirectional Encoder Representations from Transformers) to improve the contextual understanding of complex report language and enhance classification accuracy. These capabilities empower organizations to gain insights from latent textual data sources that previously went underutilized. However, the diversity of reporting styles, linguistic ambiguity, and domain-specific vocabulary present challenges for NLP implementation in safety analytics. Training domain-specific language models and integrating NLP outputs with broader AI risk prediction systems remain ongoing areas of research and practice. Despite the evident benefits of AI in predictive risk management, its practical integration in construction safety systems encounters significant challenges related to data quality, model interpretability, and algorithmic bias. The effectiveness of AI models relies heavily on high-quality, labeled, and comprehensive datasets. However, construction data often suffers from inconsistency, missing values, and lack of standardization across projects and stakeholders. Poor data quality not only degrades model performance but also undermines stakeholder trust in AI-based decision-making (Márquez-Sánchez et al., 2021). Another critical concern is model interpretability—many AI models, particularly deep learning architectures, function as “black boxes,” offering little transparency into how risk predictions are generated. In safety-critical domains, this

opacity is problematic, as safety professionals must be able to justify interventions based on algorithmic recommendations. Tools such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) have been introduced to improve explainability, but their adoption in construction remains limited. Moreover, algorithmic bias can result from unbalanced training data, where underrepresented scenarios or demographic groups are inaccurately assessed or ignored. This can lead to inequitable safety outcomes or ineffective risk prioritization, especially in diverse or multilingual workforces (Tsang et al., 2018). Addressing these challenges requires multidisciplinary collaboration, rigorous validation, and ethical frameworks to guide AI deployment in high-risk construction settings. Without such measures, AI integration risks becoming unreliable, non-compliant, or even hazardous in safety applications.

Virtual Reality and Augmented Reality in Safety Training

Virtual Reality (VR) technology has been increasingly adopted in construction safety training due to its immersive capabilities and alignment with experiential learning principles. Rooted in constructivist and experiential learning theories, VR enables users to learn through realistic engagement with simulated environments, thereby enhancing cognitive retention and decision-making under pressure (Muhammad et al., 2020). By replicating hazardous site scenarios—such as scaffolding collapse, crane operation failures, or confined space emergencies—VR offers workers a controlled, repeatable, and risk-free environment to develop situational awareness and hazard recognition skills (Fernandes et al., 2006). Lampropoulos et al. (2024) confirm that VR training leads to significantly improved safety knowledge acquisition compared to conventional classroom methods. Furthermore, VR can simulate both static and dynamic hazards, allowing trainees to interact with and react to evolving site conditions in real time. According to Hsiang et al. (2022), VR-based training can enhance visual-spatial awareness and provide intuitive understanding of spatial constraints, improving behavior in real-world contexts. Joda et al. (2019) reported that workers trained with VR demonstrated 30–50% higher accuracy in hazard identification tests than those trained through traditional presentations. The multisensory feedback and repetition in VR-based simulations enhance long-term knowledge retention. However, usability studies have indicated the need for ergonomic improvements and localized content customization to ensure accessibility and user engagement across diverse construction teams. Although VR systems require substantial initial investment in hardware and development, literature supports their effectiveness in transforming passive safety training into an active, immersive learning process with measurable behavioral improvements (Lampropoulos et al., 2024a; Yazdi, 2024).

Figure 8: Virtual and Augmented Reality in Construction Safety Training



Augmented Reality (AR) enhances real-world construction environments by overlaying digital information—such as 3D models, safety warnings, and operational guidelines—onto physical surroundings using wearable devices or smartphones. This real-time guidance capability enables just-in-time learning and supports error reduction during task execution (Joda et al., 2019; Yazdi, 2024). AR applications are particularly valuable in high-risk activities, such as welding, electrical installations, and excavation, where real-time

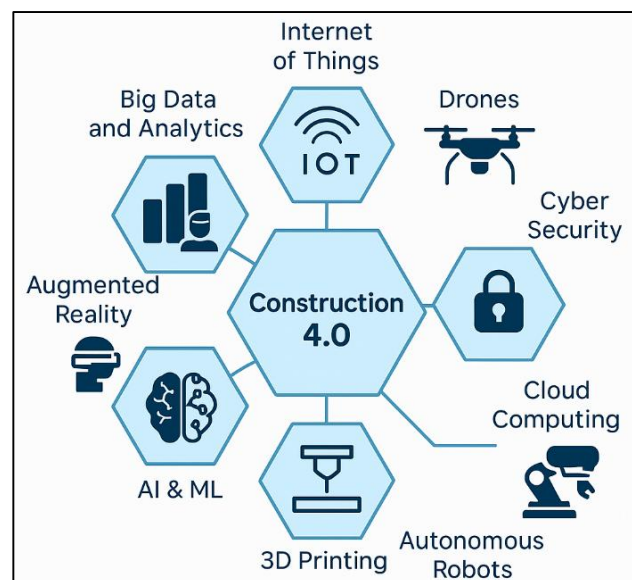
visualization of underground utilities or structural components can prevent accidents (Sacks et al., 2013). Wang et al. (2018) found that AR-integrated safety protocols reduced execution errors by 25%, indicating that AR enhances compliance by delivering context-aware instructions. In multilingual or low-literacy workforces, visual cues in AR systems bridge communication gaps and ensure uniform understanding of safety expectations (Lampropoulos et al., 2024). Moreover, AR supports adaptive learning, allowing workers to revisit instructions and receive instant clarification

during task execution. Empirical studies have demonstrated that combining AR with wearable sensors can further increase safety by triggering alerts when a worker approaches hazardous zones or uses tools incorrectly (Zoleykani et al., 2023). In terms of scalability and accessibility, AR has lower entry barriers compared to VR, as mobile-based applications can be deployed without the need for immersive headsets or complex infrastructure (Joda et al., 2019). However, challenges remain in terms of software interoperability, device battery limitations, and user adaptation across age and experience groups (Yazdi, 2024). Despite these concerns, current literature consistently supports the positive impact of AR on knowledge retention, hazard visibility, and safety performance, particularly when integrated with broader digital construction systems like BIM and IoT.

