Journal of Occupational Safety, Health, and Environmental Management (K3)
Vol. 01, No. 1, February 2026, Page 96-111
E-ISSN XXX-XXXX

A Conceptual Framework for Integrating AI into Risk-Based Hazard Management and Auditing in Occupational Safety and Health Systems

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Article Information
Received: April 06, 2026
Revised: May 07, 2026
Online: May 09, 2026

Keywords
Artificial Intelligence (AI), Occupational Safety and Health (OSH), Predictive Hazard Assessment, Risk-Based Management, Safety Audit and Assurance

ABSTRACT
Purpose: This study examines how artificial intelligence (AI) can enhance occupational safety and health (OSH) by integrating operational risk management and auditing within a unified, risk-based framework. It addresses the gap in understanding AI's role across the OSH lifecycle. Methods: A conceptual framework was developed based on ISO 45001:2018 principles, combining AI-enabled hazard identification, predictive risk assessment, control implementation, and feedback-driven review. Key features include machine learning analytics, sensor-based monitoring, and decision-support systems. The framework was designed by considering organizational conditions, control measures, and evidence-based decision-making, with attention to traceability and auditability. Results: The framework specifies an AI-enabled OSH lifecycle integrating hazard identification, predictive risk evaluation, control implementation, and feedback-driven review within a unified risk-based structure. It establishes traceable linkages between risk signals, control measures, and audit evidence, and defines data flows supporting continuous monitoring, anomaly detection, and risk-informed decision-making across operational and assurance functions. Implications: Integrating AI into OSH practice supports preventive, data-driven safety management, enhances certification assurance, and informs governance and policy decisions, while emphasizing responsible implementation. Conclusion: AI can serve as a coherent enabling layer connecting operational safety and assurance processes, advancing prevention-oriented, continuously improving OSH systems. The study provides a foundation for future empirical research and policy development to ensure effective and accountable AI integration in occupational safety governance.

INTRODUCTION

Occupational safety remains a critical concern across industrial sectors as organizations continue to face persistent challenges in preventing occupational injuries and managing exposure to diverse hazards. Industries such as construction, manufacturing, and healthcare are particularly affected due to the coexistence of acute physical risks and long-term exposure to environmental and chemical agents (Azizi et al., 2022; Elumalai et al., 2017). Climate-sensitive risks, particularly occupational heat stress, further intensify safety vulnerabilities and directly affect worker health and productivity in outdoor and low-resource settings (Kjellstrom et al., 2009). These challenges highlight the need for more adaptive and preventive occupational safety and health (OSH) systems beyond traditional compliance-oriented approaches (Nunfam et al., 2019).

Despite advancements in regulatory frameworks, current OSH management systems, including ISO 45001:2018, continue to rely heavily on periodic inspections, documentation-based assessments, and retrospective audit evidence. This limits their ability to detect emerging risks in real time and restricts the integration of operational safety data into continuous decision-making and assurance processes (ISO 45001, 2018). As a result, risk identification and control remain largely reactive rather than predictive. Conventional ergonomic and occupational risk assessment methods such as the NIOSH Lifting Equation (RNLE), Manual Handling Assessment Charts (MAC), Rapid Entire Body Assessment (RAMP), and Assessment of Repetitive Tasks (ART) also exhibit similar limitations, as they rely on periodic observational scoring and static exposure evaluation that do not adequately capture dynamic variations in workload, posture, and task demands in real work environments. These tools depend on periodic observational scoring and static exposure estimation, which restrict their capacity to capture dynamic variations in workload, posture, repetition, and exposure conditions in real workplace environments (Rossi et al., 2013; Waters et al., 1993). Consequently, while they provide structured and standardized assessments, they are insufficient for representing real-time risk variability in complex industrial systems.

The increasing complexity of modern workplaces has driven interest in data-driven and adaptive safety approaches. Artificial intelligence (AI), the Internet of Things (IoT), and predictive analytics enable continuous monitoring, anomaly detection, and predictive risk estimation using real-time data streams, extending the capabilities of traditional OSH systems (Abbasi, 2018). Wearable sensors and IoT devices further enhance exposure monitoring and early hazard detection at the operational level (Nithilan et al., 2024). Within such systems, machine learning and analytics support hazard detection, risk prioritization, and decision support, while human oversight remains essential to ensure interpretability, ethical validity, and contextual relevance (Usama et al., 2024). Safety audits complement implementation by verifying control effectiveness and supporting continual improvement through structured performance evaluation. However, in practice, implementation and audit functions remain weakly integrated due to reliance on static documentation rather than continuous evidence flows (Sadeghi et al., 2025).

Traditional OSH performance metrics rely on lagging indicators, such as OSHA recordable injury rates, DART (Days Away, Restricted, or Transferred) injury rates, and EMR (Experience Modification Rate), these provide retrospective insights and limited guidance for proactive prevention (Ali et al., 2022; Gil et al., 2022). This creates a well-recognized limitation, as overdependence on lagging indicators reduces organizational capacity for proactive risk management (Yorio et al., 2020). In contrast, leading indicators provide early signals of unsafe conditions and system degradation (da Silva & Amaral, 2019; Podgórski, 2015). When combined with AI and IoT systems, these indicators can be continuously updated using real-time operational data, enabling predictive and adaptive safety interventions (Islam, 2025; Quaigrain & Issa, 2023).

Workplace injuries arise from complex interactions among human, technical, and environmental factors, while occupational hazards represent potential sources of harm under specific exposure conditions (Debela et al., 2022). In manufacturing environments, structured data such as maintenance logs and production records support predictive modeling, whereas construction environments require integration of unstructured data including visual, textual, and sensor-based inputs (Almaskati et al., 2024; Birhane et al., 2022). AI-based safety models typically include structured-data learning, natural language processing, computer vision, and sensor-based anomaly detection approaches (Campo et al., 2020; Kyung et al., 2023). However, their effectiveness depends on data quality, generalizability, and validation across operational contexts (Alqahtani et al., 2022; Y. C. Lee et al., 2020; G. J. L. Micheli et al., 2022).

