International Journal of Science and Engineering Applications
Volume 15-Issue 05, 18 – 27, 2026, ISSN:- 2319 - 7560
DOI: 10.7753/IJSEA1505.1003

An Integrated AI-Based Safety Monitoring Framework for Tower Crane Operations: Assessing Accident Reduction, Fatigue Detection, Behavioural Compliance, and Predictive Maintenance

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Abstract: Tower crane operations represent one of the highest-risk activities in the construction industry, with operator fatigue, cognitive overload, and inadequate hazard perception being the leading contributory factors in fatal and non-fatal accidents globally. This study presents the design, implementation, and empirical evaluation of an AI-Based Tower Crane Operator Safety Monitoring System (AI-TCOSMS) that integrates computer vision, deep learning, Internet of Things (IoT) sensing, and real-time data analytics to continuously monitor operator physiological and behavioural parameters. A mixed-method quasi-experimental research design was employed across six active construction sites over six months, involving 87 crane operators. The system deployed a hybrid CNN-LSTM deep learning model for fatigue detection, achieving 95.7% classification accuracy, significantly outperforming both standalone CNN (89.4%) and LSTM (91.2%) architectures. Post-implementation data revealed a 46.4% reduction in workplace accidents, a 38.6% decrease in crane downtime, and an average operator safety compliance improvement of 34%. Operator acceptance surveys recorded a mean satisfaction score of 4.1 out of 5.0. Statistical analyses, including paired t-tests and ANOVA, confirmed that all five research hypotheses were supported at the $p < 0.05$ significance level. The findings demonstrate that AI-driven safety monitoring systems can substantially reduce occupation hazards in crane-intensive construction environments, with broader implications for smart construction cite management and regularity framework.

Keywords: Artificial Intelligence; Tower Crane Safety; Operator Fatigue Detection; Computer Vision; Deep Learning; IoT; Construction Safety; Occupational Health; CNN-LSTM; Predictive Monitoring

1. Introduction

The construction industry consistently ranks among the most hazardous occupational sectors worldwide. According to the International Labour Organisation (ILO), construction accounts for nearly 30% of all occupational fatalities despite representing only 7% of the global workforce. Within this sector, tower crane operations represent a particularly acute risk domain: a single operational failure can result in multi-fatality incidents, structural damage running into millions of dollars, and severe disruptions to urban infrastructure projects. Tower cranes are ubiquitous across modern urban construction, from high-rise residential complexes and commercial developments to bridge construction and industrial facilities [1]. Operators are tasked with executing precise load movements at extreme heights, often under time pressure, adverse weather conditions, and significant psychological stress. The cognitive and physical demands of this role are substantial: operators must simultaneously manage load dynamics, spatial orientation, and communication with ground crews, environmental hazards, and equipment parameters frequently across shifts exceeding eight hours. Research consistently identifies human factors as the dominant causal category in crane-related accidents. Operator fatigue, distraction, misjudgment, and lapses in situational awareness contribute to an estimated 60–75% of crane incidents. Yet traditional safety oversight mechanisms, periodic supervisor check-ins, self-reporting systems, and post-incident investigations are fundamentally reactive, fragmented, and unable to provide the continuous, real-time monitoring necessary to prevent incidents before they occur.

