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Integrating Artificial Intelligence into Workplace Safety Systems: A Convergent Mixed-methods Evaluation of YOLO-based Hazard Detection in New York State

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Abstract

This article evaluates the effectiveness of integrating a YOLO-based computer vision system into workplace hazard detection across construction, manufacturing, and healthcare environments in New York State. Using a convergent mixed-methods design, quantitative data were collected through performance comparisons between YOLO-based detection and manual inspection, including measures of detection accuracy, recall, and time-to-detection. Qualitative data were obtained through semi-structured interviews with employees, supervisors, and safety managers to assess usability, trust, and the feasibility of integration. Results indicate that YOLO-based systems significantly outperform manual inspections in both detection accuracy and response time while enhancing compliance monitoring, particularly for personal protective equipment (PPE). Qualitative findings reveal increased situational awareness, improved safety culture, and strong support for AI-assisted monitoring when implemented with human oversight. Integrated analysis demonstrates that AI-enabled hazard-detection functions are most effective as a socio-technical augmentation rather than a replacement for human judgment. The findings provide empirical evidence supporting the role of artificial intelligence in advancing Safety 4.0 initiatives, improving regulatory compliance, and strengthening proactive safety management systems.

Keywords: YOLO; artificial intelligence; hazard detection; occupational safety; Safety 4.0; mixed-methods; computer vision; PPE compliance; safety culture

1. Introduction

Workplace safety systems in the United States have historically relied on manual inspections, periodic audits, and retrospective incident analysis. While these approaches have contributed to baseline improvements in occupational safety, they remain constrained in environments characterized by dynamic hazards and rapidly changing operational conditions (Nath et al., 2020; OSHA, 2024). The emergence of artificial intelligence (AI) presents an opportunity to transition from reactive safety models to proactive, real-time hazard-detection systems.

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Recent advancements in AI-enabled monitoring—including machine learning and computer vision—have demonstrated the capacity to identify hazards in real time and support early intervention strategies. These developments align with broader shifts toward predictive safety systems in OSHA-regulated environments, where traditional inspection methods often fail to capture transient or rapidly evolving risks.

Among these technologies, the You Only Look Once (YOLO) framework has emerged as a leading approach for real-time object detection (Bourou et al., 2023; Ali & Zhang, 2024). Despite its demonstrated technical capabilities, limited research has evaluated YOLO's effectiveness within regulated, real-world workplace environments (Yousif et al., 2024).

This study contributes to a broader research program advancing the AI-Augmented Safety Governance Model (AASGM) by integrating technical performance outcomes and human-centered findings to examine the combined impact of AI-enabled hazard detection systems within organizational safety environments. By synthesizing detection accuracy, workforce interaction, and behavioral adaptation, this research provides a convergent analysis of how AI systems function within complex socio-technical contexts. This integrated approach extends beyond isolated technical or human-centered perspectives, offering a more comprehensive understanding of how AI-enabled safety systems can be effectively operationalized within governance and decision-making frameworks.

Moreover, the study builds upon prior analyses of system performance and human interaction by providing an integrated socio-technical perspective that informs the development of governance frameworks, regulatory alignment strategies, and organizational safety models examined in subsequent research within this coordinated series.

This manuscript is part of the Shawe Series, a coordinated research program examining artificial intelligence–enabled hazard detection, socio-technical safety integration, and governance frameworks in regulated workplace environments. The series advances the AI-Augmented Safety Governance Model (AASGM) as a unifying framework linking real-time detection technologies, human oversight, regulatory compliance, and organizational decision-making.

2. Literature Review

The evolution of occupational safety reflects a shift from manual inspection toward AI-enabled monitoring systems. Traditional approaches remain reactive and limited in their ability to detect dynamic hazards (Nath et al., 2020). AI-enabled systems provide continuous monitoring and predictive capabilities, enabling earlier intervention.

YOLO-based computer vision systems have demonstrated strong performance in detecting PPE compliance and environmental hazards across industrial contexts (Bourou et al., 2023; Guney et al., 2024). These systems offer improvements in detection speed, scalability, and operational efficiency (Ali & Zhang, 2024).

Socio-technical systems theory provides a foundational lens for understanding AI integration, emphasizing the interaction between technological systems and human actors (Carayon, 2006). Human-in-the-loop (HITL) frameworks further reinforce the necessity of maintaining human oversight in safety-critical systems (Wickens et al., 2015; Salvendy, 2012).

