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A Theoretical Framework for Real-time Construction Workers' Safety Enhancement using Technological Integration

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Abstract

Construction sites remain high-risk workplaces due to changing conditions and diverse tasks. Most existing safety systems emphasize pre-work planning and regulatory compliance but provide limited support once operations begin. This paper presents an AI-Based Safety Control Room (AISCR) as a practical framework for real-time site safety. The framework integrates three data streams: (i) historical records, including OSHA reports and past incidents; (ii) live inputs from IoT sensors, wearables, and cameras; and (iii) contextual sources such as BIM models and site layouts. These inputs are processed and structured to train computer vision and time-series models for hazard detection and prediction. Identified risks are scored and visualized through dashboards connected to a digital twin of the project. Supervisors can review alerts, confirm events, and give feedback, which is then used to refine system performance. The objective is to shift construction safety from a reactive approach toward timely, data-driven decisions that help lower accidents and near-miss events.

Keywords
Construction Safety Management, Artificial Intelligence (AI), Digital Twin, Real-Time Monitoring, IoT and Wearable Sensors

1. Introduction

Construction is among the most hazardous industries, with workers exposed to dynamic site conditions and complex tasks. In the United States, it consistently records the highest number of workplace deaths among private industries. According to the Bureau of Labor Statistics (2024), 1,075 construction workers lost their lives in 2023, representing a large share of the 5,283 occupational fatalities reported nationwide. Falls from height accounted for 421 of these deaths, followed by struck-by, electrocution, and caught-in/between accidents (U.S. Bureau of Labor Statistics, 2024). These four categories, widely recognized as OSHA's "Fatal Four," are responsible for nearly two-thirds of annual construction fatalities.

Although regulations, safety training, and inspection programs have been in place for decades, fatality rates remain unacceptably high. Traditional safety management methods are mainly reactive, addressing hazards during scheduled inspections or after incidents (Zhou et al., 2015). This delay between the emergence of risks and their detection often allows conditions to worsen before any corrective action is taken. For example, scaffold instability caused by improper assembly or overloading may not be identified until after a near miss or serious accident. As construction projects grow larger and more complex, with multiple contractors working under tight deadlines, the limitations of these conventional methods become even more apparent. These challenges highlight the need for proactive, real-time systems capable of monitoring site conditions, forecasting hazards, and supporting timely decisions to prevent accidents before they occur.

Recent advances in digital technology have brought new tools to construction safety, including Building Information Modeling (BIM), Internet of Things (IoT) sensors, wearable devices, computer vision, and extended reality (XR). Digital twin, robotics and drone have been widely used for hazard identification during the design stage, but its application rarely extends into the active construction phase for continuous risk monitoring (Wang et al., 2013; Zhang et al., 2013). IoT systems have improved site awareness by tracking environmental conditions such as temperature, dust, and gas levels. However, most of these applications remain limited in scale and are not well connected to broader safety management processes (Alizadehsalehi et al., 2020).

Computer vision has been tested for automatic detection of safety issues, such as missing personal protective equipment (PPE) or unsafe worker–equipment interactions. While effective in isolated use, many of these systems function as independent tools without integration into centralized safety platforms (Delhi et al., 2020). Similarly, XR technologies have been applied to safety training through immersive simulations but are still rarely used for live site monitoring or decision support (Muñoz-La Rivera et al., 2025). Taken together, these technologies mark steady progress, but their isolated use has created a fragmented landscape. The following sections provide a more detailed review of key safety-related technologies, examining their current capabilities and limitations in construction projects.

1.1 Artificial Intelligence (AI) for Proactive Safety Management

Artificial Intelligence (AI) is becoming an important tool for improving safety in construction. While its use on active sites is still new, AI has the potential to move safety practices from reacting to accidents toward preventing them before they happen. Using machine learning and deep learning, AI can study past incidents and real-time data to find patterns, predict risks, and help managers make quick decisions (Jiang et al., 2021). One common use of AI is computer vision, which uses cameras to watch site activities and detect issues like missing PPE or workers getting too close to dangerous equipment (Lee & Lee, 2023). AI can also make the construction process smoother by improving decision-making and linking different safety tools together. When combined with IoT sensors, wearable devices, and digital twins, AI works as the “brain” of the system, bringing all the data into one place for real-time alerts and risk scores (Vukicevic et al., 2024). However, most AI efforts today are small-scale or stand-alone projects, showing the need for integrated systems that can manage site-wide safety more effectively (Berlato et al., 2025).