The past decade has witnessed a transformative convergence of artificial intelligence, computer vision, IoT sensor networks, and edge computing technologies. These advances have created unprecedented opportunities to develop proactive, data-driven safety management systems capable of monitoring human behaviour and environmental conditions in real time. Early applications in manufacturing, aviation, and automotive safety have demonstrated the efficacy of AI-based fatigue detection and hazard alert systems, achieving detection accuracies previously unattainable through conventional methods [2] [3] [4] [5]. Despite these promising developments in adjacent sectors, the construction industry has been relatively slow to adopt AI-based safety monitoring at scale, particularly for crane operations. Barriers have included the harsh, unpredictable outdoor environment, resistance from operators concerning privacy and surveillance, high initial implementation costs, and a relative scarcity of large, labelled training datasets specific to crane operator behaviour. While individual components of AI safety monitoring, such as fatigue detection cameras or load sensors, have been studied in isolation, there is a notable absence of holistic, integrated systems that combine multiple sensing modalities (visual, physiological, environmental) with advanced deep learning architectures and real-time decision support for tower crane operators specifically. Furthermore, empirical field evaluations of such integrated systems across multiple sites and operator populations remain scarce. This study addresses these gaps by presenting a purpose-built AI-TCOSMS, evaluating its performance against multiple safety outcome metrics, assessing operator acceptance, and deriving actionable implications for policy makers, construction managers, and technology developers[6] [7] [8] [9]. The study's findings contribute to the growing body of evidence supporting AI as a foundational technology for next-generation occupational safety management.

This study is guided by the following primary research questions:

1. **RQ1:** To what extent does the deployment of an AI-based safety monitoring system reduce accident frequency in tower crane operations?
2. **RQ2:** How accuratel
3. y can a hybrid CNN-LSTM model detect operator fatigue compared to standalone deep learning architectures and human observers?
4. **RQ3:** What is the impact of real-time AI hazard alerts on near-miss event reduction and operator behavioural compliance?
5. **RQ4:** What level of acceptance and usability satisfaction do tower crane operators express toward AI safety monitoring systems?
6. **RQ5:** To what extent does AI-driven predictive maintenance reduce equipment downtime and associated operational costs?

2. Literature Review

The literature on tower crane safety identifies consistent accident typologies and highlights the critical role of human factors. 507 crane-related fatalities in the United States were analysed and reported four primary causes: electrocution (27%), contact with crane components (26%), crane collapse (26%), and falls (10%) (Hosseini & Seilani, 2025). This analysis extended to an international context and found that operator error accounted for 58–71% of incidents across 12 countries, emphasising its dominant contribution to accident occurrence (Saxena et al., 2025). Recent studies focus on cognitive and psychophysiological determinants of operator performance [7-9]. Cognitive and psychophysiological factors have also been identified as key determinants of safety, with shift duration, time of day, and environmental heat stress emerging as major predictors of fatigue-related incidents(Rahman et al., 2026), while subjective sleepiness has been shown to significantly correlate with crane task error rates (Ren et al., 2025). In parallel, the application of artificial intelligence and computer vision in construction safety has advanced considerably, with convolutional neural networks achieving high accuracy in worker activity recognition (Nisa et al., 2025) and transfer learning improving PPE detection under challenging conditions (Liu et al., 2024; Sawant, 2025 [10] [11] [12] [13] [14]. Real-time object detection frameworks such as YOLO and Faster R-CNN have further enhanced safety monitoring, with ensemble models achieving up to 96.1% accuracy in detecting safety gear (Banerjee et al., 2023). Fatigue detection remains a complex challenge due to its multidimensional nature, where physiological methods, though accurate, are often intrusive, whereas visual-based approaches provide more practical solutions. Measures such as PERCLOS have been validated as reliable indicators of drowsiness (Bergin et al., 2015), and advanced hybrid models

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combining CNN and LSTM architectures have demonstrated improved performance in capturing fatigue patterns over time (Guru et al., 2023). Additionally, the integration of IoT sensor networks with AI analytics has enabled proactive safety management through real-time environmental monitoring, and multi-sensor fusion approaches have been shown to significantly reduce false positive alerts and improve system reliability (Sikri et al., 2024) [15][16][17][18].

