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Machine Learning in Occupational Health and Safety: A Review of Knowledge Gaps

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Abstract: Machine learning is revolutionizing the way we work and the field of occupational health and safety (OHS) has significant knowledge gaps for its implementation. This review synthesizes current applications across hazard identification, risk assessment, ergonomics, PPE compliance monitoring, and environmental surveillance, while identifying critical areas for future research. Even with promising advances, challenges persist in developing machine learning models that work effectively across industries, integrate multi-modal data streams, and adapt to dynamic work environments. Key limitations include the need for more robust assessment tools, personalization capabilities, and solutions to data quality and privacy concerns. The field particularly lacks standardized frameworks for data collection and sharing, as well as clear ethical guidelines for implementing machine learning in workplace safety contexts. This analysis reveals promising research directions, including the development of explainable AI systems to support OHS decision-making, learning applications to address data scarcity, and privacy-preserving learning approaches. The integration of machine learning with internet-of-things (IoT) and extended reality technologies offers additional avenues for innovation. Advancing these opportunities requires interdisciplinary collaboration between OHS professionals, computer scientists, lawyers, and subject matter experts. This review concludes that realizing the full potential of machine learning in OHS depends on addressing both technical and organizational challenges. A focus on these identified research priorities in this field can make significant advances toward creating more effective, data-driven tactics to workplace safety and health management.

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1. Introduction

Machine learning has emerged as a transformative technology that may be utilized in occupational health and safety (OHS), offering new approaches to risk assessment, hazard identification, and safety management. Several knowledge gaps and areas for further research exist in the application of machine learning in OHS. This review explores the current landscape of machine learning in OHS, with a particular focus on identifying and analyzing knowledge gaps. A total of twelve knowledge gaps were categorized based upon commonalities within existing literature.

2. Methodology

2.1. Objectives

The primary focus of this research review is to identify gap areas in the implementation of machine learning within the field of occupational health and safety. Many key performance indicators are reliant on data that may include variables such as hours worked, total incidents, number of violations, number of days past-due on training, and so on. Managed correctly, the use of machine learning and other data science tools can help occupational health and safety professionals conduct anything from predictive modeling to a more robust root cause analysis.

2.2. Screening Process

The author's university library was the source for finding existing literature on this subject matter (Figure 1). Scholarly peer-reviewed articles were searched using the following keywords: accident;

analysis; industrial hygiene; machine learning; occupational health; safety; prediction modeling; and workplace.

Figure 1. University search engine dialog .

The screened literature (n = 111) was analyzed through a bibliometric network mapping tool [1]. The full list of keywords from these papers (n = 462) were mapped according to connections between papers and is presented in Figure 2. Like most word mapping algorithms, certain keywords were truncated but have no meaningful impact on findings.

