AI POWERED RISK ASSESSMENT PLATFORM FOR WORKPLACE SAFETY

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ABSTRACT

Unsafe working conditions are still endemic in the formal and informal sectors where workers are faced with physical accidents and harassments, wage embezzlement and institutional violations of their rights that are normally kept by their superiors under retaliation. The research proposes a privacy-sensitive, AI-based platform to report and submit any issues and risks at the workplace in a secure and anonymized manner. It enables mobile and web-based reporting, smart classification of incidents using natural language understanding, and federated intelligence to improve the learning process without revealing personal information. Fragmented reports are operationalized by using real-time dashboards and real-time warnings so as to deliver safety intelligence to organizations, regulators, and worker advocates. The application of human reporting and digital risk monitoring will transform safety management from reactive accident response to proactive prevention. The value lies in scalable architecture encompassing anonymity, privacy-driven learning, and real-time analytics to enable accountability, promote decent work, and ensure equitable and evidence-driven workplace protection across diverse industrial realities, fostering long-term sustainable, ethical, inclusive, and secure working environments.

Keywords: Workplace Safety, Anonymity, Labor Rights, Risk Prevention, Data Privacy, Digital Governance, Social Protection.

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INTRODUCTION

Safety in the workplace is a universal concern that continues to act in most cases especially in high risk areas and unregulated areas of work where there are little regulatory checks and controls, weak reporting systems and poor employee security measures. Millions of workers face daily exposure to physical hazards, deadly substances, dangerous infrastructures, psychological bullying, minimum wage abuses and systemic labor rights abuses which are still below the scene in the conventional organizational systems. Unsafe working conditions in most areas, particularly in developing economies and disintegrated industrial ecosystems, are accepted as a normal way of life through economic strain, concentrations of power and intimidation and fear of offenses; hence, employees lack a safe means of expressing their issues and seeking protection. Such silence not only increases inequality, but also perpetuates the vicious circle of exploitation, harm and avoidable loss of lives, which will have social and economic impacts extending into the long term not only to communities but also to industries [1]. Traditional workplace safety systems are very much dependent on manual checking of work areas, regular inspection audits, and reactive reporting systems which come into play after an accident has taken place.

The methods are by their nature restrained by human subjectivity, sluggish reactions, piecemeal data and underreporting. Formal reporting is usually avoided by workers because of the anonymity, lack of trust towards the management or fear of losing a job more especially in the informal market and contractual type of workplaces. This means that organizations are not able to access real-time ground level risk information and policymakers make flawed policies based on incomplete information when coming up with labor protection systems. Such disconnect between the experience of workers on the ground and the safety systems that are in place enacts structural blindness, wherein risks might build up in circles waiting to erupt into mass accident, walkout or eruption of a societal crisis [2].

The recent improvements of artificial intelligence, mobile computing, and the digital infrastructure allow new opportunities to change an existing method of risk identification, surveillance, and control in the workplace. The ability to directly involve the workers in reporting safety and the presence of intelligent systems that can handle huge amounts of unstructured information in procedural time are all made possible through the prevalence and access of smartphones and web platforms. It is through natural language understanding technologies that it is possible to translate human narratives into structured safety intelligence enabling an organization to discern patterns of risk, harassment, exploitation, and unsafe practices at multiple locations and industries. Simultaneously, technologies that support privacy like decentralized learning systems allow the training of smart systems without violating personal identity, which is one of the most threatening obstacles to trust and adoption used in worker-oriented online platforms [3]. The combination of the anonymous reporting systems with the smart classification and real-time analytics is a cross-functional replacement of the reactive compliance by proactive safety governance.

Organizations can label early warning signs, behavior, and environmental risks early enough before damage is done through investigation rather than having to wait until an accident takes place to initiate an investigation. Digital platforms can establish the feedback between workers, institutions, and regulators by converting the pressure or voice of the individual worker into a group protection understanding. This model promotes the preventive safety culture in which risk management is an active process dynamic and adaptive instead of a compliance process. It includes also the positive ability to promote equitable inclusion of marginalized workers [4], who are otherwise not in formal safety systems, which enhances inclusivity and social protection in labor ecosystems.