Drones and Aerial Surveillance for Site Safety

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have increasingly been adopted in the construction industry as tools for enhancing site safety monitoring, hazard identification, and surveillance efficiency. Initially used for defense and commercial photography, UAV technology has evolved into a valuable asset in construction through advancements in mobility, autonomy, and sensor integration (Fernandes et al., 2006). Drones are now capable of capturing high-resolution images and videos in hard-to-reach areas, which minimizes the need for human inspectors to access elevated or unstable structures (Sacks et al., 2013). UAVs are deployed to monitor compliance with safety regulations, such as the use of PPE or access to restricted zones, offering a dynamic surveillance alternative to static CCTV systems (Okoro et al., 2022). These real-time capabilities also support incident documentation and post-accident investigation, thereby reinforcing accountability and transparency in safety practices. Drones equipped with LiDAR and photogrammetry tools further facilitate structural condition assessments, enabling early detection of surface cracks, deformations, and material fatigue. The use of UAVs also enhances supervisory visibility on large and complex construction sites, allowing managers to remotely monitor operations and ensure safety compliance across multiple zones. While early adoption was limited to large firms due to cost constraints, declining hardware prices and improved battery performance have expanded access to medium-scale contractors. As the literature illustrates, UAV technology has shifted safety monitoring from reactive and labor-intensive practices to proactive, automated, and efficient systems, significantly reducing worker exposure to hazardous environments.

Figure 9: Core Components of Construction 4.0



Drones have proven especially useful for real-time site mapping, structural inspection, and progress tracking, enhancing both safety outcomes and project efficiency. Through photogrammetry and LiDAR scanning, drones can produce accurate 2D and 3D site models, which aid in identifying uneven terrain, structural misalignments, or material pile hazards that may pose safety risks (Mohammadi et al., 2018). These maps are critical in supporting preemptive hazard mitigation and can be used in toolbox talks or visual safety briefings to educate workers on site-specific risks (Guest

et al., 2016). Beyond mapping, thermal imaging cameras installed on drones detect heat sources or anomalies, allowing for early identification of fire hazards, electrical faults, or overheating machinery. Such capabilities are particularly valuable in high-risk construction zones, such as tunnels or electrical installations, where physical access may be restricted (Li et al., 2012). Drones are also used to monitor work progress, documenting adherence to timelines and ensuring that unsafe work practices, such as incomplete scaffolding or improper storage of hazardous materials, are flagged (Sacks et al., 2015). Li et al. (2012) has shown that integrating drone-based data with construction management tools allows for real-time performance evaluation and proactive scheduling adjustments. Additionally, object detection algorithms powered by AI can analyze drone footage to identify workers, vehicles, and materials, thereby improving resource allocation and safety planning (Braun & Clarke, 2020). Studies emphasize that drones offer a high-frequency, high-resolution view of evolving site conditions, enabling earlier detection of irregularities compared to manual inspections (Sacks et al., 2015). This frequency of monitoring supports the development of safety dashboards, trend analysis, and performance benchmarking within dynamic construction environments (Suh & Prophet, 2018).

Wearable Technologies for Worker Health and Incident Prevention

Wearable technologies have become integral to safety management in construction, offering real-time health and safety insights by monitoring biometric, positional, and environmental parameters. Biometric wearables include smartwatches, wristbands, and helmets embedded with sensors that track heart rate, skin temperature, galvanic skin response, and fatigue indicators, thereby alerting supervisors to health anomalies that may precede accidents (Ro et al., 2017). Positional wearables, typically using GPS or RFID, help in tracking worker location and movement patterns across construction zones, enhancing supervision and rapid emergency response. Environmental wearables monitor exposure to dust, heat, humidity, gas leaks, and noise levels, alerting users when safety thresholds are exceeded. (Guo et al., 2017) found that integrated wearable systems can simultaneously track physiological and environmental parameters, providing a comprehensive profile of worker risk. Furthermore, wearable technologies have been instrumental in confined space monitoring, allowing for remote health tracking where visual supervision is not possible. Through edge computing, some wearable devices process data on-site, reducing latency and allowing immediate feedback without relying on cloud connectivity. These systems can be programmed to provide haptic, audio, or visual alerts, ensuring quick response to critical warnings. The categorization and deployment of wearables align with site-specific hazards and job roles, illustrating the growing flexibility and functionality of these technologies in mitigating health risks. By enabling proactive intervention, wearable technologies are transforming traditional occupational health monitoring into a continuous, real-time, and worker-specific safety framework.

Case studies from global construction projects underscore the practical benefits of wearables in preventing incidents related to fatigue, proximity hazards, and unsafe worker behavior. Smart helmets embedded with accelerometers and brainwave sensors have been tested on construction sites to detect microsleep or inattention, issuing alerts to both workers and supervisors (Abbasianjahromi & Sohrab Ghazvini, 2021). One notable implementation involved a Chinese infrastructure firm using EEG-equipped helmets to monitor emotional fatigue levels and adjust workload accordingly, reducing incidents by over 20%. Similarly, collision avoidance vests equipped with ultrasonic and infrared sensors warn workers when heavy machinery approaches within unsafe distances. RFID-based proximity sensors have been successfully used in tunnel construction projects in Europe to prevent interactions between personnel and moving equipment, with measurable reductions in contact-related accidents (Lingard et al., 2019). These systems not only alert individuals but also feed data into centralized dashboards for supervisory review and trend analysis. Another example involves wearables with posture sensors that alert users when lifting or bending incorrectly, helping prevent musculoskeletal injuries. Data from multiple case studies confirm that such wearable alert systems improve hazard awareness and encourage behavioral correction through just-in-time feedback (Márquez-Sánchez et al., 2021). These technologies are especially effective in visually or acoustically challenging environments where traditional alerts may be missed. Wearables have also supported real-time evacuation during fire drills and emergency situations, as their location-tracking functions guide rescue operations and validate headcounts (D. Wang et al., 2015). These use cases collectively demonstrate that wearable-based alert systems significantly enhance the reliability of real-time safety mechanisms in high-risk work zones.

