# Fostering AI-Human Collaboration in Industry 5.0 Manufacturing

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**Abstract.** In the transition to Industry 5.0, the integration of artificial intelligence (AI) with human-centric principles emerges as a pivotal strategy to enhance manufacturing efficiency and safety while minimizing human errors. This paper explores the symbiotic relationship between AI and human workers, leveraging wearable technology and real-time data collaboration to foster a harmonious environment. By analyzing existing literature and employing a methodology rooted in Industry 5.0 values, this study investigates how AI-driven systems can mitigate human errors without displacing human involvement. Results show that the use of an AI-powered model, utilizing machine learning algorithms to detect anomalies and proactively address risks, is promising to augment operational efficiencies. Moreover, the study extends existing research by incorporating a novel approach that combines STPA-PSO[1] modeling with machine learning, resulting in a dynamic system capable of continuous improvement. Discussion emphasizes the collaborative nature of AI, empowering human workers with intelligent tools while preserving creativity and enhancing working conditions. Ultimately, this research underscores the imperative for AI deployment to align with human-centric principles, fostering a synergistic relationship that propels manufacturing practices towards safer and more efficient outcomes in the Industry 5.0 era.

**Keywords:** Human error, Manufacturing, Machine-Learning, Industry 5.0.

## 1 Introduction

In the rapidly evolving landscape of manufacturing, the emergence of Industry 5.0 marks a paradigm shift towards a harmonious integration of artificial intelligence (AI) and human-centric principles. Industry 5.0 laid the groundwork for this transformation, emphasizing the role of intelligent machines in minimizing human error and enhancing operational efficiencies [1]. However, as we advance into the next industrial era, there is a growing recognition that technological innovation must not come at the expense of human involvement, creativity, and safety [2, 3]. Human errors pose challenges in manufacturing processes, and it is promising to leverage AI to mitigate these risks while maintaining human involvement [4, 5]. While previous industrial revolutions have

[1] STPA-PSO: Systems-Theoretic Process Analysis- Particle Swarm Optimization

introduced automation and interconnected systems, Industry 5.0 presents a unique opportunity to foster a collaborative environment where AI augments and supports human capabilities rather than supplants them. In manufacturing, human errors are being minimized to increase efficiency and safety. Researchers are working on ways to reduce human involvement by using AI to prevent errors [4].
This study aims to investigate the effective integration of AI with human-centered principles in manufacturing. By analyzing the potential of wearable technology, real-time data collaboration, and machine learning algorithms, we endeavor to develop a model that optimizes manufacturing processes while safeguarding against errors and prioritizing worker safety and creativity. By establishing a path towards harmonizing AI and human-centric principles, we endeavor to propel the manufacturing industry towards safer, more efficient, and sustainable practices in the Industry 5.0 era. The remainder of the paper is organized as follows: Section two provides the methodology employed in this study. Section three presents the AI-powered model proposed. Finally, section four delves into a comprehensive discussion, and presents the concluding remarks.

## 2 Methodology

Based on the core value of Industry 5.0, manufacturing should be human-centered. Data can be utilized by AI systems in order to enhance operational efficiency and reduce risks, including those associated with human error. A machine learning algorithm can identify patterns and anomalies indicating potential failures in machinery by analyzing data collected from sensors and other sources. Additionally, AI can provide real-time monitoring and alerts, enabling prompt action to be taken in case of any abnormalities or deviations from normal operating conditions. [6]. By utilizing machine learning and obtaining proper guidance, manufacturers are able to predict potential risks before beginning production, which prevents financial loss [7].
Building upon the of Karevan & Nadeau (2024) work, who introduced a novel STPA-PSO model to evaluate the risks associated with human error when using smart glasses to address human errors without removing humans from the equation [8], this study extends their research by integrating a machine-learning approach. In this paper, the primary objective is to design a roadmap for integrating a machine-learning algorithm into the methodology, rather than focusing on a specific type of algorithm. This methodology involves analyzing loss scenarios, systematically updating the entire model, and generating a new model structure with each iteration using the collected data. **Fig. 1** shows the base procedures of this work.
The STPA-PSO method begins with a comprehensive assessment, pinpointing losses, hazards, and system-level constraints. It progresses by constructing a functional control model, followed by the crucial task of identifying unsafe control actions. Next comes the assessment of model risk, and this results in the identification of loss scenarios. In this paper, a novel step is introduced, integrating a machine learning algorithm seamlessly into the process. This step is integral to each phase, gathering data continuously throughout. Leveraging this data, analysis is conducted to provide decision-makers -be they supervisors, workers, etc.- with actionable strategies to enhance the model or, in

simpler terms, to minimize the model's risks. **Fig. 1** illustrates the collaborative potential between humans and AI within this methodology. It highlights the synergistic interactions where human expertise guides the initial analysis and decision-making process, while AI enhances these efforts through advanced data processing and iterative learning.