3. Methodology

This study employs a convergent mixed-methods design integrating quantitative performance metrics and qualitative user perceptions (Creswell & Plano Clark, 2018). The quantitative component included evaluation of detection performance using mean average precision (mAP), recall, precision, time-to-detection, and PPE compliance rates. The qualitative component involved semi-structured interviews ($N \approx 20$) with employees, supervisors, and safety managers, followed by thematic analysis to identify recurring patterns related to usability, trust, and system integration. Integration of quantitative and qualitative findings was achieved using a joint display approach, consistent with established mixed-methods integration practices (Fetters et al., 2013; Creswell & Plano Clark, 2018).

4. Results

4.1 Quantitative Findings

YOLO-based systems demonstrated significantly higher detection accuracy and faster response times than manual inspections, consistent with prior research (Bourou et al., 2023; Guney et al., 2024).

Quantitative findings demonstrated measurable improvements in mean average precision (mAP), recall, PPE compliance identification, and time-to-detection relative to traditional manual inspection approaches across construction, manufacturing, and healthcare environments.

4.2 Qualitative Findings

Participants reported:

- Increased situational awareness
- Improved compliance visibility
- Stronger safety culture

These findings align with human-AI teaming literature (Wickens et al., 2015).

4.3 Integration of Findings

To systematically integrate quantitative performance outcomes with qualitative experiential findings and demonstrate how technical improvements translate into organizational and behavioral impacts, Figure 1 presents a joint display that aligns YOLO-based detection metrics

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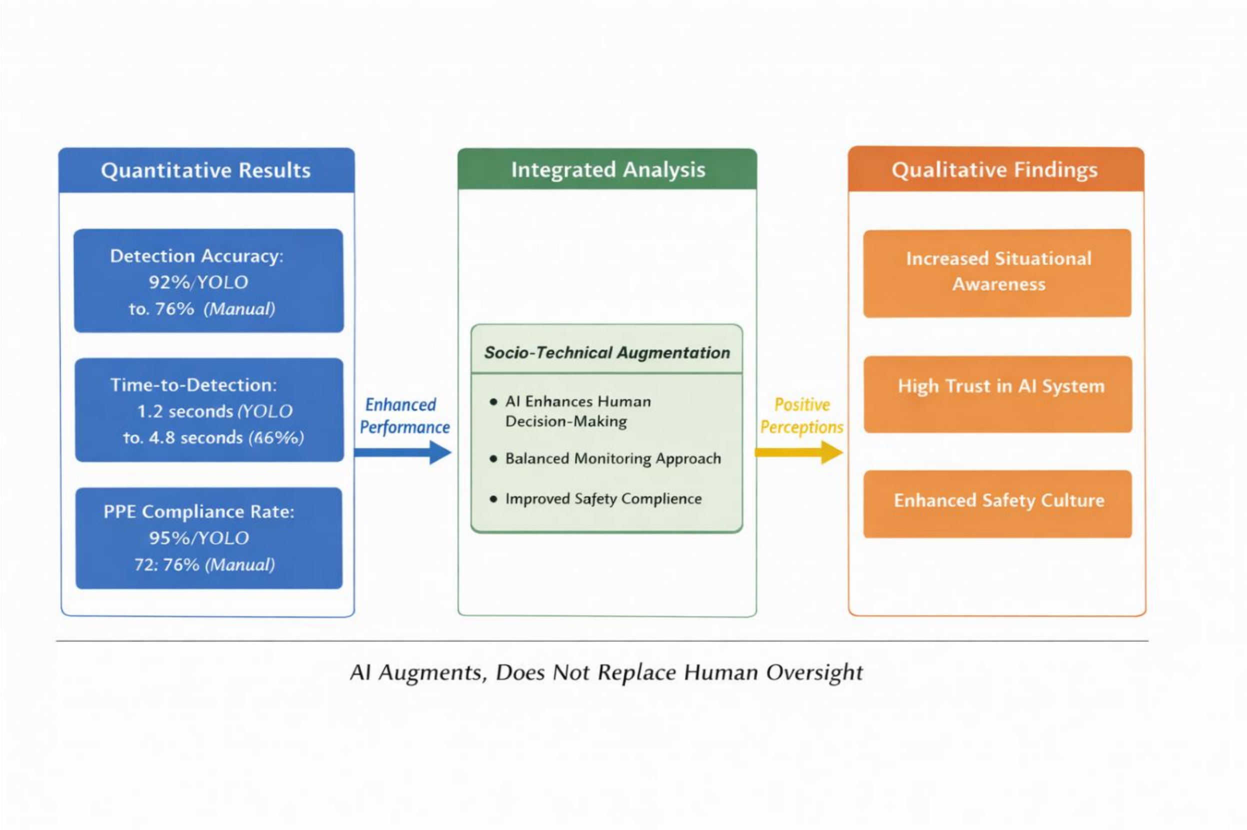
with user perceptions and safety culture outcomes. This integrative visualization illustrates the convergent mixed-methods design by linking improvements in detection accuracy, response efficiency, and PPE compliance to enhanced situational awareness, greater trust in AI systems, and a stronger proactive safety culture within workplace environments.