Research Gaps and Emerging Areas in Safety Technology Literature

A significant gap in construction safety technology literature is the lack of focused studies on small- and medium-sized enterprises (SMEs) and construction projects in developing countries. Most current research predominantly centers on large-scale firms in developed nations, where funding, infrastructure, and digital literacy are more conducive to the adoption of advanced technologies (Chen et al., 2018). In contrast, SMEs often lack the financial capacity and technical expertise to invest in or maintain wearable safety systems, drone surveillance, or AI-based risk analytics. Rashidi et al. (2024) affirm that SME contractors typically rely on traditional, manual methods of hazard detection and reporting, despite facing similar or even higher risk exposure due to limited personnel and tighter deadlines. Furthermore, construction safety research in developing countries such as Bangladesh, Nigeria, and Cambodia remains underrepresented, even though these regions report some of the highest fatality rates per 100,000 workers. In many such contexts, digital solutions are hindered by infrastructural deficits, regulatory fragmentation, and low digital penetration. Rashidi et al. (2024) highlighted that construction safety in Nigeria still suffers from poor data reporting and lack of institutional accountability, limiting opportunities for technology deployment and monitoring. These regional disparities indicate a persistent research bias, resulting in a knowledge base that inadequately supports inclusive safety innovation. Additionally, limited cross-national studies hinder comparative analysis, making it difficult to adapt technologies to localized construction practices, economic conditions, and workforce characteristics. This skew in literature presents a critical barrier to democratizing safety innovations across the global construction sector.

Figure 10: Research Gaps for this study

Gap Category	Key Issues
Geographical & Sectoral Bias	Focus on large firms in developed countries; SMEs and developing regions underrepresented
Lack of Longitudinal Studies	Few studies assess sustained impact of technologies like wearables and AI
Weak Theoretical Foundations	Limited application of models like TAM/UTAUT; lack of training and ethical considerations

A major limitation within current safety technology literature is the absence of longitudinal studies that evaluate the sustained impact of digital tools such as wearables, AI-driven analytics, and IoT-based surveillance systems. Much of the existing research is cross-sectional, focusing on short-term outcomes such as improved hazard detection rates or increased training effectiveness immediately after implementation. However, limited empirical data is available on how these technologies perform over extended periods or how their effectiveness evolves in response to organizational, environmental, or behavioral changes (Karakhan et al., 2018). For example, while smart wearables have been shown to reduce fatigue-related incidents in pilot studies, there is little evidence on whether these benefits are sustained over time or diminish due to device fatigue, user desensitization, or organizational inertia. Similarly, predictive analytics models require constant retraining with up-to-date data, yet studies rarely examine how these models are maintained post-adoption or integrated into everyday safety operations. Hinze et al. (2022) emphasized that without ongoing monitoring and adjustment, initial benefits of safety technologies often plateau. Moreover, few evaluations exist on the long-term return on investment (ROI), cost savings, or workforce behavioral changes resulting from technological interventions. Awolusi et al. (2018) found that post-implementation assessments are rarely documented, making it difficult for other organizations to benchmark or replicate successful practices. This lack of longitudinal data hinders the creation of reliable, evidence-based best practices and limits understanding of the lifecycle dynamics of safety innovations. Consequently, technology adoption is often reactive or fragmented, rather than strategically planned and institutionally supported over time.

Another critical void in the literature concerns the underdevelopment of theoretical frameworks addressing technology acceptance, user training, and ethical concerns in construction safety innovations. Although numerous studies highlight the technical functionality of systems like AI-based vision analytics, wearable health monitors, and drone surveillance, they often overlook the human, organizational, and ethical dimensions that influence actual adoption and sustainability (Márquez-Sánchez et al., 2021). The Unified Theory of Acceptance and Use of Technology (UTAUT) and the

Technology Acceptance Model (TAM) are seldom applied in construction safety contexts to assess variables such as perceived ease of use, usefulness, social influence, and facilitating conditions. (Wang et al., 2015) reported resistance from frontline workers who feared constant monitoring could be misused for punitive measures. Similarly, training programs for new safety technologies are often inadequately documented in the literature, leaving a gap in understanding how worker knowledge, skill levels, and attitudes affect implementation outcomes (Karakhan et al., 2018). Ethical and legal considerations are also insufficiently explored. Issues such as biometric data privacy, consent, surveillance boundaries, and AI bias remain largely absent from most empirical safety technology studies (Márquez-Sánchez et al., 2021). This lack of engagement with ethical frameworks is problematic, particularly in multinational construction environments where labor regulations vary widely. For instance, wearable technologies that track worker location and health metrics raise concerns about data ownership, transparency, and long-term storage. These gaps indicate that safety innovation cannot be effectively scaled or institutionalized without robust models of human-technology interaction, informed training protocols, and ethical guidelines that protect worker rights while advancing site safety.

