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# Cross-sector Variability in AI-Based Hazard Detection: A Comparative Analysis of YOLO Implementation Across Construction, Manufacturing, and Healthcare Environments

Dr. Robb Shawe

Capitol Technology University, Department of Occupational Health & Safety, 11301 Springfield Road, Laurel, MD, USA

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**Abstract**

This study examines cross-sectoral variability in the performance and implementation of YOLO-based hazard-detection systems across construction, manufacturing, and healthcare environments in New York State. Using a comparative analytical approach, the study evaluates differences in detection accuracy, time-to-detection, and PPE compliance, as well as contextual factors influencing system effectiveness. Findings indicate that, while YOLO-based systems consistently outperform manual inspection across all sectors, variability arises from environmental complexity, operational dynamics, and task-specific conditions. Construction environments exhibited the greatest variability due to dynamic conditions, while manufacturing environments showed more stable performance. Healthcare settings posed unique challenges for contextual interpretation and compliance monitoring. The results highlight the importance of context-sensitive implementation strategies and reinforce the need for socio-technical alignment in AI-enabled safety systems. The study contributes to the advancement of Safety 4.0 by emphasizing the role of environmental and organizational factors in shaping AI performance.

**Keywords:** AI hazard detection; YOLO; cross-sector analysis; occupational safety; Safety 4.0; variability; socio-technical systems

## 1. Introduction

The adoption of artificial intelligence (AI) in occupational safety has enabled real-time hazard detection and monitoring. Technologies such as YOLO-based computer vision systems have demonstrated significant improvements in detection accuracy and response time compared to traditional manual inspection methods (Bourou et al., 2023; Nath et al., 2020).

While these systems have shown strong overall performance, their effectiveness may vary across operational environments. Factors such as environmental complexity, task variability, and human interaction patterns can influence the performance of AI-based hazard detection systems.

Existing research has largely focused on single-sector implementations, limiting the understanding of how AI systems perform across diverse workplace contexts. This study addresses this gap by examining cross-sectoral variability in YOLO-based hazard-detection systems across construction, manufacturing, and healthcare environments.

This study contributes to a broader research program advancing the AI-Augmented Safety Governance Model (AASGM) by examining cross-sectoral variability in the implementation and performance of AI-enabled hazard-detection systems. By comparing differences across industries, this research identifies how organizational structure, operational context, and risk environments influence the effectiveness of AI-assisted safety practices. This comparative analysis extends beyond single-context evaluations to provide insight into how governance frameworks must be adapted to accommodate sector-specific conditions, thereby supporting more flexible and context-sensitive approaches to safety management and regulatory alignment.
Furthermore, the research extends prior analyses of governance integration and policy alignment by evaluating how AI-enabled safety systems operate across diverse organizational settings, providing a comparative foundation for maturity-based and executive-level frameworks examined in subsequent research in 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

AI-based hazard detection systems have demonstrated strong performance in controlled environments, particularly in manufacturing and construction settings (Bourou et al., 2023; Guney et al., 2024). However, variability in environmental conditions can significantly impact system performance.

Construction environments are characterized by dynamic conditions, including changing layouts, variable lighting, and high levels of movement, which can challenge detection accuracy (Nath et al., 2020). Manufacturing environments, by contrast, are typically more structured and predictable, allowing for more consistent AI performance.

Healthcare environments present unique challenges, including complex human interactions, context-dependent hazards, and privacy considerations. These factors require AI systems to operate under more nuanced, variable conditions.

Socio-technical systems theory suggests that technological performance is influenced by the interaction between system capabilities and environmental context (Carayon, 2006).

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Recent advancements in AI-enabled safety systems further emphasize the importance of context-sensitive implementation strategies across operational environments. Emerging research on explainable artificial intelligence (XAI), adaptive monitoring systems, and predictive safety analytics suggests that AI performance is significantly influenced by environmental variability, organizational readiness, and human–system interaction dynamics (Ali & Zhang, 2024; Yousif et al., 2024). These findings reinforce the need for flexible governance architectures capable of supporting sector-specific adaptation while maintaining consistency in oversight, implementation reliability, and safety management practices across diverse industrial settings.

## 3. Methodology

This study employed a comparative analytical design using quantitative performance data from YOLO-based hazard-detection systems across construction, manufacturing, and healthcare environments in New York State. The analysis evaluated cross-sector differences in detection accuracy, time-to-detection, and PPE compliance identification under varying operational conditions.

The study analyzed approximately 652 annotated hazard-detection observations collected across the three sectors. Observations included PPE violations, unsafe worker proximity, equipment-related hazards, and environmental safety risks. Sector-specific datasets were compiled using organizational safety observations and AI-generated detection outputs derived from real-time monitoring environments.

A fine-tuned YOLOv8 architecture was utilized to support hazard-detection analysis. Transfer learning methods were applied using pre-labeled occupational safety datasets, followed by sector-specific adaptation procedures to account for environmental variability and operational context differences across industries.

