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Human–AI Interaction in Occupational Safety: Worker Perceptions, Trust, and Safety Culture Implications of YOLO-based Hazard Detection Systems

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Abstract

This research examines workers' and supervisors' perceptions of YOLO-based hazard-detection systems and their impact on safety culture in New York State workplaces. Using a qualitative research design, semi-structured interviews were conducted with employees, supervisors, and safety managers across construction, manufacturing, and healthcare environments. Thematic analysis revealed that AI-enabled hazard-detection systems enhance situational awareness, improve visibility into compliance, and contribute to a more proactive safety culture. Participants reported high levels of trust in AI-assisted monitoring when systems were implemented with transparency and human oversight. However, concerns related to privacy, over-surveillance, and potential over-reliance on automation were also identified. Findings indicate that the successful integration of AI in occupational safety depends on socio-technical alignment, human-centered implementation, and governance structures that reinforce trust and accountability. The study contributes to the understanding of human–AI interaction in safety-critical environments. The findings support the role of AI as an augmentation to human decision-making rather than a replacement.

Keywords: Human–AI interaction; occupational safety; safety culture; trust; qualitative research; computer vision; YOLO; Safety 4.0

1. Introduction

Occupational safety systems are increasingly influenced by advances in artificial intelligence (AI), particularly in real-time hazard detection and monitoring. While traditional safety systems rely on manual inspections and reactive interventions, AI-enabled systems provide continuous monitoring and predictive capabilities that support proactive safety management (Nath et al., 2020; OSHA, 2024).

The integration of AI into workplace safety introduces not only technical improvements but also significant human and organizational implications. Human–AI interaction plays a critical role in determining whether these technologies are effectively adopted and integrated within safety systems. Research indicates that trust, usability, and perceived fairness are central factors influencing the acceptance of AI technologies in occupational settings (Wickens et al., 2015; Salvendy, 2012).

YOLO-based computer vision systems represent a key advancement in AI-enabled hazard detection, offering real-time hazard identification and PPE compliance verification. However, the success of such systems depends not only on technical performance but also on how workers perceive and interact with them.

This study examines workers' and supervisors' perceptions of YOLO-based hazard-detection systems and their impact on safety culture across multiple industries in New York State.

Moreover, the study contributes to a broader research program advancing the AI-Augmented Safety Governance Model (AASGM) by examining the human and organizational dimensions of AI-enabled hazard detection systems. Specifically, the study explores how workforce interaction, trust, usability, and behavioral adaptation influence the effectiveness of AI-assisted safety practices. By situating human factors within a socio-technical and governance-oriented framework, this research extends beyond technical performance to address how AI systems are interpreted, adopted, and operationalized within organizational safety environments. This study builds upon the empirical performance foundation established in prior analysis by examining the human and organizational factors that shape the effective integration of AI-enabled safety systems within workplace environments.

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

Human–AI interaction in safety-critical environments is a growing area of research, emphasizing the importance of trust, usability, and system transparency. Studies have shown that AI systems are more likely to be accepted when users perceive them as supportive tools rather than autonomous decision-makers (Wickens et al., 2015).
Socio-technical systems theory provides a framework for understanding the interaction between technology and human behavior, highlighting the importance of aligning technological capabilities with organizational structures and human needs (Carayon, 2006; Carayon et al., 2015).

AI-enabled safety systems, including computer vision technologies, have been shown to improve hazard detection and compliance monitoring. However, concerns related to privacy, surveillance, and over-reliance on automation remain significant barriers to adoption (Salvendy, 2012).

Vol. 11, No. 03; 2026

ISSN: 2456-3676

Prior research further supports the transition from reactive to proactive safety systems, demonstrating how AI technologies enhance real-time hazard detection and intervention capabilities.

3. Methodology

This study employs a qualitative research design, using semi-structured interviews to explore workers' and supervisors' perceptions of YOLO-based hazard detection systems.

Participants

Participants included employees, supervisors, and safety managers across construction, manufacturing, and healthcare environments ($N \approx 20$).

Participants represented multiple organizational roles, including frontline employees, site supervisors, and occupational safety personnel. The sample included participants from the construction, manufacturing, and healthcare sectors to support cross-industry thematic comparison and capture diverse perspectives on AI-enabled safety monitoring. Participants were selected using purposive sampling to ensure that interviewees possessed direct experience with workplace safety systems and exposure to AI-assisted hazard-detection technologies.