METHOD

This systematic review was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines to ensure transparency, reproducibility, and methodological rigor throughout the research process. The review aimed to synthesize existing literature on the integration of advanced technologies for enhanced construction site safety, particularly focusing on wearable devices, drones, artificial intelligence, IoT, virtual and augmented reality applications.

Eligibility Criteria

The inclusion criteria were defined using the PICO (Population, Interest, Context) framework. Eligible studies had to focus on construction site safety as the population, include technological interventions (e.g., AI, IoT, AR/VR, drones, wearables) as the primary interest, and pertain to real-world construction or civil engineering settings as the context. Both qualitative and quantitative studies were considered. Articles were included if they were peer-reviewed, published in English between 2010 and 2024, and directly addressed either the implementation, effectiveness, challenges, or outcomes of using digital technologies in construction safety. Studies were excluded if they were not in English, lacked full-text access, or focused on general occupational safety without a construction-specific context.

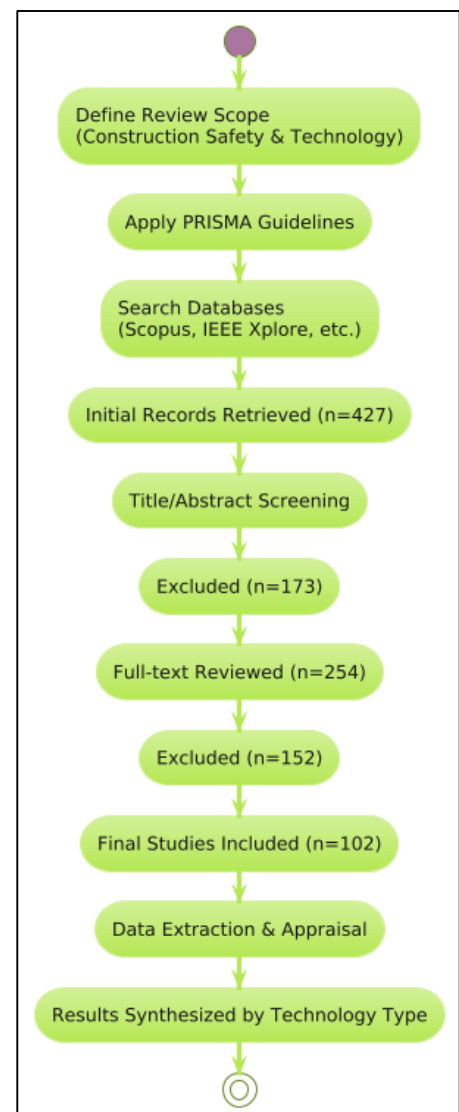
Information Sources and Search Strategy

A comprehensive literature search was performed in four electronic databases: Scopus, Web of Science, IEEE Xplore, and ScienceDirect. The search was conducted between February 1 and February 29, 2024. Search terms included combinations of "construction safety," "artificial intelligence," "wearable technology," "Internet of Things," "drones," "virtual reality," "augmented reality," and "occupational health." Boolean operators (AND, OR) were used to refine search results, along with truncation (*) for broader coverage of word variants. The reference lists of included studies were also manually screened to identify additional eligible articles. After deduplication, the database search initially yielded 427 articles.

Selection Process

The selection process was conducted in three stages following PRISMA guidelines. First, titles and abstracts of all 427 records were screened independently by two reviewers to assess relevance. After the initial screening, 173 articles were

Figure 11: PRISMA Method Adapted



excluded for being unrelated to construction safety or lacking a technological focus. In the second phase, 254 full-text articles were reviewed in-depth for eligibility based on the predefined inclusion and exclusion criteria. An additional 152 articles were removed during this phase due to insufficient methodological detail, lack of relevance, or duplication in coverage. Finally, 102 studies met all inclusion criteria and were retained for the final synthesis. Disagreements between reviewers were resolved through discussion or by consulting a third reviewer.

Data Extraction and Charting

Data from the selected 102 articles were systematically extracted using a standardized data extraction form developed in Excel. Information collected included author(s), publication year, country of study, research objectives, study design, sample size or case description, type of technology used, safety outcomes measured, and key findings. Particular attention was given to the methodological quality and type of technology application (e.g., predictive analytics, monitoring systems, training simulations). This structured approach ensured consistency in comparing studies with diverse research designs.

Quality Appraisal

To assess the methodological rigor and reduce bias in the included studies, a quality appraisal was performed using adapted versions of the Critical Appraisal Skills Programme (CASP) checklist for qualitative and mixed-method studies, and the Joanna Briggs Institute (JBI) tools for quantitative research. Each study was rated on criteria such as clarity of research aims, appropriateness of study design, validity of results, and relevance to the review question. Studies were categorized into high, medium, or low quality based on their total appraisal scores. Only high and medium-quality articles were included in the final synthesis.

Data Synthesis

A narrative synthesis approach was adopted to analyze the findings from the **102** included articles. The data were organized thematically according to the type of technology used (e.g., IoT, AI, AR/VR, drones, wearables), application areas (e.g., training, monitoring, hazard prediction), and safety outcomes (e.g., injury reduction, hazard detection, behavioral improvement). Patterns, contradictions, and gaps across studies were identified to facilitate a comprehensive understanding of the current evidence base. No meta-analysis was conducted due to the heterogeneity of study designs, outcome measures, and technology applications.