1.2 Building Information Modeling (BIM) for Safety Planning and Visualization

Building Information Modeling (BIM) is now a well-established tool for improving safety in the design and pre-construction phases. It allows stakeholders to build digital models of structures, where hazards can be identified and risks simulated before physical work begins (Zhang et al., 2013). For example, temporary works such as scaffolding and formwork can be modeled to highlight possible points of failure or access problems (Kim et al., 2016). However, BIM’s role in safety during the construction phase remains limited. It is seldom linked with real-time data sources such as sensor feeds or worker location systems that could support continuous monitoring of risks while work is in progress (Wang et al., 2013). This means that while BIM offers strong capabilities for visualization and planning, it is often disconnected from day-to-day site management, leaving an important gap in proactive safety control.

1.3 Internet of Things (IoT) for Environmental and Process Monitoring

The Internet of Things (IoT) has opened new possibilities for collecting real-time environmental and operational data on construction sites. IoT devices can monitor conditions such as temperature, noise, dust, vibration, and the presence of harmful gases, giving safety managers improved awareness of site conditions (Awolusi et al., 2018). These systems are particularly useful in high-risk environments, such as confined spaces or tall structures, where conventional monitoring is difficult. Despite these benefits, IoT applications in construction are often narrow in scope. Many systems focus on a limited set of variables and operate in isolation from other safety technologies or management tools (Anjum & Luz, 2024). Without integration into broader safety platforms, much of the data generated remains unused, reducing its value for proactive incident prevention.

1.4 Wearable Sensors for Worker Tracking and Health Monitoring

Ahn et al. (2019) reviewed 75 studies on wearable technologies for position tracking and health monitoring, covering a broad range of devices. These tools contribute to worker safety by recording physiological, environmental, and movement-related data. For instance, kinematic sensors such as accelerometers and gyroscopes can detect awkward body postures or identify near-fall events (Nath et al., 2017; Yang et al., 2017). Similarly, smartwatches and activity trackers are able to monitor heart rate, stress, and other health indicators, offering valuable information on fatigue and physical strain (Guo et al., 2017; Hwang et al., 2016). Table 1 summarizes different categories of wearable devices and their functions, highlighting how these technologies can support construction safety in diverse ways.

Table 1. Types of wearable sensors, their main purposes, and common uses in construction safety

S.No.	Wearable Device	Objective	Uses
1	IMU sensor	Track orientation, movement, and stability	Smartphones, wearables, drones, vehicles, VR/AR headsets, cameras
2	PPG sensor	Measure blood volume changes for vital signs	Heart rate, oxygen saturation, respiratory rate, blood pressure trends
3	EDA sensor	Detect changes in skin conductance related to stress/anxiety	Wearables for monitoring emotional state or PTSD
4	EMG sensor	Record electrical activity of muscles	Wearables, exoskeletons, rehabilitation, sports science
5	Eye tracker	Analyze gaze patterns and pupil size	Safety fatigue studies, VR/AR interfaces, attention tracking

Wearable devices support proactive safety by linking worker health and location data with site-level risk monitoring. They can track vital signs, physical strain, and worker movements, offering valuable information for early detection of unsafe conditions. Yet, much like IoT systems, these technologies are often deployed as stand-alone solutions without connection to wider safety management platforms. This lack of integration restricts their overall effectiveness and limits their contribution to preventing incidents (Awolusi et al., 2018).

1.5 Computer Vision for Automated Hazard Detection

Computer vision has become an important tool for automated safety monitoring in construction. Using cameras and deep learning models, these systems can identify risks such as missing personal protective equipment (PPE), unsafe proximity to heavy machinery, and fall hazards without guardrails (Lee & Lee, 2023). By processing video streams continuously, computer vision supports real-time detection and reduces dependence on manual inspections, which are often periodic and subject to oversight. However, most current applications operate as stand-alone tools, separate from broader safety management systems. This lack of integration limits their capacity to trigger coordinated site-wide actions or to combine visual data with other information sources, such as IoT sensors and BIM models (Lee & Lee, 2023). As a result, while computer vision is effective for detecting specific hazards, its potential as part of an integrated, proactive safety framework remains underused.