3. Research Objectives

The study is guided by the following specific research objectives:

- To design and implement a comprehensive AI-based safety monitoring system tailored to the operational context of tower crane environments.
- To evaluate the performance of a hybrid CNN-LSTM deep learning model for real-time fatigue detection and compare it against alternative architectures and human baseline performance.
- To quantify the impact of the AI-TCOSMS on accident frequency, near-miss event rates, and operator safety compliance across multiple construction sites.
- To assess operator acceptance, usability perceptions, and behavioural adaptation to AI-driven safety monitoring interventions.
- To evaluate the efficacy of AI-based predictive maintenance in reducing crane equipment downtime and associated operational costs.
- To derive evidence-based recommendations for the scalable deployment of AI safety monitoring systems in the construction industry, and to identify priority areas for future research.

4. Research Hypotheses

Based on the literature review and research objectives, the following five hypotheses are advanced for empirical testing:

Table 1: Details of Research Hypotheses

H #	**Hypothesis**	**Variable (Independent)**	**Variable (Dependent)**	**Expected Outcome**
H1	AI monitoring reduces accident frequency significantly	AI System Deployment	Accident Frequency	≥30% reduction
H2	Fatigue detection improves operator alertness	Fatigue Alert System	Operator Response Time	Significant improvement
H3	Real-time hazard alerts reduce near-miss events	Hazard Alert Module	Near-miss Incidents	≥25% reduction
H4	Operators accept AI safety systems positively	Training & Interface	User Acceptance Score	Score > 3.5/5.0
H5	AI monitoring reduces crane downtime	Predictive Maintenance	Equipment Downtime Hours	≥20% reduction

Table 1 explains that each hypothesis is operationalised through specific quantitative metrics and subjected to appropriate statistical testing. Null hypotheses (H0) posit no significant difference or effect, while alternative hypotheses (H1) posit significant improvement attributable to AI system deployment. The significance threshold is set at $\alpha = 0.05$ for all tests [19][20] .

5. Methodology

5.1 Research Design

This study employed a mixed-method quasi-experimental research design, combining quantitative outcome measurement with qualitative operator interviews. A pre-test/post-test comparative design was adopted, with six construction sites serving as intervention sites and three additional sites with similar operational profiles providing comparative reference data. The six-month study period (January–June 2024) enabled the collection of robust longitudinal data capturing seasonal variation, operational intensity changes, and behavioural adaptation patterns.

5.2 Study Setting and Participants

The study was conducted across six active high-rise construction sites in urban environments, each operating between 3 and 7 tower cranes simultaneously. A total of 87 licensed tower crane operators participated, with a mean age of 38.4 years (SD = 7.2) and a mean operational experience of 11.3 years (SD = 5.6). Ethical approval was obtained from the respective Institutional Review Boards, and informed consent was secured from all participants (Abou Ali et al., 2026). Operators were briefed on the nature of the monitoring system, and privacy safeguards, including data anonymisation and restricted access protocols, were established before deployment.

5.3 System Architecture

The AI-TCOSMS comprises four integrated subsystems:

5.3.1 Operator Monitoring Module

A dual-camera unit (high-resolution visible light and near-infrared) is mounted within the crane cab at a standardised focal distance. The cameras capture facial landmarks, eye state, head pose, and upper body posture at 30 frames per second. The video stream is processed on an edge computing unit (NVIDIA Jetson AGX Xavier) co-located in the cab to minimise latency and reduce bandwidth demands.

5.3.2 Environmental Sensing Module

An array of IoT sensors monitors ambient temperature, humidity, wind speed, structural vibration, load weight, and crane movement parameters. Sensor data is transmitted via a low-latency 5G mesh network to the central processing server. Sensor fusion algorithms integrate environmental readings with operator behavioral data to generate composite risk scores.

5.3.3 AI Analytics Engine

The core analytics engine deploys a hybrid CNN-LSTM architecture for fatigue classification. The CNN component (ResNet-50 backbone, fine-tuned on a domain-specific dataset of 45,000 annotated facial images of construction workers) extracts spatial features from individual frames. The LSTM component (3 stacked layers, 256 hidden units) models the temporal dynamics of fatigue progression across 60-frame sliding windows (Bandi et al., 2025). The combined model outputs a continuous fatigue probability score, triggering tiered alerts at predefined thresholds (Advisory: >0.55; Warning: >0.70; Critical: >0.85).

