Nugroho. Andrianto W., Atiekasari, Ayu N., Akbar, Satria M., Rayadi, Adi Tisna., Stiefani, Natasya., & Setyawan, Bagus H. (2026). AI-based safety monitoring using SKOPIA for preventing accidents in heavy equipment operations at Jragung Dam construction project. In F. Hamzeh, M. Poshdar, N. P. Garcia-Lopez, & V. Gan (Eds.), *Proceedings of the 34th Annual Conference of the International Group for Lean Construction* (IGLC34) (pp. 74–84). https://doi.org/10.24928/2026/0180

AI-BASED SAFETY MONITORING USING SKOPIA FOR PREVENTING ACCIDENTS IN HEAVY EQUIPMENT OPERATIONS AT JRAGUNG DAM CONSTRUCTION PROJECT

Andrianto Widhi Nugroho[1], Ayu Nindya Atiekasari[2], Satria Maulana Akbar[3], Adi Tisna Rayadi[4], Natasya Stiefani[5] & Bagus Hendri Setyawan[6]

ABSTRACT

Construction projects involving heavy equipment operations present significant safety risks due to close interactions between workers and heavy equipment, limited visibility, and reliance on manual supervision. Heavy equipment-related accidents remain one of the leading causes of fatal incidents in infrastructure projects. This study examines the implementation of an artificial intelligence (AI)-based safety monitoring system, SKOPIA (Smart Kit & Observation Platform for Industrial Awareness), to prevent heavy equipment accidents in a dam construction project. A case study approach was adopted at the Jragung Dam Construction Project Package V in Indonesia. The system utilizes computer vision, machine learning, and real-time alert mechanisms to monitor worker and equipment movements within hazardous zones. Data were collected through field observations, near-miss records, and operational comparisons before and after implementation. The signalman observation period is January – May 2025 while the SKOPIA observation period is June – September 2025. Observations are carried out every day when work is carried out with the Transport Lift Aircraft. The findings indicate that AI-based monitoring enhances early hazard detection, reduces response time, and minimizes dependency on manual signalmen. This study contributes empirical evidence on integrating AI-enabled monitoring into proactive safety management, supporting lean construction principles and risk-based accident prevention in large-scale infrastructure projects.

KEYWORDS

AI, safety, lean construction, heavy equipment operations, dam projects.

[1] Project Manager, Jragung Dam Construction Project, Division of Infrastructure 1, PT Wijaya Karya (Persero) Tbk, Jakarta, Indonesia, andrianto.nugroho@wikamail.id , orcid.org/0009-0000-6152-9686

[2] Site Manager of HSE, Jragung Dam Construction Project, Division of Infrastructure 1, PT Wijaya Karya (Persero) Tbk, Jakarta, Indonesia, nindya@wikamail.id , orcid.org/0009-0008-1324-3841

[3] Staf of Engineer, Jragung Dam Construction Project, Division of Infrastructure 1, PT Wijaya Karya (Persero) Tbk, Jakarta, Indonesia, satria.maulana@wikamail.id , orcid.org/0009-0007-6704-8876

[4] Manager of Quantity Survey, Division of Infrastructure 1, PT Wijaya Karya (Persero) Tbk, Jakarta, Indonesia, aditisna@wikamail.id , orcid.org/0009-0004-3242-9941

[5] Junior Expert of Risk Management, Division of Infrastructure 1, PT Wijaya Karya (Persero) Tbk, Jakarta, Indonesia, natasya.s@wikamail.id , orcid.org/0009-0003-2877-696X

[6] Staff of Quantity Survey, Division of Infrastructure 1, PT Wijaya Karya (Persero) Tbk, Jakarta, Indonesia, bagus.hs@wikamail.id , orcid.org/0009-0006-3419-4597

INTRODUCTION

The construction industry is widely recognized as one of the most hazardous sectors, with a high incidence of occupational accidents, particularly those involving heavy equipment operations. Interactions between workers and heavy machinery such as excavators, bulldozers, and rollers frequently occur under conditions of limited visibility and dynamic site environments, increasing the likelihood of collisions, crushing, and fatal injuries.