Despite these advances, existing research remains fragmented, with AI applications largely limited to isolated predictive tasks such as hazard detection or incident classification, without integration into end-to-end occupational safety management systems (Li et al., 2025; Tixier et al., 2016). Similarly, ISO 45001-based systems continue to lack mechanisms for integrating real-time predictive risk intelligence into audit and certification processes, creating a disconnect between operational risk detection and formal assurance structures (Podgórski, 2015). This gap is further reinforced by the limited integration of AI-driven predictive systems with audit governance frameworks, particularly in ensuring traceability, explainability, and validation of risk-based decisions (Karanikas et al., 2022; Ozobu et al., 2025). Although AI improves predictive capability, concerns related to model reliability, bias, and contextual validity require structured oversight and system-level integration (Amodei et al., 2016; J. Lee et al., 2018; M. Micheli et al., 2020).

To address this gap, this study develops a conceptual framework that positions AI as an enabling layer across both OSH implementation and auditing within a unified risk-based management system. The framework differentiates two interconnected functions: (i) OSH implementation, where AI supports predictive risk assessment, real-time hazard detection, and adaptive control of unsafe conditions, and (ii) OSH auditing, where AI enables continuous verification of control effectiveness, compliance monitoring, leading indicator tracking, and structured audit evidence generation aligned with ISO 45001 requirements. This integrated perspective advances a lifecycle-oriented OSH model in which AI enhances not only preventive risk control but also the traceability, transparency, and auditability of occupational safety management systems.

METHODS

The study develops a conceptual framework integrating AI into OSH implementation and auditing across hazard identification, risk evaluation, control selection, and performance verification through iterative feedback loops. Grounded in ISO 45001:2018 and occupational risk mapping principles, it establishes a unified risk-based OSH cycle linking operational control with audit and assurance functions. Unlike conventional approaches that separate implementation and auditing, the model reflects their convergence through digital data integration and analytics, enabling continuous and predictive risk oversight across the OSH lifecycle. The framework uses occupational risk maps as the primary analytical representation for structuring hazard–risk–control relationships.

1. Conceptual Framework Development

Occupational risk maps provide the analytical basis for modern OSH management systems by structuring relationships between hazards, exposure scenarios, and consequences. Within this study, they are used as a core representation for structuring risk information to support risk-based decision-making under ISO 45001:2018 across routine and non-routine conditions (ILO, 2019). Compared with checklist-based approaches, risk maps offer a dynamic representation of workplace risk, enabling prioritization of high-risk activities and evolving hazard conditions (Colletaz et al., 2013; Kiral, 2025).

Within integrated safety management systems, risk maps operationalize the linkage between hazard identification, risk evaluation, and control planning through classification by likelihood and severity (Cinar & Cebi, 2021). From an audit perspective, they provide traceable links between identified risks and corresponding control measures, enabling evaluation of compliance and effectiveness during certification processes (Jespersen & Hasle, 2017). By aligning risk representation with operational units such as tasks, zones, and processes, they strengthen both preventive control and auditability (Noch, 2024).

2. Functional Boundaries of OSH Implementation and Audit

OSH implementation and OSH auditing perform complementary but distinct functions within risk-based safety management systems. Implementation focuses on hazard identification, risk assessment, and execution of preventive and protective controls in routine operations, supported by worker participation and continuous improvement. In contrast, OSH auditing provides independent assurance by evaluating whether these processes are adequately designed, consistently applied, and compliant with applicable standards and legal requirements (BIS:14489, 2018; ISO 45001, 2018). Audits do not directly manage risks but verify the effectiveness and traceability of risk control measures. This functional separation supports audit objectivity, while audit feedback contributes to continual improvement of OSH implementation under risk-based management principles.

3. Risk Representation Using Occupational Risk Maps

Effective occupational safety requires systematic assessment of hazards, processes, and controls. AI enables predictive risk modeling, near real-time monitoring, and data-driven decision-making, supporting earlier hazard detection and optimization of preventive interventions (Ozobu et al., 2025; Tixier et al., 2016). However, AI systems are limited by data dependency, model bias, and reduced generalizability under dynamic conditions. Performance degradation under dataset shift requires continuous validation and human oversight, reinforcing human-in-the-loop governance and context-sensitive interpretation (Amodei et al., 2016; J. Lee et al., 2018; M. Micheli et al., 2020). These constraints highlight the need for human-in-the-loop governance and context-sensitive interpretation.

Traditional audits rely on compliance checks and post-incident review, offering limited predictive capability. AI-enabled audits extend these functions through predictive analytics, anomaly detection, and continuous data streams, enabling earlier hazard identification, targeted interventions, and improved operational responsiveness (Karadağ, 2024), aligned with ISO 45001 principles and sustainability objectives (ILO, 2023; ISO 45001, 2018).

4. Role of AI Across the OSH Lifecycle

Across the OSH lifecycle, AI supports both risk-based implementation and audit-based assurance, aligned with the Plan–Do–Check–Act cycle of ISO 45001 (Karanikas et al., 2022). During planning and risk assessment, AI integrates multi-source data to generate leading risk indicators for preventive decision-making (Abbasi, 2018; Usama et al., 2024). In the implementation phase, integration with IoT sensors, wearables, and vision systems enables continuous monitoring of exposures, unsafe conditions, and procedural deviations, supporting timely interventions beyond periodic inspections (Y. C. Lee et al., 2020).