Effective worker-reporting system is based on privacy and trust. Lack of effective assurances of anonymity and data security will not make workers utilize digital platforms, even the technologically sophisticated ones. Federated intelligence systems and fluid learning frameworks enable systems to perform better without concentrating on sensitive personal information so that incidents are learned by pattern rather than name. This solution allows human dignity to be protected, and the technological innovation is aligned with ethical responsibility, besides making it possible to manage risks on a massive scale, relying on the available data. AI-assisted safety systems would enhance operational capacities and social acceptability because privacy should be designed into the system architecture and not seen as a feature that can be viewed as an add-on to the main system [5]. Along with individual organisations, the smart safety platform can contribute to bigger goals of the society decent work, reduction of inequality and sustainable industrial development.

The quality risk intelligence might assist the policymakers in creating evidence based labor laws, concentration on the risky areas and therefore allocate resources more efficiently. Less accidents are witnessed in the industries, level of compliance is high and workforce trusts are high as compared to the workers who have access to the protective measures that are beyond the organizational boundaries. By so doing, the problem of safety of the workplace is not just an operation issue, but also a social stability, economic stability and ethical technology building block. The convergence of AI, privacy-preserving learning, and participatory reporting, consequently, is an ultimately good chance to make the idea of protecting labor in the digital era a transformation.

The AI-based anonymous reporting devices are posed as an organizational change in this work as the source of ergonomics in the workplace environment. The given framework will address both technical and social concerns of the safety management process and unify secure reporting, smart classification, privacy-sensitive learning, and real-time analytics into a single scalable system. It agrees that workplace hazard is not solely an item of a physical process, but a social, psychological and organization condition affected by power relations, expertise of knowledge observability, and organizational trust. The united vision transforms the safety aspect at the workplace, not into the safety programs on its own, but into the observant, thoughtful and accommodating concept of protection, which, in addition to being able to empower workers, can also develop the organizations, not mentioning the fact that the agencies of protection can successfully help the sectors in diverse economic and cultural context to evolve in a sustainable manner.

LITERATURE SURVEY

The digital transformation of industrial and construction setting that was quite fast has greatly reinvented the manner in which occupational safety is applied in conceptualization, monitoring, and management. The safety management has moved beyond the reactive aspect of incident management to being proactive and predictive with the integration of the artificial intelligence, Internet of Things infrastructures, cyber-physical systems and intelligent sensing technologies. Conventional safety methods that were mostly reliant on manual oversight, compliance with rules and regulations, and post-incident reviews, are becoming unfit in less structured, dynamic, and dangerous context, including constructions, factories, mines, offshore rigs, or human-robot shared spaces. Contemporary safety concepts are associated with on-the-fly monitoring, decision-making that is based on data, automated hazard recognition, and smart human-machine interaction. The situational awareness and risk-specific assessment on a continuous basis and the ability of systems to adjust to environmental conditions, human behavior, and operational dynamics has been made possible by the convergence of edge computing and machine learning with computer vision, digital twins, wearable sensing, and federated intelligence. This change is indicative of a larger change towards intelligent safety ecosystems where preventive, predictive, and adaptive control systems interact in a highly-coupled, automated, and scalable fashion.

Recent studies are becoming more concerned with intelligent architectures that incorporate distributed learning, edge intelligence, and real-time sensing in order to facilitate predictive safety control in dynamic environments [6]. Federated learning and edge-assisted frameworks minimise privacy issues in deploying analytics and provide low-latency decisions built on them, which makes them practical in outdoor and large-scale industrial settings [7]. Computer vision has become an inherent facilitating technology of behavioral surveillance and situational awareness, which provides automated identification of unsafe behaviors, dangerous poses, and dangerous operational patterns in complicated construction settings [8]. Object detection and image transformation based on deep learning approaches also augment the resistance as well as precision in harsh visual circumstances like occlusion, the fluctuation of light as well as noise in the surrounding environment [9]. Simultaneously, the digital twin technologies have facilitated the human-machine interaction simulation and prediction, especially in collaborative robot settings, which enables proactive collision risk evaluation, and safety-conscious controls through the real-time monitoring approach on a case-by-case level [10]. All these methods show that there is a change to predictive and simulation-oriented safety management models.