According to data from the Ministry of Manpower, there were 462,241 workplace accidents throughout 2024 (Susanto, 2025). This number consisted of 423,644 cases involving wage earners, 34,364 cases involving non-wage earners, and 4,233 cases in the construction services sector. Meanwhile, in 2023, there were a total of 370,747 workplace accidents, with the construction services sector contributing approximately 2,971 of these cases.

National accident statistics in Indonesia indicate a persistently high number of workplace accidents, with construction consistently contributing a significant share of severe and fatal incidents. Previous studies have identified collisions between workers and construction machinery as a dominant cause of fatal accidents, highlighting the critical need for improved safety controls in heavy equipment activities.

Occupational safety is a crucial issue in the construction industry due to the high complexity of field activities, human-heavy equipment interactions, and the ever-changing dynamics of the work environment. Conventional safety approaches that rely on manual inspections, administrative procedures, and worker compliance have proven limited in anticipating hazards in real time. As the rate of workplace accidents increases, particularly in high-risk activities such as heavy equipment and moving materials, the need for proactive, data-driven safety systems becomes increasingly urgent. In this context, artificial intelligence (AI) has emerged as an innovative approach capable of improving the effectiveness of construction safety management.

Zhili Gao and Asad Sultan (2023) emphasize that the integration of AI into construction safety systems enables a transformation from a reactive approach to a predictive and preventive one. Through the use of machine learning, computer vision, and deep learning, AI can continuously analyse visual and sensory data to identify potential hazards, unsafe behaviours, and risky working conditions before accidents occur. Their study shows that AI can detect dangerous interactions between workers and heavy equipment, safety zone violations, and non-conformities in work procedures with a high degree of accuracy. Thus, AI functions not only as a monitoring tool but also as a safety decision support system in complex construction environments.

In line with these findings, Badhan and Samsami (2025) through a systematic literature review confirmed that AI has a strong correlation with improved construction safety performance, particularly through real-time monitoring and automated early warning systems. They concluded that the application of AI based on computer vision and predictive analytics can significantly reduce the potential for workplace accidents by reducing reliance on human supervision. AI enables a more objective, consistent, and adaptive risk identification process to changing field conditions. Therefore, the integration of AI in construction safety management systems is seen as a strategic element for creating a safer, more efficient, and more sustainable work environment, especially in high-risk activities such as heavy euipment operations.

In practice, many construction projects rely on manual supervision using signalmen to control equipment movement and warn workers of hazardous conditions. While effective to a degree, this approach is highly dependent on human vigilance, which is susceptible to fatigue, limited coverage, and delayed response. These limitations indicate a gap between current safety practices and the need for continuous, proactive monitoring systems.

This study aims to address this gap by investigating the application of an AI-based safety monitoring system to enhance accident prevention in heavy equipment operations. The research

objective is to evaluate how AI-enabled computer vision can support proactive safety management and reduce heavy equipment-related risks in dam construction projects.

LITERATURE REVIEW

SAFETY RISKS IN HEAVY EQUIPMENT OPERATIONS

Heavy equipment operations are among the most hazardous activities in construction projects due to blind spots, complex coordination requirements, and simultaneous worker presence within operational zones. Previous research has shown that inadequate monitoring and delayed hazard recognition significantly increase accident probability.

AI AND COMPUTER VISION IN CONSTRUCTION SAFETY

Recent advancements in AI and computer vision have enabled automated detection of workers, equipment, and unsafe interactions in construction environments. Vision-based systems using deep learning algorithms have demonstrated potential for real-time hazard identification, near-miss detection, and early warning systems, reducing reliance on manual observation.

LEAN CONSTRUCTION AND PROACTIVE SAFETY

Lean Construction focuses on removing waste, ensuring workflow reliability, and continuous value generation in construction processes. Foundational work from Koskela (2000) conceptualizes production as a transformation–flow–value (TFV) system, where variability and disruptions negatively impact performance. In this context, safety incidents and near-misses can be understood as a form of process waste that interrupts workflow, reduces productivity, and destabilises operations.

From a Lean perspective, unsafe conditions are closely related to the concept of Making-Do (Koskela, 2004), where tasks are executed without all necessary prerequisites in place. In heavy equipment operations, this may occur when workers enter hazardous zones without adequate situational awareness or when coordination between workers and equipment is insufficient. The Last Planner System (Ballard, 2000) further emphasizes reliable planning and constraint removal; however, traditional safety approaches relying on manual supervision, such as signalmen, are limited in continuously identifying and eliminating safety constraints in real time, leading to gaps between planned and actual safe conditions.