Data Collection

Semi-structured interviews were conducted to capture:

- Perceptions of system usability
- Trust in AI-based monitoring
- Impact on safety culture
- Concerns related to privacy and surveillance

To ensure methodological rigor, this study applied established qualitative trustworthiness criteria, including credibility through thematic consistency, dependability through systematic coding procedures, and confirmability through alignment between participant responses and identified themes. The inclusion of participants across multiple industry contexts supported transferability.

Data Analysis

Thematic analysis was used to identify recurring patterns and themes, following established qualitative research methodologies (Creswell & Plano Clark, 2018).

Interview transcripts were systematically reviewed and coded using iterative thematic categorization procedures. Initial open coding was conducted to identify recurring concepts related to trust, usability, surveillance concerns, and safety culture. Codes were subsequently

Vol. 11, No. 03; 2026

ISSN: 2456-3676

refined into broader thematic categories through comparative analysis across participant responses and industry contexts. Triangulation was supported through cross-sector comparison of recurring themes to enhance analytical consistency and interpretive credibility.

4. Results

4.1 Emergent Themes

The analysis identified four primary themes:

1. **Increased Situational Awareness**
   Participants reported improved awareness of hazards due to real-time detection.
2. **Trust in AI Systems**
   Trust was high when systems were transparent and supported human decision-making.
3. **Enhanced Safety Culture**
   AI systems contributed to a shift toward proactive safety practices.
4. **Concerns About Surveillance**
   Some participants expressed concerns regarding privacy and over-monitoring.

4.2 Conceptual Relationship Between Human–AI Interaction Themes

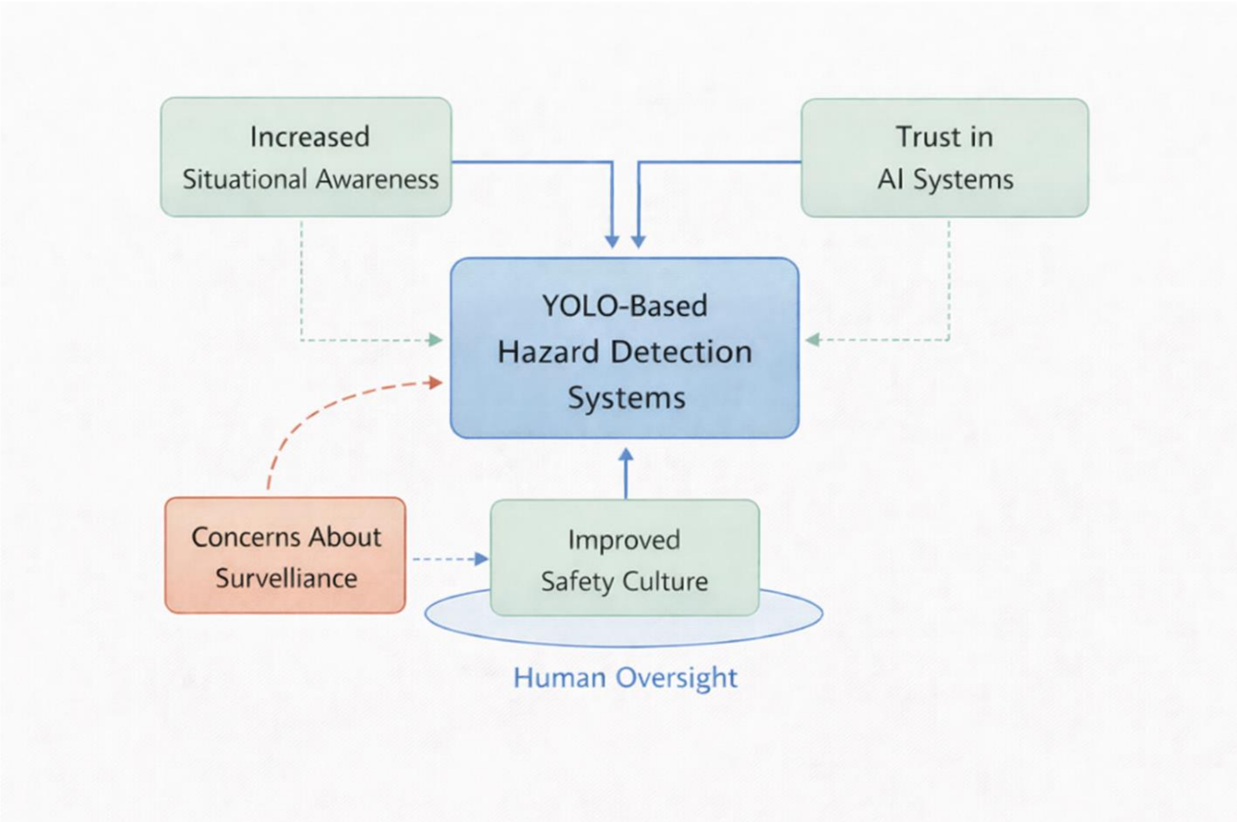
To illustrate the relationship between key qualitative themes and their influence on safety culture and human–AI interaction, Figure 1 presents a conceptual mapping of worker perceptions regarding YOLO-based hazard-detection systems. This figure highlights how increased situational awareness, trust in AI systems, and perceived improvements in safety culture interact within a socio-technical framework, while also acknowledging concerns about surveillance and system overreach.