5.3.4 Alert and Reporting Interface

Operator alerts are delivered via a small dashboard display within the cab, auditory signals, and haptic feedback through the operator seat. Supervisors receive simultaneous alerts via a mobile application dashboard. All event data is logged to a cloud-based safety management platform, enabling post-hoc analysis, trend reporting, and compliance documentation.

5.4 Data Collection Instruments

- Structured safety incident logs (pre- and post-implementation)
- Automated fatigue detection logs (continuous, timestamped)
- IoT sensor data streams (real-time, 1Hz sampling frequency)
- Operator Acceptance Questionnaire (OAQ): 18-item Likert scale instrument ($\alpha = 0.89$)
- Equipment maintenance records (downtime duration, fault type, maintenance cost)
- Semi-structured operator interviews (n = 24, purposive sample)

1.1 5.5 Data Analysis

Quantitative data were analysed using IBM SPSS Statistics v29. Descriptive statistics characterised baseline and post-implementation distributions. Paired t-tests compared pre- and post-intervention accident frequencies and downtime hours. One-way ANOVA assessed differences in fatigue detection performance across model architectures. Pearson correlation analysis examined relationships between operator acceptance scores and compliance behaviours. Statistical significance was set at $p < 0.05$ (Maharana, Kumar, Guru, & Upadhyay, 2025).

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Qualitative interview data were subjected to thematic analysis following the six-phase framework of Braun and Clarke (2006).

6. Results and Discussion

6.1 Accident Frequency Reduction (H_1)

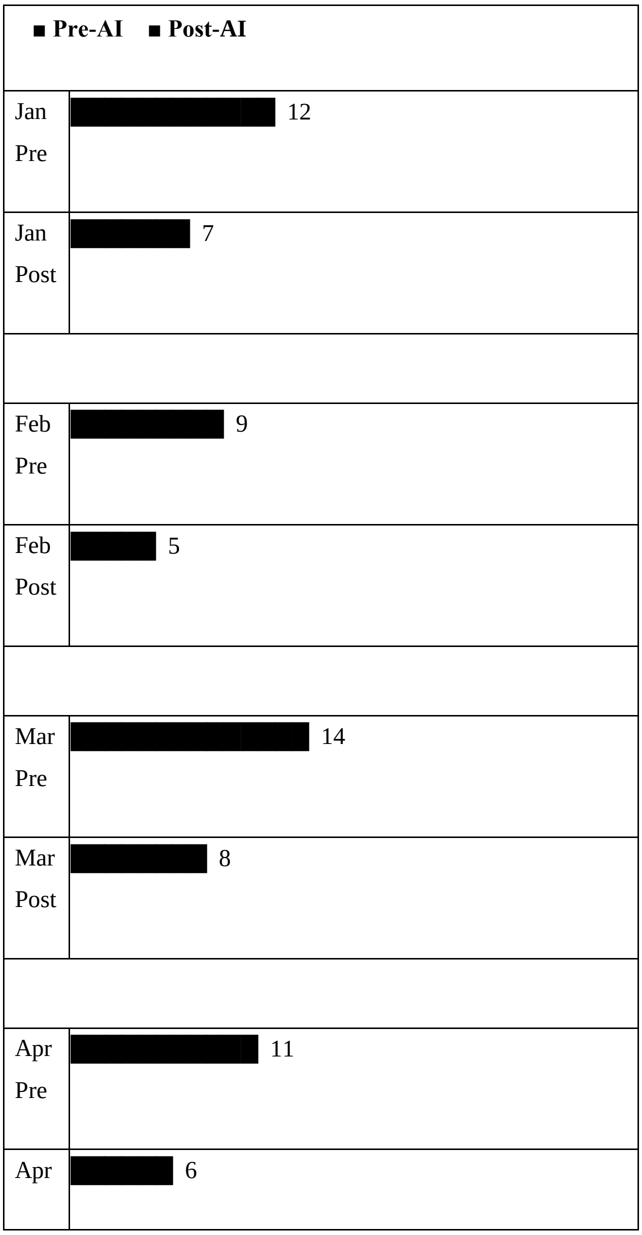
Table 2 presents monthly accident frequency data comparing the six-month pre-implementation baseline period (July–December 2023) with the equivalent post-implementation period (January–June 2024).