Safety has also been linked to production system design, where it should be managed as an integral part of workflow reliability rather than as a separate control function (Mitropoulos et al., 2005). In this regard, AI-based monitoring systems such as SKOPIA can enhance Lean implementation by enabling real-time detection of unsafe conditions, reducing variability, and supporting continuous improvement through data-driven feedback. Thus, SKOPIA acts as a digital enabler of Lean principles by improving flow reliability and reducing safety-related waste in heavy equipment operations.

RESEARCH METHODOLOGY

RESEARCH DESIGN

This study adopts a mixed-method (qualitative–quantitative) case study approach to examine the real-world application of an AI-based safety monitoring system in an active construction project. Incidents related to Transport Aircraft in 2025 within the scope of the WIKA Group need to be of special concern to all personnel in the field. Qualitative data collected by interviewing the workers directly involved in carrying out training and training. Quantitative data on the greatest potential hazards of the heavy equipment factor was obtained from the recording of accidents on the current project with the results of heavy equipment accidents contributing 33.3% to the total accidents in the WIKA Group. This study addresses the following research questions: How does the implementation of SKOPIA affect near-miss

detection compared to conventional signalman-based supervision? To what extent does the SKOPIA system improve response time to hazardous conditions? How does AI-based monitoring support proactive safety management in heavy equipment operations?

CASE STUDY DESCRIPTION

The case study was conducted at the Jragung Dam Construction Project Package V, a large-scale earth fill dam project in Indonesia characterized by intensive heavy equipment operations. The research focused on the core embankment area, where multiple heavy equipment units and manual workers operate simultaneously, creating high-risk interaction zones. This environment provides a suitable context for evaluating safety monitoring systems due to:

a. High interaction frequency between worker and equipment
b. Dynamic movement and limited visibility
c. Elevated risk of struck-by and caught-in accidents

AI-BASED MONITORING SYSTEM (SKOPIA)

SKOPIA (Smart Kit & Observation Platform for Industrial Awareness) is an AI-enabled safety monitoring system designed to enhance construction safety through automated visual detection. The system integrates:

a. CCTV cameras for visual data capture,
b. Computer vision algorithms for object detection and distance estimation, and
c. Internet of Things (IoT)-based devices to alert workers (sirens and mobile notifications)

Hazard zones are predefined, and when a worker enters a dangerous proximity to operating equipment, the system triggers visual and audible alerts.

The main objectives of the SKOPIA system are to improve occupational safety through automatic detection and warnings, provide real-time monitoring based on Artificial Intelligence (AI) and produce analytical data related to the movement and interactions between heavy equipment and workers in construction areas.

Figure 1: Workflow Diagram SKOPIA

This system was developed using AI, Machine Learning, Deep Learning, Computer Vision, and Internet of Things (IoT) technologies. This combination of technologies enables SKOPIA to automatically detect the presence of people and heavy equipment from video footage, while also providing early warnings when someone enters the equipment's danger zone.

With these capabilities, SKOPIA is part of a digital-based Early Warning System (EWS) aimed at preventing workplace accidents, transforming a safer work culture, and maintaining the quality and accuracy of safety data in the field.

SYSTEM IMPLEMENTATION

The implementation of the SKOPIA system follows a structured workflow that integrates data acquisition, AI-based detection, spatial analysis, and safety reporting to enable real-time monitoring of heavy equipment operations. This workflow ensures that safety-related data are continuously captured, processed, and transformed into actionable insights.

DATA COLLECTION

Data were collected through:

1. **Visual Data Capture**

   CCTV cameras (including PTZ cameras) are installed in work areas or around heavy vehicles to capture images and videos of project activities. These recordings document the type of equipment, worker activities, and equipment movement during heavy equipment operations. The data are transmitted through a wireless network infrastructure to a central processing system for real-time analysis. In addition to site-specific data, supplementary image datasets obtained from online sources were utilized to enhance model training and increase detection robustness across varying conditions.