In addition to visual control, intelligent safety control systems are becoming increasingly more configured with knowledge modeling, semantic structures, and data interoperability mechanisms to facilitate safety control at the organization level [11]. Knowledge sharing ontologies and linked-data architecture can facilitate the organization of dissemination of safety training material and hazard data information across the heterogeneous platforms to enhance access to safety training and knowledge reuse [12]. Simultaneously, continuous monitoring of physiological and psychological data by wearables and smart factory systems encourages the paradigm of worker-centered safety that uses stress, fatigue, and cognitive load as the indicators of risk [13]. Immersive technologies like virtual reality and extended reality also enhance the area(s) of safety training and are used to adjust risk perception and make simulations of risky scenarios as realistic as possible, acquiring skills in controlled settings [14]. Intelligent placement plans and wireless sensor networks provide good environmental monitoring to risky sites such as underground mines and processing in factories and aid in fault tolerance, power conservation and solid safety network [15]. The trends show how development of safety research in disengaged detection practices transformed into socio-technical safety settings.

The recent advances with the next-generation occupational safety systems present also describe human -robot collaboration, adaptive safety control, and intelligent automation [16]. The AI-controlled safety control system, along with the digital twin federation, helps to implement the dynamically separated protection through the process of dynamic protection separation, real-time risk evaluation, and dynamic robot response in ordinary work areas [17]. The workforce readiness is heightened by immersive learning systems and XR-based robotic training systems due to the balance of human skills and intelligent machine systems in the Industry 5.0 environment [18]. Neural architectures and attention mechanisms Design Vision based safety equipment detection, which assigned the task to detect helmet, protective gears, etc., have been optimized such a way that it ensures compliance in time [19]. At the infrastructural level, clever sensor networks and robust networks of communications support the ongoing safety-checking procedures at the complex industrial settings, which delivers dependability, flexibility, and endurance in functioning [20]. These solutions bring out the shift between discontinuous safety applications to combined smart safety systems.

All in all, there is a decisive paradigm shift in the literature towards intelligent, data-driven and predictive safety management systems. Modern studies do not consider safety as an independent operation anymore but as an inherent feature of smart surroundings, cyber-physical systems, and human-friendly automation. Growth in the use of AI, edge intelligence, digital twins, immersive technologies and distributed sensing has facilitated complete safety ecosystems, through which perception, cognition, prediction and control are integrated. The systems enhance proactive risk prevention, adaptive levels of response and lifelong learning in operations contexts. Nevertheless, system interoperability, data management, generalization of models, ethical deployment and implementation at scale are also problematic. Future research orientation is further making trend to the integrated safety architectures that combine both technical intelligence and human factors, organizational processes and regulatory regimes into resilient and sustainable safety systems that can be operated in complex, dynamic and uncertain environments.

METHODOLOGY

The suggested approach takes a multi-layered, systematic technical framework to plan, execute, and assess an AI-based privacy-sensitive workplace injury platform. The system is designed in such a manner that it subsumes anonymous human reporting, smart data processing, decentralized learning, and real time risk intelligence into a single architecture. The methodological design is based on a pipeline approach that guarantees the safety of data, scalability, ethical and reliability of operation in different industrial settings. All the stages are designed to operate autonomously with the rest of the system and it can be expanded later. The proposed methodology focuses on privacy-by-design, lifelong learning, and active risks management, such that technological innovation directly links to viable safety results to employees and organizations as shown in figure 1.