From an audit and assurance perspective, AI enhances risk-based auditing by improving traceability between identified risks, implemented controls, and performance outcomes. Predictive analytics, anomaly detection, and automated data processing support more consistent, evidence-based compliance evaluation, reducing reliance on lagging indicators and retrospective assessments (BIS:14489, 2018; ISO 45001, 2018; PRYTULSKA et al., 2019).

Through continuous feedback loops, AI integrates implementation and auditing into a unified system of anticipatory risk control and continual improvement, while maintaining human oversight and accountability (Amodei et al., 2016; ISO 45001, 2018; Karanikas et al., 2022; Ozobu et al., 2025). Computer vision and sensor analytics further strengthen hazard detection by identifying unsafe behaviors, PPE non-compliance, and abnormal process states often missed in periodic inspections. When combined with predictive analytics, these tools extend AI from task-level monitoring to lifecycle-wide risk anticipation and control optimization, reinforcing prevention-oriented OSH management (El-Helaly, 2024).

5. Conceptual Framework for AI-Enabled OSH

To operationalize risk-based thinking in a digital OSH environment, this study develops a conceptual architecture in which AI acts as an enabling layer across the OSH lifecycle, linking implementation with audit and assurance functions.

The framework (Figure 1) integrates heterogeneous data sources, including structured data (e.g., production logs, maintenance records, exposure measurements) and unstructured data (e.g., incident narratives, safety observations, and visual feeds). These inputs are processed using multiple AI techniques, including supervised learning for risk prediction, natural language processing (NLP) for hazard extraction from textual data, computer vision for detecting unsafe behaviors and PPE compliance, and time-series and anomaly detection models for sensor and wearable data streams.

Core algorithmic implementation includes Random Forest and Gradient Boosting for risk prediction, convolutional neural networks (CNNs) for image and video-based safety detection, NLP models for textual hazard identification, and anomaly detection techniques for real-time monitoring of operational deviations.

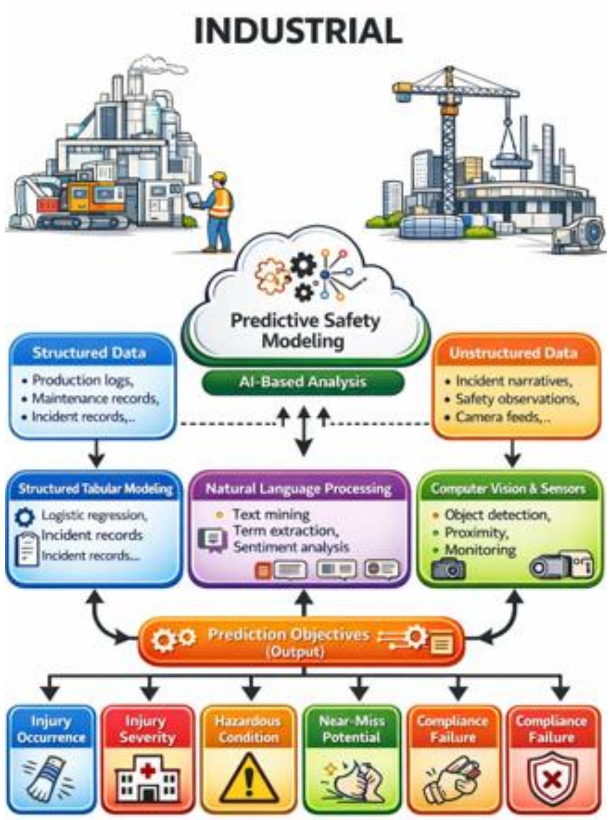

Figure 1. Conceptual Framework for AI-Enabled OSH Implementation and Auditing

Together, these components transform raw operational data into predictive risk indicators, control-relevant signals, and auditable evidence. The architecture aligns with ISO 45001 principles of risk-based thinking and continual improvement (BIS:14489, 2018; ILO, 2019; ISO 45001, 2018), and supports early identification of precursor conditions such as unsafe acts, hazardous exposures, and near-miss events (Marhavilas et al., 2022).

Within this structure, ergonomic risk is treated as multidimensional, encompassing physical factors (e.g., posture, force, repetition), psychosocial conditions (e.g., workload, stress, job demands), and individual variability. These dimensions are captured through multimodal inputs, including wearable sensors, task-level observations, and contextual indicators, enabling a comprehensive system-level representation of occupational risk.

6. Operationalisation of the AI-Enabled OSH Framework

Building on the conceptual architecture presented in Figure 1, the framework is operationalized as a continuous risk management cycle comprising hazard identification, AI-supported risk evaluation, control implementation, and feedback-driven review. The cycle is iterative and driven by continuous data flows, enabling adaptation to evolving operational risk conditions. Figure 2 illustrates this transformation of conceptual components into a dynamic workflow for real-time OSH decision-making.

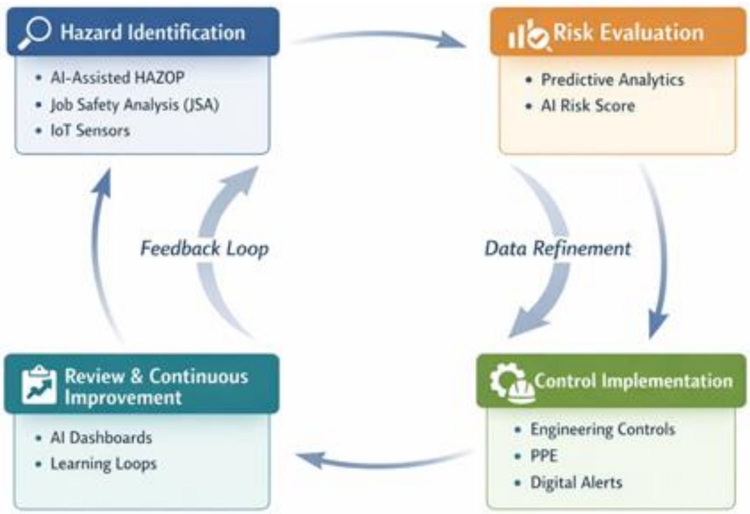

Figure 2. AI-enabled risk assessment cycle operationalizing the conceptual OSH framework.