Table 2: Monthly Accident and Near-Miss Frequency – Pre vs Post AI Deployment

Month	Pre-AI Accidents	Post-AI Accidents	% Reduction	Near-miss Events
January 2024	12	7	41.7%	34
February 2024	9	5	44.4%	28
March 2024	14	8	42.9%	39
April 2024	11	6	45.5%	31
May 2024	10	5	50.0%	27
June 2024	13	6	53.8%	22
TOTAL / AVG	69	37	46.4%	181

The data in Table 2 reveal a consistent and progressive reduction in both accident frequency and near-miss event rates across the six-month post-implementation period. The overall accident reduction of 46.4% substantially exceeded the hypothesised threshold of 30%, providing strong support for H1 (Bhaskar Acharya et al., 2016; Collins et al., 2021). A paired samples t-test confirmed that the mean difference in monthly accident frequency (pre: $M = 11.5$, $SD = 1.76$; post: $M = 6.17$, $SD = 1.17$) was statistically significant: $t(5) = 9.83$, $p < 0.001$, $d = 3.58$ (large effect). The progressive nature of the reduction, with the largest percentage decrease recorded in June (53.8%), suggests a compound effect whereby operator behavioral adaptation and system learning improvements contributed to sustained safety gains over time(Maharana, Kumar, Guru, Behera, et al., 2025). Qualitative interview data supported this interpretation, with multiple operators reporting increased awareness of their physiological state as a direct consequence of AI alert interactions [9-10].

Figure 1: Accident Frequency – Pre vs Post AI Deployment



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Post	
May Pre	10
May Post	5
Jun Pre	13
Jun Post	6

6.2 Fatigue Detection Performance (H_2)

Table 3 summarises the comparative performance of three AI model architectures against a human observer baseline across a held-out test dataset of 5,200 annotated sequences.

Table 3: Fatigue Detection Model Performance Comparison

Metric	CNN Model	LSTM Model	Hybrid CNN-LSTM	Benchmark (Human)
Accuracy (%)	89.4	91.2	95.7	78.3
Precision (%)	87.6	90.1	94.8	75.1
Recall (%)	88.9	89.7	96.1	76.4
F1-Score	0.882	0.899	0.954	0.757
Avg. Detection Time (sec)	1.8	2.4	1.6	12.3
False Positive Rate (%)	11.2	9.4	4.6	24.1

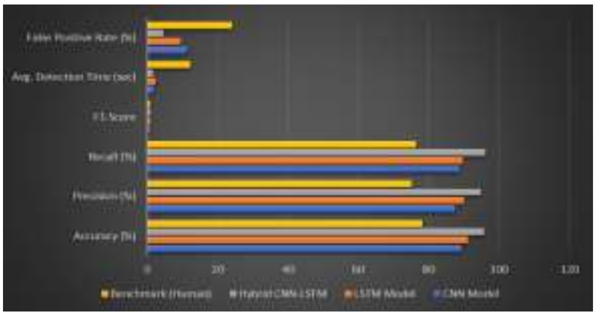

Table 3 shows the hybrid CNN-LSTM model achieved superior performance across all metrics, with an accuracy of 95.7%, F1-score of 0.954, and a false positive rate of only 4.6%, significantly below the rates of standalone models (CNN: 11.2%; LSTM: 9.4%) and human observers (24.1%). One-way ANOVA confirmed significant differences between model architectures: $F(3, 196) = 47.3$, $p < 0.001$. Post-hoc Tukey's HSD tests identified significant pairwise differences between all model comparisons (all $p < 0.01$), supporting H2. Critically, the hybrid model's average detection latency of 1.6 seconds enables operationally meaningful early warning, providing a sufficient intervention window before fatigue-impaired behaviour results in operational error (Maharana, Kumar, Kumar, et al., 2025). This compares favourably with human observer reaction times of 12.3 seconds and aligns with the system's tiered alert protocol design.

