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Toward an AI Safety Governance Maturity Model: Extending the AI-Augmented Safety Governance Model (AASGM) for Organizational Readiness and Implementation Capability

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Abstract

This manuscript extends the AI-Augmented Safety Governance Model (AASGM) by introducing an AI Safety Governance Maturity Model to assess organizational readiness and implementation capability for AI-enabled hazard-detection systems. The model defines five levels of maturity, ranging from manual safety systems to fully integrated, adaptive AI-driven safety governance frameworks. Drawing on empirical findings from YOLO-based hazard-detection systems and socio-technical systems theory, the model provides a structured approach to evaluating technological integration, human oversight, organizational alignment, and regulatory compliance. The maturity model supports organizations in transitioning from reactive safety practices to proactive, data-driven safety governance systems. The framework advances Safety 4.0 by providing a scalable tool for benchmarking and guiding AI implementation in occupational safety.

Keywords: AI maturity model; safety governance; AASGM; Safety 4.0; occupational safety; artificial intelligence; socio-technical systems

1. Introduction

The integration of artificial intelligence (AI) into occupational safety systems has created new opportunities for improving hazard detection and risk management. While technologies such as YOLO-based computer vision systems demonstrate strong performance in real-time hazard detection, organizations vary significantly in their ability to implement and sustain these systems effectively (Bourou et al., 2023; Nath et al., 2020).

Existing safety frameworks do not provide structured guidance for assessing organizational readiness for AI integration. As a result, organizations often face challenges related to governance, human oversight, and regulatory compliance when adopting AI-enabled safety systems.

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This paper addresses this gap by extending the AI-Augmented Safety Governance Model (AASGM) into a **maturity model** that defines progressive levels of AI integration and governance capability.

The research contributes to a broader research program advancing the AI-Augmented Safety Governance Model (AASGM) by introducing a maturity-based framework for the progressive integration of AI-enabled hazard-detection systems into organizational safety practices. Building on prior analyses of technical performance, human factors, socio-technical integration, governance frameworks, and regulatory alignment, this research outlines a structured set of stages for organizations to develop, implement, and optimize AI-enabled safety systems. The proposed maturity model provides a systematic pathway for transitioning from initial adoption to advanced, data-driven governance, enabling organizations to align technological capabilities with evolving safety, regulatory, and operational requirements.

Furthermore, the study builds on prior comparative and governance analyses by establishing a phased implementation framework to facilitate the practical deployment and scalability of AI-enabled safety systems. This framework provides a foundation for executive decision-making and strategic integration, which are explored in subsequent research within this coordinated research 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. Theoretical Foundation

The development of maturity models is well-established in both organizational and technological domains, providing structured frameworks for assessing capabilities and progression. Models such as NIST CSF and C2M2 demonstrate the value of maturity-based approaches in guiding implementation and benchmarking performance. The structure of this maturity model is informed by established capability and governance maturity frameworks, which conceptualize organizational progression as a staged evolution from reactive practices to optimized, data-driven decision-making systems. The staged progression structure of the proposed model is further informed by established capability maturity frameworks, including the Capability Maturity Model Integration (CMMI Institute, 2018), process maturity concepts introduced by Paulk (1995), and organizational risk-management principles reflected in ISO 31000 (ISO, 2018).

Socio-technical systems theory further emphasizes the need to align technological capability with human and organizational factors (Carayon, 2006). The integration of AI into safety systems requires coordinated development across these domains. Effective implementation of AI-enabled safety systems also depends on organizational trust, strategic alignment, and

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decision-support integration, which are consistent with prior research on trust in automation and strategic organizational performance management (Kaplan & Norton, 2004; Lee & See, 2004). Progression across maturity levels is driven by the organization's ability to integrate technological capabilities with governance structures, human oversight mechanisms, and regulatory alignment, reflecting an iterative, capability-dependent evolution rather than a linear transition.

3. AI Safety Governance Maturity Model

The proposed AI Safety Governance Maturity Model defines five progressive levels of organizational capability. At Level 1, Reactive Safety Systems, organizations rely primarily on manual inspections, exhibit limited data integration, and operate through reactive incident response mechanisms. At Level 2, Assisted Detection, basic AI tools are introduced, but integration remains limited, and decision-making remains predominantly human-driven.

At Level 3, Integrated AI Systems, artificial intelligence is embedded within operational workflows, resulting in improved hazard detection, enhanced reporting processes, and the establishment of structured human oversight mechanisms. At Level 4, Proactive Safety Governance, organizations leverage real-time monitoring and predictive risk management capabilities supported by well-developed governance frameworks that enable data-driven decision-making.