Hazard identification is supported through AI-assisted HAZOP, job safety analysis, and real-time sensing systems. Risk evaluation applies analytical models to multimodal data streams to generate quantitative risk scores and anomaly flags. These outputs activate predefined decision thresholds that trigger appropriate engineering, administrative, or digital control measures. The review stage integrates dashboards and audit trails to evaluate control effectiveness and ensure traceability between hazards, controls, and outcomes, embedding operational learning through feedback loops.

From an implementation perspective, the framework follows an input–process–output structure. Inputs include structured data (incident logs, exposure records) and unstructured data (inspection reports, images, and sensor streams). These are processed using defined AI model classes, including Random Forest and Gradient Boosting for risk prediction, CNNs for visual detection of unsafe behaviors and PPE compliance, NLP models for textual hazard extraction, and anomaly detection techniques for sensor-based streams. This processing generates risk scores, anomaly flags, and threshold-based alerts, supporting OSH decision-making and audit traceability within the ISO 45001 PDCA cycle. Decision thresholds determine escalation or control activation, while outputs include performance indicators such as detection frequency, false positive rate, and response latency (M. Micheli et al., 2020; Saito & Rehmsmeier, 2015), enabling continuous system improvement.

Thresholds are calibrated using historical data, regulatory limits, or defined risk tolerance levels. A hypothetical scenario (e.g., construction site monitoring using wearable sensors and anomaly detection) illustrates operational feasibility. Continuous data refinement and feedback loops enable adaptive, risk-based OSH management while maintaining alignment with ISO 45001 requirements. Empirical validation of model performance and system effectiveness is identified as a key direction for future research.

RESULTS

This section presents the outcomes of the proposed AI-enabled OSH framework, focusing on its application across implementation and auditing functions within an ISO 45001:2018-aligned risk-based management system. The results are organized into two interrelated dimensions: (i) AI-enabled OSH implementation and (ii) AI-supported risk mapping for control and audit assurance.

1. AI-Enabled OSH Implementation

AI-enabled OSH implementation integrates data-driven technologies across hazard identification, risk assessment, and control processes in alignment with ISO 45001:2018 (ISO 45001, 2018). By combining structured data (e.g., incident records, maintenance logs, exposure measurements) and unstructured data (e.g., safety observations, narratives, images, and video), AI enhances detection frequency, reduces decision variability, and improves response latency in occupational risk management (Ravi & Janarthanan, 2024; Tixier et al., 2016).

At the hazard identification and risk assessment stage, machine learning and predictive analytics enable dynamic risk profiling by detecting unsafe patterns, emerging hazards, and high-risk task–environment interactions that are not captured through periodic assessments (Tian et al., 2025). This facilitates precursor-level risk detection and shifts OSH management from static reporting to continuous risk evaluation.

During operational control, AI-enabled systems such as IoT sensors, computer vision, and wearable devices support near real-time monitoring of workplace conditions. These systems detect unsafe proximity, PPE non-compliance, abnormal process states, and fatigue-related indicators through continuous data streams and anomaly detection models. Predictive outputs generate risk scores and threshold-based alerts that enable targeted interventions at task, area, or equipment levels, ensuring alignment between risk prediction and managerial control units (Kim et al., 2016; Park et al., 2017; Saxena, 2024). AI also supports emergency preparedness through scenario-based modeling, threshold-triggered alerts, and decision-support systems under abnormal conditions, improving organizational response capability (Gupta & Roy, 2024). In addition, AI-driven analytics generate leading safety indicators and feedback loops that support management review, corrective actions, and continuous improvement. This complements traditional lagging indicators and strengthens overall OSH system effectiveness (Erinjogunola et al., 2025).

2. AI-Enabled OSH Audit, Assurance, and Certification

AI-derived risk scores and anomaly flags are systematically mapped to threshold-based control measures across key hazard domains, including physical, psychosocial, and operational risks (Table 1). This framework extends implementation logic into an audit-support function by establishing structured and traceable links between identified risks and corresponding control actions. It further enables the generation of auditable evidence for engineering, administrative, and technological controls, thereby supporting both OSH implementation and certification audits within risk-based management systems. During audit processes, this mapping facilitates verification of risk-based decision-making, adequacy of controls, and continual improvement in alignment with ISO 45001 requirements.

Table 1. AI-Enabled Risk Assessment and Control Mapping in OSH

Audit Aspect	Hazard Category	AI-Enabled Risk Category	Control Measures

Electrical Safety	Shock, Fire	Voltage/current, thermal sensors; anomaly detection (overload, heat rise)	Smart PPE, automated earthing checks, predictive maintenance
Material Handling	Ergonomic (physical), Mechanical	Wearable IMU sensors (posture, force, repetition) + ML risk scoring; workload indicators	Robotic lifting aids, task rotation/ scheduling, ergonomics training
Process Safety	Chemical, Explosion, Psychosocial	Gas sensors (VOC, CO, H_2S); predictive models; workload indices (task duration, frequency) and stress proxies (physiological or survey-based)	Isolation, substitution, ventilation control, shift/ workload management

AI-enabled OSH auditing extends traditional compliance verification by incorporating data-driven evidence, predictive analytics, and continuous monitoring into assurance and certification processes. In line with ISO 45001:2018 and ILO guidance, audits must assess not only procedural conformity but also the effectiveness of risk-based controls and continual improvement mechanisms (ISO 45001, 2018). In the Indian context, BIS IS 14489 further strengthens audit practice through structured principles for safety audit execution and evaluation of control effectiveness (BIS:14489, 2018).