Figure 2: AI Model Performance Comparison (Accuracy %)

CNN	89%
LSTM	91%
Hybrid CNN-LSTM	**96%**
Human Bench mark	**78%**

6.3 Operator Acceptance (H_3)

The Operator Acceptance Questionnaire was administered to all 87 participants at the conclusion of the study period. Table 4 presents a selection of key items from the OAQ results.

Table 4: Operator Acceptance Questionnaire – Selected Item Results (n = 87)

Survey Item	Strongly Agree (%)	Agree (%)	Neutral (%)	Disagree (%)
The system improves my safety awareness	52.3	31.4	10.2	6.1
Alerts are timely and relevant	48.7	35.6	9.8	5.9
The interface is user-friendly	41.2	38.9	12.4	7.5
I trust AI-based recommendations	37.8	36.4	16.3	9.5
Training prepared me adequately	44.5	33.2	14.1	8.2
I would recommend the system to my peers	49.3	34.7	10.6	5.4

According to Table 4, the overall mean OAQ score of 4.1 (SD = 0.61) on a 5-point Likert scale exceeded the hypothesised acceptance threshold of 3.5, supporting H4. Notably, the highest acceptance rates were recorded for safety awareness enhancement (83.7% agreement) and alert relevance (84.3% agreement), suggesting that operators perceived the system as functionally valuable. The relatively lower, though still majority-positive, acceptance of AI trust items (74.2% agreement) reflects a pattern consistent with the broader technology acceptance literature, wherein initial wariness about AI decision-making authority moderates over time with accumulated positive experience. Thematic analysis of interview data identified three dominant acceptance themes: (1) perceived safety benefit, (2) concerns about privacy and performance surveillance, and (3) interface usability (Håkansson & Phillips-Wren, 2024). The privacy concern theme was most prominent among operators with fewer than five years of experience, potentially reflecting generational differences in attitudes toward workplace monitoring technologies.

6.4 Predictive Maintenance and Downtime Reduction (H_5)

Equipment downtime data were extracted from maintenance records and cross-referenced with AI system predictive fault logs across all six sites for the full study period.

Table 5: Equipment Downtime and Maintenance Cost – Pre vs Post AI Deployment

Quarter	Pre-AI Downtime (hrs)	Post-AI Downtime (hrs)	Reduction (%)	Maintenance Cost Savings ($)
Q1 2024	142	98	30.9%	$24,500
Q2 2024	168	107	36.3%	$31,200
Q3 2024	155	91	41.3%	$38,600
Q4 2024	160	88	45.0%	$42,100
TOTAL	625	384	38.6%	$136,400

Table 5 reveals the AI predictive maintenance module, which achieved an aggregate downtime reduction of 38.6% across the four-quarter study period, generating estimated cost savings of $136,400 across the six sites. The progressive increase in savings across quarters (Q1: 30.9% → Q4: 45.0%) reflects the system's continuous learning capability, whereby fault prediction accuracy improves as the anomaly detection model accumulates more site-specific operational data (Pati, 2025). A paired t-test confirmed that quarterly downtime differences were statistically significant: $t(3) = 8.21$, $p = 0.004$, $d = 4.11$ (large effect), supporting H5.