At Level 5, Adaptive AI Safety Ecosystem, organizations achieve full integration of AI-enabled safety systems, enabling continuous learning, system optimization, and dynamic alignment with regulatory and operational requirements. At this stage, governance structures evolve from compliance-focused oversight to strategically integrated systems that support executive-level decision-making through real-time data insights.

To provide a structured representation of organizational progression in AI-enabled safety systems and to illustrate how technological capability, governance, and human oversight evolve across implementation stages, Figure 1 presents the AI Safety Governance Maturity Model derived from the AASGM framework. The model highlights the transition from reactive safety practices to fully integrated, adaptive AI-driven safety ecosystems.

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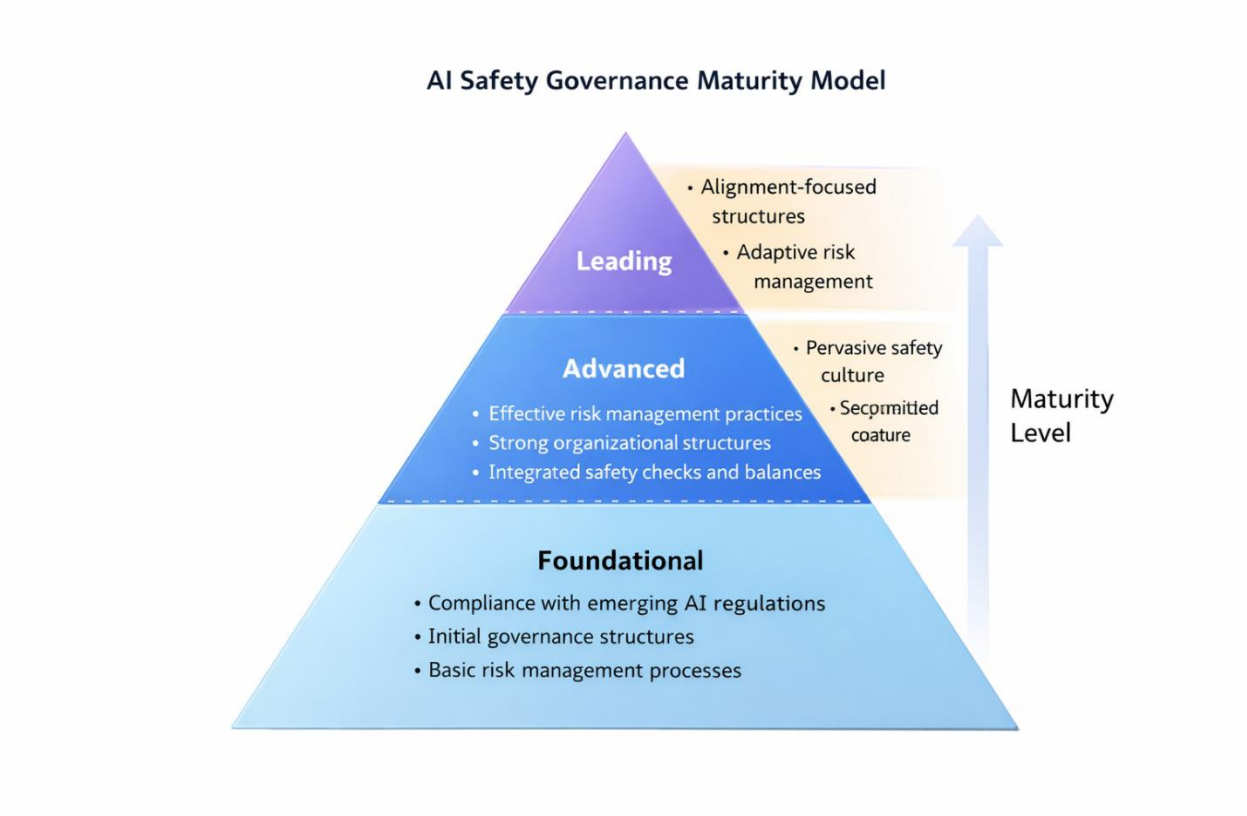
Figure 1

AI safety governance maturity model based on the AASGM framework



Note. Author created. The model illustrates five levels of organizational maturity in AI-enabled safety systems, progressing from manual, reactive approaches to fully integrated, adaptive AI-driven governance systems.