Within this framework, AI supports audit enhancement through anomaly detection, trend analysis, and predictive risk mapping. These capabilities improve visibility of evolving risks; however, their reliability depends on data quality, model validation, and contextual interpretation, requiring human oversight to manage bias, drift, and false signals (Amodei et al., 2016; M. Micheli et al., 2020). AI-generated audit trails provide traceable links between hazards, risk levels, and implemented controls, enabling more objective and evidence-based conformity assessment across operational states (Noch, 2024; Ozobu et al., 2025). This reduces reliance on episodic inspections and retrospective documentation, allowing auditors to assess control performance across normal, abnormal, and emergency operating conditions.

From a governance perspective, AI also strengthens risk-based audit planning by prioritizing high-risk processes using real-time and historical risk signals (Usul & Alpay, 2025). For certification and surveillance audits, this improves consistency, detection capability, and evidence traceability while preserving auditor independence and professional judgment. Overall, AI functions as a decision-support layer that enhances, not replaces, audit credibility, transparency, and continual improvement under ISO 45001-based systems (ISO 45001, 2018; Skeja & Sadiku-Dushi, 2025).

DISCUSSION

The proposed AI-enabled OSH framework has important implications for how occupational safety is implemented, audited, and governed in complex industrial systems. By embedding AI across both operational risk control and assurance functions, the study demonstrates a shift from fragmented, compliance-oriented safety management toward an integrated, risk-based, and anticipatory OSH lifecycle.

1. Implications for Practice

From a practical standpoint, AI enables continuous sensor-based hazard monitoring with defined sampling intervals and anomaly detection, predictive risk modeling, and adaptive control feedback. Real-time data from sensors, logs, and observations allow organizations to identify emerging risks before they materialize into incidents, supporting targeted interventions and resource prioritization. Importantly, this strengthens frontline decision-making and reinforces worker participation by reducing response time and enabling context-specific, data-driven interventions. However, effective deployment requires data governance, workforce competence, and clear accountability to avoid over-reliance on automated outputs.

In comparison with conventional ergonomic and risk assessment tools such as the Revised NIOSH Lifting Equation (RNLE) (Waters et al., 1993), MAC (Górny, 2020), RAMP (Rose et al., 2020), and ART (Khandan et al., 2017), which rely on periodic observation and predefined scoring systems, the proposed framework introduces continuous data acquisition, higher temporal resolution, and predictive risk estimation (da Silva & Amaral, 2019; Podgórski, 2015). While traditional tools provide standardized and interpretable outputs, they are limited by snapshot-based assessments and reduced sensitivity to dynamic risk conditions. In contrast, AI-enabled approaches increase detection frequency and enable early identification of risk precursors, but introduce dependencies on data quality, model calibration, and computational infrastructure (Tixier et al., 2016).

2. Implications for Audit, Certification, and Assurance

For auditing and certification, AI increases audit frequency, data coverage, and detection sensitivity in assurance practices. AI-enabled audits move beyond periodic, retrospective assessments toward continuous, evidence-based verification of risk controls and system performance. This aligns strongly with the risk-based and continual improvement principles of ISO 45001 and related standards, while also complementing structured audit requirements such as those articulated in BIS IS 14489. Nevertheless, AI does not replace professional judgment; auditors remain responsible for validating AI outputs, interpreting contextual and psychosocial risks, and ensuring ethical, transparent, and explainable use of digital tools.

Compared to conventional audit approaches that rely on document review and periodic site verification, AI-enabled auditing supports continuous evidence generation and anomaly-based audit triggers. This increases audit coverage and reduces reliance on retrospective indicators; however, it also introduces challenges related to model interpretability, validation of automated outputs, and auditor dependence on algorithmic recommendations. These limitations highlight that AI systems may fail silently or degrade under changing conditions, reinforcing the need for human oversight and auditable validation mechanisms (Amodei et al., 2016).

3. Implications for Governance and Policy

The integration of AI into occupational safety and health management has important governance and policy implications. AI applications such as predictive analytics, wearable monitoring, and automated inspections enhance proactive hazard identification, but require regulatory oversight to ensure reliability, accountability, and compliance (El-Helaly, 2024; Ozobu et al., 2025). Limitations related to data quality, contextual variability, and dependence on historical datasets may reduce predictive robustness in dynamic environments, necessitating continuous validation and performance monitoring (El-Helaly, 2024; Li et al., 2025).

From a technical perspective, AI systems are affected by model drift, contextual sensitivity, and reduced stability under non-stationary conditions, consistent with broader AI safety concerns regarding robustness and failure modes (Amodei et al., 2016; J. Lee et al., 2018; M. Micheli et al., 2020). In addition, many machine learning models function as "black boxes," limiting interpretability and thereby constraining auditability and regulatory acceptance (Amodei et al., 2016). Algorithmic bias arising from imbalanced or context-specific data may further lead to systematic under-detection of hazards across certain tasks or worker groups (J. Lee et al., 2018; M. Micheli et al., 2020).

Within OSH governance frameworks, responsibility for risk control remains with employers and duty holders under regulatory requirements. AI therefore operates as a decision-support system rather than an autonomous authority, requiring human oversight, continuous validation, and auditable decision pathways.

Ethical considerations related to transparency, privacy, and accountability further necessitate structured governance mechanisms. Regulatory and certification systems may need to evolve to evaluate AI-supported controls, data integrity, and oversight processes in alignment with ISO 45001 principles and international labour standards (Karanikas et al., 2022). Overall, AI should be positioned as an auditable augmentation tool that strengthens, rather than replaces, human judgment and regulatory accountability.