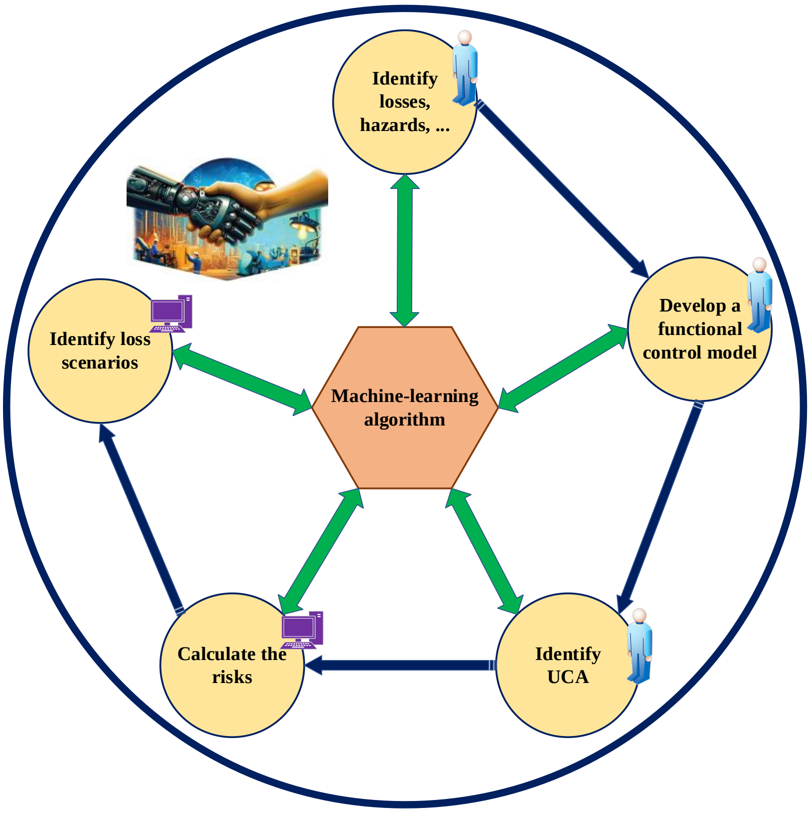


**Fig. 1.** Methodology Process

## 3 Results

To effectively utilize a reliable machine learning algorithm, it is essential to clearly define the relationships between each level of the methodology. This approach ensures a structured and comprehensible roadmap, facilitating accurate analysis and decision-making. Based on the results derived from using a smart wearable device in the assembly of a refrigerator, it is crucial to establish network connections between these outcomes. Identification of these connections is essential when using the STPA-PSO method. The process begins with the identification of loss scenarios. Following this, connections are established between these loss scenarios and their corresponding unsafe control actions. Next, connections are drawn to the responsible system-level constraints, followed by their associated hazards, and finally, the resulting losses. This

comprehensive mapping allows for tracing back from any high-risk event, thereby providing a clear overview from the origin to the conclusion of the model.
When the algorithm highlights a specific reason as having the most significant impact on a high-risk event, this mapped relationship network helps decision-makers understand how to mitigate these risks effectively. The connections and relationships illustrated in this methodology enable decision-makers to identify the primary causes of high-risk events and implement appropriate actions to reduce these risks.

**Table 1**- Losses and Hazards ([8])

| Losses | Hazards |
|---|---|
| L1: Injury to the worker. | H1: This hazard encompasses harmful activities such as ergonomic issues, limited field of view, distraction, and fatigue, which may lead to injuries among workers |
| L2: Unacceptable damage to the product. | H2: The hazard is related to insufficient training of workers, posing potential risks |
| L3: Unacceptable damage to the component and equipment. | H3: This hazard occurs when materials (parts) are not received on time, potentially causing delays |
| L4: Financial loss resulting from delayed operations. | H4: The hazard relates to the absence of timely feedback, potentially leading to operational inefficiencies |
| | H5: This hazard concerns the transmission or reception of wrong data, which could lead to various issues |

**Fig. 2** illustrates the mentioned connections, providing a visual representation of the methodology. Also, **Table 1**, **Table 2**, **Table 3** offer detailed definitions of each element used in **Fig. 2**. This structured approach ensures that all aspects of risk are comprehensively analyzed, aiding in the development of effective risk reduction strategies.