Figure 2: Data set for workers classification and heavy equipment detection

2. **AI Model Development**

   The system utilizes a deep learning-based object detection and classification model based on the YOLO (You Only Look Once) architecture to detect and classify objects within the footage. The model was configured to identify:

   a. Workers (person class)
   b. Heavy equipment and vehicles (e.g., excavators, dumb trucks, dozers, water-tanks)

   In addition, detected persons were further classified into workers, HSE teams and equipment operators based on visual factors, i.e. the colour of safety vests. This classification enables differentiation between personnel directly involved in operating equipment, HSE members and those exposed to potential hazards in the surrounding area.

Figure 3: Detection of heavy equipment and workers by SKOPIA

3. **Model Evaluation and Tuning**

   The model was evaluated and refined to increase its detection performance in the construction environment. Several adjustments were conducted to improve system robustness under varying conditions, such as lighting changes, zoom level, occlusions, and dynamic movements. This part ensures that the model maintains more reliable detection performance for safety applications.

4. **Distance Estimation**

The system determines risk levels by calculating the distance between each worker and heavy vehicle based on their positions in the video frame, using a homographic technique, which transforms perspective image coordinates from the CCTV into real-world spatial measurements on the ground plane. The distance estimation was further calibrated on the construction plane to improve measurement accuracy in the operational environment. These distances are used to classify interactions into predefined safety zones based on proximity thresholds. This threshold-based approach enables the system to identify potentially hazardous interactions between workers and heavy equipment and trigger appropriate safety alerts in real time. This spatial analysis creates the for identifying hazardous situations and potential near-miss events.

5. **Real-Time Analysis and Alerts**

When the system detects workers within a dangerous radius of heavy equipment, SKOPIA automatically sends real-time alerts via:

a. IoT sirens (audible and visual alarms) on-site.

Figure 4: The siren sounds when a worker approaches/violates the safety limit with the tool.

b. Notification to the K3 officer's mobile device along with a screenshot of the violation.

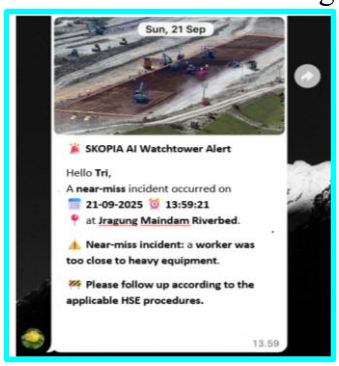

Figure 5: WA messages sent to HSE and SOM officers when a worker violates the limits

6. **Recording and Reporting**

All detected activities and violations are recorded in a digital dashboard. This data is used for:

a. Near-miss statistical analysis.

b. Automated reporting via AppSheet.

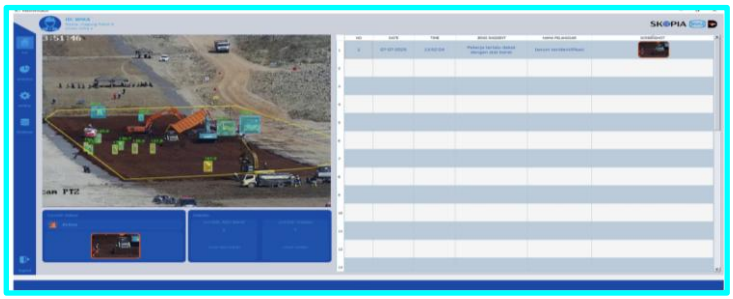

Figure 6: Dashboard SKOPIA

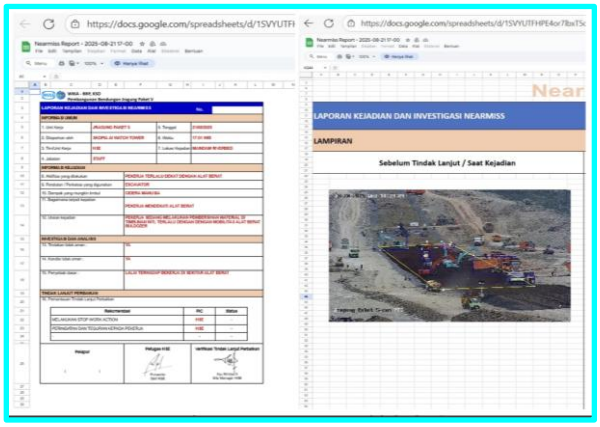

Figure 7: Near-miss Report by SKOPIA

7. Data Analysis

The analysis focused on comparing safety performance indicators, response times, and monitoring effectiveness between the AI-based system and conventional signalman-based supervision. A comparative evaluation was conducted using data collected during the baseline period (January–May 2025) and the intervention period (June–September 2025). The following safety performance indicators are used to assess and compare the effectiveness of the AI-based monitoring system and conventional signalman-based supervision. To ensure comparability, both observation periods were conducted under similar operational conditions, including comparable equipment usage, workforce size, and work schedules.