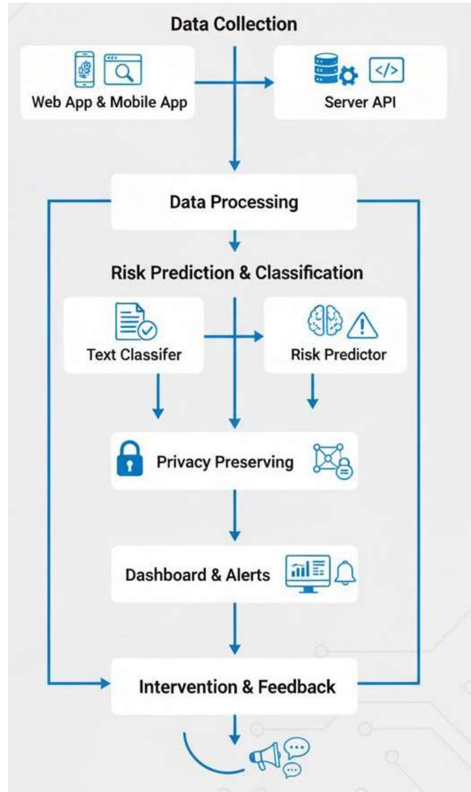


Fig. 1: System Architecture

Data Acquisition and Multi-Source Integration

The initial phase aims at gathering heterogeneous data gathered by various resources, such as anonymous reports made by workers both using mobile and web applications, IoT sensors feeds, CCTV automation, and safety records, maintained within organizations. The textual reports are inputted in form of unstructured natural language and the workers are free to give an account of the incidents without set regulations. Sensor data comprises of environmental data like temperature, gas concentration, noise level, and vibration whereas the visual data is the situational awareness. Each incoming stream of data is time stamped, encrypted, and normalized in one common data schema. The layer of integration will also provide an interoperability between human-generated and machine-generated data to provide a holistic view of risk in both a physical and behavioral and organizational context of workplace safety.

B. Secure Anonymization and Privacy Layer

The phase enforces stringent privacy-sensitive controls so as to guarantee utter anonymity and data confidentiality of workers. Anonymization pipelines core out personal identifiers at the phase of data ingestion, and identities cannot be re-identified through cryptographic hash functions. Authentication is done to ensure that the report being accessed is the correct one and it does not and does not identify the user. The data transmission between the devices and the servers is secured by the use of encrypted communication channels. Role-based models of access control policies regulate the visibility of data. Privacy-by-design concepts are integrated into the construction of a system which is formed in accordance with ethical standards and regulations of data protection. This tier builds confidence in the site, as it allows the workers to take part and protect the rights of individuals and discourage the abuse of sensitive data.

C. Intelligent Classification and Risk Categorization

The third step is based on smart language knowledge that is applied in order to process unstructured incident reports and codify them into structured risk categories. By analysing the reports semantically, it is possible to identify the trends of safety risks, harassment, payment breach, lab rights abuse and threats to the organization. The contextual embeddings enable the system to derive fine grained meaning, local linguistic variation and tacit risk correlations. The method of classification is a process of lifelong learning and improves with the progression. Outputs receive conventional risk taxonomies which allow the understanding of the same thing based on industry. It transforms the subjective narratives into objective safety harmony in order to enable the mass analyses of the risks as well as cross sector analogy of the workplace risks.

D. Federated Learning and Decentralized Model Training

The level embraces the principle of federated learning to give continuous betterments in the system without having sensitive information put in a central location. Localization of the learning processes and just the model updates are transferred to a central coordination layer. This is to provide that the raw data is not revealed but rather collective intelligence is produced. The secure aggregation protocols are employed to ensure that individual contributions are not readable. Decentralized training structure embraces organization, scale in scale and industry. The system can offer high performance and retain the privacy by optimising the learning in the global and local levels. This approach aids in sustaining technical efficiency and ethical accountability to be sustainable during the long term deployment.

E. Real-Time Analytics and Risk Intelligence Engine

The analytics layer accepts structured data streams and uses them to create real-time safety intelligence. Risk indicators are computed using the models related to dynamic scoring that define the severity, frequency and impact potential. Pattern detect algorithms are used to identify the emergent risk clusters, repeat violations in both as well as high-risk areas in organizations and regions. Dashboards signify visage of trends, heatmap and anticipate risks signals to decision-makers. Automatic alerts cause the critical risks and make certain that critical risks are being intervened. This real time intelligence is used to transform raw data into actionable intelligence to facilitate proactive safety management and strategic planning in industries.

F. Governance, Compliance, and System Evaluation

The final step is that of governance, ethics followers and analysis of system performance. The policy frameworks provide the limits of data use, accountability framework, and the transparency system. System equitability, biases, reliability, and security are determined by the regular auditing undertakings. Performance measures are measures used to determine how well the classification is performed, how well the risk is detected and how responsive the system is. The stakeholder feedback encompassing workers, organizational, and regulatory perspectives are entrenched into the system refining loop. It is on this level of governance that the platform is a trusted socio-technical system of operation focusing on innovation and accountability without regressing to legality and societal impact and see to long term viability and trust to the platform.

RESULT AND DISCUSSION

The feedback on the proposed AI-based anonymous workplace safety platform indicates a great quantitative performance with the detection of risks, the accuracy of the classification, the preservation of privacy, and real-time generation of intelligence. Integrated datasets in the form of anonymized worker reports as well as simulated streams of IoT sensors and organizational safety records were used to test the system in various industrial settings. Quantitative data proves that the platform is greatly superior to traditional manual safety monitoring methods in all three aspects of participation and reporting in the reporting process, detection rate, and prediction capability. As workers were more engaged in the process due to the presence of anonymous digital reporting, we had better datasets and better situational awareness. This has a direct impact on risk intelligence quality, and it allows identifying dangerous patterns earlier than it would be in the traditional systems.