## 4 Discussion and Conclusions

This study highlights the critical integration of AI and human-centric principles within the framework of Industry 5.0, focusing on minimizing human errors and enhancing operational efficiency in manufacturing processes. By employing smart wearable devices and machine learning algorithms, particularly through the STPA-PSO method, it becomes evident that a structured approach can effectively map the relationships between loss scenarios, unsafe control actions, system-level constraints, hazards, and resulting losses. This comprehensive mapping not only facilitates a thorough risk analysis but also provides a clear framework for decision-makers to trace high-risk events back to their root causes, enabling targeted risk mitigation strategies.

**Table 2**- System level constraints ([8])

| | |
|---|---|
| SC1- Workers must be trained before starting their jobs to prevent harmful activities in the workplace | SC2- Supervisor must check the workers to ensure that they do not do harmful activities |
| … | … |
| SC15- Check connection between receiver and processor and smart glasses | SC16- Workers should know to report any errors or late feedback from smart glasses |

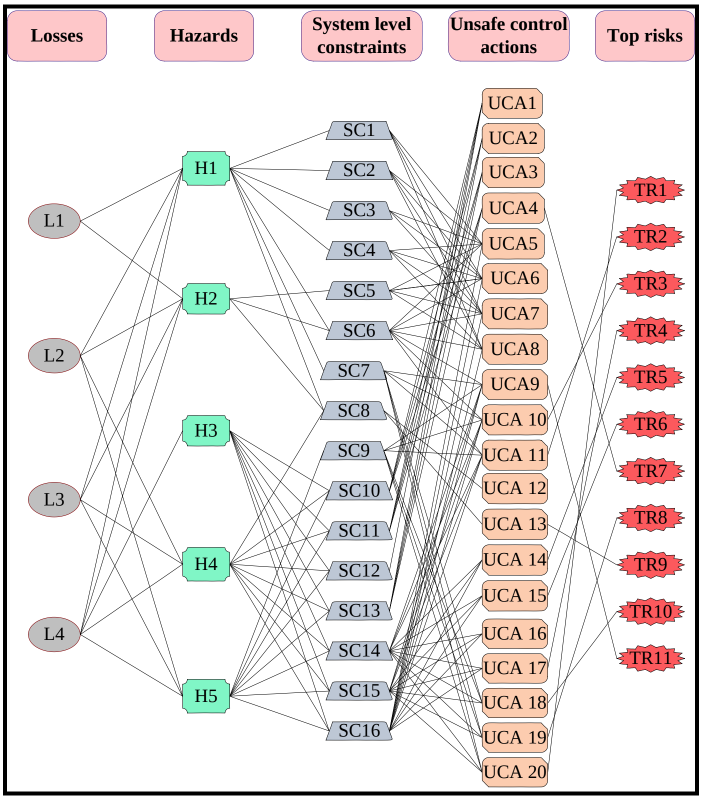


**Fig. 2**. STPA-PSO graph

**Table 3-** Unsafe Control Actions ([8]) – Top risk scenarios are demonstrated by ***

| | | | |
|---|---|---|---|
| UCA-1: The production planning department does not provide the production plan | UCA-6: The training department provides insufficient training for workers | ***UCA-11: Smart glasses provide feedback to the worker too late | UCA-16: The receiver and processor provide light commands too late |
| UCA-2: The production planning department provides a wrong production plan | UCA-7: The training department provides training late for workers | UCA-12: Smart glasses not calibrated before use | ***UCA-17: The receiver and processor provide light commands very quickly |
| UCA-3: The production planning department provides a plan too late | UCA-8: The training department stopped the training sessions too soon | ***UCA-13: Smart glasses calibrated incorrectly before use | ***UCA-18: The IT department does not provide programming for the receiver and processor |
| ***UCA-4: The production planning department stopped the previous plan too soon | ***UCA-9: The smart glasses do not provide feedback about the place of assembly to the worker | ***UCA-14: The receiver and processor do not provide light commands | ***UCA-19: The IT department provides wrong programming for the receiver and processor |
| UCA-5: The training department does not provide training for workers | ***UCA-10: Smart glasses provide wrong feedback to the worker | ***UCA-15: The receiver and processor provide wrong light commands | ***UCA-20: The IT department provides programming for the receiver and processor too late |

The practical implementation of a machine learning algorithm within this methodology underscores its potential to continuously update the risk model with real-time data, thereby refining risk assessments and decision-making processes dynamically. The approach aligns with Industry 5.0's core value of enhancing human capabilities by leveraging AI to support, rather than replace, human expertise. The structured roadmap, supported by continuous data analysis from AI, offers a robust framework for proactive risk management. The results indicate that this integration can significantly improve safety and operational efficiency, addressing the dual imperatives of maintaining human involvement and minimizing errors. Future research should explore the adaptability of this integrated approach across various manufacturing domains and consider advancements in AI and wearable technology to further refine risk assessments.

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