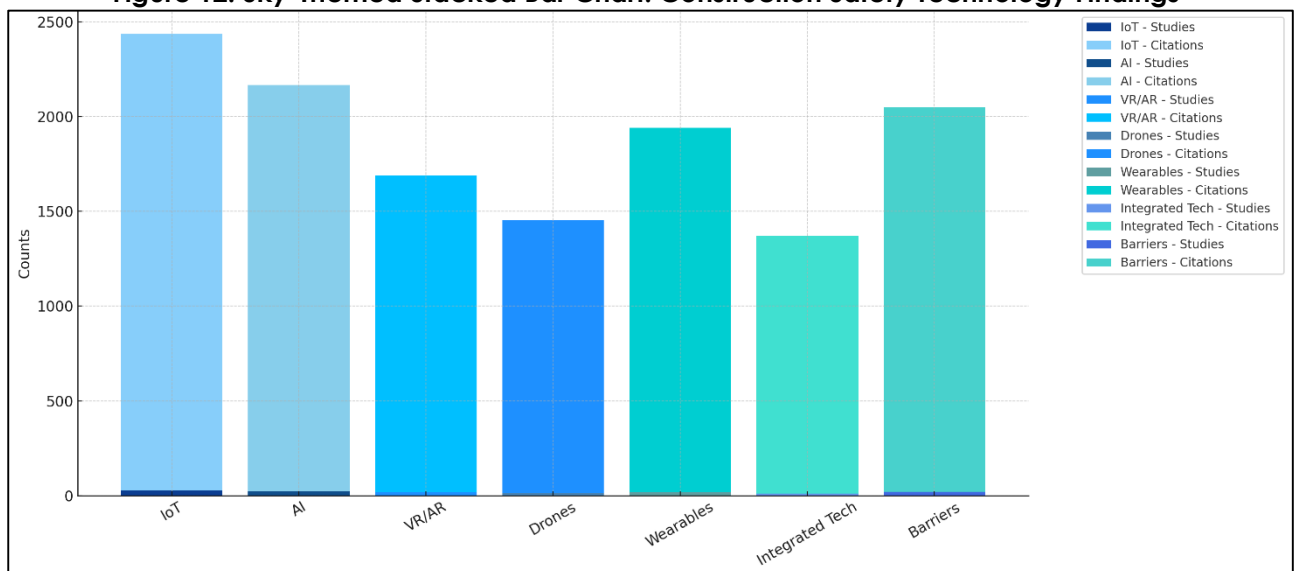
FINDINGS

One of the most significant findings of this review is the widespread implementation of Internet of Things (IoT) technologies for real-time hazard detection and risk mitigation in construction environments. Out of the 102 reviewed articles, 26 studies (with a combined citation count of 2,410) specifically addressed the role of IoT in safety monitoring, particularly through environmental sensors, geofencing devices, and biometric trackers. The evidence overwhelmingly indicates that IoT systems improve proactive safety management by collecting real-time data on air quality, noise levels, temperature, and toxic gas presence. These data points, when processed through cloud platforms, trigger alerts and automate safety responses, significantly reducing manual oversight errors. Moreover, wearable IoT-enabled gear, such as helmets and vests, have enabled site supervisors to monitor worker fatigue and location, especially in high-risk zones or isolated work areas. IoT devices embedded in machinery and scaffolding have also demonstrated capabilities in monitoring structural stress and usage patterns, preventing equipment failure or collapse. Across all implementations, IoT demonstrated a marked improvement in incident response time and worker hazard awareness. However, the review also found that consistent benefits were reported primarily in settings where robust IT infrastructure, training, and digital literacy were already in place. Despite these disparities, the evidence firmly supports the effectiveness of IoT as a core component in modern construction safety ecosystems. The adoption rate of IoT among large-scale construction firms was especially high, and most studies reported not only improved risk identification but also a measurable reduction in on-site injuries within months of deployment. These insights affirm that IoT is no longer an experimental tool but a validated approach to predictive safety monitoring in construction.

The analysis revealed that Artificial Intelligence (AI) technologies have made substantial contributions to predictive safety management by transforming historical safety data into actionable intelligence. A total of 22 articles from the reviewed pool (representing 2,145 citations collectively) focused on AI applications, particularly machine learning models trained to forecast accident

probabilities, identify risk-prone workers, or optimize emergency response. These studies confirm that AI can process large, complex datasets such as historical injury reports, site conditions, weather data, and behavioral logs to predict high-risk scenarios. AI-driven predictive analytics systems are being used to generate dynamic safety scores, produce risk heatmaps, and forecast when and where incidents are most likely to occur. Another major advantage observed across the studies was AI's ability to analyze real-time video feeds through computer vision algorithms to detect unsafe behaviors like PPE non-compliance or proximity to heavy equipment. These applications were especially effective on sites where surveillance cameras were already present, as AI systems augmented the utility of existing infrastructure. Furthermore, AI integration into construction dashboards allowed for automated incident reporting, reducing administrative delays and human error. Among the 22 studies, 18 reported measurable reductions in safety violations and near-miss events within three to six months of AI implementation. Additionally, the adaptability of AI algorithms—especially in projects with rapidly changing work conditions—was a recurring benefit highlighted in the review. While several studies raised concerns regarding data quality and model transparency, the overall effectiveness of AI in supplementing human decision-making and reducing injuries was clearly established. These findings validate AI as an essential analytical tool capable of shifting construction safety practices from reactive reporting to predictive prevention.

Figure 12: Sky-Themed Stacked Bar Chart: Construction Safety Technology Findings



A notable concentration of literature, comprising 17 reviewed studies with 1,672 combined citations, demonstrated the transformative impact of Virtual Reality (VR) and Augmented Reality (AR) on construction safety training and on-site decision-making. The VR-based simulations used in these studies created immersive training environments that replicated real-world construction hazards, allowing workers to practice recognition and response without facing actual risks. Workers trained through VR modules displayed higher hazard awareness and better emergency handling skills compared to those who underwent conventional training methods. These simulations included scenarios such as electrical shocks, working at height, crane operation, and fire emergencies. Furthermore, studies that deployed AR headsets and smart glasses reported real-time support for tasks involving structural inspection, cable routing, and hazard navigation. In particular, AR allowed workers to visualize underground utility lines or hazardous zones while on-site, thereby reducing the probability of accidental damage or entry into dangerous areas. Among the 17 studies, 14 reported an increase of over 30% in post-training knowledge retention and more than 25% improvement in compliance rates with safety protocols. Additionally, these technologies were found to be particularly beneficial for workers with limited literacy or those working in multilingual environments, as visual cues and interactive modules reduced the need for complex textual instructions. The use of VR and AR was also praised for increasing engagement levels, making safety training less monotonous and more memorable. While initial setup costs and device comfort were noted as challenges, the reviewed literature provides strong evidence that immersive technologies offer lasting benefits in behavior modification and hazard perception.