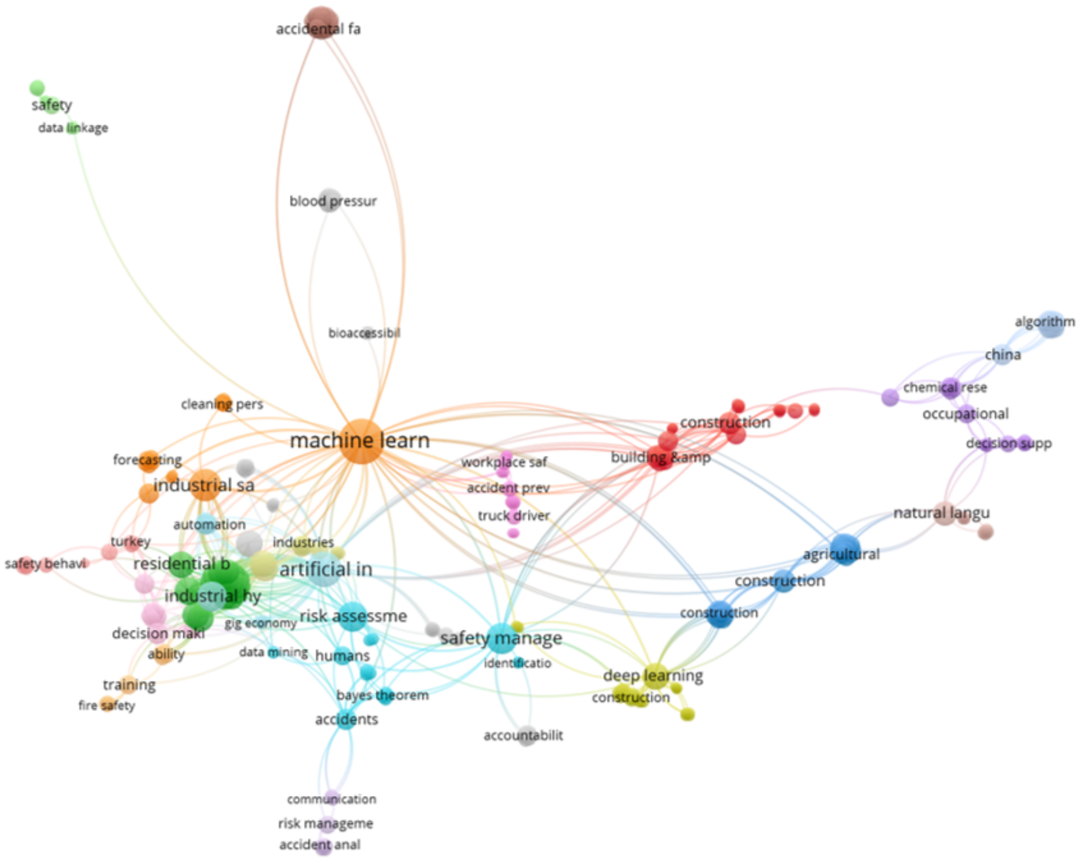

Figure 2. Map of keywords extracted from literature.

A PRISMA map is presented in Figure 3 and represents the flow of studies through the different phases of the literature selection process. PRISMA stands for Preferred Reporting Items for Systematic Reviews and Meta-Analyses [2]. This is typically structured as a flow chart that shows how studies were identified, screened, assessed for eligibility, and finally included in the review.

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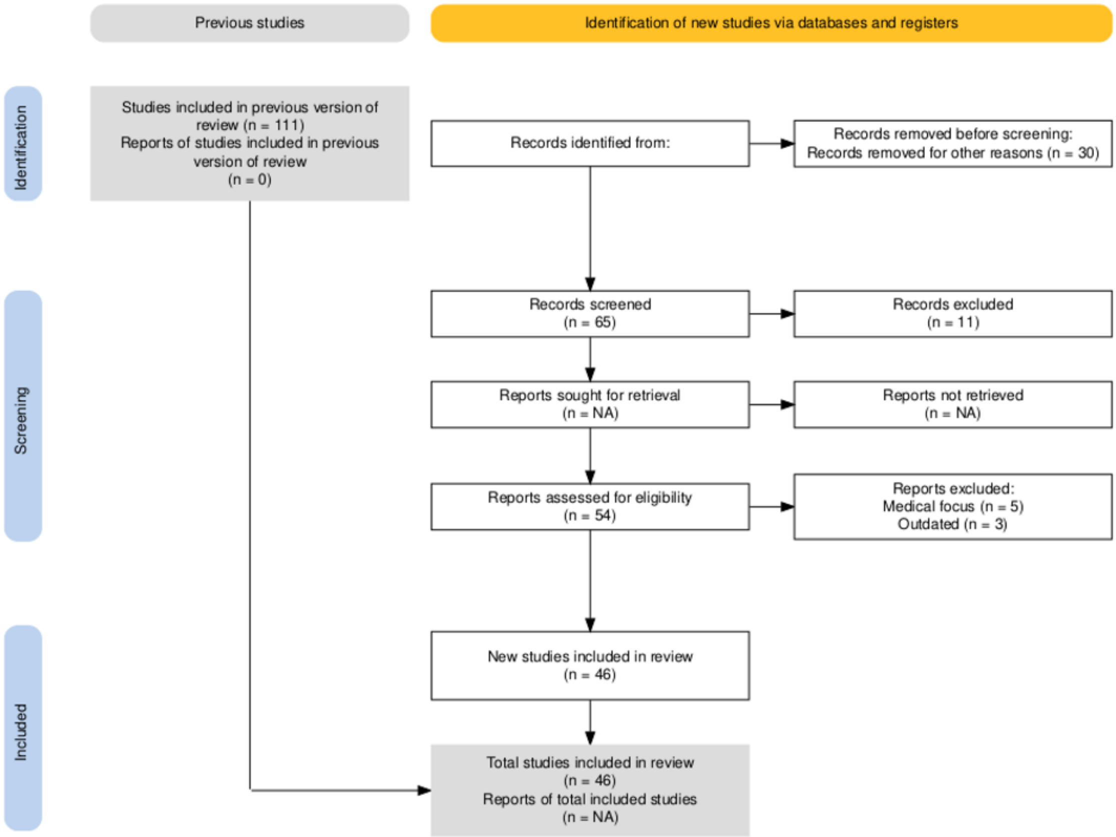

Figure 3. PRISMA diagram (Haddaway et al., 2022) of literature review.