Cost Metric

To evaluate economic feasibility, the following cost-related metrics were analyzed using two parameters; i.e. development cost as initial investment required for system implementation and operating cost as recurring cost associated with system operation over time. A comparative cost analysis was conducted between SKOPIA and signalman-based monitoring to evaluate long-term financial implications.

Quality of Monitoring Metric

Monitoring quality was evaluated based on system responsiveness, reporting efficiency, and operational reliability. The following indicators were considered:

- Information delivery time represents time required to notify HSE personnel of a hazard
- Report generation time represents time required to create near-miss reports
- Document processing time represents time required to upload and store incident reports

This evaluation highlights the differences between manual and automated monitoring approaches in terms of responsiveness and operational consistency.

Safety Performance

Safety performance was evaluated based on the system's ability to detect and respond to hazardous interactions between workers and heavy equipment. Due to limitations in available quantitative data, this evaluation was conducted in an exploratory manner, focusing on:

- Detection of worker–equipment proximity
- Identification of potential near-miss events
- Responsiveness of hazard detection and alert systems

This assessment provides insight into the potential of AI-based monitoring to support proactive safety management. A before–after comparison was conducted to evaluate differences between conventional and AI-based monitoring approaches, focusing on:

- Cost efficiency
- Improvement in response time
- Differences in monitoring consistency and reliability
- Potential impact on safety performance

This analysis enables a comprehensive evaluation of the effectiveness of SKOPIA in improving monitoring performance in construction heavy equipment operations.

RESULT & DISCUSSION

AI MODEL PERFORMANCE

The Performance of the YOLO-based object detection model was evaluated to ensure its reliability for real -time monitoring in construction environment. The model was trained to detect workers and heavy equipment, as well as classify personnel into workers, operators, and HSE personnel based on safety vests. Model performance was assessed using precision metrics, which indicate the accuracy of object detection results. Figure and table below demonstrating a high level of accuracy in identifying relevant objects within the frame. In addition, the training process was evaluated using learning curves, as shown in Figure above. The training curve indicates a consistent decrease in loss and convergence of the model over training epochs, suggesting stable learning behavior and effective model generalization.

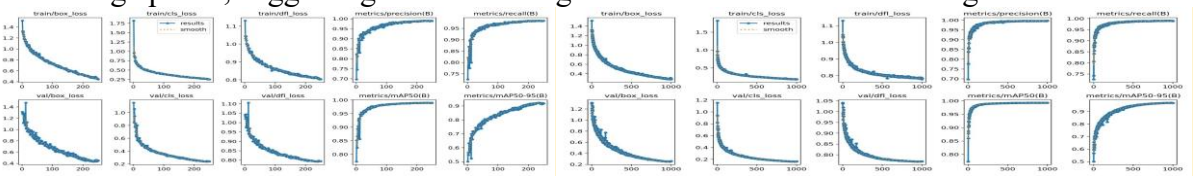

Figure 8: Training and validation curves for object detection (top) and worker classification (bottom)

Table 1: Trained AI model metrics

No.	Model Type	Data Training	Epoch	Precision	mAP50	mAP50-95
1	Object Detection	>5000	250	0.98	0.98	0.96
2	Worker Classification	>11000	1000	0.98	0.98	0.97

The analysis focused on comparing safety performance indicators, response times, and monitoring effectiveness between the AI-based system and conventional signalman-based supervision.

a. Safety Performance Indicators

Development Costs

The total cost of the SKOPIA program comprises artificial intelligence (AI), software, hardware components, as well as other operational expenses such as electricity, telecommunications credit, and operational personnel (PIC), amounting to IDR 300,000,000. Meanwhile, the development of Signalman requires training costs to ensure the workforce has adequate skills and understanding to carry out their duties as Signalman. The training costs are Rp 5,000,000 per person. Six units of heavy equipment are operating in the core embankment area.