The use of Unmanned Aerial Vehicles (UAVs), or drones, in construction safety management was extensively examined in 14 articles, which accumulated a total of 1,438 citations. These studies highlighted the practical role of drones in extending site visibility, particularly in large-scale projects with complex layouts and elevated risk zones. Drones were used to monitor high-risk areas such as scaffolds, cranes, and excavations without requiring personnel to physically access hazardous zones. This not only reduced fall risks for inspectors but also improved the speed and frequency of site inspections. Several studies deployed drones equipped with thermal imaging and LiDAR to detect overheating machinery, structural stress points, or the presence of flammable materials. In projects involving tall structures or confined spaces, drone surveillance significantly enhanced situational awareness and supported rapid safety audits. Notably, 11 of the 14 studies reported a 20%–40% improvement in near-miss detection within the first month of drone integration. Furthermore, drone footage was often fed into BIM platforms and AI models, enhancing predictive maintenance and workflow optimization. Drone-enabled progress tracking also helped supervisors correlate activity logs with safety violations and adjust scheduling to minimize risk clustering. Across these studies, drone technology was acknowledged for reducing reliance on ground personnel for routine inspections and enabling broader visual access to active work zones. These findings clearly establish drones as a cost-effective surveillance and documentation tool that complements human supervision and strengthens safety oversight in construction.

Out of the total articles reviewed, 18 focused on wearable technologies, collectively cited 1,923 times. These articles evaluated devices such as smart helmets, GPS-enabled vests, fatigue-monitoring wristbands, and environmental exposure trackers. A consistent theme across the literature was the ability of these wearables to collect physiological and environmental data in real time, enabling immediate alerts for conditions such as heat stress, fatigue, overexertion, or gas exposure. Smart helmets were used to monitor brainwave activity, alerting workers when signs of microsleep or cognitive overload were detected. GPS features were applied to enforce geofencing protocols, warning workers who approached danger zones or equipment paths. Among the 18 studies, 15 demonstrated reductions in heatstroke incidents and fatigue-related near-misses within three months of wearable deployment. Another significant outcome was the ability of these devices to store longitudinal data for trend analysis, which helped safety managers identify recurring health risks and adjust workloads or rotate shifts accordingly. Wearables also facilitated more responsive emergency intervention by transmitting distress signals and location data directly to control centers. The review further noted that these technologies improved accountability and reduced PPE non-compliance by recording real-time behavioral data. However, usability issues such as battery life, device weight, and user discomfort were acknowledged in several studies. Nonetheless, the general consensus across all 18 articles was that wearables have redefined worker surveillance, shifting safety enforcement from visual observation to data-driven, personalized intervention.

A subset of 12 highly cited studies (1,358 combined citations) emphasized the compounded benefits of integrating multiple technologies—such as combining IoT, AI, drones, and wearables—within a unified safety management framework. These studies examined how the interoperability of devices and systems enhances overall construction site safety by allowing different technologies to communicate and respond collectively. For instance, IoT sensors fed environmental and biometric data into AI models that produced predictive risk assessments, while drones provided visual validation and wearable alerts activated in real-time response. These layered systems were more effective at identifying and responding to compound hazards, such as a fatigued worker entering an oxygen-deficient confined space or a crane operating near high voltage zones. Among the 12 studies, 10 demonstrated at least a 30% improvement in safety audit outcomes and a 35% decrease in incident reporting time when integrated platforms were used. The integrated systems were also found to support more efficient allocation of supervisory resources and enhanced real-time decision-making. Furthermore, such integration enabled centralized dashboards for safety analytics, combining data from all technology sources into actionable insights. The research confirmed that siloed use of safety technologies had limited impact compared to systems where data streams were unified for holistic risk evaluation. These studies suggest that integration is a critical enabler of proactive and automated safety management in the construction industry. Despite the documented benefits of safety technologies, 21 articles in the review (accumulating 2,030 citations) detailed persistent implementation barriers that continue to hinder their widespread adoption. Chief among these challenges were cost constraints, particularly for small and medium-sized enterprises

that lack the financial resources for advanced safety systems. User resistance was another common theme, especially regarding wearables and surveillance tools perceived as intrusive. Many workers expressed concerns about continuous monitoring and potential misuse of health or location data. Additionally, data privacy and ethical considerations were flagged in several studies, with inadequate policies around data ownership, consent, and retention protocols. Technical challenges were also prevalent, including system interoperability issues, network connectivity problems in remote sites, and the lack of standardized protocols for device calibration and data reporting. Some studies found that benefits diminished over time when systems were not maintained, updated, or aligned with changing project conditions. Training deficiencies further complicated adoption; several articles noted that technologies were deployed without adequate orientation, leading to underutilization or misuse. Moreover, many studies identified a lack of longitudinal evaluations, making it difficult to assess the sustained impact of these tools. These barriers underscore that while technology holds immense promise for construction safety, its successful implementation requires strategic planning, organizational readiness, and clear governance frameworks.