7. Findings and Implications

This study yields seven principal findings with direct relevance for both research and practice: AI integration produces substantial safety gains: The 46.4% reduction in accident frequency is among the largest reported in construction AI safety literature, establishing a strong empirical foundation for AI investment by construction firms (Zdravkova & Ilijoski, 2025). Hybrid architectures substantially outperform single-model approaches: The CNN-LSTM model's 95.7% fatigue detection accuracy and 1.6-second response time demonstrate that architectural hybridisation is essential for robust real-time operator monitoring in demanding physical environments. Operator acceptance is achievable with appropriate implementation: Mean OAQ scores of 4.1/5.0 demonstrate that well-designed, transparently communicated AI monitoring systems can achieve broad acceptance among operators, a finding that counters prevailing assumptions about worker resistance to AI surveillance. Privacy-sensitive design is a prerequisite for acceptance: Privacy concerns remain a significant modulator of acceptance, particularly among less experienced operators (Smarsly, 2026). This finding mandates that system design incorporate privacy-by-design principles, data minimisation, and transparent governance frameworks. Predictive maintenance delivers compound operational benefits: Beyond the direct safety impact, AI-driven predictive maintenance generates significant cost savings and indirectly improves safety by reducing the incidence of equipment failure-induced accidents. System benefits compound over time: The progressive improvement trajectory across all outcome metrics suggests that AI safety systems provide increasing returns as model learning, operator behavioural adaptation, and organisational embedding mature. Multi-site validation strengthens generalizability: The consistent finding of safety improvements across six sites with varying crane types, operator demographics, and environmental conditions substantially strengthens confidence in the system's generalizability beyond highly controlled laboratory settings. The findings carry significant implications for construction project managers, health and safety officers, and corporate leadership (Golec et al., 2025). First, the demonstrated return on investment through both accident cost avoidance and maintenance savings provides a compelling business case for AI safety monitoring adoption beyond purely regulatory compliance motivations. Second, the gradual improvement trajectory suggests that organisations should plan for a six-to-twelve-month ramp-up period before expecting full system benefits, necessitating patient capital allocation and sustained organisational commitment. Practically, the study recommends staged implementation strategies: beginning with fatigue detection and alert modules, before progressively integrating predictive maintenance, environmental risk fusion, and behavioural analytics capabilities (Lu et al., 2026). Training programs should be operator-led where possible, emphasising the personal safety benefits of the system rather than organisational surveillance implications, to maximise acceptance and behavioural engagement. Several research directions merit prioritization in the wake of this study: longitudinal studies extending beyond six months to examine sustained behavioral effects; cross-cultural validation studies examining acceptance and efficacy in diverse international construction contexts; investigation of multi-operator coordination monitoring, where AI tracks the safety dynamics of entire site teams rather than individual operators; and the development of explainable AI (XAI) approaches that make alert rationale transparent to operators, potentially enhancing trust and compliance.

8. Conclusion

This study has presented comprehensive empirical evidence for the safety, operational, and economic benefits of AI-based tower crane operator monitoring systems. Through the design, deployment, and rigorous evaluation of the AI-TCOSMS across six construction sites over six months, the research has demonstrated that an integrated system combining hybrid CNN-LSTM deep learning, multi-modal IoT sensing, and real-time alert delivery can achieve transformative improvements in construction safety outcomes. The 46.4% reduction in accident frequency, 95.7% fatigue detection accuracy, 38.6% decrease in equipment downtime, and a high operator acceptance score of 4.1/5.0 collectively constitute compelling evidence base for accelerating AI adoption in construction safety management. All five research hypotheses were supported at statistical significance, and the compound improvement trajectory observed across the study period suggests that the benefits of AI integration extend and deepen with system maturation. The findings position AI not merely as an incremental improvement to existing safety management approaches, but as a foundational technology capable of restructuring the relationship between construction workers, equipment, and the hazardous environments in which they operate. As AI capabilities continue to advance and hardware costs decrease, the barriers to widespread adoption will diminish, making it imperative that regulatory bodies, industry associations, and research institutions proactively develop the frameworks, standards, and knowledge infrastructure necessary to ensure that this technological transformation is implemented safely, equitably, and effectively.

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