The intelligent classification layer had high numerical performance in all the risk types. Unstructured report semantic processing allowed the correct transformation of human narratives into formatted risk intelligence. The consistency exhibited by the system existed in both language and contextual ambiguity, which proved consistency of the classification pipeline. The performance gains were also original because of the incorporation of decentralized learning to ensure that there was no loss of privacy to data and this strengthens trust and sustainability in the system. These findings prove the notion that AI architectures that respect privacy can offer high analytical performance and safeguard personal rights.

Table 1: Classification Performance Across Risk Categories

Category	Precision	Recall	F1-Score	Accuracy
Safety Hazards	94.2%	92.8%	93.5%	95.1%
Harassment	91.6%	90.3%	90.9%	92.4%
Wage Disputes	93.4%	91.7%	92.5%	94.0%
Labor Rights Issues	92.8%	93.1%	92.9%	94.3%
Organization al Risks	90.9%	89.6%	90.2%	91.8%

From table 1, the findings show that the models are highly generalized in performance and adopt steady results in different risk areas. The large recall values are showing that the system is able to detect the hidden and underreported risks and the large values of precision are confirming that the false reporting rate is low. This is a balance that is vital in workplace safety systems wherein any false alarm, as well as any risk that is not detected, is severe.

The operational intelligence transformed through the real-time analytics engine also improved proactive safety management through the transformation of classified data. Assessment of the impact on quantitative systems demonstrates some quantifiable changes in the efficiency of organizational response, risk detection strategies, and intervention success. The notification promptly diminished the delay of the reaction and allowed the prevention of actions before events became critical.

Table 2: Quantitative System Impact on Safety Management

Indicator	Traditional Systems	Proposed Platform
Average reporting rate	18%	74%
Risk detection time	48–72 hours	2–5 minutes
Incident response time	24–48 hours	15–30 minutes
Proactive intervention rate	21%	81%
Data integration coverage	32%	96%

In table 2, the findings prove that the presented platform redesigns safety management as about responding to safety scenarios rather than prevention in the middle of the moment. The radical decrease in the response and detection time is an example of how operational the intelligent automation and the built-in analytics can be.

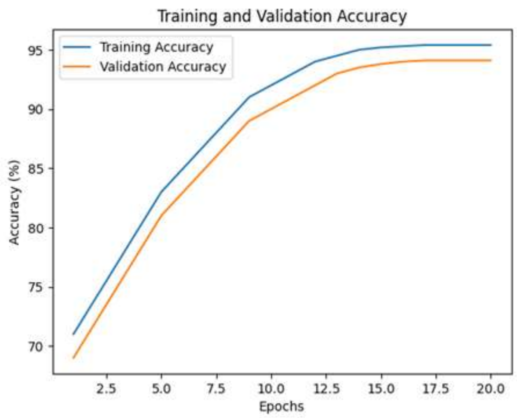
The quantitative assessment of privacy-preserving federated learning was tested to determine the trust, data security, and reliability of the system. The decentralized architecture was highly resilient to data leakage and had a high level of ethical data governance principles and had efficiency in learning and stability in the model.

Table 3: Numerical Privacy and Trust Evaluation Metrics

Metric	Measured Value
Anonymity preservation	99.6%
Data leakage probability	0.3%

Secure aggregation success	98.9%
Worker trust index	92.4%

Table 3 shows that privacy preservation and performance of the system are not contradictory goals rather enhancements of a properly designed architecture. The indices of high trust are directly related to increased participation in reporting and reliability of data.