1.5 Drones and Robots

Recent research highlights the role of drones and ground robots in improving construction safety monitoring. Drones are increasingly deployed for aerial mapping, site surveillance, and detecting safety issues such as missing PPE or unsafe work at heights, offering visibility in areas that are otherwise hazardous or inaccessible to workers (Akinsemoyin et al., 2023). Ground robots are used for close-range inspection and monitoring of confined or high-risk spaces, reducing direct worker exposure to danger (Choi et al., 2023). However, their operation introduces new risks, including potential collisions and worker distraction. To ensure safe integration, international guidelines like ISO 10218 and ISO/TS 15066 outline requirements for speed-and-separation monitoring and emergency stop mechanisms in human-robot collaborative environments (ISO, 2016; ISO, 2025).

1.6 Extended Reality (XR) for Safety Training and Visualization

Extended reality (XR) is a collective term for Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). In construction, XR has been widely applied to safety training, enabling workers to engage with immersive simulations where they can practice handling hazardous scenarios without exposure to actual risk (Zhao & Lucas, 2015; Li et al., 2018). VR platforms are especially valuable because they can combine inputs such as audio, video, and motion tracking to recreate site conditions with high realism (Li et al., 2018). AR systems, such as the Microsoft HoloLens, have also been tested to project virtual safety information directly onto construction sites, though their use is often limited by hardware and processing constraints (Chen et al., 2024). Despite these advances, most XR applications remain focused on training and education. Their adoption for real-time hazard detection or live decision support on active sites is still limited, leaving a gap between simulation-based preparation and field-level implementation.

1.7 Gap in Construction Safety Technologies

While AI, BIM, IoT, computer vision, and XR have advanced construction safety, their applications remain largely disconnected. Safety managers often rely on separate tools that provide only partial views of site conditions, slowing response times and limiting proactive hazard prevention (Berlato et al., 2025). Without a unified platform combining historical records, live sensor data, and project context, safety management stays mostly reactive (Najafzadeh & Yeganeh, 2025). For instance, IoT devices may detect poor air quality, but without links to BIM or worker location data, supervisors cannot quickly identify and protect those at risk (Wang et al., 2024). Similarly, computer vision can flag missing PPE or unsafe behavior, yet often works in isolation without triggering coordinated site-wide actions (Vukicevic et al., 2024). XR is mostly limited to training rather than real-time monitoring or decision support (Muñoz-La Rivera et al., 2025). This siloed approach prevents teams from fully benefiting from digital innovation, reinforcing the need for integrated platforms that enable continuous monitoring, predictive analytics, and faster decision-making to reduce accidents and fatalities (Jiang et al., 2021).

1.8 Proposed Framework: AI-Based Safety Control Room (AISCR)

To address the fragmentation of current safety technologies, this study introduces the AI-Based Safety Control Room (AISCR), a unified framework that integrates three streams of data: historical records such as OSHA reports, live inputs from IoT sensors, wearables, and cameras, and contextual sources including BIM models and site layouts. By combining these inputs, AISCR uses predictive analytics to monitor conditions in real time, anticipate risks, and deliver automated alerts to supervisors and workers. Unlike stand-alone tools, AISCR functions as a centralized decision-support platform. It operates as a closed-loop system that improves through feedback and machine learning while promoting coordination across devices and teams. The framework is designed to shorten response times, improve hazard prediction, and contribute to lowering the high rate of accidents in construction.

2. Data Requirements

The performance of the AI-Based Safety Control Room (AISCR) depends on the quality and range of data it receives. Construction sites generate large volumes of information, but this information is often scattered across different systems and formats. To build a complete picture of site safety, AISCR brings together data from regulatory databases, IoT sensors, wearable devices, and digital project models such as BIM.
These inputs can be grouped into three main categories:

- **Historical data** – records of past incidents, regulatory guidelines, and safety reports.
- **Real-time data** – continuous streams from sensors, wearables, and cameras that capture current site conditions.
- **Contextual data** – information about the physical and operational environment, including layouts, schedules, and geographic datasets.

By combining these streams, AISCR develops a consolidated view of site risks, supporting proactive and data-driven safety management. The following sections describe how raw inputs are processed and transformed into practical outputs for hazard prevention.