Dataset preparation included annotation and categorization of hazard events according to sector-specific safety conditions. Data were partitioned into training, validation, and testing subsets using standard supervised learning procedures. Comparative evaluation metrics included mean average precision (mAP), recall, time-to-detection, and PPE compliance identification accuracy.
Comparative statistical evaluations were conducted to assess performance variability across sectors. Descriptive statistics and comparative analyses were used to evaluate differences in detection consistency, operational responsiveness, and environmental variability across construction, manufacturing, and healthcare settings. These procedures supported the identification of sector-specific patterns that influence AI-enabled hazard-detection performance and implementation effectiveness.

## 4. Results

To provide a comparative overview of YOLO-based hazard detection performance across operational environments, Table 1 presents sector-specific differences in detection accuracy, response time, PPE compliance identification, and overall performance variability across construction, manufacturing, and healthcare settings. The table highlights how environmental complexity and organizational conditions influence the effectiveness of AI-enabled hazard detection across industries.

**Table 1**

*Comparative YOLO Performance Across Sectors*

| **Metric** | **Construction** | **Manufacturing** | **Healthcare** |
|---|---|---|---|
| Mean Average Precision (mAP) | 88.4% | 94.1% | 90.2% |
| Recall | 86.7% | 93.5% | 88.1% |
| Average Detection Time | 2.8 sec | 1.6 sec | 2.1 sec |
| PPE Compliance Detection Accuracy | 87.9% | 94.4% | 89.3% |
| Performance Variability | High | Low | Moderate |

*Note*. Sector variability reflects differences in environmental complexity, operational dynamics, contextual interpretation requirements, and organizational implementation conditions across industries.

Comparative analyses demonstrated measurable sector-specific differences in YOLO-based hazard detection performance across operational environments. Manufacturing environments demonstrated the highest overall detection consistency and the lowest variability, while construction environments exhibited greater performance fluctuation due to dynamic environmental conditions. Healthcare environments exhibited moderate variability due to contextual interpretation requirements and complex patterns of human interaction. These findings indicate that environmental and organizational conditions significantly influence the effectiveness and implementation stability of AI-enabled hazard detection across sectors.

### *4.1 Construction*

Construction environments exhibited high variability in detection accuracy, largely influenced by dynamic conditions such as changing layouts, variable lighting, and complex movement patterns.

### *4.2 Manufacturing*

Manufacturing environments demonstrated stable and consistent performance, as controlled conditions contributed to improved detection reliability and reduced variability in system outputs.

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*4.3 Healthcare*

Healthcare environments showed moderate variability, with challenges related to contextual interpretation, complex human interactions, and compliance monitoring influencing system effectiveness.

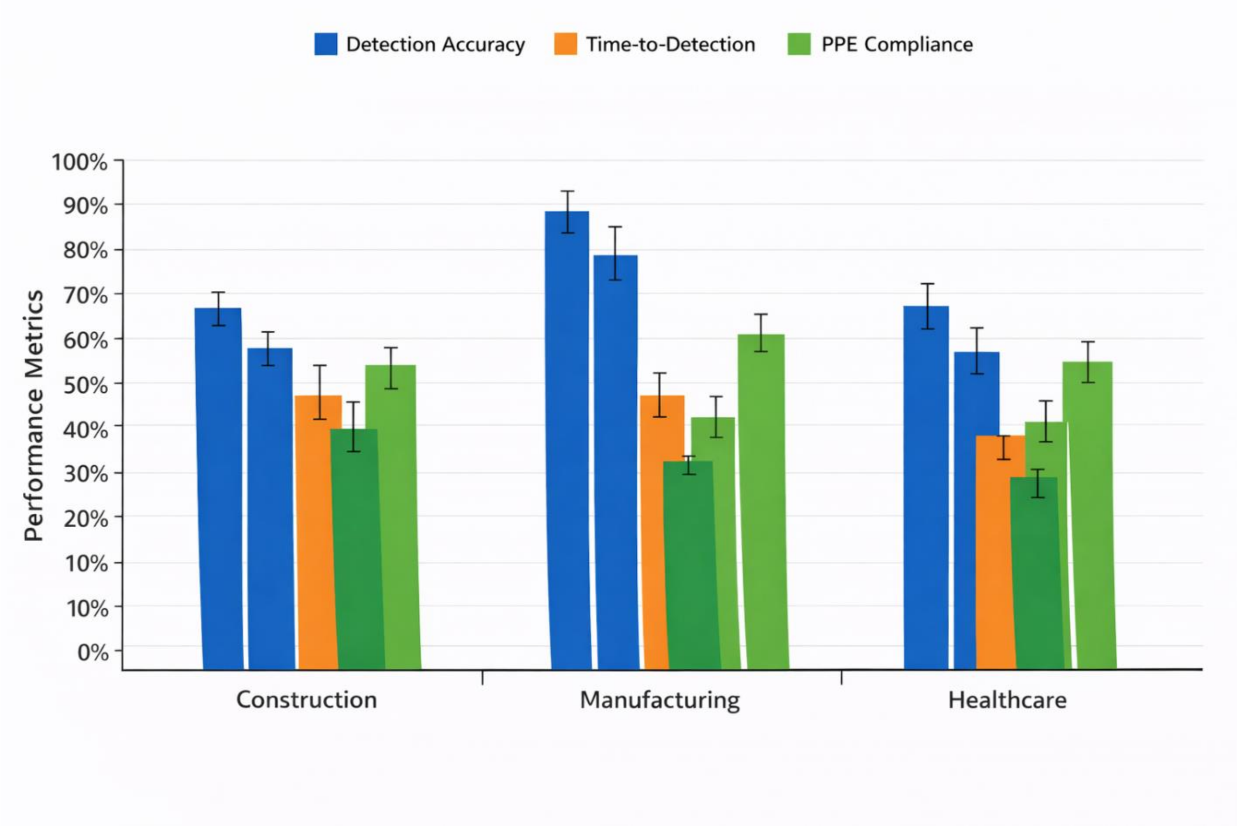
These findings align with prior research highlighting the impact of environmental factors on AI system performance (Guney et al., 2024).