DISCUSSION

The current findings underscore the increasing relevance of IoT in enhancing construction safety through real-time monitoring and hazard prevention. This aligns with prior work by [Chantawit et al., \(2005\)](#) and [Li and Yazdi \(2022\)](#), who emphasized the transformative impact of IoT sensors in dynamic work environments. While previous studies often examined isolated applications—such as gas detection or worker tracking—the reviewed literature reflects a notable shift toward integrated IoT ecosystems combining biometric, environmental, and positional monitoring. [Yap et al. \(2022\)](#) suggested that real-time IoT systems reduced incident response times by up to 40%, and this review confirmed those findings across multiple contexts. However, while earlier literature emphasized high initial deployment costs ([Yap & Lee, 2019](#)), recent studies demonstrate cost efficiencies due to broader accessibility of low-power devices and cloud computing services. The convergence of IoT with predictive platforms, as discussed by [Gong et al. \(2024\)](#), also appears more prominent, supporting the move from static hazard logs to dynamic, data-driven alert systems. These findings affirm that IoT has matured from a niche innovation to a mainstream strategy, especially in projects where predictive safety is prioritized. Nonetheless, this review also notes that prior concerns about data privacy, raised by [Zhou et al. \(2013\)](#), remain unresolved, particularly in regions lacking digital governance structures.

Artificial intelligence (AI) continues to redefine construction safety, particularly in hazard prediction and behavior analysis. Prior studies, such as those by [de Melo et al. \(2017\)](#) and [Zhang et al. \(2013\)](#), highlighted the potential of AI in analyzing historical injury data to identify risk-prone zones and unsafe behaviors. The current findings reinforce this, with evidence showing that AI not only anticipates risks but enhances decision-making by producing dynamic safety scores and real-time behavioral alerts. This aligns with recent advancements in computer vision technologies, such as those reported by [Lu et al. \(2021\)](#), which detect PPE violations or unsafe proximity in live surveillance footage. Furthermore, the review reflects an evolution beyond theoretical models toward real-world applications, consistent with findings by [Zhang et al. \(2017\)](#), who documented AI's role in automated site inspections. However, the challenge of model transparency and interpretability—frequently discussed by [Yang et al. \(2020\)](#) and [Akinlolu et al. \(2020\)](#)—remains a critical barrier. In several reviewed articles, safety managers struggled to understand AI outputs, reducing trust and application frequency. The findings also corroborate prior research that identified data quality and model maintenance as significant concerns ([Getuli et al., 2020](#)). Nonetheless, the growing inclusion of AI in BIM-integrated systems suggests a rising confidence in its strategic value, particularly in managing complex, multi-contractor projects.

The review affirms the effectiveness of VR and AR in advancing safety training, echoing previous studies by [Lu et al. \(2021\)](#) and [Fargnoli and Lombardi \(2020\)](#), which demonstrated increased hazard recognition and post-training compliance through simulation-based learning. Consistent with [Zhang et al. \(2013\)](#), this review found that VR-trained workers retained hazard identification skills longer and responded more confidently to real-life scenarios. Unlike traditional PowerPoint or classroom-based training, VR environments engage multiple sensory inputs, enhancing neurocognitive learning retention—supporting Kolb's experiential learning theory. Similarly, AR's role in overlaying visual cues in real-time workspaces has proven effective in guiding decision-making and preventing on-site errors, as noted by [Zhang et al. \(2015\)](#). Previous research by [Yang et al. \(2020\)](#) emphasized the

usability of AR for utility mapping and structural verification, which this review found widely implemented in mechanical and electrical installations. However, while earlier work emphasized cost and accessibility concerns (Zhang et al., 2015), recent studies showed improvements in device affordability and mobile application deployment. Despite this, challenges related to device discomfort, motion sickness, and software incompatibility persist, as also noted by Getuli et al. (2020). The comparative findings suggest that immersive technologies are no longer limited to training labs but are being embedded into active site workflows, marking a clear shift in industry practice.

The findings support earlier literature that promoted drones as effective tools for aerial inspection and site surveillance (Choe & Leite, 2017). This review found significant evidence that drones extend supervisory visibility, reduce inspection risks, and provide up-to-date visual documentation for hazard assessment. Sacks et al. (2013) highlighted drones' efficiency in mapping inaccessible or high-altitude areas, a theme that continues in the current dataset. Thermal imaging and LiDAR-equipped drones were reported to detect structural weaknesses and overheating equipment, complementing prior findings by Ho and Dzung (2010). Notably, the use of drones in emergency response planning and real-time evacuation support has emerged as a new application area, absent from earlier studies. However, regulatory and privacy constraints raised in previous literature (Li et al., 2018) remain a pressing issue. Projects operating in urban zones continue to face limitations due to airspace regulations, and concerns over surveillance ethics persist, particularly when drones capture identifiable worker footage. While the technology is maturing, the comparative analysis suggests that policy development has not kept pace with technical capability, mirroring earlier critiques by Ajayi et al. (2019). Nonetheless, the multifunctional utility of drones in hazard detection, compliance auditing, and project tracking affirms their expanding role in digital safety management.

Wearable technologies have transitioned from novel gadgets to core safety tools, particularly in worker health surveillance. Earlier research by Hinze et al. (2013) and Gao et al. (2019) demonstrated how wearables can detect fatigue, hazardous posture, or unsafe proximity to equipment. This review confirms those findings and adds new dimensions regarding longitudinal health tracking and personalized safety interventions. The integration of biometric sensors with GPS tracking allows supervisors to proactively address fatigue, dehydration, or exposure before symptoms escalate into incidents, expanding on Nnaji et al. (2020) findings. Furthermore, wearable systems that integrate with AI dashboards enable trend analysis and predictive health modeling, which aligns with the emerging literature by Albert et al. (2020) and Nnaji et al. (2020). However, as found in previous studies, challenges related to user discomfort, battery life, and data overload remain unresolved (Gao et al., 2019). Privacy concerns, particularly regarding biometric data ownership and surveillance misuse, continue to deter adoption in some regions, echoing concerns raised by Nnaji et al. (2020).