Operating Costs

SKOPIA's operational costs are virtually non-existent, as the system only requires a power supply to the server computer to run daily. Meanwhile, to implement the heavy equipment monitoring system with the help of a signalman, there is an operational fee in the form of

a salary (wages) for the signalman of Rp 100,000 per unit per day. Six pieces of heavy equipment are employed at the core embankment of the Jragung Dam Project Package V.

Table 2: Comparison of costs between Signalman and SKOPIA

No.	Item Name	SKOPIA	Signalman
1	Development Cost	Rp. 300,000,000	Rp. 30,000,000
2	Operating Cost in 2 years	-	Rp. 432,000,000
	Total Cost	**Rp.300,000,000**	**Rp. 462,000,000**

QUALITY OF MONITORING AND RESPONSE TIME

The implementation of SKOPIA significantly improves monitoring responsiveness and reporting efficiency. The system enables real-time detection and immediate notification of hazardous situations through automated alerts, eliminating delays associated with manual reporting processes. Here's a comparison of near-miss reports between Signalman and SKOPIA. SKOPIA can generate near-miss reports in real time along with photos of the incident, while Signalman cannot, SKOPIA can monitor the device continuously without fatigue, while Signalman can experience fatigue, illness, or personal needs such as toileting, response times and Near-miss incident reporting is done in real time, automatically by the SKOPIA system and recorded/stored in Google Drive. Meanwhile, for Signalman, near-miss reports must be created manually. Signalman informs the HSE officer, who then prepares a report and uploads it to Google Drive if desired.

Table 3: Comparison of near-miss reports between Signalman and SKOPIA

No.	Item Name	SKOPIA	Signalman
1	Information to HSE Officers	Real time	5 Minutes
2	Creation of Near-miss report	Real time	15 Minutes
3	Upload Document	3 Minutes	3 Minutes
	Amount	**3 Minutes**	**18 Minutes**

IMPROVEMENT IN SAFETY MONITORING

The implementation of SKOPIA enabled continuous, real-time monitoring of heavy equipment operations without interruption. Unlike manual supervision, the system maintained consistent vigilance regardless of operational duration.

REDUCTION IN HUMAN DEPENDENCY

The findings indicate a significant reduction in reliance on signalmen for hazard detection. While signalmen remain important for coordination, AI-based monitoring provided an additional safety layer that minimized the impact of human fatigue and limited visibility.

EARLY WARNING AND NEAR-MISS REPORTING

At the time of the use of signalman, very little near-miss reporting was reported, so to mitigate the risk of work accidents, there was a lack of data and as if there were no unsafe action & conditions at the job site. SKOPIA successfully detected unsafe interactions and generated immediate alerts through on-site sirens and mobile notifications to safety personnel. Near-miss incidents were automatically recorded with visual evidence, improving the accuracy and timeliness of safety reporting.

The results demonstrate that AI-based safety monitoring supports a shift from reactive to proactive safety management. From a lean construction perspective, the system reduces

safety-related waste by preventing accidents before they occur and minimizing work stoppages caused by incidents. AI functions as an enabler rather than a replacement for human supervision, strengthening overall safety governance through continuous data-driven monitoring.

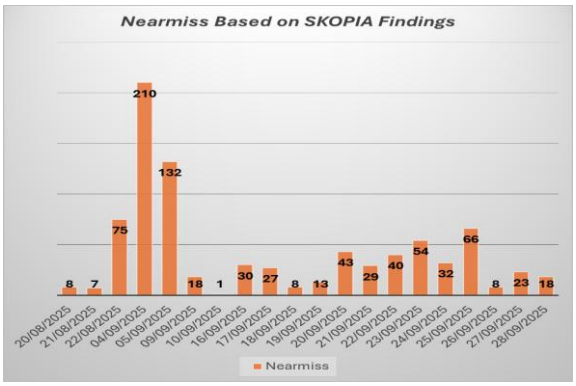

Figure 9: Nearmiss Based on SKOPIA Findings

Nearmiss reports are increasing, so that they can be followed up immediately and reduce the chance of work accidents. Good nearmiss report quality in terms of data and reporting time (real time). Supporting the efficiency of paper use through digitization. Increased awareness related to the line of fire in every movement of the transport aircraft. The change in the work culture where previously workers and tools worked together, became a culture of workers and tools working alternately.