3. Results

3.1. Applications for Machine Learning in OHS and Associated Knowledge Gaps

3.1.1. Hazard Identification and Risk Assessment

Knowledge Gap 1: Applicability of machine learning models for hazard identification.

Sarkar and colleagues demonstrated the potential of deep learning for predicting workplace accidents, achieving 85% accuracy in identifying high-risk scenarios [**?**]. However, their study was limited to a single manufacturing plant, highlighting a significant knowledge gap: the generalizability of machine learning models across different industries and workplace contexts. Very few studies have been conducted to demonstrate the positive and negative aspects of integrating AI into the risk assessment process and occupational health surveillance [3]. The researchers believe the integration of AI in the industry is still in its early stages, with the focus on its impact on immediate safety concerns.

Knowledge Gap 2: Integration of multi-modal data for comprehensive hazard detection.

Several studies have implemented computer vision systems for real-time detection of safety hazards on construction sites [4–8]. While systems showed promise, they focused primarily on visual hazards, leaving a gap in the detection of non-visual risks such as exposure to harmful substances, extreme temperatures, and obstacles. The time of day also has been identified as a factor in hazard detection. Vision training has almost been exclusively done during daytime (i.e., illuminated) hours and application of machine learning models based on dimmer lighting have shown underperformance [7].

3.1.2. Ergonomics and Biomechanics

Knowledge Gap 3: Robustness of machine learning-based ergonomic assessment in varied and dynamic work environments.

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Wearable sensors and machine learning algorithms have been used to analyze worker postures [9]. Questions about the effectiveness of such systems in the real-world, dynamic work settings have been raised since the study was conducted in a controlled environment. The lack of diversified workplace settings has also been raised, since the majority of studies have focused more on construction sites and not as much on warehouse or manufacturing environments [10]. It has been suggested that the costs of using and maintaining wearable sensors has been an obstacle for the implementation of them in safety systems [11].

Knowledge Gap 4: Personalization of machine learning models for individual worker characteristics and adaptation over time.

Hernandez and colleagues developed an machine learning-based fatigue prediction model for manual material handling [12]. While promising, their model did not account for individual differences in physiology or long-term adaptations to work tasks. Variables such as age and sex have been identified as individual characteristics that impact models, particularly with prediction of musculoskeletal disorders [13]. Findings for safety behavior in agricultural settings has been skewed with an oversampling of older male workers [14].

3.1.3. Personal Protective Equipment Compliance

Knowledge Gap 5: Assessment of PPE effectiveness beyond mere presence/absence.

Nath and colleagues achieved high accuracy in detecting PPE usage using deep learning algorithms [15]. This system was limited to visual detection and did not address the proper use or fit of PPE. Availability of data for unsafe behaviors on construction sites is very limited, which in turn does not allow for the development of an unsupervised machine learning system [16].

Knowledge Gap 6: Long-term feasibility and ethical implications of smart PPE systems.

Edirisinghe proposed a framework for smart PPE with embedded machine learning capabilities [17]. While innovative, this concept raises questions about the long-term durability and cost-effectiveness of such technology, as well as potential privacy concerns. When there is continuous monitoring of a worker, they may feel that they are being watched too closely and remove the wearable or even give it to a colleague [18].

3.1.4. Environmental Monitoring

Knowledge Gap 7: Integration of human factors and process dynamics in environmental monitoring models.

Researchers have developed an machine learning-based system for air quality forecasting in industrial settings [19]. While effective, their system did not account for the potential impact of worker behavior or process changes on air quality. Patton and colleagues [20] suggest that personal monitoring devices are mainly worn by high exposure workers and overestimations of air concentrations will skew algorithm responses.

Knowledge Gap 8: Development of machine learning models for predicting and mitigating multiple environmental hazards simultaneously (e.g., air quality, noise, temperature, vibration).