2.1 Data Pre-Processing and Integration

The data collected for AISCR differs greatly in format and quality. Historical records are often unstructured narratives, IoT and wearable devices generate continuous high-frequency streams, and contextual inputs such as BIM files are complex digital models. Before analysis, this information must be pre-processed and integrated to ensure reliability and consistency. The process begins with data cleaning, which removes duplicates, handles missing values, and filters out noise from sensors or video feeds. The next step is standardization, aligning data sources into compatible formats. For example, OSHA injury reports are converted into structured fields using natural language processing (NLP), while IoT and wearable outputs are synchronized through unified timestamps and standardized units of measurement. BIM files are converted into open formats such as Industry Foundation Classes (IFC) to ensure interoperability. Once prepared, all streams are merged into a centralized platform, where historical, real-time, and contextual inputs can be analyzed together.This preparation stage provides a dependable foundation for AISCR, improving the performance of AI models for hazard prediction and supporting timely, data-driven decision-making.

2.2 Detailed Description of Data Categories

Once data is collected and processed through cleaning and integration, it is organized into three structured streams within the AISCR framework: historical, real-time, and contextual data. At the raw stage, these inputs are often noisy, incomplete, or inconsistent—for example, IoT sensors producing unsynchronized feeds, or BIM files with complex formats. Pre-processing makes the data standardized and interoperable, allowing it to be grouped according to its role in proactive safety management.

2.2.1 Historical Data

Historical data enables the AISCR to learn from past events and regulatory records. By studying patterns of incidents, recurring hazards, and violation histories, the system can identify high-risk tasks and anticipate failures before they happen. Such datasets are important for training AI models to recognize early indicators of accidents, including falls from height, equipment-related injuries, or scaffold collapses.

Well-established public sources of historical safety data include:

- OSHA Severe Injury Database (OSHA, 2024): records of severe work-related injuries reported by employers in the United States, including details on the type of incident, body part affected, and circumstances.
- Bureau of Labor Statistics (BLS) Census of Fatal Occupational Injuries (U.S. Bureau of Labor Statistics, 2024): national-level statistics on fatal workplace injuries, classified by occupation, event type, and industry sector.
- NIOSH Fatality Assessment and Control Evaluation (FACE) reports (NIOSH, 2024): detailed case investigations of workplace fatalities, with descriptions of contributing factors and recommendations for prevention.

These records provide reference points for comparing present site conditions with known risks and support the creation of hazard classification models aimed at improving prevention.

2.2.2 Real-Time Data

Real-time data gives the AISCR direct visibility into ongoing site activities and environmental conditions. By streaming inputs from IoT devices, wearables, and computer vision systems, the platform can detect unsafe situations as they emerge and issue timely alerts to reduce the likelihood of accidents.
Publicly available datasets that can support research and testing in real-time monitoring include:

- NIOSH Exposure Data Portal (NIOSH, 2024): measurements of noise, dust, and toxic gases collected from occupational settings.
- OpenStreetMap Foundation (OpenSenseMap, 2024): an open database of environmental IoT sensor readings covering temperature, air quality, and related conditions.
- USGS (PhysioNet, 2024): collections of physiological signals such as heart rate, respiration, and electrocardiograms that can be used to model wearable device applications.
- Safety Helmet Detection Dataset (andrewmvd, n.d.): annotated images for training and evaluating computer vision models that detect helmet use on construction workers.
- COCO Dataset (Lin et al., 2014): a large-scale image dataset widely used for pre-training computer vision models, supporting tasks such as object detection and recognition.

This data stream is central to moving safety management away from periodic inspections toward continuous oversight, enabling faster responses to hazards before they escalate into serious incidents.

2.2.3 Contextual Data

This data category provides the spatial awareness required to interpret historical and real-time information while also supporting autonomous monitoring through robotics and Unmanned Aerial Vehicle (UAV) systems. It includes BIM models, project layouts, schedules, and geographic datasets that allow AISCR to track where risks are emerging and guide automated inspections of high-risk zones.
Publicly available resources include:

- National BIM Library: standardized digital building models for research and simulation (National BIM Library, 2024).
- USGS Open Data Portal: geospatial and environmental datasets such as terrain and hazard maps, also supporting safe flight path planning (USGS, 2024).
- OpenStreetMap: open mapping data on site layouts and access points, useful for geolocation and robot/drone navigation (OpenSenseMap, 2025).
- Open-Source IFC Models: sample Industry Foundation Classes (IFC) models shared through community BIM repositories.