CONCLUSIONS

This study presents a conceptual framework positioning artificial intelligence (AI) as an enabling layer across both OSH implementation and auditing within a risk-based management system. By integrating predictive risk assessment, real-time monitoring, and data-driven audit evidence, the framework supports alignment between operational control and assurance processes within ISO 45001-based systems.

From a practical perspective, AI-enabled analytics offer measurable improvements in detection frequency, response timeliness, and consistency of risk evaluation, while maintaining the central role of human judgment in safety-critical decision-making.

However, the framework remains conceptual and requires empirical validation. Future research should focus on pilot implementation, scenario-based evaluation, and the development of standardized metrics and audit criteria to assess effectiveness across diverse operational contexts.

ACKNOWLEDGMENT

The author extends his appreciation to the Bhubaneswar Institute of Technology, Bhubaneswar (Odisha), for providing support in carrying out this innovative work. The author has reviewed and edited the output and takes full responsibility for the content of this publication. Satchidananda Mishra has contributed to Conceptualization, Supervision, Visualization, and Writing – Review & Editing. The corresponding author has read and approved the final version of the manuscript and agrees to its submission for publication.

REFERENCES

Abbasi, S. (2018). Defining safety hazards & risks in mining industry: a case-study in United States. *Asian J. Appl. Sci. Technol.(AJAST)*, *2*(2), 1071–1078. https://doi.org/10.1016/j.jsm.2018.07.005

Ali, M. X. M., Arifin, K., Abas, A., Ahmad, M. A., Khairil, M., Cyio, M. B., Samad, M. A., Lampe, I., Mahfudz, M., & Ali, M. N. (2022). Systematic literature review on indicators use in safety management practices among utility industries. *International Journal of Environmental Research and Public Health*, *19*(10), 6198. https://doi.org/10.3390/ijerph19106198

Almaskati, D., Kermanshachi, S., Pamidimukkala, A., Loganathan, K., & Yin, Z. (2024). A review on construction safety: hazards, mitigation strategies, and impacted sectors. *Buildings*, *14*(2), 526. https://doi.org/10.3390/buildings14020526

Alqahtani, B. M., Alruqi, W., Bhandari, S., Abudayyeh, O., & Liu, H. (2022). The relationship between work-related stressors and construction workers' self-reported injuries: a meta-analytic review. *CivilEng*, *3*(4), 1091–1107. https://doi.org/10.3390/civileng3040062

Amodei, D., Olah, C., Steinhardt, J., Christiano, P., Schulman, J., & Mané, D. (2016). Concrete problems in AI safety. *ArXiv Preprint ArXiv:1606.06565*, 29. https://doi.org/ 10.48550/arXiv.1606.06565

Azizi, H., Aaleagha, M. M., Azadbakht, B., & Samadyar, H. (2022). Identification and Assessment of health, safety and environmental risk factors of Chemical Industry using Delphi and FMEA methods (a case study). *Anthropogenic Pollution*, *6*(2). https://doi.org/ 10.22034/ ap.2022.1971680.1138

Birhane, G. E., Yang, L., Geng, J., & Zhu, J. (2022). Causes of construction injuries: a review. *International Journal of Occupational Safety and Ergonomics*, *28*(1), 343–353. https://doi.org/10.1080/10803548.2020.1761678

BIS:14489. (2018). *Occupational Health and Safety Code of Practice: Vol. First Revi* (Issue October, p. 28). Bureau of Indian Standards.

Campo, G., Cegolon, L., De Merich, D., Fedeli, U., Pellicci, M., Heymann, W. C., Pavanello, S., Guglielmi, A., & Mastrangelo, G. (2020). The Italian national surveillance system for occupational injuries: Conceptual framework and fatal outcomes, 2002–2016. *International Journal of Environmental Research and Public Health*, *17*(20), 7631. https://doi.org/10.3390/ijerph17207631

Cinar, U., & Cebi, S. (2021). A novel approach to assess occupational risks and prevention of hazards: the house of safety & prevention. *Journal of Intelligent & Fuzzy Systems*, *42*(1), 517–528. https://doi.org/10.3233/JIFS-219208

Colletaz, G., Hurlin, C., & Pérignon, C. (2013). The Risk Map: A new tool for validating risk models. *Journal of Banking & Finance*, *37*(10), 3843–3854. https://doi.org/10.1016/j.jbankfin.2013.06.006

da Silva, S. L. C., & Amaral, F. G. (2019). Critical factors of success and barriers to the implementation of occupational health and safety management systems: A systematic review of literature. *Safety Science*, *117*, 123–132. https://doi.org/10.1016/j.ssci.2019.03.026

Debela, M. B., Azage, M., Begosaw, A. M., & Kabeta, N. D. (2022). Factors contributing to occupational injuries among workers in the construction, manufacturing, and mining industries in Africa: a systematic review and meta-analysis. *Journal of Public Health Policy*, *43*(4), 487–502. https://doi.org/10.1057/s41271-022-00378-2

El-Helaly, M. (2024). Artificial Intelligence and Occupational Health and Safety, Benefits and Drawbacks. *La Medicina Del Lavoro*, *115*(2), e2024014. https://doi.org/10.23749/mdl.v115i2.15835

Elumalai, V., Brindha, K., & Lakshmanan, E. (2017). Human exposure risk assessment due to heavy metals in groundwater by pollution index and multivariate statistical methods: a case study from South Africa. *Water*, *9*(4), 234. https://doi.org/10.3390/w9040234