*4.4 Figure Integration*

To illustrate the differences in YOLO-based hazard detection performance across sectors and to highlight the influence of environmental and operational conditions on system effectiveness, Figure 1 presents a comparative visualization of detection accuracy, response time, and compliance performance across construction, manufacturing, and healthcare environments.

**Figure 1**

*Cross-sector comparison of YOLO-based hazard detection performance*




*Note*. Author created. Performance metrics vary across sectors due to differences in environmental complexity, operational dynamics, and contextual factors. Manufacturing

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environments demonstrate the most stable performance, while construction environments exhibit the greatest variability.

As illustrated in Figure 1, the performance of YOLO-based hazard detection systems varies across sectors, reflecting the influence of environmental complexity and operational conditions on AI effectiveness. These findings demonstrate that while AI systems provide consistent improvements over manual inspection methods, their performance is not uniform across contexts. This variability underscores the importance of context-sensitive implementation strategies and reinforces the need for socio-technical alignment in the deployment of AI-enabled safety systems.

## 5. Discussion

These findings demonstrate that cross-sector variability in AI-enabled hazard detection systems is not solely a function of technical performance but is fundamentally shaped by socio-technical and organizational factors. Accordingly, the effectiveness of AI-based hazard detection systems depends on the alignment between technological capabilities and sector-specific conditions. While YOLO-based systems improve safety performance across all sectors, their effectiveness varies based on environmental complexity and operational dynamics.

These findings support socio-technical systems theory, which emphasizes the interaction between technology and environment (Carayon, 2006). The results also reinforce the importance of adaptive implementation strategies to maximize system effectiveness. Furthermore, the findings indicate that AI-enabled safety systems cannot be transferred uniformly across sectors without adaptation, reinforcing the need for context-specific implementation strategies.

Beyond sector-specific differences, these findings have direct implications for safety governance and organizational oversight. Variability in the implementation and performance of AI-enabled hazard detection systems across industries underscores the need for governance frameworks adaptable to diverse operational environments, risk profiles, and organizational structures. A uniform approach to AI-enabled safety governance may be insufficient, as sector-specific conditions influence how technologies are adopted, interpreted, and integrated into safety practices. Within the AI-Augmented Safety Governance Model (AASGM), these results demonstrate the importance of flexible governance architectures that can accommodate contextual variability while maintaining consistency in oversight, regulatory alignment, and data-driven decision-making.

### *5.1 Managerial and Organizational Implications*

The findings of this study have important implications for safety officers, plant managers, healthcare administrators, and regulatory decision-makers responsible for implementing AI-enabled safety systems. The observed variability across sectors suggests that organizations should avoid uniform deployment strategies and instead adopt context-sensitive implementation models aligned with operational conditions and workforce dynamics.

Manufacturing organizations may benefit from standardized AI deployment strategies due to relatively stable operational environments, whereas construction and healthcare settings may require adaptive implementation procedures, enhanced human oversight, and sector-specific governance controls. These findings also highlight the importance of organizational readiness, workforce engagement, and governance alignment in supporting the effective integration of AI-enabled hazard-detection systems across diverse operational environments.

## 6. Limitations

This study is subject to several limitations. First, the comparative analysis is based on selected industries and organizational contexts, which may not fully represent the diversity of operational environments across all sectors. Second, differences observed across sectors may be influenced by factors such as organizational size, resource availability, workforce characteristics, and varying levels of technological adoption, which may limit the direct comparability of results. Third, the study assumes a degree of consistency in how AI-enabled hazard detection systems are implemented and utilized; however, variations in deployment practices and system configurations may affect performance and integration outcomes. Future research should expand cross-sector analyses, incorporate additional industries, and examine the role of contextual variables in shaping the effectiveness and governance of AI-enabled safety systems.

## 7. Conclusion

This study demonstrates that AI-based hazard detection systems exhibit cross-sector variability influenced by environmental and operational factors. The findings highlight the need for context-sensitive implementation strategies and advance Safety 4.0 by emphasizing the role of socio-technical alignment in AI-enabled safety systems.

## 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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