In addition to these public sources, site-specific ultra-wideband (UWB) localization data is collected during deployment to enable precise tracking of workers, drones, and robots. Integrating these datasets allows AISCR to link detected hazards with exact locations, automate patrol routes, and ensure compliance with ISO 10218 safety standards (ISO, 2025).

3. AISCR Workflow

The AI-Based Safety Control Room (AISCR) follows a closed-loop process that converts raw construction data into practical safety intelligence. The workflow begins with data integration, advances through predictive analytics, delivers real-time guidance to the field, and supports decision-making with daily analytics reports. Over time, the system improves continuously through feedback and learning.

3.1 Data Processing and Integration Layer

The first stage consolidates historical, real-time, and contextual data into a unified platform. Inputs from OSHA reports, IoT sensors, wearable devices, and BIM models are cleaned, standardized, and synchronized to ensure consistency and interoperability. Natural language processing (NLP) is applied to structure unformatted text such as OSHA narratives. I Digital twin, robotics and drone has beenoT, wearable, drone, and robotic data are aligned through protocols such as MQTT, while BIM files are converted into open formats such as IFC. High-frequency streams are managed using real-time tools like Apache Kafka or cloud services. This creates a consolidated dataset that underpins hazard prediction, visualization, and decision-making.

3.2 AI Hazard Classification and Predictive Analytics Engine

The second stage applies machine learning and deep learning models to detect hazards and forecast risks.

- Historical records train predictive models to identify recurring hazards.
- Computer vision analyzes camera feeds to detect unsafe behaviors or missing PPE.
- Time-series forecasting predicts environmental risks such as heat stress or toxic gas exposure.

Together, these analytics enable AISCR to provide early warnings and prioritize interventions by severity and likelihood, shifting site safety from reactive practices toward prevention.

3.3 Robotics and UAV Operations

AISCR employs UAVs and ground robots to extend site monitoring and verify hazards safely. UAVs conduct aerial inspections of high-risk or hard-to-reach areas, capturing live imagery and mapping unsafe conditions. Ground robots support close-range inspections and deploy sensors in confined spaces, reducing worker exposure. When hazards are identified, AISCR can autonomously plan flight or patrol routes using BIM layouts, geospatial data, and dynamic geofences. Safety functions such as speed-and-separation monitoring and emergency stop controls ensure compliance with safety standards. Together, these systems expand site coverage and provide an independent stream of data that strengthens real-time analytics and decision-making.

3.4 Integrated Visualization Environment

AISCR combines BIM models, laser scans, photogrammetry, UAV mapping, and live inputs from IoT devices and robotics into a single visualization environment. This creates a dynamic digital representation of the site that reflects both the planned design and current field conditions. The environment supports desktop access for routine monitoring and immersive VR/AR modes for detailed review and training. By overlaying real-time sensor data and UAV video on the 3D model, safety managers can pinpoint hazards, judge their severity, and coordinate responses more effectively. This integration strengthens situational awareness, shortens the gap between detection and action, and supports proactive decision-making for all stakeholders.

3.5 Decision Support and Alerts

AISCR issues real-time alerts when hazards are detected, ensuring that site personnel can act quickly to prevent incidents. Notifications are sent through mobile devices, wearables, or desktop systems and include key details such as hazard type, location, and severity. High-priority alerts use visual and audio signals to avoid delays in response. This rapid communication closes the gap between hazard detection and field action, improving coordination and reducing the risk of accidents.

3.6 Validation and Continuous Improvement

AISCR will undergo field testing to verify accuracy, reliability, and compliance with ISO 10218 safety standards. UAV and robotic detections will be validated against ground-truth data, while proximity alerts will be checked for precise tracking of workers and equipment. Core safety functions, such as speed limits and emergency stops, will also be reviewed on-site. Feedback from supervisors and site managers will be used to refine models, reduce false alarms, and improve overall performance. Over time, this feedback loop will help AISCR adapt to changing site conditions, enhance accuracy, and inform company policies, OSHA compliance practices, and future safety training initiatives.