Vol. 11, No. 03; 2026

ISSN: 2456-3676

Figure 1

Conceptual representation of qualitative themes in human–AI interaction within YOLO-based hazard detection systems



Note. Author created. The model illustrates how AI-enabled hazard detection influences situational awareness, trust, and safety culture, while also highlighting concerns related to surveillance and privacy. The framework supports a socio-technical interpretation in which human oversight remains central to system effectiveness.

As illustrated in Figure 1, the interaction between trust, situational awareness, and safety culture reflects a socio-technical dynamic in which AI systems enhance, rather than replace, human decision-making. The findings indicate that the successful implementation of YOLO-based systems depends on balancing technological capability with human-centered considerations, including transparency, accountability, and privacy protections. These results reinforce the importance of designing AI-enabled safety systems that align with organizational culture and worker expectations.

Vol. 11, No. 03; 2026

ISSN: 2456-3676

5. Discussion

The findings of this study highlight the critical role of human–AI interaction in the successful implementation of AI-enabled safety systems. While YOLO-based technologies improve hazard detection capabilities, their effectiveness is closely tied to user trust and organizational integration.

These findings align with socio-technical systems theory, which emphasizes the need to align technological systems with human factors (Carayon et al., 2015). The results also support prior research indicating that AI systems are most effective when used as decision-support tools rather than autonomous systems (Wickens et al., 2015).

Beyond individual perceptions, these findings have direct implications for safety governance and organizational oversight. Worker trust, usability, and behavioral adaptation influence the effectiveness with which AI-enabled hazard detection systems are integrated into safety practices and decision-making processes. Variability in human interaction with these systems highlights the need for governance frameworks that account for workforce engagement, training, and organizational culture. Within the AI-Augmented Safety Governance Model (AASGM), these results demonstrate that the success of AI-enabled safety systems depends not only on technical performance but also on how human factors are incorporated into structured governance and oversight mechanisms.

These findings further support the AI-Augmented Safety Governance Model (AASGM) by demonstrating that organizational trust, workforce engagement, and human-centered implementation practices are essential governance components influencing the long-term effectiveness of AI-enabled occupational safety systems.

6. Limitations

This study is subject to several limitations. First, the qualitative design and sample size may limit the generalizability of the findings beyond the specific organizational contexts examined. Second, participant perceptions may be influenced by organizational culture, prior exposure to artificial intelligence technologies, and varying levels of familiarity with digital safety systems. Third, the study captures perceptions at a single point in time and does not account for how attitudes and behaviors evolve with continued exposure to and organizational integration of AI-enabled safety systems. Future research should examine longitudinal changes in workforce perception, cross-industry variability, and the relationship between human factors and measurable safety outcomes.

7. Conclusion

This study demonstrates that YOLO-based hazard detection systems positively influence safety culture and worker perceptions when implemented within a human-centered framework. The

Vol. 11, No. 03; 2026

ISSN: 2456-3676

findings underscore the importance of trust, transparency, and governance in the adoption of AI technologies in occupational safety.

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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ISSN: 2456-3676

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