Erinjogunola, F. L., Sikhakhane-Nwokediegwu, Z., Ajirotutu, R. O., & Olayiwola, R. K. (2025). Enhancing bridge safety through AI-driven predictive analytics. *International Journal of Social Science Exceptional Research. 2025*, *4*(2), 10–26. https://doi.org/10.54660/IJSSER.2025.4.2.10-26

Gil, M., Kozioł, P., Wróbel, K., & Montewka, J. (2022). Know your safety indicator–A determination of merchant vessels Bow Crossing Range based on big data analytics. *Reliability Engineering & System Safety*, *220*, 108311. https://doi.org/10.1016/j.ress.2021.108311

Górny, A. (2020). Application of the MAC Method for Risk Assessment During Handling of Loads. In P. Golinska-Dawson, K.-M. Tsai, & M. Kosacka-Olejnik (Eds.), *Smart and Sustainable Supply Chain and Logistics -- Trends, Challenges, Methods and Best Practices: Volume 1* (pp. 277–290). Springer International Publishing. https://doi.org/10.1007/978-3-030-61947-3_19

Gupta, T., & Roy, S. (2024). Applications of artificial intelligence in disaster management. *Proceedings of the 2024 10th International Conference on Computing and Artificial Intelligence*, 313–318. https://doi.org/10.1145/3669754.36698

ILO. (2019). Safety and health at the heart of the future of work-Building on 100 years of experience. In *ILO, Geneva* (Issue April). www.ilo.org/labadmin-osh

ILO. (2023). *Revolutionizing Health and Safety : The role of AI and digitalization at work.* https://www.ilo.org/publications/revolutionizing-health-and-safety-role-ai-and-digitalization-work

Islam, M. I. (2025). AI-powered MIS for risk detection in industrial engineering projects. *Authorea Preprints*, 28. https://doi.org/10.36227/techrxiv.175825736.65590627/v1

ISO 45001. (2018). *Occupational health and safety management systems — Requirements with guidance for use*. International Organization for Standardization.

Jespersen, A. H., & Hasle, P. (2017). Developing a concept for external audits of psychosocial risks in certified occupational health and safety management systems. *Safety Science*, *99*, 227–234. https://doi.org/10.1016/j.ssci.2016.11.023

Karadağ, T. (2024). Transformative role of artificial intelligence in enhancing occupational health and safety: A systematic review and meta-analysis. *The European Research Journal*, *11*(3), 1–28. https://doi.org/10.18621/eurj.1561840

Karanikas, N., Weber, D., Bruschi, K., & Brown, S. (2022). Identification of systems thinking aspects in ISO 45001: 2018 on occupational health & safety management. *Safety Science*, *148*, 105671. https://doi.org/10.1016/j.ssci.2022.105671

Khandan, M., Mosaferchi, S., & Koohpaei, A. (2017). Assessing exposure to risk factors for work-related musculoskeletal disorders using ART method in a manufacturing company. *Archives of Hygiene Sciences Volume*, *6*(3), 259–267. https://doi.org/10.29252/ArchHygSci.6.3.259

Kim, K., Cho, Y., & Zhang, S. (2016). Integrating work sequences and temporary structures into safety planning: Automated scaffolding-related safety hazard identification and prevention in BIM. *Automation in Construction*, *70*, 128–142. https://doi.org/10.1016/j.autcon.2016.06.012

Kiral, I. A. (2025). Contextual Evaluation of Risk Identification Techniques for Construction Projects: Comparative Insights and a Decision-Support Model. *Buildings*, *15*(20), 3806. https://doi.org/10.3390/buildings15203806

Kjellstrom, T., Holmer, I., & Lemke, B. (2009). Workplace heat stress, health and productivity–an increasing challenge for low and middle-income countries during climate change. *Global Health Action*, *2*(1), 2047. https://doi.org/https://doi.org/10.3402/gha.v2i0.2047

Kyung, M., Lee, S.-J., Dancu, C., & Hong, O. (2023). Underreporting of workers' injuries or illnesses and contributing factors: a systematic review. *BMC Public Health*, *23*(1), 558. https://doi.org/10.1186/s12889-023-15487-0

Lee, J., Davari, H., SIngh, J., & Pandhare, V. (2018). Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. *Manufacturing Letters*, *18*, 20–23. https://doi.org/ 10.1016/j.mfglet.2018.09.002

Lee, Y. C., Hariatfar, M., Rashidi, A., & Lee, H. W. (2020). Evidence-driven sound detection for prenotification and identification of construction safety hazards and accidents. *Automation in Construction*, *113*, 103127. https://doi.org/10.1016/j.autcon.2020.103127

Li, X., Cheng, Y., Møller, C., & Lee, J. (2025). Data issues in industrial AI systems: A meta-review and research strategy. *Computers in Industry*, *173*, 104361. https://doi.org/10.1016/j.compind.2025.104361

Marhavilas, P. K., Pliaki, F., & Koulouriotis, D. (2022). International management system standards related to occupational safety and health: An updated literature survey. *Sustainability*, *14*(20), 13282. https://doi.org/10.3390/su142013282

Micheli, G. J. L., Farné, S., & Vitrano, G. (2022). A holistic view and evaluation of health and safety at work: enabling the assessment of the overall burden. *Safety Science*, *156*, 105900. https://doi.org/10.1016/j.ssci.2022.105900

Micheli, M., Ponti, M., Craglia, M., & Berti Suman, A. (2020). Emerging models of data governance in the age of datafication. *Big Data & Society*, *7*(2), 2053951720948087. https://doi.org/ 10.1177/2053951720948087

Nithilan, K., Kumar, M. V., Vishal, N., & Thangadurai, A. (2024). Advancing Workplace Safety with IoT-Enabled Industrial Monitoring. *2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO)*, 1–4. https://doi.org/10.1109/ICRITO61523.2024.10522367