As illustrated in Figure 1, the progression from reactive safety systems to adaptive AI-driven ecosystems reflects increasing levels of technological integration, governance sophistication, and organizational alignment. The maturity model demonstrates that successful implementation of AI-enabled safety systems requires not only advanced detection capabilities but also the development of supporting governance structures, human oversight mechanisms, and regulatory alignment. This progression reinforces the AASGM's role as a foundational framework for guiding organizational transformation in occupational safety.

4. Discussion

The proposed maturity model provides a structured approach for assessing organizational readiness and guiding the implementation of AI-enabled safety systems. The model highlights

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the importance of aligning technological capability with governance and human factors, consistent with socio-technical systems theory (Carayon, 2006).

This maturity progression highlights that the effectiveness of AI-enabled safety systems is not solely dependent on technological capability, but on the organization's ability to integrate governance, human oversight, and decision-making structures into a cohesive operational framework. Organizations can use the model to benchmark their current capabilities and identify pathways to advance toward advanced safety governance systems.

5. Limitations

This study is subject to several limitations. First, the proposed maturity model is conceptual in nature and has not yet been empirically validated across diverse organizational settings. Second, organizations may progress through maturity stages at different rates depending on factors such as resource availability, leadership commitment, workforce readiness, and regulatory pressures, which may limit the model's uniform applicability. Third, the model assumes a degree of linear progression; however, real-world implementation may involve iterative development, regression between stages, or hybrid maturity states. Future research should focus on empirical validation of the maturity model, including case-based implementation, cross-sector evaluation, and the assessment of its effectiveness in supporting governance, regulatory alignment, and organizational decision-making.

6. Conclusion

This study introduces an AI Safety Governance Maturity Model that extends the AI-Augmented Safety Governance Model (AASGM) to support organizational readiness, implementation capability, and governance integration for AI-enabled safety systems. Unlike traditional maturity frameworks that primarily evaluate technological capability or process optimization, the proposed model integrates socio-technical alignment, human oversight, regulatory adaptation, and governance maturity into a unified implementation structure for occupational safety environments.

The model contributes to the advancement of Safety 4.0 by providing organizations with a scalable framework for assessing progression from reactive safety practices to adaptive, AI-driven governance ecosystems. In contrast to generalized capability maturity models, the proposed framework specifically addresses the operational, regulatory, and organizational complexities associated with AI-enabled hazard detection and real-time safety management.

By integrating technological capability with governance and implementation readiness, the maturity model provides organizations with a practical pathway for aligning AI-enabled safety systems with workforce needs, regulatory expectations, and evolving operational demands. Future research should focus on empirical validation, cross-sector implementation assessment,

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and the development of benchmarking metrics to support practical adoption across diverse organizational environments.

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.

Any use of external sources has been properly cited in accordance with APA 7 standards. The author affirms that the manuscript is free from plagiarism, duplication, or unauthorized reuse of prior publications.

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References

Carayon, P. (2006). Human factors of complex sociotechnical systems. *Applied Ergonomics*, *37*(4), 525–535.

CMMI Institute. (2018). *CMMI for development, version 2.0*. Carnegie Mellon University.

ISO. (2018). *ISO 31000: Risk management—Guidelines*. International Organization for Standardization.

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ISSN: 2456-3676

Kaplan, R. S., & Norton, D. P. (2004). Strategy maps: Converting intangible assets into tangible outcomes. Harvard Business School Press.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors, 46*(1), 50–80.

National Institute of Standards and Technology (NIST). (2024). *Cybersecurity framework (CSF) 2.0*. U.S. Department of Commerce.

Paulk, M. C. (1995). Capability maturity model for software. *Carnegie Mellon University Software Engineering Institute*.

Rasmussen, J. (1997). Risk management in a dynamic society: A modelling problem. *Safety Science, 27*(2–3), 183–213.

Shawe, R. (2025). From reactive to proactive: Artificial intelligence and predictive safety systems in OSHA-regulated environments. *International Journal of Advanced Engineering and Management Research, 10*(6), 78–92.

Shawe, R. (2025). Evaluating the efficiency of occupational safety and health systems in New York's small and mid-size enterprises. *International Journal of Advanced Engineering and Management Research, 10*(6), 226–241.

Wickens, C. D., Lee, J. D., Liu, Y., & Gordon-Becker, S. (2015). *An introduction to human factors engineering* (2nd ed.). Pearson.

Yousif, A., Al-Dahoud, A., & Al-Momani, A. (2024). Safety 4.0: The role of artificial intelligence in occupational safety systems. *Safety Science, 170*, 106356.