Different machine learning techniques (i.e., regression modeling, clustering analysis, and confusion matrices) have been proposed and used in environmental studies [21–28] as well as in health and safety research [13,29–35], but the models typically focus on one specific outcome. The ability to predict multiple outcomes will strengthen current safety management systems.

3.2. Challenges, Limitations, and Associated Knowledge Gaps

3.2.1. Data Quality and Availability

Knowledge Gap 9: Development of standardized frameworks for OHS data collection and sharing.

Tixier highlighted the challenge of data quality and availability in applying machine learning to OHS [36]. This issue points to a significant knowledge gap in understanding how to effectively collect, standardize, and share safety data across organizations and industries. Accident reports are often prepared in an unstructured format, so searching for trends in an industry become cumbersome [37]. A web-crawler algorithm has been developed to predict and understand construction incidents through accident reports [38] but still requires data improvement and scalability for true effectiveness.

3.2.2. Privacy Concerns and Ethical Considerations

Knowledge Gap 10: Ethical frameworks for machine learning implementation in OHS that protect worker privacy while maximizing safety benefits.

Bodie explored the legal and ethical implications of using machine learning for worker monitoring [39]. However, there remains a lack of consensus on best practices for balancing safety benefits with worker privacy rights. Digital tools such as smartphones, smartwatches, and cameras are the more common implementations that workers feel infringe on their privacy [40]. Cagno and colleagues warn that "it is crucial to establish clear guidelines for maintaining compliance with privacy regulations." Recent advancements have shown early success in incorporating blockchain technology into privacy preservation, while calling for the need to develop more comprehensive privacy algorithms [41].

3.2.3. Integration with Existing OHS Management Systems

Knowledge Gap 11: Strategies for harmonizing machine learning-based safety systems with existing OHS management frameworks.

Badri examined the challenges of integrating machine learning within the context of Industry 4.0 [42]. Their work revealed a gap in understanding how to effectively combine machine learning-driven insights with traditional safety management practices. Adding machine learning into current health and safety management systems would enhance the continuous improvement model and create positive outcomes on productivity, risk prioritization, and organization within the management system.

3.2.4. Interpretability of Complex Machine Learning Models

Knowledge Gap 12: Development of user-friendly interfaces and explanation methods for complex machine learning models in OHS applications.

Molnar [43] discussed the importance of interpretable machine learning in high-stakes decision-making contexts like OHS. However, there is still a lack of research on how to make complex machine learning models truly understandable to safety professionals and workers. Natural language processing and large language models have shown high precision (>97%) in automated compliance checking of building code [44]. As rules and regulations often change, this technique stays up to date and may require little oversight.

3.3. Future Directions and Research Opportunities

3.3.1. Integration of Machine Learning with Internet of Things (IoT)

Alam [45] reviewed the potential of augmented and virtual reality combined with IoT for safety monitoring. However, the integration of these technologies with machine learning for comprehensive OHS management is still in its infancy. Real world accident scenarios can be "re-lived" in a virtual reality environment so that workers can revisit the scene of an incident to get insights into the events (Pedro et al., 2024). The technology is readily available to introduce this tool into the workplace with just a capable computer, an account with virtual reality building software (such as Unity), and practice. Unmanned aerial vehicles (UAV) usage on construction sites continues to grow and allows for UAV pilots to view high risk areas without the need to send in crews [46].

4. Discussion

This review highlights both the promise and challenges of implementing machine learning technologies within occupational health and safety contexts. Machine learning applications have

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demonstrated potential to enhance occupational health and safety in hazard identification, risk assessment, ergonomic evaluation, personal protective equipment (PPE) compliance, and environmental monitoring (Figure 4), but limitations do exist (Figure 5).