Noch, M. Y. (2024). A Critical Analysis of Risk Auditing: An Auditor's Approach. *Golden Ratio of Auditing Research*, *4*(1), 1–13. https://doi.org/https://doi.org/10.52970/grar.v4i1.383

Nunfam, V. F., Adusei-Asante, K., Van Etten, E. J., Oosthuizen, J., Adams, S., & Frimpong, K. (2019). The nexus between social impacts and adaptation strategies of workers to occupational heat stress: a conceptual framework. *International Journal of Biometeorology*, *63*(12), 1693–1706. https://doi.org/10.1007/s00484-019-01775-1

Ozobu, C. O., Adikwu, F. E., Odujobi, N. O., Onyekwe, F. O., & Nwulu, E. O. (2025). Advancing occupational safety with AI-powered monitoring systems: A conceptual framework for hazard detection and exposure control. *World Journal of Innovation and Modern Technology*, *9*(1), 186–213. https://doi.org/10.56201/wjimt.v9.no1.2025.pg186.213

Park, J., Kim, K., & Cho, Y. K. (2017). Framework of automated construction-safety monitoring using cloud-enabled BIM and BLE mobile tracking sensors. *Journal of Construction Engineering and Management*, *143*(2), 5016019. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001223

Podgórski, D. (2015). Measuring operational performance of OSH management system–A demonstration of AHP-based selection of leading key performance indicators. *Safety Science*, *73*, 146–166. https://doi.org/10.1016/j.ssci.2014.11.018

PRYTULSKA, N., ANTIUSHKO, D., & GUSAREVICH, N. (2019). International standard ISO 19011: 2018: perspectives of implementation. *INTERNATIONAL SCIENTIFIC-PRACTICAL JOURNAL COMMODITIES AND MARKETS*, *32*(4), 5–15. https://doi.org/10.31617/tr.knute.2019(32)01

Quaigrain, R. A., & Issa, M. H. (2023). Comparative analysis of leading and lagging indicators of construction disability management performance: an exploratory study. *International Journal of Construction Management*, *23*(7), 1205–1213. https://doi.org/10.1080/15623599.2021.1963921

Ravi, P., & Janarthanan, S. (2024). Machine learning models for intelligent hazard management. In *AI for Climate Change and Environmental Sustainability* (pp. 88–97). CRC Press. https://doi.org/10.1201/9781003452393

Rose, L. M., Eklund, J., Nord Nilsson, L., Barman, L., & Lind, C. M. (2020). The RAMP package for MSD risk management in manual handling – A freely accessible tool, with website and training courses. *Applied Ergonomics*, *86*, 103101. https://doi.org/10.1016/j.apergo.2020.103101

Rossi, D., Bertoloni, E., Fenaroli, M., Marciano, F., & Alberti, M. (2013). Analytic hierarchy process to support the safety and ergonomic assessment of alternatives in "manuable" material handling. *IFAC Proceedings Volumes*, *46*(9), 525–530. https://doi.org/10.3182/20130619-3-RU-3018.00305

Sadeghi, H., Mohandes, S. R., Yunusa-Kaltungo, A., Cheung, C., & Manu, P. (2025). A state-of-the-art review of safety leading indicators across diverse industries. *Journal of Safety Science and Resilience*, 100272. https://doi.org/10.1016/j.jnlssr.2025.100272

Saito, T., & Rehmsmeier, M. (2015). The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. *PloS One*, *10*(3), e0118432. https://doi.org/10.1371/journal.pone.0118432

Saxena, V. (2024). Predictive analytics in occupational health and safety. *ArXiv Preprint ArXiv:2412.16038*. https://doi.org/10.48550/arXiv.2412.16038

Skeja, A., & Sadiku-Dushi, N. (2025). Toward sustainable AI leadership: ethical blind spots, accountability gaps and the CARE governance framework. *Leadership & Organization Development Journal*, 1–19. https://doi.org/https://doi.org/10.1108/LODJ-06-2025-0530

Tian, K., Zhu, Z., Mbachu, J., Ghanbaripour, A., & Moorhead, M. (2025). Artificial intelligence in risk management within the realm of construction projects: A bibliometric analysis and systematic literature review. *Journal of Innovation & Knowledge*, *10*(3), 100711. https://doi.org

/10.1016/j.jik.2025.100711

Tixier, A. J.-P., Hallowell, M. R., Rajagopalan, B., & Bowman, D. (2016). Automated content analysis for construction safety: A natural language processing system to extract precursors and outcomes from unstructured injury reports. *Automation in Construction*, *62*, 45–56. https://doi.org/10.1016/j.autcon.2015.11.001

Usama, M., Ullah, U., Muhammad, Z., Islam, T., & saba Hashmi, S. (2024). AI-enabled risk assessment and safety management in construction. In *Ethical Artificial Intelligence in Power Electronics* (pp. 105–132). CRC Press. https://doi.org/https://doi.org/10.1201/9781032648323

Usul, H., & Alpay, B. Y. (2025). Digital Transformation in Internal Audit: Paradigm Shifts, Emerging Risks, and Strategic Resilience. *European Journal of Digital Economy Research*, *6*(1), 23–36. https://doi.org/10.5281/zenodo.15660150

Waters, T. R., Putz-Anderson, V., Garg, A., & Fine, L. J. (1993). Revised NIOSH equation for the design and evaluation of manual lifting tasks. *Ergonomics*, *36*(7), 749–776. https://doi.org/10.1080/00140139308967940

Yorio, P. L., Haas, E. J., Bell, J. L., Moore, S. M., & Greenawald, L. A. (2020). Lagging or leading? Exploring the temporal relationship among lagging indicators in mining establishments 2006–2017. *Journal of Safety Research*, *74*, 179–185. https://doi.org/10.1016/j.jsr.2020.06.018