IMPLICATION FOR LEAN CONSTRUCTION

The findings demonstrate that AI-based safety monitoring supports a transition from reactive to proactive safety management. By enabling continuous detection and immediate response to unsafe conditions, SKOPIA reduces variability and interruptions in construction workflows. From a Lean Construction perspective, safety incidents and near-misses can be interpreted as forms of process waste that disrupt workflow and reduce productivity. The implementation of SKOPIA contributes to minimizing such waste by preventing accidents before they occur and maintaining operational continuity. Rather than replacing human supervision, SKOPIA functions as a complementary tool that strengthens safety governance through continuous, data-driven monitoring.

CONCLUSION

This study concludes that the implementation of the SKOPIA (Smart Kit & Observation Platform for Industrial Awareness) system is an effective program for improving occupational safety in construction projects, particularly in preventing accidents caused by being hit or run over by heavy equipment.

The SKOPIA system utilizes Artificial Intelligence (AI), Computer Vision, and Internet of Things (IoT) technology to detect worker presence and provide real-time early warnings when workers enter dangerous areas around heavy equipment.

Compared to conventional methods such as the use of Signalman, the SKOPIA system has several key advantages, including:

a. Nearmiss report increases, so that it can be followed up immediately and reduce the chance of work accidents
b. Good nearmiss report quality in terms of data and reporting time (real time)
c. Reduces operational costs by eliminating additional daily labor.
d. Digital recording and reporting features that support near-miss incident analysis.
e. Speed of response to potential hazards to heavy equipment in the field.

With these advantages, the SKOPIA system can be part of a digital-based Early Warning System (EWS) that supports the creation of a safe work culture on construction projects.

REFERENCES

Kementerian Ketenagakerjaan Republik Indonesia. (2025). *Kasus kecelakaan kerja 2023 & 2024*. Satuan Data Kementerian Ketenagakerjaan. https://satudata.kemnaker.go.id/data/kumpulan-data/1728

Bria, T. A., Chen, W. T., Muhammad, M., & Rantelembang, M. B. (2024). Analysis of fatal construction accidents in Indonesia: A case study. *Buildings, 14*(4), 1010. https://doi.org/10.3390/buildings14041010

Teizer, J., Allread, B. S., Fullerton, C. E., & Hinze, J. (2017). Autonomous pro-active real-time construction worker and equipment operator proximity safety alert system. *Automation in Construction, 84*, 33–45.

Fang, Q., Li, H., Luo, X., Ding, L., Luo, H., Rose, T., & An, W. (2020). Detecting non-hardhat-use by a deep learning method from far-field surveillance videos. *Safety Science, 130*, 104869.

Mitropoulos, P. (2015). Production practices and safety: A cognitive perspective. *Journal of Construction Engineering and Management, 141*(2), 04014082.

Golparvar-Fard, M., Peña-Mora, F., & Savarese, S. (2012). Monitoring changes of 3D building information models from unordered photo collections. *Automation in Construction, 24*, 15–23.

International Organization for Standardization. (2018a). *ISO 45001:2018 occupational health and safety management systems—requirements with guidance for use*.

International Organization for Standardization. (2018b). *ISO 31000:2018 risk management—guidelines*.

Badhan, S. J., & Samsami, R. (2025). Artificial intelligence (AI) in construction safety: A systematic literature review. *Buildings, 15*(22), 4084. https://doi.org/10.3390/buildings15224084

Koskela, L. (2000). *An exploration towards a production theory and its application to construction*. VTT Technical Research Centre of Finland.

Koskela, L. (2004). Making-do – The eighth category of waste. In *Proceedings of the 12th Annual Conference of the International Group for Lean Construction (IGLC-12)*.

Ballard, G. (2000). *The last planner system of production control* (Doctoral dissertation). University of Birmingham.

Mitropoulos, P., Abdelhamid, T. S., & Howell, G. A. (2005). Systems model of construction accident causation. *Journal of Construction Engineering and Management, 131*(7), 816–825. https://doi.org/10.1061/(ASCE)0733-9364(2005)131:7(816)