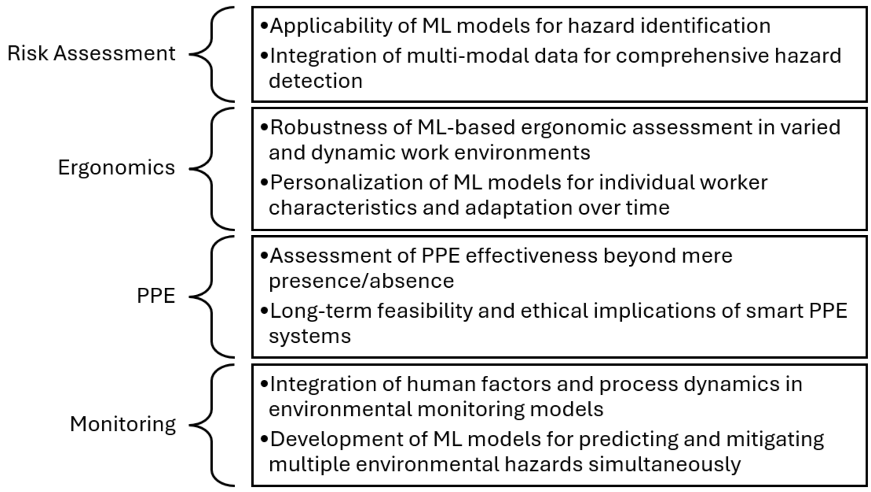

Figure 4. Identified knowledge gaps of machine learning applications.

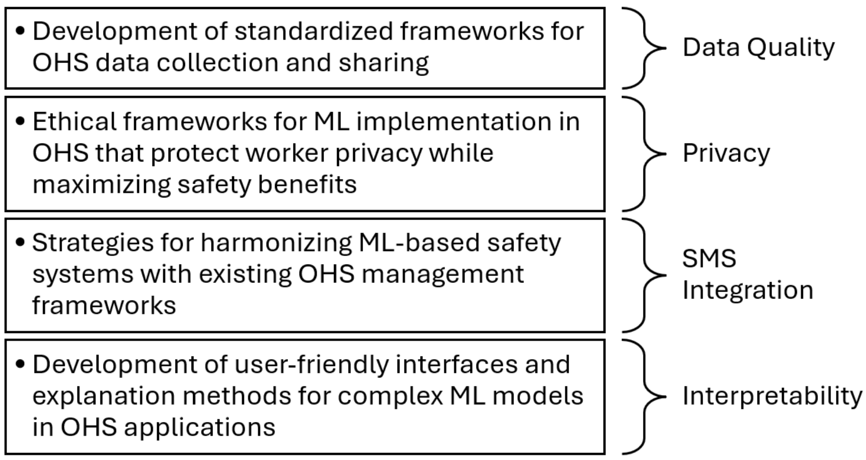

Figure 5. Challenges and limitations.

One of the primary findings concerns the limited generalizability of current machine learning models across different industries and environments. Most models are developed and tested in specific contexts—such as manufacturing or construction—which limits their applicability in diverse workplace settings.

The review reveals challenges in applying machine learning for ergonomic assessments, particularly in dynamic and unpredictable environments. Most current machine learning applications are restricted to controlled environments, limiting their effectiveness in real-world settings. Furthermore, personalization features remain underdeveloped, with existing models often failing to account for individual worker characteristics such as age, body type, and task adaptations over time.

Privacy concerns remain a significant barrier to the widespread adoption of machine learning in occupational health and safety. Continuous monitoring and data collection, particularly through wearable devices, may be perceived as intrusive by employees. This perception can hinder machine learning adoption and effectiveness, as some workers may choose not to comply or misuse the technology.

Unstructured data sources, like accident reports, pose challenges for consistency and scalability. Developing standardized frameworks for data collection and sharing across industries is essential to improve machine learning model accuracy and reliability.

5. Conclusions

While machine learning has shown great promise in enhancing occupational health and safety practices, this review has identified several significant knowledge gaps that require further research. These gaps span technical challenges, such as model generalizability and multi-modal data integration, to broader issues like ethical considerations and integration with existing safety management systems.

Addressing these knowledge gaps will require interdisciplinary collaboration between data scientists, safety professionals, ethicists, and policymakers. Future research should focus on developing more robust, interpretable, and adaptable machine learning models that can account for the complex and dynamic nature of workplace environments. Additionally, there is a pressing need for standardized frameworks for data collection and sharing, as well as ethical guidelines for the implementation of machine learning in occupational health and safety contexts.

As the field of machine learning in occupational health and safety continues to evolve, tackling these knowledge gaps will be crucial in realizing the full potential of these technologies to create safer and healthier workplaces. The identified research opportunities offer promising directions for future studies that could significantly advance our understanding and application of machine learning in occupational health and safety.

Conflicts of Interest: The author declares no conflicts of interest.

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