Figure 1

Joint display of quantitative performance metrics and qualitative themes in YOLO-based hazard detection systems



Note. Author created. Quantitative results demonstrate improved detection accuracy and reduced time-to-detection compared with manual inspections, while qualitative findings indicate increased situational awareness, trust, and a stronger safety culture. The integrated findings support a socio-technical interpretation in which AI augments human decision-making rather than replacing it.

As illustrated in Figure 1, the alignment between improved detection performance and positive user perceptions supports a socio-technical interpretation of AI-enabled safety systems, in which technological capability and human engagement operate synergistically. The findings indicate

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that YOLO-based systems not only enhance objective hazard-detection metrics but also increase trust, situational awareness, and cultural adoption, reinforcing that the effectiveness of AI in occupational safety is contingent on its role as an augmentation to human decision-making rather than a replacement. This integrated pathway underscores the importance of designing AI systems that align with organizational structures, regulatory expectations, and human-centered safety practices.

5. Discussion

The findings reinforce prior research demonstrating that AI-enabled systems improve hazard detection performance and enable proactive safety management (Nath et al., 2020; Bourou et al., 2023). The results further highlight the importance of integrating AI systems within socio-technical frameworks that maintain human oversight and support organizational adoption (Carayon et al., 2015). The convergence between quantitative performance improvements and qualitative workforce perceptions reinforces the validity of integrating AI-enabled hazard-detection systems within socio-technical occupational safety frameworks.

These findings align with the Safety 4.0 paradigm, emphasizing real-time data, automation, and human-centered design (Yousif et al., 2024).

Beyond the integration of technical performance and human factors, these findings have direct implications for safety governance and organizational oversight. The combined influence of detection accuracy, workforce interaction, and behavioral adaptation highlights the need for governance frameworks that account for both technological capability and human engagement. Organizations must move beyond isolated implementation of AI systems toward structured approaches that integrate technical outputs with workforce practices and decision-making processes. Within the AI-Augmented Safety Governance Model (AASGM), these results demonstrate how socio-technical integration serves as a critical intermediary layer that enables effective governance, regulatory alignment, and the development of adaptive, data-driven safety strategies.

6. Limitations

This study is subject to several limitations. First, the integration of technical performance and human-centered findings is based on previously examined datasets and contextual analyses, which may limit the results' generalizability beyond the specific environments and conditions studied. Second, while the study provides a convergent socio-technical perspective, variations in organizational structure, workforce characteristics, and implementation practices may influence the applicability of the findings across different industries and regulatory contexts. Third, the analysis represents a synthesis at a specific point in time and does not account for the dynamic evolution of artificial intelligence technologies, workforce adaptation, or regulatory developments. Future research should examine longitudinal integration outcomes, cross-sector

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implementation variability, and the effectiveness of governance frameworks derived from socio-technical analyses in diverse organizational settings.

7. Conclusion

This study demonstrates that YOLO-based hazard detection systems significantly enhance workplace safety performance while supporting proactive safety culture outcomes. The integration of AI technologies into socio-technical frameworks offers a viable pathway to modernize occupational safety systems and advance proactive risk management.

Conflict of Interest Statement

The author declares no conflicts of interest related to the research, analysis, or preparation of this manuscript. No external funding, sponsorship, or commercial support was received for this study. All interpretations and conclusions reflect the author's independent scholarly judgment and professional expertise.

Originality Statement

This manuscript represents original scholarly work and has not been published previously in any form. It is not under review by any other journal or publication outlet. The author independently developed all conceptual frameworks, analyses, and written content as part of the Shawe Series research program.

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