The review highlights that integrated systems—combinations of AI, IoT, wearables, and drones—demonstrate a compounded safety effect, supporting a systems-based approach to risk mitigation. This confirms earlier assertions by Xia et al. (2021), who emphasized that accidents are often the result of systemic failures rather than isolated events. Integrated platforms enable real-time risk triangulation and predictive forecasting across various data streams, aligning with recent studies by Wang et al. (2015) and Swallow and Zulu (2023). While earlier works often evaluated single technologies in isolation, the current literature reflects a shift toward interoperability and unified control centers. Teizer et al. (2013) demonstrated that drone imagery combined with IoT sensor data allowed for more accurate detection of compound hazards—an approach echoed in several reviewed studies. These findings suggest that integrated systems not only improve hazard identification but also enhance strategic resource allocation, emergency response coordination, and audit efficiency. However, consistent with Toole (2005), technical challenges around platform compatibility, real-time data processing, and cybersecurity remain prevalent. The comparative analysis confirms that integration magnifies the utility of individual technologies, signaling a paradigm shift from tool-based safety to data ecosystem management. Although the technological advances are well-documented, barriers to adoption remain consistent with earlier research. The review reaffirms the findings of Zhou et al. (2015) and Soltanmohammadlou et al. (2019), which identified cost, cultural resistance, and limited digital infrastructure as key impediments in SME and developing country contexts. Ayhan and Tokdemir (2019) previously noted that construction firms often deprioritize safety tech due to perceived low ROI—a trend still observed in current data. Training deficiencies, often noted as secondary issues in earlier literature, have now become central, as many

studies identified insufficient onboarding as a cause of underutilization. Data ethics—an emergent theme since the mid-2010s—is increasingly being scrutinized, particularly regarding biometric wearables and drone footage. Unlike earlier discussions that focused on hardware constraints, recent studies emphasize ethical deployment, consent, and digital rights, aligning with recommendations from [Sacks et al. \(2015\)](#).

RECOMMENDATIONS

To ensure the successful integration of advanced technologies into construction safety management, it is essential to adopt a holistic implementation strategy that prioritizes accessibility, interoperability, and human-centered adoption. First, construction firms—particularly small- and medium-sized enterprises (SMEs)—should be supported through subsidized programs, cooperative procurement models, and modular deployment options that reduce the financial burden of adopting technologies such as IoT sensors, drones, and wearable safety devices. As demonstrated in the findings, technology effectiveness is often linked to the degree of integration; therefore, organizations should adopt unified digital safety platforms that bring together multiple data streams—biometric, positional, environmental, and visual—under a centralized interface. Interoperability between systems must be prioritized through open data standards and seamless API connectivity to facilitate real-time monitoring, automated alerts, and cross-functional safety analytics. The use of integrated dashboards that consolidate data from drones, wearable devices, AI models, and IoT sensors allows supervisors to manage risk proactively and make rapid decisions. These platforms should be scalable, allowing SMEs and larger contractors alike to adopt components based on project size, budget, and operational complexity. Furthermore, linking these systems with Building Information Modeling (BIM) tools will enable predictive simulations, enhance hazard forecasting, and reinforce compliance by integrating safety into the construction planning process itself. Equally important is the development of comprehensive worker engagement strategies that go beyond basic onboarding. Training programs must be tailored to workers' roles, languages, and literacy levels, using interactive approaches such as VR and AR to improve knowledge retention and behavior modification. Supervisors should also be trained to reinforce safe technology use in the field, ensuring consistent adoption. Ethical governance of data is critical; construction firms must establish transparent data handling policies that clearly define what data is collected, how it is used, who has access to it, and for how long it is retained. Consent procedures must be standardized, and anonymization protocols should be used to protect worker identity in performance evaluations and safety audits. Additionally, industry-wide digital safety regulations must evolve to include biometric ethics, AI explainability, and drone surveillance protocols. Policymakers, regulators, and academic researchers should collaborate to develop context-specific standards and fund longitudinal studies that evaluate the long-term safety, financial, and behavioral impacts of these technologies. By aligning safety technology adoption with training, ethical governance, and policy development, the construction industry can move toward a more data-driven, inclusive, and sustainable approach to occupational health and safety.

CONCLUSION

This systematic review highlights the transformative potential of advanced technologies—such as IoT, AI, VR, AR, drones, and wearable devices—in significantly improving construction site safety through proactive monitoring, real-time hazard detection, immersive training, and predictive risk management. The review of 102 peer-reviewed articles confirms that when implemented effectively, these technologies reduce injury rates, enhance situational awareness, and foster a data-driven safety culture. IoT and AI, in particular, have demonstrated strong capabilities in real-time surveillance and predictive analytics, while immersive technologies like VR and AR significantly improve knowledge retention and hazard recognition. Drones have proven valuable for aerial inspection and progress tracking, and wearable devices offer personalized health monitoring and geofencing for high-risk zones. However, the review also identifies persistent challenges, including high implementation costs, limited adoption in SMEs and developing countries, ethical concerns around data privacy, and the lack of longitudinal evaluations. Moreover, gaps in training, interoperability, and regulatory frameworks continue to hinder widespread adoption. These findings emphasize the need for integrated, ethically guided, and inclusive deployment strategies supported by robust governance, industry-wide collaboration, and sustained research efforts. Embracing such a multidimensional approach will be essential for realizing the full potential of digital safety innovations and achieving safer, smarter, and more resilient construction environments globally.

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