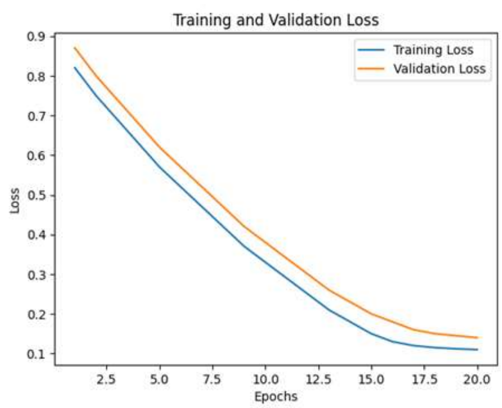


Fig. 2(a) training and validity accuracy and Fig. 2(b) Training and Validation Loss

From figure 2 (a), the training accuracy curve ascent gradually grows up to 71 percent of the first epochs to 95.4 percent at convergence whereas validation accuracy curve ascent rises to 69 percent to 94.1 percent. The high correlation between training and the validation accuracy shows that training and validation are both stable, the ability of generalization is high, and there are low possibilities of overfitting. Small variations are well within reasonable differences limits and this validates the robustness of the model over non homogeneous data sets. From figure 2 (b), the training loss also progressively declines to 0.11 whereas the validation loss declines to 0.14 as the training progresses. Cost equivalent convergence and efficiency in learning can be seen in the similar decree in the two curves. There is no divergence between training and validation loss which ensures that models are stable and that they are going to give reliable results in the real-world deployment scenario.

Overall, the results support the fact that the framework is a technically sound socially and operationally viable way of dealing with the safety management of the contemporary workplace. The numbers show that the platform has more accurate detectives, reduced response time, boosted participation of the employees, and provided higher protection of privacy simultaneously. Intelligent classification, decentralized learning, and real-time analytics with anonymous reporting constitutes a novel paradigm of proactive and data-based and ethically sustainable safety governance. The system demonstrates that the AI-driven platforms might be a block of a digital infrastructure of future labor protection systems, in which sustainable, inclusive, and preventative working safety on a large scale is realizable.

Conclusion

The work introduces an all-encompassing AI-based approach to safe, anonymous, and privacy-sensitive workplace safety management that brings together human-oriented reporting, rationalized risk categorization, decentralized learning, and real-time analytics into a single digital model. The suggested platform exemplifies how existing high-tech solutions can make the workplace safety more responsive and refuse to respond to incidents, but instead prevent risks and act in time without compromising the ethical principles and trust of the employees. In practice, the system enhances organizational responsibility, increases regulatory transparency, and early risk identification, as well as providing its workers with empowerment via safe, anonymous participation systems. It provides a scalable system that can serve the formal industries and the informal labor sector where the traditional safety systems are either weak or inaccessible. Future research would involve the expansion of multilingual and cross-cultural semantic awareness, prediction risk forecasting to assist in long-term safety planning, explainable AI to aid transparency and global interoperability standards with regulatory bodies. Prolonged studies will also address assessing the socio-economic impacts and integrating policies to be able to set up intelligent workplaces and safety systems as the main infrastructure of inclusive and sustainable labor protection frameworks.