3.7 Data Visualization Dashboard for Insights

In addition to real-time alerts, AISCR generates daily analytics through a visualization dashboard that compiles site-wide data into a structured overview. This includes safety violations, zone-specific risk predictions, PPE compliance metrics, accident probability forecasts, and long-term hazard trends. Unlike immediate alerts, the dashboard provides supervisors and executives with a broader perspective on safety performance, supporting resource allocation, progress tracking, and strategic planning. These daily reports also serve as a historical record for audits, regulatory compliance, and continuous improvement. Figure 1 illustrates the overall AISCR workflow.

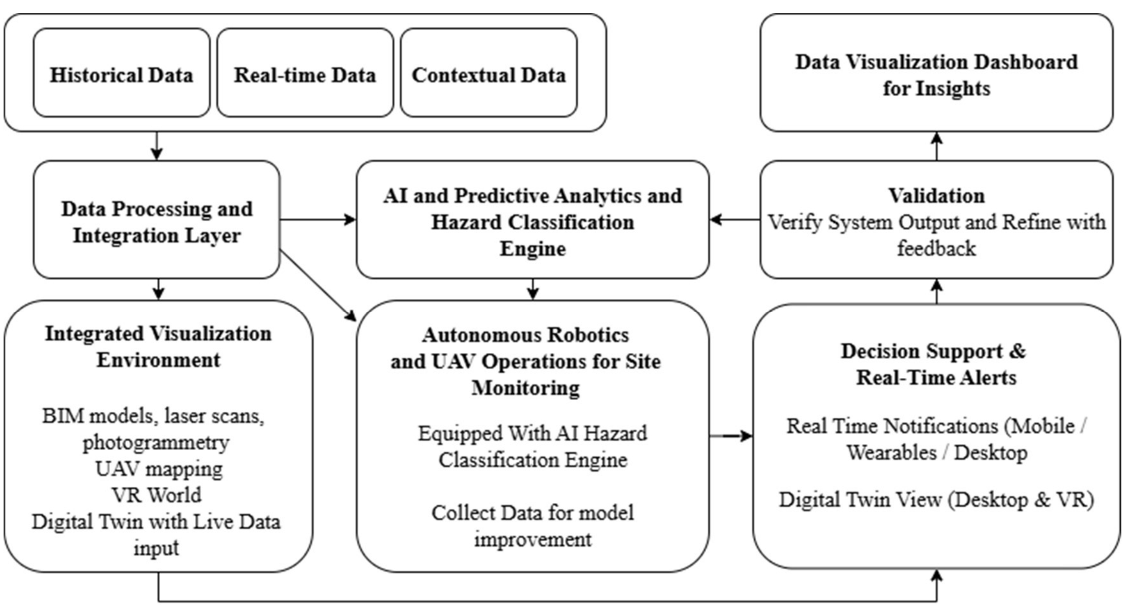

Figure 1. Theoretical Framework for Real-time Construction Workers' Safety Enhancement using Technological Integration

4. Conclusion and Recommendations

This study introduced a theoretical framework for an AI-Based Safety Control Room (AISCR) that seeks to shift construction safety management from a reactive model toward a proactive, data-driven approach. By combining historical, real-time, and contextual data, AISCR creates a comprehensive view of site conditions. The framework uses predictive analytics to detect hazards, issue instant alerts to workers and managers, and visualize risks through a digital twin accessible by desktop or VR. A daily analytics dashboard further compiles safety violations, compliance indicators, and recurring hazard patterns to support both immediate decision-making and long-term planning.

The framework has the potential to shorten incident response times, improve hazard anticipation, and strengthen prevention practices. However, its success will depend on the quality and availability of data, the reliability of IoT and wearable devices, and effective integration with construction workflows. Careful pilot testing on active sites, combined with training for managers and workers, will be essential to address practical issues such as sensor calibration, network stability, and data governance. As the system evolves through feedback and scaling strategies, AISCR can serve as a practical step toward connected and resilient construction safety management, reducing accidents and supporting better decisions across all levels of project operations. Partnerships with insurance companies and regulators also are an effective set of strategies to further refine the safety and wellbeing of construction workers; and finally, the improved safety culture through data driven training and safety technology adoption will ensure continuous and real-world protection for construction workers.

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