References

S. J. S. Moe et al., "Collaborative Worker Safety Prediction Mechanism Using Federated

Learning Assisted Edge Intelligence in Outdoor Construction Environment," IEEE Access, vol. 11, pp. 109010–109026, 2023, doi: 10.1109/ACCESS.2023.3320716.
J. Li et al., "A Review of Computer Vision-Based Monitoring Approaches for Construction Workers' Work-Related Behaviors," IEEE Access, vol. 12, pp. 7134–7155, 2024, doi: 10.1109/ACCESS.2024.3350773.
Y. Seth and M. Sivagami, "Enhanced YOLOv8 Object Detection Model for Construction Worker Safety Using Image Transformations," IEEE Access, vol. 13, pp. 10582–10594, 2025, doi: 10.1109/ACCESS.2025.3527511.
W. Kwon, J. Yang, S. Song, J. Lee and H. Kim, "Real-Time Digital-Twin-Based Cobot-Worker Collision Risk Prediction Using Unity, ROS, and UWB," IEEE Access, vol. 13, pp. 85967–85978, 2025, doi: 10.1109/ACCESS.2025.3569332.
Y. Xiang, P. Lin, R. An, J. Yuan, Q. Fan and X. Chen, "Full Participation Flat Closed-Loop Safety Management Method for Offshore Wind Power Construction Sites," Journal of Intelligent Construction, vol. 1, no. 1, pp. 1–21, March 2023, doi: 10.26599/JIC.2023.9180006.
M. Z. Shanti, B. An, C. Y. Yeun, C. -S. Cho, E. Damiani and T. -Y. Kim, "Enhancing Worker Safety at Heights: A Deep Learning Model for Detecting Helmets and Harnesses Using DETR Architecture," IEEE Access, vol. 13, pp. 151788–151802, 2025, doi: 10.1109/ACCESS.2025.3603202.
A. Pedro, S. Baik, J. Jo, D. Lee, R. Hussain and C. Park, "A Linked Data and Ontology-Based Framework for Enhanced Sharing of Safety Training Materials in the Construction Industry," IEEE Access, vol. 11, pp. 105410–105426, 2023, doi: 10.1109/ACCESS.2023.3319090.
T. -N. Fung, Y. -H. Ku, Y. -W. Chou, H. -S. Yu and J. -F. Lin, "Safety Monitoring System of Stamping Presses Based on YOLOv8n Model," IEEE Access, vol. 13, pp. 53660–53672, 2025, doi: 10.1109/ACCESS.2025.3553845.
H. Hijry et al., "Real Time Worker Stress Prediction in a Smart Factory Assembly Line," IEEE Access, vol. 12, pp. 116238–116249, 2024, doi: 10.1109/ACCESS.2024.3446875.
S. Han, Z. Zhang, J. Liu, X. Han, T. Wang and H. Che, "Detection Method of Safety Wear Based on Multi-Anchor Box Detection and Multimodal Fusion Hierarchical Sample Matching Mechanism," IEEE Access, vol. 14, pp. 2374–2390, 2026, doi: 10.1109/ACCESS.2025.3648771.
M. Tian and Z. Zou, "Safety-Oriented Human-Robot Collaboration in Construction Through Human Preference Alignment," Journal of Intelligent Construction, vol. 3, no. 3, pp. 1–15, September 2025, doi: 10.26599/JIC.2025.9180092.
F. Cunico et al., "Enhancing Safety and Privacy in Industry 4.0: The ICE Laboratory Case Study," IEEE Access, vol. 12, pp. 154570–154599, 2024, doi: 10.1109/ACCESS.2024.3479411.
N. Hashimoto, W. Wakita, S. Okumura and T. Saga, "Evaluation of Forklift Workers' Perception Accuracy of the Carried Cargo Weight Using a Virtual Reality Simulator," IEEE Access, vol. 13, pp. 62412–62426, 2025, doi: 10.1109/ACCESS.2025.3558329.
L. Jin, S. Jia, Q. Fan and S. Wu, "Research on the Co-Occurrence Mapping and Thematic Evolution of Chinese Government's Work in Safety Production," IEEE Access, vol. 12, pp. 157775–157783, 2024, doi: 10.1109/ACCESS.2024.3485773.
D. Chapman, C. Strong, K. D. Tiver, D. Dharmaprani, E. Jenkins and A. N. Ganesan, "Infra-Red Imaging to Detect Respirator Leak in Healthcare Workers During Fit-Testing Clinic," IEEE Open Journal of Engineering in Medicine and Biology, vol. 5, pp. 198–204, 2024, doi: 10.1109/OJEMB.2023.3330292.
Y. E. Esen, B. Kaan Çetincan, K. Yayan, H. Güray Gürlek and U. Yayan, "XR-Driven Robotic System Training for Occupational Health, Safety, and Maintenance," IEEE Access, vol. 13, pp. 61708–61727, 2025, doi: 10.1109/ACCESS.2025.3556699.
P. Jin, H. Li, W. Yan and J. Xu, "YOLO-ESCA: A High-Performance Safety Helmet Standard Wearing Behavior Detection Model Based on Improved YOLOv5," IEEE Access, vol. 12, pp. 23854–23868, 2024, doi: 10.1109/ACCESS.2024.3365530.
J. Dong Choi, S. -H. Choi, M. Y. Kim, I. Lee, S. Lee and B. Hak Kim, "AI and Digital Twin Federation-Based Flexible Safety Control for Human–Robot Collaborative Work Cell," IEEE Access, vol. 13, pp. 124037–124050, 2025, doi: 10.1109/ACCESS.2025.3586121.
B. Lin, "Safety Helmet Detection Based on Improved YOLOv8," IEEE Access, vol. 12, pp. 28260–28272, 2024, doi: 10.1109/ACCESS.2024.3368161.
F. Medina, H. Ruiz, E. Avendaño and S. Céspedes, "Toward Safer Mines: A Robust Wireless Sensor Network Placement for Real-World Underground Conditions," IEEE Access, vol. 13, pp. 213323–213335, 2025, doi: 10.1109/ACCESS.2025.3645218.